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Interactive Language-Based Agents

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ABSTRACT

Deep neural network architectures have led to remarkable achievements in the area of natural language processing (NLP) in recent years. Through scaling up the model size and self-supervised pre-training on the vast amount of textual data available on the internet, generalization and complex reasoning capabilities have been unlocked, even when provided with a small number of specific examples. However, most progress in NLP has been made based on a *static* learning paradigm where models are trained once on a fixed dataset to learn a specific skill and remain fixed after that. In this thesis, we turn our attention to *interactive agents* for NLP, i.e., language-based models that engage with a dynamic environment or user. Across three different application areas, (i) text-based games, (ii) query reformulation, and (iii) conversation, we investigate and develop agents interacting with different forms of adaptive environments.

The thesis is structured into three parts, reflecting the three application areas. In the first part, we develop a deep reinforcement learning (RL) agent for text-based games that generalizes across families of games that are similar in structure but with new objects and instructions.
The second part focuses on query reformulation, which we approach from two angles. First, we consider the *learning to search* problem where an agent is trained to interact with an information retrieval (IR) system using natural language. Observing the IR component's results, it adapts the initial user query and collects an improved set of evidence documents. Within this setting, we develop two agents learning successful interactive search strategies: one model trained by pure reinforcement learning and the other through (self-) supervised learning. In the subsequent chapter, we turn our attention to *neural* retrieval models and develop agents for interactive query suggestions. To this end, we train a *query decoder* model that, given a point in the shared paragraph-query embedding space, generates

the corresponding query in textual form. We employ this decoder to generate a synthetic dataset of directional query refinements, which we use to train a powerful reformulation model.

In the last part of the thesis, we propose different approaches to developing conversational agents. We suggest modularizing the architecture of dialogue models to output intermediate text sequences on which subsequent modules are conditioned. First, we show that generating the knowledge output as an intermediate step before the dialogue response can increase knowledge utilization and factual correctness in open-domain dialogue. Next, we develop a single model that sequentially generates (i) a search engine query, (ii) a knowledge output, and (iii) a final response. We show that it outperforms previous state-of-the-art dialogue models on knowledge-grounded conversation and, applied to topical prompt completions, improves upon models with a vastly larger number of parameters. Finally, we explore improving dialogue models after deployment and propose an objective that allows iteratively training a language model on binary labeled examples of its generations.

KURZFASSUNG

Tiefe neuronale Netze haben in den letzten Jahren zu bemerkenswerten Erfolgen auf dem Gebiet der Verarbeitung natürlicher Sprache (Natural Language Processing, NLP) geführt. Durch besser skalierbare Architekturen sowie der riesigen Menge an zur Verfügung stehenden Trainingsdaten im Internet, erlangen heutige Sprachmodelle beeindruckende Schlussfolgerungsfähigkeiten, selbst wenn nur eine kleine Anzahl spezifischer Beispiele zur Verfügung steht. Die meisten Fortschritte im Bereich von NLP wurden jedoch auf der Grundlage eines *statischen* Lernparadigmas erzielt, bei dem Modelle einmal auf einem fixen Datensatz trainiert werden, um eine bestimmte Fähigkeit zu erlernen, und danach unverändert bleiben. In dieser Arbeit richten wir unsere Aufmerksamkeit auf *interaktive Agenten* für NLP, d.h. Modelle, die mit einer dynamischen Umgebung oder einem Benutzer interagieren. In drei verschiedenen Anwendungsbereichen, (i) textbasierte Spiele, (ii) Umformulierung von Suchanfragen und (iii) Konversation, untersuchen und entwickeln wir Agenten, die mit adaptiven Umgebungen interagieren.

Die Dissertation ist in drei Teile gegliedert, basierend auf den drei genannten Anwendungsbereichen. Im ersten Teil entwickeln wir einen Deep Reinforcement Learning (RL) Agenten für textbasierte Spiele mit ähnlicher Struktur, aber unterschiedlichen Objekten und Anweisungen.

Der zweite Teil konzentriert sich auf die Umformulierung von Suchanfragen. Hier betrachten wir zunächst das Problem des *Lernen zu Suchen*, bei dem ein Agent trainiert wird, mit einem Informationsrückgewinnungssystem (Information Retrieval, IR) unter Verwendung natürlicher Sprache zu interagieren. Anhand der Ergebnisse der IR-Komponente passt er die ursprüngliche Benutzeranfrage an, um bessere Suchergebnisse zu finden. In diesem Rahmen entwickeln wir zwei Agenten, die erfolgreiche interaktive Suchstrategien erlernen:

ein Modell, das durch reines *reinforcement learning* (RL) trainiert wird, und das andere durch überwachtes Lernen (supervised learning). Im darauffolgenden Kapitel richten wir unsere Aufmerksamkeit auf *neuronale* IR Modelle und entwickeln Agenten für die Generierung von interaktive Suchvorschläge. Zu diesem Zweck trainieren wir ein *Query-Decoder*-Modell, das bei Vorgabe eines Punktes im gemeinsamen Paragraph-Suchanfrage-Einbettungsraum die entsprechende Suchanfrage in Textform generiert. Wir setzen diesen Decoder ein, um einen synthetischen Datensatz von Anfrageverfeinerungen zu generieren, den wir zum Trainieren eines leistungsstarken Reformulierungsmodells verwenden.
Im letzten Teil der Arbeit schlagen wir verschiedene Ansätze zur Verbesserung von Konversationsmodellen vor. Wir empfehlen, die Architektur zu modularisieren, um Zwischentexte auszugeben, auf denen die nachfolgenden Module aufbauen. Zunächst zeigen wir, dass die Generierung des Wissensoutputs als Zwischenschritt vor der Dialogantwort die faktische Korrektheit in Dialogen erhöhen kann. Anschließend entwickeln wir ein Modell, das nacheinander (i) eine Suchmaschinenanfrage, (ii) eine Wissensausgabe und (iii) eine endgültige Antwort erzeugt. Wir zeigen, dass dieses Modell bei wissensbasierter Konversation besser abschneidet als bisherige Dialogmodelle, und dass es, angewandt auf die Vervollständigung thematischer Texte, Modelle mit einer weitaus größeren Anzahl von Parametern übertrifft. Zum Schluss untersuchen wir die Verbesserung von Konversationsmodellen nach deren Einsatz und schlagen eine Verlustfunktion vor, die es ermöglicht, ein Sprachmodell iterativ auf binär markierten Beispielen zu trainieren.

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PUBLICATIONS

The following publications are at the core of my PhD research and hence covered in this dissertation:

1. Leonard Adolphs and Thomas Hofmann.
   "LeDeepChef: Deep Reinforcement Learning Agent for Families of Text-Based Games"
   AAAI 2020, [AH20]

2. Leonard Adolphs, Benjamin Börschinger, Christian Buck, Michelle Chen Huebscher, Massimiliano Ciaramita, Lasse Espeholt, Thomas Hofmann, Yannic Kilcher, Sascha Rothe, Pier Giuseppe Sessa, Lierni Sestorain.
   "Boosting Search Engines with Interactive Agents"
   TMLR 2022, [Ado+22c]

3. Leonard Adolphs, Michelle Chen Huebscher, Christian Buck, Sertan Girgin, Olivier Bachem, Massimiliano Ciaramita, Thomas Hofmann.
   "Decoding a Neural Retriever's Latent Space for Query Suggestion"
   EMNLP 2022, [Ado+22b]

4. Leonard Adolphs, Kurt Shuster, Jack Urbanek, Arthur Szlam, Jason Weston.
   "Reason first, then respond: Modular generation for knowledge-infused dialogue"
   EMNLP Findings 2022, [Ado+21]

5. Kurt Shuster, Mojtaba Komeili, Leonard Adolphs, Stephen Roller, Arthur Szlam, Jason Weston.
   "Language models that seek for knowledge: Modular search & generation for dialogue and prompt completion"
   EMNLP Findings 2022, [Shu+22a]

6. Leonard Adolphs, Tianyu Gao, Jing Xu, Kurt Shuster, Sainbayar Sukhbaatar, Jason Weston. "The Cringe Loss: Learning what language *not* to model"
   arXiv preprint 2022, [Ado+22a]

The following publications originated during my time as a PhD Student but are not covered in this dissertation:

7. Jonas Kohler, Leonard Adolphs, Aurelien Lucchi
   "Adaptive norms for deep learning with regularized Newton methods"
   NeurIPS Workshop: Beyond First-Order Optimization Methods in Machine Learning 2019, [KAL19]

8. Leonard Adolphs, Shehzaad Dhuliawala, Thomas Hofmann. "How to Query Language Models?"
   arXiv preprint 2021, [ADH21]

9. Shehzaad Dhuliawala, Leonard Adolphs, Rajarshi Das, Mrinmaya Sachan.
   "Calibration of Machine Reading Systems at Scale"
   ACL Findings 2022, [Dhu+22]

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1 INTRODUCTION

1.1 EVOLUTION OF NLP

Designing machines capable of understanding natural language is a long-standing goal of artificial intelligence (AI) research. The area of natural language processing (NLP) lies at the intersection of computational linguistics and computer science and attempts to bridge the communications gap between humans and machines (Foo19). Already in 1950, Alan Turing considered the question "Can machines think?" and devised the famous "imitation game" – now known as the Turing test (Tur50). To succeed in this test, a machine needs to engage in natural language conversation, indistinguishable from a human.

Approaches to NLP have been dominated by handwritten rules (Wei66; Win71; Leh81) until the 1980s, followed by statistical models until the 2010s (Bro+90; Koe05; Fer+10). In the 2010s, neural methods started to take over. Based on the *neural language model* idea (Ben+03) to embed words in a latent vector space, self-supervised methods have been developed that make use of the vast amount of training data that was starting to be available through the internet (Col+11; Mik+13; PSM14b). Subsequent work generalized these ideas and developed models that assign *contextualized* representations to words (Pet+18), making use of recurrent neural networks (RNN) (HS97). The proposed neural architectures scaled and generalized so well that they would quickly claim state-of-the-art across a range of NLP benchmarks, including question answering, sentiment analysis, named entity extraction, and textual entailment.

The Transformer (Vas+17) architecture broadly replaced RNNs as it allowed for larger-scale models that were shown to significantly boost performance on most NLP tasks. Devlin et al. [Dev+18]'s BERT model revolutionized the field by pre-training a large (transformer-based) language model on a huge corpus that can be fine-tuned to achieve then state-of-the-art performance on datasets like GLUE (Wan+18), SQuAD (Raj+16a; RJL18), and SWAG (Zel+18). It also surpassed the threshold to be widely applicable and useful in applications beyond academic tasks, e.g., in 2020 Google reported that *almost every* English-based query is powered by BERT (Sch20). Subsequent years in NLP research have been shaped by the quest for ever larger and more powerful language models (Rad+19; Yan+19b; Sho+19; Ros20; Raf+20a; Bro+20; Zha+22). Scaling limits have yet to be shown with models further generalizing and developing few-shot and even zero-shot capabilities with an increase in the number of model parameters (Bro+20; Zha+22). At the time of writing, large pre-trained language models are at the core of almost all specialized systems for individual NLP applications: from question answering (IG21b; Lew+20b), over machine translation (Raf+20b; TT20), to dialogue models (Shu+22b; Pen+22). In this thesis, we will use transformer-based pre-trained language models in all chapters except for Chapter 3 on text-based games.

PERFORMANCE IMPROVEMENT BEYOND SCALING As discussed above, increasing the number of parameters in a language model leads to significant reasoning and task-specific improvements. However, there is a limit on the information you can store in the weights of a model (RRS20). Moreover, the knowledge quickly becomes stale as it is frozen at the time of training – hence, it is not suitable for a dynamically changing world. Additional downsides observed in large language models are that they tend to *hallucinate* and generate factually incorrect yet plausible-sounding statements, challenging to recognize by humans (Shu+21a). Recently, it has been shown that adding an information retrieval (IR) component to a language model can alleviate these issues to some extent. Significant improvements have been made in the area of question answering using language models with neural-retriever-in-the-loop approaches (Lew+20c; IG21b). In conversational models, such methods lead to more knowledgeable agents that generate fewer hallucinations (Shu+21a). Yet, neural retrieval is usually done over a knowledge collection that is not updated and is small in size compared to the information available on the internet. Hence, Komeili et al. [KSW22] propose to use an internet search engine as an intermediate step of a conversational model. This ensures access to continually updated information. The model generates a search query to obtain results and uses those to generate knowledgeable and factually-correct responses. At the time of writing, state-of-the-art conversational models, as well as question-answering models, rely on intermediate knowledge retrieval steps from an external source (IG21b; Shu+22b; Pen+22).

This thesis investigates multiple approaches to improving task-specific language-based models beyond scaling the number of parameters. In Chapter 4 and 5, we focus on information retrieval components that interactively reformulate the query and can lead to better search results. In Chapter 6 and 7, we investigate approaches to improve conversational agents with access to IR components. More specifically, in Chapter 6, we propose to modularize the reasoning and the response generation step of dialogue models and show that this can further decrease hallucination in neural-retriever-in-the-loop approaches. In Chapter 7, we extend the modularization idea to language models using an internet search engine step. We show that it outperforms previous dialogue models regarding knowledgeability and consistency and, applied to topical prompt completion, outperforms models that are more than two orders of magnitude larger.

1.2 INTERACTIVE AGENTS

The term *interactive* is defined as "involving the actions or input of a user" (Dic). We understand *interactive agents* as models that engage with some form of environment during training or inference. The environment in this setting can be a human user or another system. This definition covers various possible applications, from dynamic (game) environments, to conversational models considering the user's utterance, and training procedures with a human in the loop. Yet, as described in the previous section, many successful NLP models are trained once on a large static dataset and remain fixed after that. This leaves a research gap to design and develop agents capable of adapting to a dynamically changing environment or user. We want to evolve methods beyond the *static* learning paradigm where predictions are made based on a fully observed initial state. This is an essential direction for NLP research because most real-life scenarios are partially-observable problems where not all context is available a priori. Take the example of an ordinary dialogue between two humans that meet for the first time: it involves an inevitable back-and-forth between the two parties until each has built an approximate theory of mind (FF05) of the partner to engage in a meaningful discussion. Even answering a supposedly simple question about, e.g., a person's birthplace, changes from *Mannheim* to *close to Frankfurt* to *southern Germany*, depending on the information gathered about the dialogue partner and the constructed model of their mind (here, in particular, their geographical knowledge about Germany). Despite its importance in real-world tasks, the interactivity of systems is not reflected in most popular NLP benchmarks (Wan+18; Wan+19). In this work, we draw our attention to three different areas of interactive NLP, reflected in the three parts of this thesis:

TEXT-BASED GAMES AGENTS With text-based games (TBG), we have a restricted world environment in which we train agents to navigate and solve tasks through interaction. The motivation for this research area is to develop methods to solve games with increasingly complex dynamics until they are usable outside the game engine on real-world user tasks.

QUERY REFORMULATION AGENTS In the second part of the thesis, we focus on query reformulation. Here, the *environment* with which the agent interacts is a (neural) information retrieval system. In Chapter 4 and 5, we investigate interactive search with query reformulation from two different angles. First, we train agents to modify the user's query by interacting with the (non-neural) IR component and gathering improved search results. In the next chapter, we extend part of this work to neural retrieval systems and train a query suggestion model capable of proposing improved search queries to the user after interacting with the search engine.

CONVERSATIONAL AGENTS The last part of the thesis considers conversational agents, which are naturally interactive as the agent has to adapt at each turn based on the user's previous utterance. In Chapter 6, we propose to modularize models for dialogue generation and split the knowledge and response generation parts. This not only improves the issue of hallucination but also allows for interactive updates, information injection in the intermediate steps, and more

interpretable generations. The following chapter extends this idea and adds a modular search engine step.
In Chapter 8, we investigate continuous learning of dialogue models. As described in Section 1.1, NLP models recently crossed a line to be useful in real-world applications. With neural machine translation (Dee21), internet search (Sch20), conversational agents (Shu+22b), and general text completion (Ope22), we see that large language models are starting to be used in production. The promise of machine learning over heuristics and rule-based methods is that it learns from data and interactions. Yet only recently, there has been more work on utilizing the feedback from users (Ouy+22b; Xu+22; Shi+22). We follow this line of research in Chapter 8 and propose an interactive method to continuously train a conversational agent on its own positive and negative generations.

This thesis aims to contribute to interactive language-based agents. We focus on the three identified NLP research areas, yet many of the approaches developed are more generally applicable.

1.3 ORGANIZATION AND SUMMARY OF CONTRIBUTIONS

This section gives an overview of the content of the following chapters of the thesis. We provide summaries of the contributions we made towards interactive language-based agents for each area.
As explained in the previous section, this thesis is structured into three parts corresponding to different areas of application for interactive language-based agents: (i) text-based games, (ii) query reformulation, and (iii) conversation. We first give a general background on relevant topics in Chapter 2 before diving into each of the three parts.

Part I: Text-Based Games Agents

In the first part of the thesis, we focus on agents situated in text-based games (TBG).

CHAPTER 3 We present our agent *LeDeepChef* that was ranked second in the "First TextWorld Problems: A Language and Reinforcement Learning Challenge". The games from the challenge all share the same theme, namely cooking in a modern house environment, but differ significantly in the arrangement of the rooms, the presented objects, and the specific goal (recipe to cook). To build an agent that achieves high scores across a whole family of games, we use an actor-critic framework and prune the action space by using ideas from hierarchical reinforcement learning and a specialized module trained on a recipe database. To design a successful agent, we make the following contributions:

- We design an architecture that uses different parts of the context to rank a set of commands. Through recurrency over time steps, we construct a model that is aware of the past context and its previous *decisions*.

- We improve generalization to unseen environments by abstracting away standard to *high-level* commands similar to feudal learning approaches (DH93). We show that this reduces the action space and therefore accelerates and stabilizes the optimization procedure.

- We incorporate a task-specific module that predicts the missing steps to complete the task. We train it supervised on a dataset based on TextWorld recipes augmented with a list of the most common food items found in freebase to make it resilient to unseen recipes and ingredients.

We make the code to train the agent publicly available at https://github.com/leox1v/FirstTextWorldProblems.

Part II: Reformulation Agents

The second part of the thesis considers the task of query reformulation from two different angles, reflected in the individual chapters.

CHAPTER 4 We develop search agents that learn meta-strategies for iterative query refinement in information-seeking tasks. Here, refinements are considered augmentations to the original query that typically specify or generalize the query to obtain improved retrieval results. Our approach uses machine reading to guide the selection of refinement terms from aggregated search results. Agents are then empowered with simple but effective search operators to exert finegrained and transparent control over queries and search results. In this setting, we make the following contributions:

- We develop a novel way of generating synthetic search sessions that allow us to successfully learn (self-)supervised search agents based on transformer-based language models.
- We develop a reinforcement learning agent with dynamically constrained actions that learns interactive search strategies from scratch.
- We provide evidence for the ability of search agents to discover successful search policies in a task characterized by multi-step episodes, sparse rewards, and high-dimensional, compositional action spaces.

We make the code to train the agents publicly available at https://github.com/google-research/google-research/tree/master/muzero and https://github.com/google-research/language/tree/master/language/search_agents.

CHAPTER 5 In this chapter, we extend the learning to search problem to neural retrieval models and focus on the application of query suggestion, i.e. generating rewrites of the original query to better capture the user's information need. Neural retrieval models have superseded classic bag-of-words methods such as BM25 as the retrieval framework of choice for many NLP tasks. However, neural systems lack the interpretability of bag-of-words models; it is not trivial to connect a query change to a change in the latent space that ultimately determines the retrieval results. To shed light on this embedding space and make progress towards the task of query suggestion, we make the following contributions in this chapter:

- We learn a *query decoder* that, given a latent representation of a neural search engine, generates the corresponding query. We show that it is possible to decode a meaningful query from its latent representation and, when moving in the right direction in latent space, to decode a query that retrieves the relevant paragraph. In particular, the query decoder can be useful for understanding "what should have been asked" to retrieve a particular paragraph from the collection.

- Based on the query decoder, we develop a generic way to generate training data for directional query refinement by traversing the latent space between queries and relevant documents.
- We build a powerful reformulation model that we evaluate on a novel benchmark inspired by the query suggestion task.

We make the generated traversal dataset publicly available at `https://github.com/leox1v/query_decoder`.

Part III: Conversational Agents

In the final part of the thesis, we draw our attention toward conversational agents. The first two chapters of this third part are concerned with modularizing the architecture of dialogue models and generating intermediate outputs. The third chapter focuses on the continual learning of conversational agents.

CHAPTER 6 We address the common phenomenon that large language models can produce fluent dialogue but often hallucinate factual inaccuracies (Shu+21a). These models face the difficult challenge of both reasoning to provide correct knowledge and generate conversation simultaneously. Hence, we propose a modular model, Knowledge to Response (K2R), for incorporating knowledge into conversational agents, which breaks down the problem into two easier steps. In particular, we make the following contributions in this chapter:

- We develop the K2R model that first generates a knowledge sequence, given a dialogue context, as an intermediate step. After this *reasoning step*, the model then attends to its own generated knowledge sequence, as well as the dialogue context, to produce a final response.
- We conduct extensive experiments across three different datasets and tasks. We find that the model improves knowledge utilization and factual correctness in open-domain dialogue. Furthermore, it allows us to fuse pre-trained QA models with dialogue models, without requiring any re-training.

We make the agent's code publicly available at `https://parl.ai/projects/k2r`.

CHAPTER 7 In this chapter, we extend the K2R approach to include internet search as a module. In particular, we make the following contributions in this chapter:

- We propose the SeeKeR (Search-engine→Knowledge→Response) method that applies a single language model to three modular tasks in succession: search, generating knowledge, and generating a final response.
- We show that using SeeKeR as a dialogue model, it outperforms the previous state-of-the-art model BlenderBot 2 [Che+21b] on open-domain knowledge-grounded conversations for the same number of parameters, in terms of consistency, knowledge, and per-turn engagingness.
- SeeKeR applied to topical prompt completions as a standard language model outperforms GPT2 [Rad+19], and GPT3 [Bro+20] in terms of factuality and topicality, despite GPT3 being a vastly larger model.

We make the agent's code and checkpoints available at http://parl.ai/projects/seeker.

CHAPTER 8 The final chapter in the conversational agent part focuses on iteratively training models to unlearn unwanted behavior. Standard language model training employs gold human documents or human-human interaction data and treats all training data as positive examples. Growing evidence shows that even with very large amounts of positive training data, issues remain that can be alleviated with relatively small amounts of negative data – examples of what the model should not do. Towards this problem, we make the following contributions in this chapter:

- We propose a novel procedure to iteratively train with data of negative examples called the CRINGE loss (ContRastive Iterative Negative GEneration). We introduce a simple additional term to the loss function for training with negative sequences, not requiring any architectural change of the model or inference-time update.

- We show the effectiveness of this approach across three different experiments on the tasks of safe generation, contradiction avoidance, and open-domain dialogue.

We make the agent's code publicly available at `https://parl.ai/projects/cringe`.

In the conclusion Chapter 9, we do a final reflection on the topics discussed in the thesis and provide an outlook on the directions of future research in the field.

2 BACKGROUND

2.1 TEXT-BASED GAMES

A Text-based game (TBG) is a special computer game where the sole interaction modality is text. In an iterative process, the player issues commands in natural language and, in return, is presented with a (partial) textual description of the environment. The player works towards goals that may or may not be specified explicitly and receives rewards upon completion. To frame it more formally, both the observation and action space are comprised of natural language and, thus, inherit its combinatorial and compositional properties (Côt+18). Training an agent to succeed in such games requires overcoming several common research challenges in reinforcement learning (RL), such as partial observability, large and sparse state and action space, and long-term credit assignment. Moreover, the agent needs several human-like abilities, including understanding the environment's feedback (e.g., realizing that some command did not affect the game's state), and common sense reasoning (e.g., extracting affordance verbs to an object in the game) (Ful+17).

While TBGs reached their peak of popularity in the 1980s with games like Zork (Inf80), they provide an interesting test-bed for AI agents today. Due to the dialog-like structure of the game and the goal to find a policy that maximizes the player's reward, they show great similarity to real-world tasks like question answering and open dialogue generation. Games like Zork are usually contained in a single environment requiring various complex problem-solving abilities. This thesis focuses on Microsoft's TextWorld framework (Côt+18). Unlike Zork, it generates a family of games with different worlds and properties but with straightforward and, most importantly, similar tasks. Therefore, one can argue that it is more similar to human skill acquisition: once learned, a skill can also be performed in a slightly different environment or with new objects (YM19b).

Text-based games can be divided by their type of input interaction: (i) parser-based, where the agent issues commands in free form, and (ii) choice-based, where the agent is presented with a set of admissible commands at every turn. Assuming a fixed maximum length of the commands as well as a fixed-size vocabulary, a parser-based game is a special instance of a choice-based game with the set of all possible combinations of words in the vocabulary as the set of admissible commands. This illustrates the problem arising from combinatorial action spaces: they result in a huge set of possible options for the agent, which it cannot possibly explore in a reasonable amount of time. Hence, the major challenge is the generation of a small set of *reasonable* commands for a given context, known as *affordance generation*.

Since the pioneering work of Mnih et al. [Mni+13a] that combines deep neural networks with reinforcement learning techniques to successfully play Atari games, there has been an increasing interest in modifying these algorithms for a variety of problems. However, applying it to natural language tasks is particularly challenging due to its combinatorial and compositional properties, resulting in huge action and state spaces. Text-based games are regarded as a good testbed for research at the intersection of RL and NLP (Côt+18). Even though they heavily simplify the environment – compared to, e.g., a real-world open dialogue – they present a broad spectrum of challenges for learning algorithms.

2.2 QUESTION ANSWERING

Building models to answer natural language questions has a rich history in NLP research (VOO01; DKL+07; BGA20). The question-answering (QA) task is typically divided along two different axes:

(i) Extractive vs. Generative QA: In the *extractive* QA setting, the answer to the posed question is a span that can be extracted from a provided evidence paragraph. This setting is often referred to as machine reading comprehension. On the other hand, the *generative* QA setting requires the model to generate a response as free text.

(ii) Evidence Context: QA settings can be distinguished by the property of whether or not the question is provided with an evidence document. Throughout this thesis, we will focus on the setting where no specific evidence paragraph is provided, but a large collection of documents is provided in the form of a knowledge store or search engine (LCT19a; Kar+20).

The Stanford question answering dataset (SQuAD) (Raj+16b) has nourished the research on extractive QA models. Here, the evidence for each question is provided as a short paragraph, and the answer can be extracted as a span from it. Many sophisticated extractive QA models have been proposed that ultimately surpassed human performance on SQuAD (Dev+19; Yan+19b). The SQuAD2.0 dataset (RJL18) adds adversarially-constructed questions that are not answerable given the provided context. A model needs to learn to avoid answering specific questions to succeed.

With the Natural Questions (NQ) dataset (Kwi+19), Google released an open-domain question-answering dataset from real user search queries. Each question comes with a full Wikipedia article, as opposed to a short passage in SQuAD, and can be answered by a paragraph (long answer) or a short span (short answer). While this is technically still an extractive QA dataset, it was adapted to reflect an open generative QA task without evidence contexts. Lee et al. [LCT19a] and Karpukhin et al. [Kar+20] construct NQ-derived datasets (OpenNQ) without supporting articles or passages. Those datasets require models to both successfully retrieve paragraphs from a large collection and extract the correct answer.

Consequently, research on the QA task's retriever (search engine) side thrived. Chen et al. [Che+17a] retrieve Wikipedia evidence paragraphs based on bigram hashing and TF-IDF. Lee et al. [LCT19a] and Karpukhin et al. [Kar+20] propose neural retrievers based on a dual encoder framework instead of the classic bag-of-words IR approaches. Leveraging large pre-trained language models to encode the query and the paragraphs separately into a shared latent space led to a performance boost across multiple datasets, not just in the retrieval metrics but also in exact-match scores. While Karpukhin et al. [Kar+20] use an extractive reader on the top-k returned paragraphs, Lewis et al. [Lew+20c] further improve using a generative reader (BART (Lew+20a)). This design combines the strengths of a parametric memory – the pre-trained LM – with a non-parametric memory – the retrieved Wikipedia passages supplied into the reader's context. This idea of combining a dense retriever with a generative reader is further refined by Izacard and Grave [IG21b], who fuse multiple documents in the decoding step. A recent line of work is concerned with constraining the model in terms of the number of parameters or retrieval corpus size while remaining close to state-of-the-art performance (Min+21). This effort led to a synthetic dataset of 65 million *probably asked* questions (Lew+21b) used to do a nearest neighbor search on the question, with no learned parameters needed.

2.3 NEURAL RETRIEVER

Classic retrieval systems such as BM25 (RZ09) use term frequency statistics to determine the relevancy of a document for a given query. Recently, *neural* retrieval models have become more popular and started to outperform classic systems on multiple search tasks. Karpukhin et al. [Kar+20] use a dual-encoder setup based on BERT-base (Dev+19), called DPR, to encode query and documents separately and use maximum inner product search (SL14) to find a match. They use this model to improve recall and answer quality for multiple open-domain question-answer datasets, including OpenQA-NQ (LCT19b). Ni et al. [Ni+21] show that scaling up the dual encoder architecture improves the retrieval performance. They train a shared dual encoder model, based on T5 (Raf+20a), in a multi-stage manner, including fine-tuning on MSMarco (Ngu+16), and evaluate on the range of retrieval tasks of the BEIR benchmark (Tha+21). Izacard et al. [Iza+21] show that one can train an unsupervised dense retriever and be competitive against strong baselines on the BEIR benchmark. Xiong et al. [Xio+21a] propose approximate nearest neighbor negative contrastive learning (ANCE) to learn a dense retrieval system. On top of this dense retriever, Li et al. [Li+22] consider a pseudo-relevance feedback method.

APPLICATIONS OF NEURAL RETRIEVERS Neural retrieval models have been at the core of recent improvements in various NLP tasks. As described in the previous paragraph, Lee et al. [LCT19a] and Karpukhin et al. [Kar+20] use neural retrievers to answer open-domain questions. Lewis et al. [Lew+20c] and Izacard and Grave [IG21b] further improve upon these methods by fusing the neural retrieval and answer generation components. Answering questions by abstractive generation, instead of extracting spans from the text, boosts the performance on OpenNQ(IG21b). Shuster et al. [Shu+21a] use neural retrieval models to improve conversational agents in knowledge-grounded dialogue. They show that the issue of hallucination – i.e., generating factual incorrect knowledge statements – can be significantly reduced when using a neural-retriever-in-the-loop architecture. We show in Chapter 6 and 7 that separating the retrieval-augmented knowledge generation and the conversational response generation can further improve the issue of hallucination in knowledge-grounded dialogue and helps fuse modular QA and dialogue models.

SHORTCOMING OF NEURAL RETRIEVERS Embedding queries and passages in a joint latent space and ranking them based on their vector similarity is a powerful approach to finding semantic similarities between queries and documents. However, compared to classic methods based on term-frequency statistics, the results lack certain interpretability. For a bag-of-words method, it is trivial to compose a query to retrieve a specific passage – one needs to match descriptive (high tf-idf) keywords available in the passage. For a neural model, on the other hand, this is much more complex. Adding a term to the model's input might change its encoding in unpredictable ways and retrieve different passages. Hence, connecting a query change to an updated document set is non-trivial. In Chapter 5, we will investigate how to decode the latent space of a neural retriever and hence increase the interpretability property of neural retrievers.

2.4 QUERY REFORMULATION

LEARNING TO SEARCH Can machines learn to use a search engine as an interactive tool for finding information? Web search is the portal to a vast ecosystem of general and specialized knowledge designed to support humans in seeking relevant information and making wellinformed decisions. Utilizing search as a tool is intuitive, and most users quickly learn interactive search strategies characterized by sequential reasoning, exploration, and synthesis (Hea09; RFC15; Rus19). The success of web search relies on machines learning human notions of relevance but also on the users' ability to (re-)formulate appropriate queries grounded in a tacit understanding of the strengths and limitations of search engines. Given recent breakthroughs in language models (LM) (Vas+17; Dev+19; Bro+20) as well as in reinforcement learning (RL) (Mni+13b; Sil+16; Ber+19), it seems timely to ask *whether*, and *how*, agents can be trained to use search engines interactively. However, the lack of expert search sessions puts supervised learning out of reach, and RL is often ineffective in complex natural language understanding (NLU) tasks. The feasibility of autonomous search agents hence remains an open question.

It has been a powerful vision for more than 20 years to design search engines that are intuitive and simple to use. Despite their remarkable success, search engines are imperfect and may not yield the most relevant result(s) in one shot. This is particularly true for rare and intrinsically difficult queries, which may require interactive exploration by the user to be answered correctly and exhaustively.

It can be difficult for users to formulate effective queries because of the information gap that triggers the search process in the first place (BOB82). O'Day and Jeffries [OJ93] found that reusing search results content for further search and exploration is a systematic behavior (aka "orienteering"), a key ingredient for solving the information need. Lau and Horvitz [LH99] analyzed a dataset of one million queries from the Excite search engine logs and reported an average session length of 3.27 queries per informational goal and categorized follow-up queries primarily in terms of specification, generalization, and reformulation. Teevan et al. [Tee+04] noticed that users facing complex queries could even decide to partially bypass the search engine by issuing a more general query and then navigating the links within the returned documents to find an answer. Downey et al. [Dow+08] observed that a user's initial query is typically either too specific or too general. The amount of work required to optimize it depends on the query frequency, with infrequent queries requiring longer search sessions. They estimate from logs that tail information needs require more than four queries, while common ones require less than two (on average). Contextual query refinement is a common

technique (JBS09), even among children (RFC15), used to improve search by combining evidence from previous results and background knowledge (HE09). Such refinements often rely on inspecting result snippets and titles or skimming top-ranked documents' content. This process is iterative and may be repeated until (optimistically) a satisfactory answer is found.
It seems natural to envision artificial search agents that mimic this interactive process by learning the basic step of generating a follow-up query from previous queries and their search results while keeping track of the best results found along the way. We call this the *learning to search* problem that we investigate in more detail in Chapter 4.

QUERY SUGGESTION As motivated above, many search engine users need to issue additional clarification queries to retrieve results that satisfy their information needs. While an interactive search engine, as described in Chapter 4, might help alleviate this problem, it is limited by the expressiveness of the original search query: for an ambiguous query (e.g., "us open champion"), it can only rely on learned biases to retrieve the correct results (e.g., for the sport of tennis over golf), or try to mix results for all possible meanings. From a user's perspective, this might not be ideal, as a simple clarification from their side would resolve the problem and hence lead to the desired search results. A good search engine should be capable of proposing improved search queries based on the retrieved documents from the user's query. In our *us open* example, it should observe that the retrieved results are mixed between *tennis* and *golf* and propose, e.g., "us open champion tennis" and "us open champion golf" as follow-ups to the user. We refer to this problem as *query suggestion* and address it in more detail in Chapter 5. Since query suggestion is most relevant for ambiguous or misspecified queries, it is closely related to the task of rewriting ill-formed questions (Chu+20).

2.5 CONVERSATIONAL AGENTS

SCALING-UP CONVERSATIONAL AGENTS Building an open-domain conversational model is a long-standing challenge in NLP research (Che+17b; GGL18). With the introduction of the Transformer (Vas+17) architecture as a building block for large language models, the scale and capabilities of dialogue models have risen rapidly. In the diagram of Figure 2.1, we show the number of parameters of the best dialogue models over time. In only a few years, models have scaled up from the 762M parameters of DialoGPT (Zha+20) in 2019 to the 9B parameter model BlenderBot (Xu+20) in 2020, and most recently in 2022, to up to 175B parameter of GODEL (Pen+22) and Blenderbot 3 (Shu+22b).

KNOWLEDGE-AWARE CONVERSATIONAL AGENTS Conversational agents are typically trained on large datasets of human-human conversations. Hence, the model only learns from a single snapshot of time. It results in a static language model saving all its knowledge in its fixed parameters that do not account for the dynamics of the real world. Thus, it is prone to produce stale results leading to an unsatisfying user experience when confronted with current topics. Improving dialogue systems by increasing their knowledgeability has been tried in several different ways: from integrating knowledge bases (Zhu+17; Liu+18; Wan+20), to recent neural retrieval models (Shu+21a; Thu+21). Knowledge-grounded open-domain dialogue datasets (Din+19b; KSW21; ZPB18; Gop+19) foster the research and development of knowledge-aware generative dialogue models. A known issue of such models, referred to as "hallucination", is that they mix up facts and generate factually inaccurate statements. Shuster et al. [Shu+21a] try to alleviate hallucination by using recent advancements in retrieval-augmented generative models developed for open-domain QA tasks (Lew+20b; IG21b).
BlenderBot 2 (Che+21b) learns to generate search queries based on the conversational history and grounds its utterances based on the search results. This intermediate search step makes the model more knowledgeable and factually consistent than its predecessor, even though it has fewer parameters. Subsequent dialogue models, like LaMDA (Tho+22), BlenderBot 3 (Shu+22b), and GODEL (Pen+22) all make use of some form of external knowledge base that is queried before generating a response.

FUSION OF QA AND CONVERSATION Previous work has explored the intersection of QA and dialogue models from multiple different angles. The DREAM dataset (Sun+19) consists of multiple-choice questions about a conversation. Yang and Choi [YC19] propose a question-

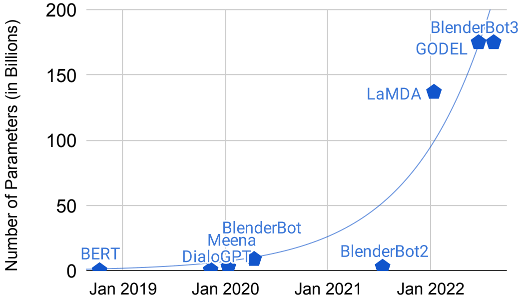


Figure 2.1: The number of parameters (in billions) over the years for the top dialogue models. We add BERT in the diagram as reference.

answering task based on dialogue histories of the TV show *Friends*. The QuAC (Cho+18) and CoQA (RCM19) datasets are designed to have the questions asked in the conversational flow, with possibly, multiple follow-ups. However, while these datasets require a model to understand a dialogue's history, the target responses are short-form answers. Therefore, these tasks do not train a dialogue model that generates an engaging, conversationally appropriate response; instead, they result in a QA model that understands dialogue-structured context. In Chapter 6 and 7, we investigate how to bring QA capabilities to dialogue models and propose a modular architecture that first generates a knowledge response on which the model conditions its final dialogue response. The proposed architecture is used in the BlenderBot3 (Shu+22b) model – a state-of-the-art publicly-available conversational model at the time of writing.

ITERATIVE TRAINING OF LANGUAGE MODELS Despite the remarkable gain in performance, conversational models still suffer from a number of issues, including offensive language (Geh+20), inherent biases (Din+20), repetition (Wel+19), and lack of long-term coherence (Nie+21). These problems can partially be attributed to the training method: models are tasked with learning from human-human conversations on the internet. Hence, they inherit their toxic and biased behavior. To address the named issues, new forms of training are developed that focus on iteratively unlearning unwanted behavior by training the model with negative examples. Unlikelihood training was shown to improve repetition issues by training on the model's own generations [Wel+19]. Iterative training of language models on human preferences has been successfully applied in several summarization (Zie+19; Sti+20; Böh+19; Wu+21) and dialogue settings (Jaq+19; Han+19). Lu et al. [Lu+22] train a language model to unlearn unwanted behavior using generated samples. They label and quantize the model's generations and perform conditional training by prepending the sequences with their corresponding reward token. The InstructGPT model (Ouy+22b) uses reinforcement learning from human feedback (RLHF) (Chr+17) to align a language model to follow instructions. Here, the human feedback is used to train a reward model which guides a proximal policy optimization (PPO) (Sch+17) algorithm to fine-tune the language model. In Chapter 8, we further investigate the iterative training of conversational agents. We develop a novel method that allows us to learn from binary feedback in an iterative fashion.

Part I

TEXT-BASED GAMES AGENTS

3 INTERACTIVE AGENTS FOR TEXT-BASED GAMES

3.1 INTRODUCTION & BACKGROUND

"*You are hungry! Let's cook a delicious meal. Check the cookbook in the kitchen for the recipe. Once done, enjoy your meal!*", that's the starting instruction of every game in Microsoft's *First TextWorld Problems: A Language and Reinforcement Learning Challenge*; a competition that evaluates an agent on a family of unique and unseen text-based games (TBGs). While all the games share a similar theme, cooking in a modern house environment, they differ in multiple aspects like the number of rooms, connection, and arrangement of rooms, the goal of the game (i.e., different recipes), as well as actions and tools needed to succeed.

Prior research on TBGs has mainly focused on either learning a single game to high accuracy (NKB15; He+15; AR19) or generalization to a completely new family of games(Kos+17) with only very poor performance. Microsoft's TextWorld Challenge aims to cover a new research direction that is in between the two extremes of the single game and the general game setting. To succeed here, an agent needs to have generalization capabilities that allow it to transfer its learned *cooking skills* to never-before-seen recipes in unfamiliar house environments.

In this chapter, we present our agent – *LeDeepChef* – that achieved the highest score on the (hidden) validation games and was ranked

This Chapter is based on our AAAI 2020 paper "LeDeepChef: Deep Reinforcement Learning Agent for Families of Text-Based Games" (AH20). The research presented in this chapter was supported by the Swiss National Science Foundation (SNSF) grant number 407540_167176.

second in the overall competition. The code to train the agent, as well as an exemplary walkthrough of the game (with the agent ranking next moves), can be found on GitHub[1].

DEEP RL FOR TBGS To solve TBGs, Narasimhan et al. [NKB15] developed a deep RL model that utilizes the representational power of the hidden state of Long Short-Term Memory (HS97) to learn a Q-function. An adaption of this approach by He et al. [He+15] uses two separate models to encode the context and commands individually and then uses a pairwise interaction function between them to compute the Q-values. Since then, a variety of researchers (AR19; YM19b; YM19a) used some form of DQN to solve TBGs; however, we find that an advantage-actor-critic approach (Mni+16) helps to improve performance and speeds up convergence. Using Narasimhan et al. [NKB15]'s LSTM-DQN or He et al. [He+15]'s adjusted DRRN on the family of games of the TextWorld challenge leads to extremely slow convergence due to the huge combinatorial action space that arises from games with different objects and the combinatorial nature of natural language (AR19).

AFFORDANCE GENERATION To succeed in a parser-based TBG, an agent needs to have the ability to generate *reasonable* commands for a given context, so-called affordances. Using a supervised learning approach with a pointer-softmax model Vinyals et al. [VFJ15], Tao et al. [Tao+18], as well as Yuan et al. [Yua+18b], can generate admissible commands given a context for a specific TBG. A more general approach by [Ful+17] learns to map nouns to *affordant* verbs by extracting replacement vectors from word embeddings using canonical examples. Zahavy et al. [Zah+18], on the other hand, start from an over-complete set of actions and learn a binary action-elimination network by using the feedback provided by the game engine. Similarly, Ammanabrolu and Riedl [AR19] also prune the available actions but using a fixed scoring function on top of a graph representation of the game's state. As far as we know, our model is the first in the area of TBGs to consider grouping commands together into *high-level* actions as a way to reduce the action space.

[1] https://github.com/leox1v/FirstTextWorldProblems

```
You are hungry! Let's cook a delicious meal. Check the cookbook in the kitchen
for the recipe. Once done, enjoy your meal!

-= Kitchen =- You're now in the kitchen. I guess you better just go and list everything you see here. You hear a noise behind you and spin around, but you can't see anything other than a fridge. The fridge is empty! This is the worst thing that could possibly happen, ever! You see a closed oven. You make out a table. The table is massive. On the table you can make out a cookbook. You can make out a counter. The counter is vast. On the counter you can make out a sliced fried red hot pepper, a red apple, a yellow bell pepper and a knife. You smell an intriguing smell, and follow it to a stove. You shudder, but continue examining the stove. But the thing is empty, unfortunately. Hm. Oh well.

> examine recipe
You open the copy of "Cooking: A Modern Approach (3rd Ed.)" and start reading:
Recipe #1
---------
Gather all following ingredients and follow the directions to prepare this tasty
meal.
Ingredients:
  red hot pepper
Directions:
  slice the red hot pepper
  fry the red hot pepper
  prepare meal

> inventory
You are carrying nothing.

> take red hot pepper
You take the red hot pepper from the counter.
Your score has just gone up by one point.

> inventory
You are carrying:
  a sliced fried red hot pepper

> prepare meal
Adding the meal to your inventory.
Your score has just gone up by one point.

> eat meal
You eat the meal. Not bad.
Your score has just gone up by one point.

                    *** The End ***
```

Figure 3.1: Simple game that shows the basic structure of the task. The player's commands are highlighted in yellow.

3.2 GAMEPLAY

This section provides an overview of the structure of the games in the TextWorld challenge and explains the problems an agent needs to overcome to succeed. Figure 3.1 shows an example of a straightforward game that helps understand the basic structure. The agent starts at a random room around the house with the instruction to find the cookbook and prepare the meal therein. The initial description

of the surrounding exemplifies one of the key challenges, namely filtering the vital information from the text: sentences like *you hear a noise behind you and spin around, ...* or *This is the worst thing that could possibly happen, ever!* provide no useful information for the game and make it harder to understand the context.
Once the agent finds the room with the cookbook (in the example in Figure 3.1, it is in the starting room already), the *examine recipe* reveals the recipe. It consists of two parts: the ingredients and the directions. While the ingredients part lists the items that need to be collected, the directions give information about the status they need to be in to prepare the meal. In our example, the pepper needs to be sliced and fried. Here, the agent needs to be careful, because the initial description of the surrounding states that the pepper is already sliced and fried and additional frying, for example, would lead to burning the pepper and hence losing the game. The agent, therefore, needs to remember and recognize states of ingredients mentioned in the context. With the *inventory* command, the agent can list all items it is currently carrying. Once all ingredients, in their correct state, are in the inventory, the agent can prepare and then eat the meal.

3.3 AGENT

We train an agent to select, at every step in the game, the most promising command (in terms of discounted future score) from a list of possible commands, given the observed context. Building a successful agent—not just for TBGs but for a wide range of sequential decision-making applications—is primarily determined by the presented set of choices at each time-step. Therefore, one of the most crucial questions is about how to generate the list of possible commands. The smaller this set is, the less time and *effort* the agent wastes in its exploratory phase on "useless" strategies. To effectively reduce the size of the action space, we use an approach inspired by hierarchical reinforcement learning, that we explain in the next section about "Command Generation". In the current section, we outline the architecture and training procedure of the agent, acting on a given set of commands.

MODEL CONTEXT We build a textual context as an approximation for the (non-observable) game's state. It consists of the following text-based features:

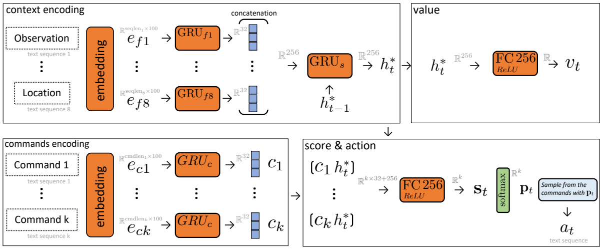


Figure 3.2: Illustration of the model. From a textual description of the context together with k different possible commands, it computes a categorical distribution over the commands as well as a scalar representing the value of the current game state.

1. Observation: The response from the game engine at the current time step. It can either be a description of what the agent sees in this room or a direct response to its last command.

2. Missing items: The list of items that are in the recipe but not yet in the inventory. This information is constructed using the neural recipe model described in the Section "Command Generation".

3. Unnecessary items: The list of items that are in the inventory but are not needed to execute the recipe. We extract this information from the last response to the *inventory* command.

4. Description: The description of the current room. It is the output of the last *look* command.

5. Previous commands: The list of the ten previously executed commands.

6. Required utilities: The list of kitchen appliances needed for the recipe, e.g., knife or stove. This list is a result of the prediction by the recipe model described in the Section "Command Generation".

7. Discovered locations: The list of previously visited locations.

8. Location: The name of the current location, extracted from the last observation (if it included a location).

The architecture of the model is shown in Figure 3.2. It consists of four building blocks: context encoding, commands encoding, computation of the value of the current state, and the command scoring.

CONTEXT ENCODING The input to the context encoding are the eight text-based features described above. Each of them is a sequence of words that we embed using a trainable 100-dimensional word embedding, initialized with pre-trained GloVe (PSM14a). This results in eight matrices of shape ($\text{seqlen}_i \times 100$ for $i = 1, \ldots, 8$) that are fed into eight separate bi-directional GRUs (GRU_{fi}). Using the last hidden vector of each GRU, we construct a fixed size encoding of size 32 for every feature input sequence. By concatenating the individual vectors, we obtain a representation for the full context with a fixed size of 256. To obtain the final context encoding h^*, we pass this representation into another GRU (GRU_s) that has its recurrency over time, i.e., it takes as hidden state the context encoding from the previous time-step (Yua+18a).

COMMANDS ENCODING At every time step, the model has a set with varying lengths k_t of different possible commands to choose from. Each command is embedded using the same embedding matrix as the context, resulting in a set of k matrices of size ($\text{cmdlen}_i \times 100$)[2]. A single GRU ($\text{GRU}_c$) is used to encode the k different commands individually to fixed-size representations $c_i \in \mathbb{R}^{32}$ for $i = 1, \ldots, k$.

VALUE COMPUTATION As described in more detail in the upcoming paragraph, we use an advantage-actor-critic approach to train the agent. This approach requires a *critic* function that determines the value of the current state. In our model, we compute this scalar value by passing the encoded context h^* through an MLP with a single hidden layer of size 256 and ReLU activations.

SCORING AND COMMAND SELECTION For each possible command, we compute a scalar score by feeding the concatenation of the encoded context h^* and the encoded command c_i for $i = 1, \ldots, k$ into an MLP with a single hidden layer of size 256 and ReLU activations. We obtain a score vector $\mathbf{s}_t \in \mathbb{R}^k$ that ranks the k possible commands.

[2] The sequence lengths of commands vary since the commands range from single words, e.g., *inventory*, to short sentences, e.g., *cook the red hot pepper with grill*.

On top of the score vector, we apply a softmax to turn it into a categorical distribution $\mathbf{p}_t$. Based on $\mathbf{p}_t$, we sample the final command from the presented set of input commands.

ACTOR-CRITIC We use an online actor-critic algorithm with a shared network design to optimize the agent. We compute the return $\mathcal{R}_t$ of a single time-step t in the session of length T by using the n-step temporal difference method (SB18, ch. 7)

$$\mathcal{R}(s_t, a_t) = \gamma^{T-t} v(s_T) + \sum_{\tau=0}^{T-t} \gamma^{\tau} r(s_{t+\tau}, a_{t+\tau}) \tag{3.1}$$

where γ denotes the discount factor, and $v(s_T)$ denotes the value of the state, determined by the critic network, that depends on the state s_T. The game-environment determines the score r, based on the state s, and the chosen action a.

From $\mathcal{R}_t$ we compute the advantage $\mathcal{A}_t$ at time-step t by subtracting the state value from the critic network, i.e.

$$\mathcal{A}(s_t, a_t) = \mathcal{R}(s_t, a_t) - v_t(s_t). \tag{3.2}$$

While the value function from the critic v captures how good a certain state is, the advantage informs us how much extra reward we obtain from action a compared to the expected reward in the current state s. For the sake of brevity, we will drop the indication of dependence of the state s and action a from now on.

OBJECTIVE The full objective $\mathcal{L}$ consists of three individual terms: the policy loss, the value loss, and the entropy loss. The policy term optimizes the parameters of the actor network while keeping the critic's weights fixed. It encourages (penalizes) the current policy if it led to a positive (negative) advantage. The policy loss is given by the following formula

$$\mathcal{L}_p = -\frac{1}{T} \sum_{t=1}^{T} \mathcal{A}_t^* \log \boldsymbol{p}_t[a_t] \tag{3.3}$$

where $\mathcal{A}_t^*$ is the advantage $\mathcal{A}_t$ removed from the computational graph, and $\boldsymbol{p}_t[a_t]$ is the probability of the chosen command a_t determined by

the actor.
The value term uses a mean squared error between the return $\mathcal{R}$ and the value of the critic v_t to encourage them to be close, i.e.

$$\mathcal{L}_v = \frac{1}{2T} \sum_{t=1}^{T} (\mathcal{R}_t - v_t)^2. \tag{3.4}$$

Finally, the entropy loss penalizes the actor for putting a lot of probability mass on single commands and therefore encourages exploration:

$$\mathcal{L}_e = -\frac{1}{T} \sum_{t=1}^{T} \boldsymbol{p}_t^T \log \boldsymbol{p}_t. \tag{3.5}$$

The final training objective is chosen as a linear combination of the three individual terms.

3.4 COMMAND GENERATION

One of the primary challenges in TBGs is the construction of possible—or rather *reasonable*—commands in any given situation. Due to the combinatorial nature of the actions, the size of the search space is vast. Thus, brute-force learning approaches are infeasible, and RL optimization is extremely difficult. We solve this problem by effectively generating only a small number of the most promising commands, as well as combining multiple actions to a single *high-level* command. We find that this step of reducing the action space is the most important to guarantee successful and stable learning of the agent. To this end, we train a helper model—called *Recipe Manager*—that effectively extracts from the game's state which recipe actions still need to be performed. By comparing the state of the ingredients in the inventory with the given recipe and the description of the environment, it generates the next commands in the cooking process.

RECIPE COMMANDS The task of this model is to determine, from the raw description of the inventory and the recipe, the following information for every listed ingredient:

- Does it still need to be collected?
- Which cooking actions still need to be performed with it?

Figure 4(b) in the Appendix shows an example of how the model extracts from the raw textual input the structured information needed. To achieve this, we train a model in a supervised manner with a self-constructed dataset. The dataset consists of recipes and inventories similar to those of the training games but augmented with multiple additional ingredients and adjectives to foster its generalization capabilities. Here, we query the freebase database to obtain a large selection of popular food items to make our classifier more resilient to ingredients not present in the training games.

MODEL The input to the recipe model is the individual recipe directions and the current inventory of the agent. We do a binary classification of each direction about whether or not it needs to be performed. The necessary information about the state of the ingredient is present in the inventory. Hence, we need to map and compare each direction to it. The names of the ingredients are of varying length and can have multiple adjectives describing it, e.g., *a sliced red hot pepper* or *some water*. Therefore, we treat each direction and the inventory as a variable-length sequence that we encode using a GRU, after embedding it with pre-trained GloVe (PSM14a). Using pre-trained embeddings not just speeds up the convergence of the model but also helps to make it generalize across unseen ingredients, because all food-related items are close in the embedding space (PSM14a). As can be seen in Figure 4(c) in the Appendix, each of the encoded recipe directions is concatenated with the encoded inventory to serve as the input to an MLP. The network outputs a single value for each of the inputs that represent the probability of the given direction still being necessary to perform.

ADDING RECIPE ACTIONS TO THE POSSIBLE COMMANDS The recipe manager adds two high-level commands to the action set. First, the *take all required ingredients from here* command, grouping all the necessary "take" commands, that can be performed in the current room. We construct this list by the intersection of needed ingredients (determined by the recipe model) and ingredients present in the current context description. Second, the *drop unnecessary items* command that lists "drop" commands for all the ingredients labeled as unnecessary from the learned recipe model. It is indeed crucial to learn to drop unwanted items because the inventory has a fixed capacity. In addition to the abstract high-level commands, it adds all action commands—specified by the recipe model—if the specific ingredient is in the inventory and the corresponding utility in the room. Figure 4(a) in the Appendix provides an example for how the mapping from high-level to low-level commands is constructed based on the room description, the inventory, and the output from the neural recipe model.

NAVIGATION COMMANDS Another crucial challenge for an agent in a TBG is to efficiently navigate through the game world; an especially hard task when presented with unseen room configurations at test time. This process can be divided into two tasks, namely (i) understanding from the context in which direction it is possible to move, and (ii) the planning required to move through the rooms efficiently. While the latter is learned by the model as part of its policy, the challenge of extracting the movement directions from the unstructured text remains. Moreover, in the TextWorld environment, every connected room can be blocked by a closed door that the agent has to explicitly open before going in this direction. Therefore, it is necessary not only to understand in which cardinal direction to move for the next room but also to identify all closed doors in the way. For this task, we learned the *Navigator* model, which is supervised trained on augmented walkthroughs to identify (i) cardinal directions that lead to connected rooms, and (ii) find all *closed* doors in the current room. The model takes any room description as input and encodes the sequence with a GRU to obtain a fixed-size vector representation. This is fed into four individual MLPs that make a binary prediction on whether the corresponding cardinal direction leads to a connected room. To obtain the closed doors in the room, the hidden representation from each word of the description is fed into a shared binary MLP that predicts whether or not a particular word is *part of the name of a closed door*. This approach is necessary because there can be multiple different closed doors in a room, and the name of each door can consist of multiple words, e.g., *sliding patio door*.
The navigator adds for every *detected* cardinal direction (east, south, west, north) the respective *go* command to the list of possible commands. Additionally, it adds *open <doorname>* for every closed door in the room's description.

OTHER COMMANDS Besides the commands that handle navigation and cooking, a few additional actions are necessary to succeed in the game. Since the number of these commands is minimal, they are either added at every time step to the set of possible commands or based on very simple rules. We provide the list of additional commands and their rules in Table 3.1.

Command	**Rule**
look, inventory	Added at every step, except if they were just performed in the previous command.
prepare meal	Added once the recipe manager does not output any recipe direction as missing anymore and the agent's location is the kitchen.
eat meal	Added if *meal* is in agent's inventory.
examine cookbook	Added if the cookbook is in the room's description.

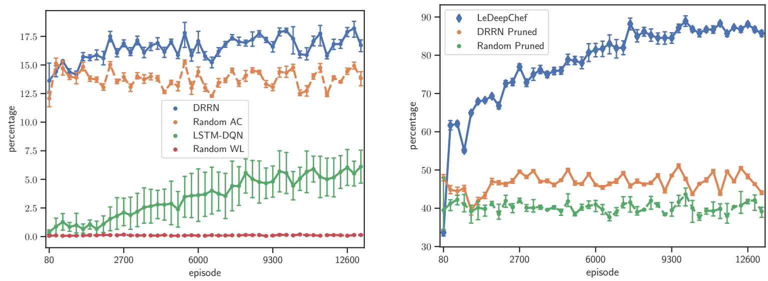
Table 3.1: Rules for additional commands to be added to the list of possible commands.

3.5 RESULTS

First and foremost, the model was evaluated quantitatively against more than 20 competitors in Microsoft's TextWorld challenge, where it scored 1st on the (hidden) validation set and 2nd on the final test set of games. To show that our agent improves upon existing models for TBGs on never-before-seen games of the same family, we compare it against several baselines on the competition's training, validation, and test set.

As a metric, we always report the points per game relative to the total achievable points. A single game terminates upon successful completion of the task or when the agent fails by either damaging an item or reaching the maximum number of a hundred steps.

[3] Result on their own validation set, which is hold-out data from the official training set of games. However, the dynamics and difficulty of both sets of games are comparable.



(a) Training games scoring percentage of DRRN and LSTM-DQN over three epochs. The two baselines *Random AC* and *Random WL* show the performance of a random agent on the admissible commands (like for DRRN) and the word-level (like LSTM-DQN), respectively.

(b) Training games scoring percentage of LeDeepChef compared to a DRRN model and a random baseline on the same pruned commands generated by the recipe module.

Figure 3.3: Comparison of our model to several baseline models on the TextWorld challenge games, as points per game relative to total achievable points throughout the training of 3 epochs with 10 different random seeds. Each shown point is an average over the past 80 games. The model details of the baselines can be found in Table 3 in the Appendix.

BASELINE Figure 3.3 (a) demonstrates that standard baselines for TBGs are not able to learn generalization capabilities to sufficiently solve a whole family of games. Both, LSTM-DQN (NKB15) and DRRN (He+15), do not exceed the 20% mark of points per game relative to total achievable points[4] during 3 epochs of training. The input to both of these models is the concatenated game's state, consisting of the room's description, the agent's inventory, the recipe, the feedback from the last command, and the set of previously issued commands. The main difference between DRRN and LSTM-DQN is that the former ranks the provided admissible commands, while the latter ranks (pre-selected) verbs and objects, from which a command is formed then. Due to the combinatorial nature of possible commands from the LSTM-DQN, the effective action space is significantly larger

[4] 20% would be equivalent to 12th place in the competition if the admissible commands are known at every step, as for DRRN (= handicap 5), or 9th place if not (= LSTM-DQN).

Method	valid		test	
	%	steps	%	steps
Random WL	0.1 ±.04	97.5 ±.27	0.0 ±.03	98.9 ±.02
LSTM-DQN	2.2 ±.00	97.0±.00	1.0±.00	99.3±.00
Random AC	11.7±.59	43.7±1.67	12.8±.64	50.1±.31
DRRN	14.0±.12	39.3±1.65	13.2±.25	50.2±.05
Random Pruned	33.5±.66	90.6±.81	39.6±.14	95.8±.36
DRRN Pruned	34.3±.31	89.8±.41	44.1±2.01	92.2±1.80
[YM19b]	58[3]	30	-	-
	-	-	-	-
LeDeepChef 👨‍🍳	**74.4**±.18	**24.1**±.23	**69.3**±.20	**43.9**±.19

Table 3.2: Results on the unseen set of validation and test games from the TextWorld Challenge. We report the mean and standard deviation over ten runs with different random seeds of each best performing model on the training set.

than for DRRN. Thus, a random agent on this *word-level* task—*Random WL*—performs much worse than an agent that selects randomly from the admissible commands, *Random AC*. Both DRRN and LSTM-DQN significantly outperform their random counterpart over the course of the training but are not able to learn to solve the games to a sufficient degree. The big scoring difference between the two random agents underlines the importance of effective action space reduction.

COMPARISON ON PRUNED COMMANDS In a second experiment, we use the same DRRN architecture as before, but with a pruned version of the admissible commands to exactly match the commands presented to our model; though, without the grouping to high-level actions. As we see in Figure 3.3 (b), the reduced set of possible commands massively improves both the random and the DRRN model to up to 50%[5]. However, the DRRN model is still not capable of improving a lot upon the random model and—as before—does not show a steady upward trend throughout the training procedure. Our

[5] 50% is equivalent to the 5th place in the competition.

model, on the other hand, improves its percentage significantly over the training iterations to its final score of around 87%. We believe that the advantage of our model over this specific baseline is mainly due to (i) the grouped high-level commands that let the agent learn a strategy more efficiently in an abstract space, (ii) the improvements in the neural architecture that acts on a more sophisticated version of the input features, and (iii) the superiority of the actor-critic over the DQN approach.

COMPARISON ON TEST SET Table 3.2 shows the quantitative results of different models on the (unseen) validation set, as well as the final test set of Microsoft's TextWorld challenge. As expected, our model generalizes best to the unseen games with a mean percentage of 74.4 and 69.3 for the respective sets of games. The standard baselines are not able to exceed the 15% mark, indicating that they are not suitable to be applied "out-of-the-box" on the specific task of solving families of TBGs. A recent model by Yin and May [YM19b], designed explicitly for the TextWorld environment, uses a curriculum learning approach to train a DQN model and achieves 58% on their validation set (hold-out data from the challenge's training set).

3.6 LIMITATIONS

Our approach of explicitly modeling the intermediate representation trades the ability to easily transfer to another domain (i.e., a different family of games) for gains in performance and interoperability. It allows us to massively reduce the action space which makes the RL training feasible. In contrast, models like DRRN and LSTM-DQN, which only implicitly learn the intermediate representations, struggle to succeed in the given task. To transfer the agent to another family of games, we need to replace our *recipe manager* model as it provides the agent with explicit intermediate information about the *cooking process*. For any given family of games, a similar *manager* model can be trained with little changes and used to guide the agent.

3.7 CONCLUSION

In this chapter, we presented how to build a deep RL agent that not only performs well on a single TBG but generalizes to never-before-seen games of the same family. To achieve this result, we designed a model that effectively ranks a set of commands based on the context and context-derived features. By incorporating ideas from hierarchical RL, we significantly reduced the size of the action space and were able to train the agent through an actor-critic approach. Additionally, we showed how to make the agent more resilient against never-before-seen recipes and ingredients by training with data augmented by a food-item database. The performance of our final agent on the unseen games of the FirstTextWorld challenge is substantially higher than any standard baseline. Moreover, it achieved the highest score, among more than 20 competitors, on the (unseen) validation set and beat all but one agent on the final test set.

Part II

QUERY REFORMULATION AGENTS

4 BOOSTING SEARCH ENGINES WITH INTERACTIVE AGENTS

4.1 INTRODUCTION & BACKGROUND

In this chapter, we focus on training agents that can use search engines as an interactive tool for finding information. We pursue a design philosophy in which search agents operate in structured action spaces defined as generative grammars, resulting in compositional, productive, and semantically transparent policies. Further domain knowledge is included through the use of well-known models and algorithms from NLU and information retrieval (IR). Most notably, we develop a self-supervised learning scheme for generating high-quality search session data, by exploiting insights from relevance feedback (Roc71), used to train a supervised LM search agent based on T5 (Raf+20a). We also build an RL search agent based on MuZero (Sch+20) and BERT (Dev+19), which performs planning via rule-constrained Monte Carlo tree search and a learned dynamics model.
We run experiments on an open-domain question-answering task, OpenQA (LCT19b). Search agents learn diverse policies leading to deep, effective explorations of the search results. The MuZero agent outperforms a BM25 (RZ09) search function running over a Wikipedia index, on both retrieval and answer quality metrics. This result provides novel evidence for the potential of knowledge-infused RL in hard NLU tasks. The T5 agent can more easily leverage large pre-trained encoder-decoders and proves superior to MuZero. Furthermore, a straightforward ensemble of agents is comparable in performance to the current reference neural retrieval system, DPR (Kar+20),

This Chapter is based on our TMLR June 2022 paper "Boosting Search Engines with Interactive Agents" (Ado+22c).

while relying solely on interpretable, symbolic retrieval operations. This suggests new challenges for future work; e.g., involving hybrid architectures and policy synthesis. We open-source the code and trained checkpoints for both agents.[1,2]

QUERY OPTIMIZATION Query optimization is an established topic in IR. Methods range from hand-crafted rules (LG98) to data-driven transformation patterns (ALG01). Narasimhan et al. [NYB16] use RL to query the web for information extraction. Nogueira and Cho [NC17] and Buck et al. [Buc+18] use RL-trained agents to seek good answers by reformulating questions with seq2seq models. These methods are limited to one-step episodes and queries to plain natural language. This type of modeling is closely related to the use of RL for neural machine translation, whose robustness is currently debated (Cho+20; KK21). Web-GPT (Nak+21a) presents an end-to-end search modeling approach based on human demonstrations. Montazeralghaem et al. [MZA20] propose a feature-based network to score potential relevance feedback terms to expand a query. Das et al. [Das+19] propose to perform query reformulation in embedding (continuous) space and find that it can outperform the sequence-based approach. Xiong et al. [Xio+21b] successfully use relevance feedback by jointly encoding the question and the text of its retrieved results for multi-hop QA. Other work at the intersection of IR and RL concerns bandit methods for news recommendation (Li+10) and learning to rank (YJ09). Recently, interest in Deep RL for IR has grown (Zha+21). There, the search engine is the agent, and the user the environment. In contrast, we view the search problem from the user's perspective and thus consider the search engine as the environment.

SEARCH ENGINE AND QUERY OPERATIONS We make the assumption that agents interact with a search engine operating on an inverted index architecture (CMS09), which is popular in commercial engines and IR research. Specifically, we use Lucene's implementation[3] as the search engine, in combination with the BM25 ranking function (RZ09). We frame search as the process of generating a sequence of queries

[1] https://github.com/google-research/google-research/tree/master/muzero
[2] https://github.com/google-research/language/tree/master/language/search_agents
[3] https://lucene.apache.org/.

$q_0, q_1, \ldots, q_T$,[4] where q_0 is the initial query, and q_T is the final query – where the process stops. Each query q_t is submitted to the search engine to retrieve a list of ranked documents $\mathcal{D}_t$.

We focus on the case where q_{t+1} is obtained from q_t through *augmentation*. A query may be refined by adding a keyword $w \in \Sigma^{\text{idx}}$, such that $q_{t+1} = q_t w$, where Σ^{idx} is the vocabulary of terms in the search index. The new term will be interpreted with the usual disjunctive search engine semantics. Furthermore, a query can be augmented by means of *search operators*. We concentrate on three unary operators: "+", which limits results to documents that contain a specific term, "-" which excludes results that contain the term, and "$\wedge_i$" which boosts a term weight in the BM25 score computation by a factor $i \in \mathbb{R}$. In addition, the operator effect is limited to a specific document *field*, either the content or the title. As an example, the query "who is the green guy from sesame street" could be augmented with the term "+contents:muppet", which would limit the results returned to documents containing the term "muppet" in the body of the document.

Only a small fraction of users' queries include search operators, and this behavior is not well studied. Croft et al. [CMS09, Ch. 6.2] estimate that less than 0.5% use '+'. However, it is noteworthy how power users can leverage dedicated search operators, in combination with sophisticated investigative strategies, to solve deep search puzzles (Rus19). Additionally, unary operators are associated with explicit, transparent semantics and their effect can be analyzed and interpreted. Crucially, however, as we show in this chapter, these operators are also pivotal in designing effective search agents because they allow us to generate self-supervised search session training data in a principled fashion.

RESULTS AGGREGATION AND OBSERVATIONS STRUCTURE Web searchers expect the best answer to be among the top few hits on the first results page (Hea09, Ch. 5) and pay marginal attention to the bottom half of the *10 blue links* (GJG04; Joa+05; NP09; Str20). Likewise, a search agent considers only the top k documents returned by the search engine at every step; we set $k = 5$ in all our experiments.

During a search session, the agent maintains a list of the top-k documents overall, which is returned at the end as the output. To aggregate the results from different steps during the search session we use a Passage Scorer (PS) which builds upon a pre-trained

[4] We also refer to the query sequence as a session, or search episode.

BERT model. For each result document $d \in \mathcal{D}_t$, the PS component estimates the probability of d containing the (unspecified) answer $\mathrm{P}(d \ni \textsc{answer} \mid q) \in [0;1]$. This probability can be viewed as a score that induces a calibrated ranking across all result documents within a session. Notice that the score is always computed conditioning on the original query $q = q_0$ and not q_t.
At each session step, a search agent computes a structured *observation* representing the state of the session up to that point. The observation includes the query tokens and refinements describing q_t. The top-k documents in the session are represented by their title and a text snippet. The snippet is a fixed-length token sequence centered around the text span that contains the most likely answer for q, as predicted by a Machine Reader (MR) (Raj+16b). For ranking (PS) and answer span prediction (MR) tasks, we use the same BERT system as in (Kar+20). Query and aggregated results yield a segmented observation token sequence o_t which is truncated to length ≤ 512, a common input length for pre-trained transformer-based LMs (cf. Appendix 4.6 for more details and examples).
The next step involves a language model which produces an embedding $\mathbf{s}_t$ from which the search agent will generate the next query. We can represent diagrammatically the operations that lead to a query refinement as

$$\begin{bmatrix} q_0, \ldots, q_t \\ {\scriptstyle \text{search}} \downarrow {\scriptstyle \text{engine}} \\ \mathcal{D}_0, \ldots, \mathcal{D}_t \end{bmatrix} \underbrace{\xmapsto{\text{MR/PS}} o_t}_{\text{observation}} \underbrace{\xmapsto{\text{LM}} \mathbf{s}_t}_{\text{encoding}} \underbrace{\xmapsto{\text{agent}} q_{t+1}}_{\text{generation}} \tag{4.1}$$

At each step t the top-k documents in the session are identified by means of their PS score. An observation o_t is computed for the top documents by means of a machine reader (MR). Then the search agent's LM encodes the observation o_t and decodes the next query q_{t+1}. Figure 4.1 illustrates the search agent and its components at work with an example.

ROCCHIO QUERY EXPANSIONS AND ROCCHIO SESSIONS The query operations introduced above allow us to generate synthetic

[5]The answer is "Oscar the Grouch" who is a green *muppet* that lives in a *trash* can on Sesame street.

	Query and Search Results		Score
$\mathbf{q}_0$	who won season 2 great british baking show		
Top-2 documents retrieved with $\mathbf{q}_0$:			0.040
$\mathbf{d}_1$	Title	The Great American Baking Show	
	Content	... The first two seasons were hosted by Nia Vardalos and Ian Gomez, with Mary Berry from the original "GBBO" series and ...	
$\mathbf{d}_2$	Title	The Great American Baking Show (season 3)	
	Content	..., ABC announced that Vallery Lomas won the competition, beating out runners-up Cindy Maliniak and Molly Brodak in the **final** week ...	
$\mathbf{q}_1$	who won season 2 great british baking show (contents:"final"∧8)		
Top-2 documents retrieved with $\mathbf{q}_1$:			0.142
$\mathbf{d}_1$	Title	The Great British Bake Off	
	Content	... The finalists were Brendan Lynch, James Morton and John Whaite, the last of whom won the final in a surprise result. ...	
$\mathbf{d}_2$	Title	The Great American Baking Show (season 2)	
	Content	... In the final technical, Mary Berry set the challenge on the bakers to create a British Battenberg cake with a checkerboard ...	
$\mathbf{q}_2$	who won season 2 great british baking show (contents:"final"∧8) +(title:"bake")		
Top-2 documents retrieved with $\mathbf{q}_2$:			0.186
$\mathbf{d}_1$	Title	The Great British Bake Off	
	Content	... The finalists were Brendan Lynch, James Morton and John Whaite, the last of whom won the final in a surprise result. ...	
$\mathbf{d}_2$	Title	The Great British Bake Off	
	Content	... The final of the series where John Whaite was crowned the winner saw its highest ...	
$\mathbf{q}_3$	who won season 2 great british baking show (contents:"final"∧8) +(title:"bake") +(title:"2")		
Top-2 documents retrieved with $\mathbf{q}_3$:			0.552
$\mathbf{d}_1$	Title	The Great British Bake Off (series 2)	
	Content	... The competition was won by Joanne Wheatley. There was no Star Baker this week, as Paul and Mary felt ...	
$\mathbf{d}_2$	Title	The Great British Bake Off (series 2)	
	Content	... contestants went on to a career in baking or have a change of career as a result of appearing on the show. Joanne Wheatley has written two best selling books on baking ...	

Table 4.1: An observed example Rocchio session. The initially retrieved documents are wrong documents that refer to the "The Great American Baking Show". The first Rocchio expansion *boosts* the term "final". In the two subsequent steps, the procedure requires the terms "bake" and "2" to be contained in the title of the retrieved documents. In this way, the results first continue to shift from the American Baking Show to the British Bake Off and eventually settle on the desired British Bake Off (series 2). The composite IR and QA score (defined in Eq.4.15) increases from 0.040 for the original query to 0.552 for the final query.

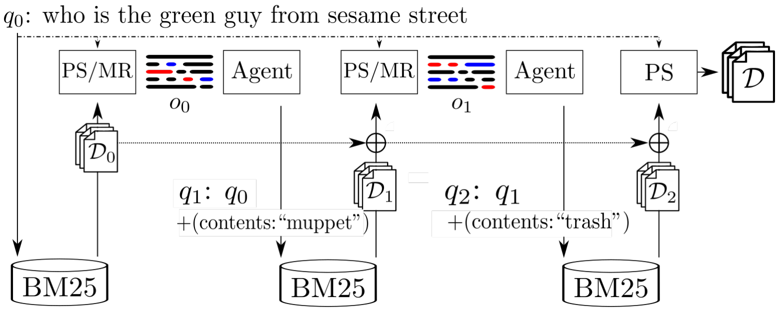


Figure 4.1: Schematic agent interaction with the search engine (BM25) for the query "who is the green guy from sesame street".[5] This is a real example from the query expansion procedure described in Chapter 4.1. After receiving an initial set of documents ($\mathcal{D}_0$) for the original question, the corresponding observation (o_0) is compiled by ranking the documents according to their Passage Score (PS) and creating snippets for the top-k documents around the answers extracted by the Machine Reader (MR). Note that PS/MR always conditions on q_0. The first action of the agent is to enforce the term "muppet" to be in the content of the search results. The new document set $\mathcal{D}_1$ is returned by the search engine and aggregated with the previous documents. Again, the set of documents is ranked by the Passage Scorer, and the subsequent observation for the agent is compiled. The agent then chooses to enforce the presence of the topical term "trash" and obtains another set of documents that are, again, aggregated and scored. The final result $\mathcal{D}$ contains the top-k documents observed during the episode, according to the Passage Score.

search sessions in a self-supervised manner, making use of question-answer pairs (q, a). We initialize $q_0 = q$ and aim to find a sequence of refinements that make progress towards identifying high-quality documents, based on a designed scoring function which combines retrieval and question answering performance (cf. Eq. 4.15, introduced in Chapter 4.3). A query is *not* further refined if no score-increasing refinement can be found or a maximal length is reached.

To create candidate refinements, we put to use the insights behind relevance feedback as suggested in Rocchio [Roc71]. Formalizing the query operations introduced in Chapter 4.1, an elementary refinement – called a *Rocchio expansion* – takes the form

$$q_{t+1} := q_t \ \Delta q_t \tag{4.2}$$

$$\Delta q_t := [+| - | \wedge_i \quad \textsc{Title} \,|\, \textsc{Content}\,] \ \ w_t \tag{4.3}$$

$$w_t \in \Sigma_t := \Sigma_t^q \cup \Sigma_t^\tau \cup \Sigma_t^\alpha \cup \Sigma_t^\beta \tag{4.4}$$

where i is the boosting coefficient and Σ_t refers to a set of terms accessible to the agent. By that, we mean terms that occur in the observation o_t – the search state at time t. We use superscripts to refer to the vocabularies induced from the observation which identify the terms occurring in the question (q), titles (τ), predicted answer spans (α) or bodies (β) of documents in o_t. Note that adding terms $\notin \Sigma_t$ would make refinements more difficult to reproduce for an agent and thus would provide supervision of low utility.

A crucial aspect of creating search sessions training data based on Rocchio expansions has to do with the search complexity of finding optimal sequences of such expansions. The success of this search relies on the notion of relevance feedback. We introduce $q_* = q + a$ as the "ideal" query: query q executed on the subset of documents that contain answer a. The results of q_* define the vocabulary Σ_*. We can now define two special dictionaries that will allow us to narrow down the candidate terms to appear in the next refinement

$$\Sigma_t^{\uparrow} = \Sigma_t \cap \Sigma_*, \quad \Sigma_t^{\downarrow} = \Sigma_t - \Sigma_* \,. \tag{4.5}$$

During the search for an optimal session, it is possible to use accessible terms w_t as additional keywords, or in combination with an exact match ("+") or weight boosting ("$\wedge$") if they also occur in the ideal result set ($w_t \in \Sigma_t^{\uparrow}$); and to exclude w_t ("-") if they are not present in the ideal results ($w_t \in \Sigma_t^{\downarrow}$). As in the Rocchio algorithm, this is meant to bring the query closer to the relevant documents and farther away from the irrelevant ones. We have found experimentally that this leads to a good trade-off between the quality of Rocchio expansions and the search effort to find them. We call a sequence of Rocchio expansions a *Rocchio session*. Table 4.1 illustrates a Rocchio session for the query 'who won season 2 great british baking show', based on the experimental setup described in Chapter 4.4.

4.2 SEARCH AGENTS

4.2.1 *Self-Supervised T5 Agent*

It is straightforward to train a generative search agent in a supervised manner on the Rocchio sessions. We use T5, a popular pretrained transformer encoder-decoder model. As a search agent, T5 learns to predict a new search expansion from each observed state. In the spirit of *everything-is-string-prediction*, state and expansions are represented as plain strings. See Appendix 4.6 for a full example.
Our T5 agent is trained via Behavioral Cloning (BC) (MBHM90). We treat each step in a Rocchio session as a single training example. As is common in sequence prediction tasks, we use the cross-entropy loss for optimization. BC is perhaps the simplest form of Imitation Learning (IL) and has been proven effective in a variety of application domains (STK18; RHVGHL19). In our query refinement task, it allows us to inherit the expressive power of the Rocchio query expansions and, differently from other IL approaches (RGB11; HE16; DDZ20), requires only *offline* interactions with the search engine. Crucially, this enables scaling to the large action spaces and model sizes typical of recent LMs. Our T5 agent can also be described as a Decision Transformer with fixed max return (Che+21a).

4.2.2 *Reinforcement Learning: MuZero Agent*

Learning to search lends itself naturally to be modeled as a reinforcement learning problem. To explore also the feasibility of learning search policies from scratch, we implement an RL search agent based on MuZero (Sch+20). MuZero is a state-of-the-art agent characterized by a learnable model of the environment dynamics. This allows the use of Monte Carlo tree search (MCTS) to predict the next action, in the absence of an explicit simulator. In our use case, MuZero aims to anticipate the latent state implied by each action with regard to the results obtained by the search engine. For instance, in the example of Figure 4.1, it may learn to predict the effect of using the term "muppet" in combination with a unary operator. This approach to planning is intuitive for search, as searchers learn to anticipate the effect of query refinements while not being able to predict specific results. Furthermore, this offers a performance advantage of many orders of magnitude against executing queries with the *real* search engine.

4.2.3 *Grammar-Guided Search*

To map observations to states, the MuZero agent employs a custom BERT with dedicated embedding layers to represent the different parts (cf. Appendix 4.6 for details). Compared to T5, MuZero has a more challenging starting point: its BERT-based representation function is pre-trained on less data, it has fewer parameters (110M vs. 11B), and no cross-attention: predictions are conditioned on a single vector, [CLS]. Moreover, it cannot as easily exploit supervised signals. However, it can more openly explore the space of policies, e.g. independent of the Rocchio expansions. Through many design iterations, we have identified it to be crucial to structure the action space of the MuZero agent and constrain admissible actions and refinement terms dynamically based on context. This provides a domain-informed inductive bias that increases the statistical efficiency of learning a policy via RL.
We take inspiration from generative, specifically context-free, grammars (CFGs) (Cho56) and encode the structured action space as a set of production rules, which will be selected in (fixed) top-down, left-to-right order. A query refinement is generated, in a way that mimics Rocchio expansions, as follows

$$Q \Rightarrow U\,Q \,|\, W\,Q \tag{4.6}$$

$$U \Rightarrow \text{Op Field } W \tag{4.7}$$

$$\text{Op} \Rightarrow + \,|\, - \,|\wedge_i \tag{4.8}$$

$$\text{Field} \Rightarrow \text{TITLE} \,|\, \text{CONTENT} \tag{4.9}$$

which allows for adding plain or structured keywords using unary operators. The selection of each refinement term W proceeds in three steps, the first two can be described by the rules

$$W \Rightarrow W_t^q \,|\, W_t^\tau \,|\, W_t^\beta \,|\, W_t^\alpha \,|\, W^{\text{idx}} \tag{4.10}$$

$$W_t^x \Rightarrow w \in \Sigma_\tau^x, \quad x \in \{q, \tau, \beta, \alpha\} \tag{4.11}$$

$$W^{\text{idx}} \Rightarrow w \in \Sigma^{\text{idx}} \tag{4.12}$$

which means that the agent first decides on the origin of the refinement term, i.e., the query or the different parts of the top-scored result

documents, and afterward selects the term from the corresponding vocabulary. As the term origin correlates strongly with its usefulness as a refinement term, this allows us to narrow down the action space effectively. The agent is forced to pick a term from the larger vocabulary (approximately 1M terms) of the search index Σ^{idx} during MCTS, as there is no observable context to constrain the vocabulary.
The third level in the action hierarchy concerns the selection of the terms. We have found it advantageous to make use of subword units; specifically, BERT's 30k lexical rules involving word pieces, to generate terms sequentially, starting from a term prefix and adding one or more suffixes. Note that this part of the generation is context-sensitive, as we restrict node expansions to words present in the vocabulary. We make use of tries to efficiently represent each Σ_τ^x and amortize computation.

4.3 THE OPENQA ENVIRONMENT

We evaluate search agents in the context of open-domain question answering (Open-QA) (Voo00; Che+17a). Given a question q, we seek documents $\mathcal{D}$ that contain the answer a using a search engine, the environment. Following common practice, we use Lucene-BM25 with default settings on English Wikipedia. BM25 has provided the reference probabilistic IR benchmark for decades (RZ09), only recently outperformed by neural models (LCT19b). The Lucene system provides search operators comparable to commercial search engines. Exploration-based learning is vulnerable to discovering adversarial behaviors. As a safeguard, we design a composite reward. The score of a results set $\mathcal{D}$, given q, interpolates three components. The first is the Normalized Discounted Cumulative Gain (NDCG) at k. See Eq. 4.13, where $w_i = \log_2(i+1)^{-1} / \sum_{j=1}^{k} \log_2(j+1)^{-1}$ are normalizing weights, and $\text{rel}(d|q) = 1$, if $a \in d, 0$ otherwise:

$$\text{NDCG}_k(\mathcal{D}|q) = \sum_{i=1}^{k} w_i \,\text{rel}(d_i|q) \tag{4.13}$$

$$\text{NDCEM}_k(\mathcal{D}|q) = \sum_{i=1}^{k} w_i \,\text{em}(d_i|q). \tag{4.14}$$

NDCG is a popular metric in IR as it accounts for the rank position, it is comparable across queries, and it is effective at discriminating ranking functions (Wan+13). NDCG alone can have drawbacks: on *easy* questions a score of 1 can be achieved in short meritless episodes, while on *hard* ones it may be impossible to find a first valid step since Eq. 4.13 takes discrete values. Hence, we introduce a second component, NDCEM_k (Eq. 4.14) where $\text{em}(d|q) = 1$ if the answer extracted from d by the reader exactly matches a, 0 otherwise. NDCEM_k helps validate results by promoting high-ranking passages yielding correct answer spans. Finally, to favor high-confidence result sets we add the normalized Passage Score of the top k results, leading to the following scoring function

$$
\begin{aligned}
\text{S}_k(\mathcal{D}|q) := (1 - \lambda_1 - \lambda_2) \cdot \text{NDCG}_k(\mathcal{D}|q) \quad (4.15) \\
+\lambda_2 \cdot \text{NDCEM}_k(\mathcal{D}|q) \quad (4.16) \\
+\lambda_1 \cdot \frac{1}{k}\sum_{i=1}^{k} \text{PS}(d_i|q) \quad \in [0, 1] \quad (4.17)
\end{aligned}
$$

Based on (4.15), we define the search step reward

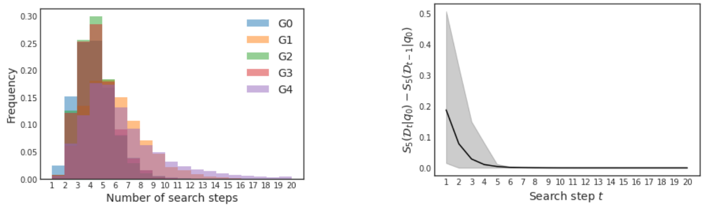
$$r_t = \text{S}_5(\mathcal{D}_t|q_0) - \text{S}_5(\mathcal{D}_{t-1}|q_0). \tag{4.18}$$

We train the MuZero agent directly on the reward. The reward is sparse, as none is issued in between search steps. The T5 agent is trained indirectly on the reward via the induction of Rocchio sessions (cf. Chapter 4.1).

4.4 EXPERIMENTS

For our experiments, we use the OpenQA-NQ dataset (LCT19b). This data is derived from Natural Questions (Kwi+19) and consists of Google queries paired with answers extracted from Wikipedia by human annotators. The data includes 79,168 train questions, 8,757 dev questions, and 3,610 for test. We use the provided partitions and Wikipedia dump. Following Lee et al. [LCT19b] we pre-process Wikipedia into blocks of 288 tokens, for a total of 13M passages. We evaluate each system on the top-5 288-token passages returned. Model selection and data analysis are performed on NQ Dev, using the reward (Eq. 4.18) as the objective.

ROCCHIO SESSIONS DATA We generate synthetic search sessions using Rocchio expansions for 5 different combinations of types of



(a) Rocchio sessions' length

(b) Score gain at each search step

Figure 4.2: The histogram on the left shows the length of the Rocchio sessions, using different grammars on NQ Dev. The plot on the right shows the average score gain (score is computed according to Eq. 4.15) for each Rocchio expansion step with grammar G4 on NQ Dev. The shaded area is between $5 - 95^{th}$ percentiles.

refinements. We refer to these as *grammars*: **G0** (allows only simple terms), **G1** (only term boosting, with weight $i \in \{0.1, 2, 4, 6, 8\}$), **G2** ("+" and "-"), **G3** (G0+G2) and **G4** (G0+G1+G2). Given the original query, a Rocchio session is generated as follows: We attempt at most $M = 100$ possible refinements for each grammar operator using terms from the constructed dictionaries $\Sigma_t^{\uparrow}$ and $\Sigma_t^{\downarrow}$ (see Eq. 4.5). For instance, for the "+" operator we attempt refinements of the form '+(*field*: "*term*")', where *term* is taken from the top-M terms in the intersection dictionary $\Sigma_t^{\uparrow}$ and *field* represents the field (content or title) where the term was found. Dictionaries $\Sigma_t^{\uparrow}$ and $\Sigma_t^{\downarrow}$ are constructed (cf. Chapter 4.1) based on the set Σ_t of top $N = 100$ terms present in the documents retrieved so far, sorted according to Lucene's IDF score. For each of such possible refinements, we issue the corresponding query to Lucene and, based on the returned documents, we evaluate the resulting score. We use the scoring function of Eq. 4.15 with coefficients λ_1=0.2, λ_2=0.6, after a search against the final quality metrics. Then, we select the refinement leading to the highest score and neglect the other ones. This process continues until no score-improving refinement can be found, for a maximum of 20 refinement steps.

In Figure 4.2a, we plot the histogram of the length of Rocchio sessions on NQ Dev, using the different grammars. We observe that most sessions terminate after a number of steps significantly smaller than

20, either because the maximum score is reached or because no score improvements can be found. For instance, using the G4 grammar, Rocchio sessions have an average length of 5.06 steps with a standard deviation of 3.28. Results are similar on NQ Train, where with grammar G4 we obtain 298,654 single Rocchio expansion steps from 77,492 questions (in Table 4.5 we report the numbers for different grammars). Moreover, we have observed the first query expansion steps produce higher score gains with respect to later ones. This can be observed in Figure 4.2b where we plot the average per-step score's gain. This indicates that performing longer Rocchio expansions yields diminishing marginal gains.

AGENTS TRAINING AND INFERENCE The machine reader and passage scorer, as well as MuZero's h_θ function, use 12-layer BERT systems.[6] To train the former, we generate for each query in NQ Train 200 candidate passages from our BM25 system, picking one positive and 23 negative passages for each query at random whenever the query is encountered during training. The reader/scorer is not trained further. MuZero's representation function is trained jointly with the rest of the MuZero system.

For the T5 agent, we start from the pretrained T5-11B (11 billion parameters) public checkpoint and continue training on the NQ Train Rocchio expansions. Training took about 5 days using 16 Cloud TPU v3. At inference time, we found that fixing the sessions to 20 steps worked best for both T5 and MuZero. Indeed, we observed performance increase monotonically with the search steps, with decreasing marginal gains (see Figure 4.4 where we plot the NQ Dev performance of one of our T5 agents as well as the supervised Rocchio sessions, as a function of the number of refinement steps).

The MuZero implementation is scaled and distributed via an agent-learner setup (Esp+18) in the SEED RL (Esp+20) framework allowing for centralized batching of inference for effective use of accelerators. MuZero is trained on NQ Train for a total of 1.6 million steps (≈10 days) using 500 CPU-based actors and 4 Cloud TPU v2 for inference and training on the learner.[7] For each step, 100 simulations are performed. During training, we limit sessions to a maximum of 20

[6] BERT-base, initialized from
https://tfhub.dev/google/bert_uncased_L-12_H-768_A-12/1.

[7] For details, see https://cloud.google.com/tpu.

steps. The agent also can decide to stop early by selecting a dedicated stop action. Training of MuZero can be improved by providing *advice* to the actors. An actor may receive information about which terms w_t should be promoted, $w_t \in \Sigma_t^{\uparrow}$, or demoted, $w_t \in \Sigma_t^{\downarrow}$. The probability of an episode receiving advice starts at 0.5 and decays linearly to 0 in one million steps.

Metric	BM25	+PS	+RM3	MuZero	T5-G1	MuZero+T5s	DPR	Rocchio-G4
NDCG@5	21.51	24.82	26.99	32.23	44.27	46.22	-	65.24
Top-1	28.67	44.93	46.13	47.97	52.60	54.29	52.47	73.74
Top-5	53.76	53.76	56.33	59.97	66.59	71.05	72.24	88.17
EM	28.53	41.14	40.14	32.60	44.04	44.35	41.50	62.35

Table 4.2: Results on the test partition of OpenQA-NQ. The **B**M25 column reports the performance of the Lucene-BM25 search engine. **B**M25+PS refers to reranking the top-5 BM25 results with the BERT passage scorer (PS). **B**M25+PS+RM3 is a pseudo-relevance feedback baseline that iteratively adds terms to the query and uses the passage scorer (PS) to aggregate the retrieved results. **M**uZero is the performance of the RL search agent using the full set of query expansion types (G4). **T**5-G1 is the best T5 search agent, trained on the G1 grammar Rocchio sessions (using only term boosting). **M**uZero+T5s is an ensemble of the documents returned by the MuZero agent and all T5 agents, ranked based on each document's PS score. For DPR's performance (**D**PR) we report the most recent Top-1 and Top-5 results from https://github.com/facebookresearch/DPR. Finally, **R**occhio-G4 is an estimate of the headroom based on the Rocchio sessions using the full grammar (G4). **N**DCG@5, **T**op-1 and **T**op-5 are retrieval quality metrics, while **EM** (Exact Match) is the answer quality metric used in machine reading.

RESULTS Table 4.2 summarizes the results on OpenQA-NQ Test. We evaluate passage retrieval quality by means of ranking (NDCG@5) and precision (Top-1, Top-5) metrics. We also report Exact Match (EM) to evaluate answer quality. The baseline is Lucene's BM25 one-shot search. Reranking the same BM25 documents by the PS score (BM25+PS) is easy and improves performance on all metrics, particularly noticeable on Top-1 and EM.[8] We also evaluate a pseudo-relevance feedback variant of the BM25+PS baseline (+RM3). Following (Jal+04; PMD13), at each iteration we pick the highest scoring term

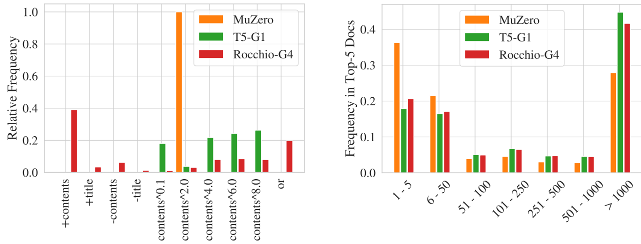
[8] Top-5 is identical to BM25 since the documents are the same.

in the search results based on the RM3 score and add that term to the previous query with the "+" operator applied to the document content. In Appendix 4.6 we provide a detailed study of the retrieval performance of this method, using all available operators, and comparing it with an alternative IDF-based term selection mechanism. Surprisingly, and somewhat against the general intuition behind pseudo-relevance feedback, we find that negating terms is more effective than promoting them. This seems to suggest that *negative* pseudo relevance feedback, in combination with reranking (e.g., by the PS score), can provide a simple and useful exploration device.
The last column (Rocchio-G4) reports the quality metrics for the best Rocchio sessions data, using the grammar with all operators (G4). Rocchio expansions make use of the gold answer and thus can be seen as a, possibly conservative, estimate of the performance upper bound. As the external benchmark, we use DPR (Kar+20), a popular neural retriever based on dual encoders, the dominant architecture for deep learning-based ad hoc retrieval (Cra+20). We note that our approach and DPR are not directly comparable in terms of engineering performance: while DPR requires a maximum inner-product search among dense vectors, our retrieval method is based on an inverted index.

T5 We evaluate T5 models trained on all 5 grammar variants. The best one, "T5-G1" in Table 4.2, is limited to term boosting (G1), and it learns to use all available weight values (Figure 4.3a). In terms of Top-1, this agent outperforms the published and the most recently posted DPR results[9] but has a worse Top-5 than both. Results for all five T5 agents are found in Table 4.8, we notice that the performance varies by relatively small amounts using different grammars, but it peaks noticeably with 'T5-G1'. Figure 4.4 shows the performance of the best Rocchio sessions data (Rocchio-G4) and that of the best T5 model (G1) as a function of the maximum number of steps allowed, both increasing monotonically as expected.

MUZERO On the retrieval task the MuZero agent outperforms all BM25 variants. While this result may seem trivial, it marked a milestone that required many iterations to achieve. The challenge for RL in IR, and NLU, is extreme in terms of state and action space dimen-

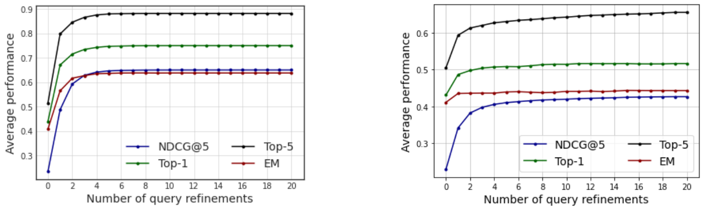
[9] https://github.com/facebookresearch/DPR.



(a) Distribution of action types. (b) Depth of documents explored.

Figure 4.3: The plot on the left shows the relative frequency of action types chosen by the best versions of the MuZero RL agent, the T5 agent that is learned on supervised episodes with the G1 grammar (only term boosting) 'T5-G1', and the Rocchio sessions with grammar G4 (complete grammar consisting of action types: simple terms, term boosting, "+", and "-") 'Rocchio-G4'. Interestingly, the MuZero agent converges to only use the *light* boosting operation with a weight of 2. The T5 agent, on the other hand, makes use of the whole spectrum of the boosting operations, including the boosting with 0.1, which down-weights a particular term. The Rocchio query expansion uses the "+" operator on the contents field most often. This can be seen as an effective but potentially dangerous operation as it is a hard filtering on the presence of a certain term, potentially reducing the resulting retrieval set drastically. The right plot shows the depth of the documents in terms of retrieval rank based on the original query explored by the three agents. Here, we see that for all three agents, a significant portion of documents are retrieved beyond rank 1000, which means that they find relevant documents entirely hidden from a system relying on BM25 with only the original query.

sionality, data sparsity, etc. (Zha+21). Our ideas for tackling some of these key challenges by fitting out agents with domain knowledge in principled ways, with the grammar-guided MCTS as the centerpiece, seem to point in a promising direction. MuZero converges to a policy that uses only the term boost action types with a weight of 2 – see Figure 4.3a for the action distributions of different policies. The MuZero agent is not able to find better-performing, diverse policies. This is an extreme case of a more general pattern. Different sub-grammars represent different tactics; e.g., "+" and "-" affect the accessible documents in irreversible ways, while boosting only affects ranking. It is challenging for all agents, and particularly MuZero, to modulate effectively multiple sub-policies.



(a) Rocchio-G4 supervised episodes

(b) T5-G1 episodes

Figure 4.4: Performance on NQ Dev as a function of the number of query refinement steps. The plot on the left shows the results for the performance of the supervised Rocchio sessions with grammar G4 (all operators), while on the right we plot the performance of the trained T5-G1 agent trained on the G1 Rocchio sessions.

AGENTS ENSEMBLE In the last experiment, we combine all trained agents, the five T5 agents, and MuZero, in one ensemble. We simply rank the union of all the documents returned by the ensemble using the PS score on each document, thus not requiring any additional parameters. This ensemble ("MuZero+T5s" in Table 4.2) has slightly better precision than the recent DPR in the top position, and slightly worse for the Top-5. This result indicates that the ability to orchestrate diverse sub-policies may indeed be the key to future progress for search agents. For the record, the current SOTA for Top-5 is 74.0 (Qu+21).

ANSWER QUALITY We conclude by discussing answer quality. Agents routinely produce answer spans, as predicted by the reader/scorer, to build observations. The MR/PS component is trained once, before the agents, on the output of BM25. However, agents deeply affect the composition of the results. As Figure 4.3b shows, search agents dig deep in the original BM25 ranking. This is positive, as behavior discovery is one of the main motivations for researching exploratory methods like RL. As a consequence, though, the MR/PS component effectively operates out of distribution and the EM numbers of the internal reader are not competitive with recent methods, Table 4.9 reports all the numbers including on NQ Dev. Ideally, one would co-train the observation builder with the search agent. However, combining the two would introduce significant engineering complexity in

	Query and Search Results		Score
$\mathbf{q}_0$	who averaged the most points in college basketball history		
Top-3 documents retrieved with $\mathbf{q}_0$:			0.027
$\mathbf{d}_1$	Title	Gary Hill (basketball)	
	Content	... one of four on that team who averaged double figures in points. Senior Larry Jones was OCU's leading scorer at 19.7 points a game, sophomore Bud Koper added 15.9...	
$\mathbf{d}_2$	Title	Kevin Foster (basketball)	
	Content	... his senior year, Foster averaged 21 points per game and was named the MVP and All-District 18-5A First Team. He was also a Texas top- 30 player his final season ...	
$\mathbf{q}_3$	who averaged the most points in college basketball history (contents:"per"∧6) (contents:"scorer"∧4) (contents:"3"∧6)		
Top-3 documents retrieved with $\mathbf{q}_3$:			0.330
$\mathbf{d}_1$	Title	Alphonso Ford	
	Content	... seasons. With 3,165 career points scored in the NCAA Division I, he is 4th on the all-time scoring list, behind only Pete Maravich, Freeman Williams, and Lionel ...	
$\mathbf{d}_2$	Title	Buzzy Wilkinson	
	Content	Buzzy Wilkinson Richard Warren "Buzzy" Wilkinson (November 18, 1932 – January 15, 2016) was an American basketball player who was selected by the Boston Celtics in ...	
$\mathbf{q}_4$	who averaged the most points in college basketball history (contents:"per"∧6) (contents:"scorer"∧4) (contents:"3"∧6) +(contents:"maravich")		
Top-3 documents retrieved with $\mathbf{q}_4$:			0.784
$\mathbf{d}_1$	Title	Alphonso Ford	
	Content	... seasons. With 3,165 career points scored in the NCAA Division I, he is 4th on the all-time scoring list, behind only Pete Maravich, Freeman Williams, and Lionel ...	
$\mathbf{d}_2$	Title	Pete Maravich	
	Content	... had posted a 3–20 record in the season prior to his arrival. Pete Maravich finished his college career in the 1970 National Invitation Tournament, where LSU finished fourth ...	

Table 4.3: Example of a T5-G4 agent session exhibiting multiple tactics. The session shows the evolution of the search query (first line in each section) and snippets of the top-2 retrieved documents from the search engine. We skip $\mathbf{q}_1$ and $\mathbf{q}_2$ for brevity. The colored spans indicate the prediction of the machine reader; blue if it is correctly predicted, red otherwise. In the top right corner of each section, we report the score of the retrieved document set at that step, according to Equation 4.15.

the current architecture. For instance, one could interleave training the two as in DQNs (Mni+13b).

	Query and Search Results		Score
$\mathbf{q}_0$	who was the last nba player to get drafted out of highschool		
Top-2 documents retrieved with $\mathbf{q}_0$:			0.081
$\mathbf{d}_1$	Title	1996 NBA draft	
	Content	...Jermaine O'Neal, Peja Stojaković, Antoine Walker), and one undrafted All-Star (Ben Wallace), for a grand total of 11 All-Stars. ...	
$\mathbf{d}_2$	Title	2009 NBA draft	
	Content	...The 2009 draft marked the first time three sons of former NBA players were selected in the top 15 picks of the draft ...	
T5-G1 $\mathbf{q}_3$	who was the last nba player to get drafted out of highschool (contents:"draftees"∧2) (contents:"thon"∧4) (contents:"satnam"∧4)		
Top-2 documents after aggregation with retrieval results from **T5-G1** $\mathbf{q}_3$:			0.946
$\mathbf{d}_1$	Title	NBA draft	
	Content	...However, because of the new age requirement put in place in 2005, **high school** seniors are no longer eligible for the draft, unless they were declared as postgraduates by the NBA, which would not happen until 2015 with Indian prospect Satnam Singh Bhamara in the second round and again in 2016 with South Sudanese–Australian prospect Thon Maker in the first round. ...	
$\mathbf{d}_2$	Title	Eligibility for the NBA draft	
	Content	...However, in recent years, other players like Satnam Singh, Thon Maker, and Matur Maker have looked to enter the NBA draft while still being **high schoolers** by exploiting a loophole where they enter the draft as **high school** postgraduates. ...	
T5-G4 $\mathbf{q}_1$	who was the last nba player to get drafted out of highschool +(contents:"highschool")		
Top-2 documents after aggregation with retrieval results from **T5-G4** $\mathbf{q}_1$:			0.081
$\mathbf{d}_1$	Title	1996 NBA draft	
	Content	...Jermaine O'Neal, Peja Stojaković, Antoine Walker), and one undrafted All-Star (Ben Wallace), for a grand total of 11 All-Stars. ...	
$\mathbf{d}_2$	Title	2009 NBA draft	
	Content	...The 2009 draft marked the first time three sons of former NBA players were selected in the top 15 picks of the draft ...	

Table 4.4: A snippet of episode examples from the T5-G1 (boosting only) agent vs. the T5-G4 agent (all operators). The T5-G1 adjustments to the query; first, boosting "draftees", and later boosting "thon", and "satnam" leads to almost perfect retrieval results with a score of 0.946. On the other hand, the T5-G4 agent decides to constraint the results in the first step to those including the term "highschool". While this is a topical term, this leads to a bad retrieval results set from which the agent cannot recover in later steps (omitted for brevity).

A simpler alternative is to add the answer prediction task to the T5 agent. Retrieval-augmented answer generation is known to produce strong results (IG21b). Multitasking would simplify the design of the generative agents and possibly produce better models. We make a first step in this direction by training a dedicated T5 agent. The system uses as training input the top-5 documents of the Rocchio-G4 episodes, but its task is to generate the gold answer instead of the query expansion. At evaluation time, based on the output of the "T5-G1" and "MZ+T5s" agents, the EM performance of the answer generation T5 is comparable to methods that build on DPR, such as RAG (Lew+20c) (44.5 EM). Although not as good as FID (IG21b) that condition on many more (100) documents.

DISCUSSION

LIMITATIONS OF CURRENT POLICIES Table 4.3 illustrates an example where the T5-G4 agent (with the full set of operators) switches policy mid-session. The question is about basketball records, and BM25 does not find good results. In the first three steps, the agent focuses on *re-ranking* by boosting terms like "per" (from the phrase "per game" in the results for q_0) and "scorer". This produces a good hit and predicted answer span ("Pete Maravich") at position 1 of step 3. The agent then switches to *filtering* mode to focus on documents containing the answer term predicted by the machine reader. While this is a clear instance of successful policy synthesis, the T5-G4 agent does not master switching between policies well enough to perform better than T5-G1, the agent that only uses boost operators. Table 4.4 provides an example that shows how T5-G1 is more robust than T5-G4. T5-G4 starts by requiring the presence of a misspelled term ("highschool") which leads to empty results and the end of the session because that step is not reversible. T5-G1, instead, makes its way gradually in the session boosting topical terms ("draftees") and players' names, eventually solving the query.

The agents' ensemble results prove that the ability to orchestrate complementary sub-policies provides a performance advantage. This suggests that the action space may benefit by including more control actions, e.g. to 'undo' or 'go back' to a specific state, to better support safe exploration and the emergence of meta policies. We plan to investigate this in future work. The previous point extends to the agents' architecture. It is reasonable to hypothesize that the superior performance of T5 is due to two main factors. T5s are bigger models, trained on more data, and rely on a more powerful prediction process based on the encoder-decoder architecture. In addition, they are finetuned on a self-supervised task which provides significant headroom. While large LMs seem the obvious choice forward there are open questions concerning exploration. It is unclear how much the model can generalize, being trained offline and never exposed to its own predictions. This moves the learning problem back toward RL. We have started to investigate approaches in the direction of decision/trajectory transformers (Che+21a; JLL21). We believe they provide a natural framework for bringing back key RL concepts which could play an important role; for example, by allowing successful policy synthesis by training from different offline policies; e.g., from Rocchio and MuZero.

ARTIFICIAL VS HUMAN SEARCH POLICIES Based on human search behavior (cf. Chapter 2.4), it seems natural to model search as an iterative, contextualized machine learning process. In terms of the number of steps required, Rocchio sessions peak at around 5 steps, while also for humans, especially for hard queries, several steps are often necessary. Qualitatively speaking, though, they look different. For a start, while powerful, search operators (at least in the current form) don't allow to easily capture the full spectrum of human search tactics. Human search sessions have been characterized broadly in terms of three types of refinement actions: specification, generalization, and reformulation (LH99; Dow+08). In this respect, the current search agents lack the ability to explicitly generalize and fully reformulate. They mostly perform filtering and reranking. Search operators may be better suited to complement, as power tools, other plain language query refinement methods rather than being the centerpiece of the agent's action space. Evaluating plain language reformulation functionality is thus an obvious next step. However, the generation of the necessary training data, in this case, is an open question. We will focus on this problem in future work.

We also point out that the policies that can be currently generated via the Rocchio sessions, or by exploration via Muzero, are artificial because they are driven by a reward which is an imperfect proxy for human relevance. In future work, we plan to investigate new learning methods that include modeling of human policies, e.g., in combination with apprenticeship learning frameworks (cf. (Nak+21a)).

THOUGHTS ON OPENQA-NQ The Natural Questions dataset (Kwi+19) is unique in that it builds from real user queries, with a great deal of attention to annotation and data quality. On the other hand, the dataset is designed for a setup where the document is given. Hence, annotations are consistent only within that document, not at the collection level. The retrieval setting implies that the vast majority of the data have not been validated by raters. Additionally, the human ratings cannot be easily and reliably aligned with a pre-computed segmentation into passages. Thus, one typically relies on the heuristic relevance function, based on the presence of the short answer string, which cannot discriminate unjustified answers. While imperfect, this setup strikes a local optimum that has driven significant innovation in IR and QA research by allowing direct comparison of many different approaches in a fast-moving landscape, e.g., from ORQA (LCT19b) to closed book QA (RRS20) to RAG (Lew+20b; Qu+21), DPR (Kar+20) etc. Another possible downside is the overlap between partitions, as pointed out in (LSR21). We for this factor periodically by splitting the dev partition into known and unknown answers (based on the presence of the answer in the train data). Consistent with (LSR21), we find a significant drop in the unknown answers but the same relative performance of methods.

BROADER IMPACT We would like to note that pre-trained language models of the kind used here have been shown to capture societal biases (TC19; Web+20), which motivates a broad discussion about potential harms and mitigations (Blo+20; Ben+21). We have no reason to believe our architectures would exacerbate biases, but the overall problems may persist. We also hope that end-to-end optimization methods based on composite rewards, as in this proposal, can contribute to addressing some of these challenges; e.g., by providing means of adversarial testing, and by including relevant metrics directly in the objective design. We stress here that while our agents yield performance comparable to neural retrievers, they rely solely on interpretable, transparent, symbolic retrieval operations.

4.5 CONCLUSION

Learning to search sets an aspiring goal for AI, touching on key challenges in NLU and ML, with far-reaching consequences for making the world's knowledge more accessible. This chapter provides the following contributions. First, we open up the area of search session research to supervised language modeling. Second, we provide evidence for the ability of RL to discover successful search policies in a task characterized by multi-step episodes, sparse rewards, and a high-dimensional, compositional action space. Lastly, we show how the search process can be modeled via transparent, interpretable machine actions that build on principled and well-established results in IR and NLU. Our findings seem to agree with a long-standing tradition in psychology that argues against radical behaviorism – i.e., pure reinforcement-driven learning, from *tabula rasa* – for language (Cho59). RL agents require a remarkable share of hard-wired domain knowledge. LM-based agents are easier to put to use, because they rely on massive pre-training and abundant task-specific data for fine-tuning. Supplied with the right inductive bias, LM and RL search agents prove surprisingly effective. Different architectures learn different, complementary policies, suggesting broad possibilities in the design space for future work.

4.6 APPENDIX

ROCCHIO SESSIONS In Table 4.5 below, we report the total number of expansion steps performed on NQ Train. These are used as supervised training data for our T5 agents.

G0	G1	G2	G3	G4
243,529	313,554	230,921	246,704	298,654

Table 4.5: Total number of Rocchio expansion steps in NQ Train for different grammars on the 77,492 Rocchio sessions.

OBSERVATION BUILDING DETAILS This section provides more details and examples about the encoding of observations for both the MuZero and the T5 agents. As described in Section 4.1, the main part of the observation consists of the top-5 documents from all results retrieved so far, $\cup_{i=0}^{t}\mathcal{D}_i$. The documents are sorted according to the PS score and reduced in size by extracting fixed-length snippets around the machine reader's predicted answer. Moreover, the corresponding Wikipedia article title is appended to each document snippet. The computational complexity of this step is determined by running a BERT-base (110M parameters) machine reader separately (albeit possibly in parallel) over five passages. In addition to the top documents, the observation includes the original question and information about any previous refinements. While the main part of the observation is shared between the MuZero and the T5 agent, there are differences in the exact representation. The following two paragraphs give a detailed explanation and example for both agents.

MUZERO AGENT'S STATE (CF. CH. 4.1) The MuZero agent uses a custom BERT (initialized from BERT-base) with additional embedding layers to represent the different parts of the observation. It consists of four individual embedding layers as depicted in Figure 4.5. At first, the standard layer for the tokens of the query, the current tree, and the current top-5 documents D. The second layer assigns a type ID to each of the tokens representing if a token is part of the query, the tree, the predicted answer, the context, or the title of a document. The last two layers add scoring information about the tokens as float values. We encode both the inverse document frequency (IDF) of a word and the documents' passage selection (PS) score. Figure 4.6 shows a concrete example of a state used by the MuZero agent.

Layer	**Query**	**Tree**	**Document Results**
Tokens	q_0	$l_0, \ldots, l_m$	$a_0, c_0, t_0, \ldots, a_n, c_n, t_n$
Type	ID_q	$\mathrm{ID}_{\mathrm{tree}}$	$\mathrm{ID}_a, \mathrm{ID}_c, \mathrm{ID}_t, \ldots, \mathrm{ID}_a, \mathrm{ID}_c, \mathrm{ID}_t$
IDF Score	$\mathrm{idf}(q_0)$	$\mathrm{idf}(l_0), \ldots, \mathrm{idf}(l_m)$	$\mathrm{idf}(a_0), \mathrm{idf}(c_0), \mathrm{idf}(t_0), \ldots, \mathrm{idf}(a_n), \mathrm{idf}(c_n), \mathrm{idf}(t_n)$
PS Score	0	0	$\mathrm{PS}(d_0), \ldots, \mathrm{PS}(d_n)$

Figure 4.5: Schematic illustration of the MuZero search agent's state for the BERT representation function.

Tokens	[CLS]	who	carries	the	burden	of	going	forward	with	evidence	in	a	trial	...
Type	[CLS]	query	query	query	query	query	query	query	query	query	query	query	query	
IDF	0.00	0.00	6.77	0.00	7.77	0.00	5.13	5.53	0.00	5.28	0.00	0.00	5.77	
PS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Tokens	[SEP]	[pos]	[content]	burden	##s	[neg]	[title]	sometimes	[SEP]	lit	##igan	##ts	[SEP]	...
Type	[SEP]	tree	tree	tree	tree	tree	tree	tree	[SEP]	answer	answer	answer	[SEP]	
IDF	0.00	0.00	0.00	9.64	9.64	0.00	0.00	4.92	0.00	10.64	10.64	10.64	0.00	
PS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-3.80	-3.80	-3.80	-3.80	
Tokens	kinds	for	each	party	,	in	different	phases	of	litigation	.	the	burden	...
Type	context	context	context	context	context	context	context	context	context	context	context	context	context	
IDF	7.10	0.00	0.00	4.36	17.41	0.00	4.18	7.46	0.00	7.92	17.41	0.00	7.77	
PS	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	-3.80	
Tokens	suspicion	"	,	"	probable	cause	"	(	as	for	[SEP]	evidence	[SEP]	...
Type	context	context	context	context	context	context	context	context	context	context	[SEP]	title	[SEP]	
IDF	7.80	17.41	17.41	17.41	7.91	5.41	17.41	17.41	0.00	0.00	0.00	5.28	0.00	
PS	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	-12.20	

Table 4.6: Example state of the MuZero search agent that is the input to the BERT representation function. The *Type* layer encodes the state part information for each token. The IDF and PS layers are additional layers with float values of the IDF and the PS score of the input tokens, respectively.

T5 AGENT'S STATE (CF. CH. 4.2.1) T5 represents the state as a flat string. The input is a concatenation of the original query, zero or more expansions, and five results. For each result, we include the answer given by the reader, the document's title, and a span centered around the answer. The prediction target is simply the next expansion. See Table 4.7 for a full example.

RESULTS Table 4.8 reports the results for the different versions of the T5 agent, evaluated on dev. We don't evaluate all agents with the

Input	Query: 'how many parts does chronicles of narnia have'. Contents must contain: lewis. Contents cannot contain: battle boost 2.0. Answer: 'seven'. Title: 'The Chronicles of Narnia'. Result: The Chronicles of Narnia is a series of *seven* fantasy novels by C. S. Lewis. It is considered a classic of children's literature and is the author's best-known work, having... Answer: 'seven'. Title: 'The Chronicles of Narnia (film series)'. Result: '"The Chronicles of Narnia", a series of novels by C. S. Lewis. From the *seven* books, there have been three film adaptations so far – (2005), "" (2008) and "" (2010)... Answer: 'seven'. Title: 'Religion in The Chronicles of Narnia'. Result: 'Religion in The Chronicles of Narnia "The Chronicles of Narnia" is a series of *seven* fantasy novels for children written by C. S. Lewis. It is considered a classic of... Answer: 'seven'. Title: 'The Chronicles of Narnia'. Result: 'Lewis's early life has parallels with "The Chronicles of Narnia". At the age of *seven* , he moved with his family to a large house on the edge of Belfast... Answer: 'Two'. Title: 'The Chronicles of Narnia'. Result: 'found in the most recent HarperCollins 2006 hardcover edition of "The Chronicles of Narnia". *Two* other maps were produced as a result of the popularity of the 2005 film ...
Target	Contents must contain: novels

Table 4.7: Example state (input) and prediction (target) of the T5 agent with linebreaks and emphasis added for readability. We use a 30 token span in our experiments.

generative answer system, for answer quality we report only the performance of the internal machine reader (EM-MR). Table 4.9 reports extended results, including for NQ Dev and the PS/MR component answer quality eval (EM-MR). Moreover, in Figure 4.4b we plot the performance of our T5-G1 agent on NQ Dev as a function of the maximum number of query refinements. We observed the performance increase monotonically with the number of refinements and that most of the performance gain is achieved in the early steps, in accordance with the respective supervised Rocchio episodes (Figure 4.4a).

Version	NDCG@5	Top-1	Top-5	EM-MR	Reward
G0	40.75	52.12	64.93	30.22	33.30
G1	43.10	52.12	66.09	29.50	35.55
G2	41.16	51.51	63.54	30.03	33.81
G3	41.69	51.34	64.17	29.77	33.95
G4	41.53	50.98	63.49	29.70	34.25

Table 4.8: Results of all T5 Agents on NQ Dev.

Metric	Data	BM25	+PS	+RM3	MuZero	T5-G1	MuZero+T5s	DPR	Rocchio-G4
NDCG@5	Dev	19.83	22.95	25.09	30.76	43.10	45.30	-	64.89
	Test	21.51	24.82	26.99	32.23	44.27	46.22	-	65.24
Top-1	Dev	28.17	43.06	44.81	46.02	52.12	54.15	-	74.99
	Test	28.67	44.93	46.13	47.97	52.60	54.29	52.47	73.74
Top-5	Dev	50.47	50.47	53.61	57.71	66.09	70.05	-	88.21
	Test	53.76	53.76	56.33	59.97	66.59	71.05	72.24	88.17
EM-MR	Dev	15.31	25.15	26.22	27.17	29.50	31.12	-	47.38
	Test	14.79	25.87	26.95	28.19	30.08	30.58	41.50	46.34
EM-T5	Dev	28.98	40.70	41.65	32.48	44.75	44.47	-	63.78
	Test	28.78	41.14	40.14	32.60	44.04	44.35	41.50	62.35

Table 4.9: Results on NQ Dev and Test.

PSEUDO-RELEVANCE FEEDBACK BASELINES We investigate the performance of multiple pseudo-relevance feedback (PRF) baselines on our setup. We employ these baselines by running search sessions of length k, where, at each step, we choose the *most relevant* term of the top-retrieved documents and add it to the query. To determine the most relevant term, we use either inverse document frequency (IDF), computed over our full retrieval corpus, or RM3 (Jal+04). For RM3, we use the model described in Eq. 20 of Pal et al. [PMD13] with $\mu = 2500$. After each expansion step, we use the passage scorer (PS) to score and rank the documents. This is an important step, as we do this approach iteratively, so the baseline is more comparable to our agent's setup. While a standard PRF baseline on top of BM25 adds a term to the query (equivalent to our "or"-operator), we investigate the effect of different Lucene operators that our agents have access to. In particular, we run for each of our 10 operators ("or", "+content", "+title", "-content", "-title", "∧.1", "∧2", "∧4", "∧6", "∧8") a PRF baseline with $k = 20$ steps (same as our agents). The results are reported in Table 4.10. Interestingly, the "-title"-operator, which limits search results not to contain any documents where the specified term is part of the title, works best across all metrics, datasets, and relevancy algorithms. This is in contrast to the standard motivation of PRF to promote relevant terms that appeared in the search results. Instead, *requesting* search results to contain *new* documents (with different titles) seems to be the stronger heuristic. We believe that these experiments underline the benefit of a learned agent to automatically pick the right operator based on the search session context.

Metric	Data	Alg	or	+c	+t	-c	-t	∧.1	∧2	∧4	∧6	∧8
NDCG@5	Dev	IDF	24.78	<u>25.13</u>	24.61	25.12	**26.81**	23.67	24.45	24.43	24.37	24.30
	Dev	RM3	25.09	<u>25.41</u>	24.78	24.98	**26.32**	23.69	24.53	24.60	24.50	24.35
	Test	IDF	26.48	26.60	26.33	<u>27.32</u>	**29.33**	25.51	26.35	26.25	26.19	26.08
	Test	RM3	<u>26.99</u>	26.98	26.70	26.90	**28.59**	25.47	26.60	26.61	26.54	26.37
Top-1	Dev	IDF	44.52	44.87	44.56	<u>45.35</u>	**47.09**	44.13	44.45	44.36	44.30	44.21
	Dev	RM3	44.81	45.21	44.45	<u>45.56</u>	**46.92**	44.17	44.53	44.54	44.42	44.32
	Test	IDF	45.93	45.90	46.10	<u>47.09</u>	**49.29**	45.84	46.18	46.01	45.98	45.90
	Test	RM3	46.13	46.41	46.30	<u>47.37</u>	**49.03**	45.78	46.41	46.24	46.18	46.10
Top-5	Dev	IDF	53.08	53.15	52.95	<u>54.27</u>	**56.49**	51.74	52.59	52.68	52.61	52.58
	Dev	RM3	53.61	53.85	53.19	<u>54.29</u>	**56.01**	51.91	52.88	53.06	52.91	52.82
	Test	IDF	55.62	55.62	55.42	<u>57.37</u>	**60.14**	54.96	55.56	55.50	55.50	55.42
	Test	RM3	56.33	56.27	56.07	<u>57.54</u>	**59.58**	55.04	55.99	56.02	55.99	55.93

Table 4.10: Results on NQ Dev and Test for the pseudo-relevance feedback sessions. Here, we run episodes of length 20 where we determine, at each step, the most relevant term from the retrieved results using either inverse-document frequency (IDF) or RM3. We add the term using one of our 10 operators: simply appending the term ("or"), enforcing the term in the *content* or *title* ("+c"/"+t"), limiting the search to documents that not contain the term in the *context* or *title* ("-c"/"-t"), and boosting the term with different values ("∧.1","∧2","∧4","∧6","∧8"). After each step in the episode, we aggregate the documents using the scores from our passage scorer (PS). The largest value in each table row is indicated in bold, and the second-largest is underlined.

5 DECODING A NEURAL RETRIEVER'S LATENT SPACE FOR QUERY SUGGESTION

5.1 INTRODUCTION & BACKGROUND

Neural encoder models (Kar+20; Ni+21; Iza+21) have improved document retrieval in various settings. They have become an essential building block for applications in open-domain question answering (Kar+20; Lew+20c; IG21b) and open-domain conversational agents (Shu+21a; Ado+21). Neural encoders embed documents and queries in a shared (or joint) latent space, so that paragraphs can be ranked and retrieved based on their vector similarity with a given query. This constitutes a conceptually powerful approach to discovering semantic similarities between queries and documents that is often found to be more nuanced than simple term frequency statistics typical of classic sparse representations. However, such encoders may come with shortcomings in practice. First, they are prone to domain overfitting, failing to consistently outperform bag-of-words approaches on out-of-domain queries (Tha+21). Second, they are notoriously hard to interpret as the similarity is no longer controlled by word overlap, but rather by semantic similarities that lack explainability. Third, they may be non-robust as small changes in the query can lead to inexplicably different retrieval results.

In bag-of-words models, it can be straightforward to modify a query to retrieve a given document: e.g., following insights from *relevance feedback* (Roc71), by increasing the weight of terms contained in the target document (Ado+22c; Hue+22). This approach is not trivially

This Chapter is based on our EMNLP 2022 paper "Decoding a Neural Retriever's Latent Space for Query Suggestion" (Ado+22b).

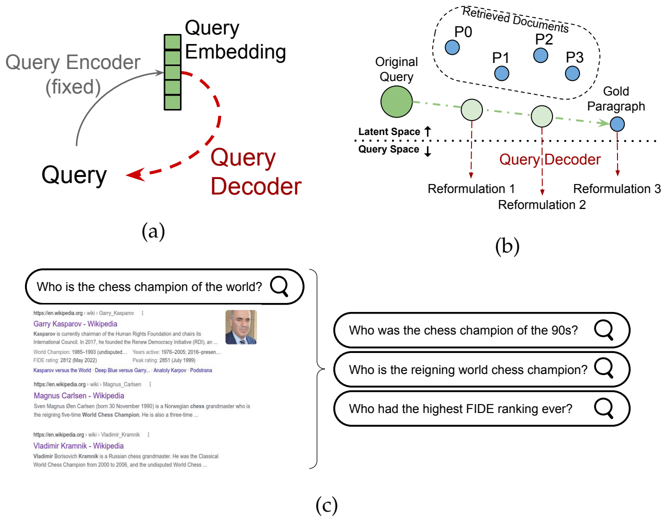


Figure 5.1: We train a query decoder (QD) model that inverts the shared encoder of a neural retrieval model (a). Then, we leverage the structure of the latent space of a neural retrieval model by traversing from query to gold paragraph embeddings and using our query decoder to generate a dataset of successful query reformulations (b). Finally, we train a pseudo-relevance feedback query suggestion model on this dataset that predicts promising rewrites, given a query and its search results (c).

applicable to neural retrieval models as it is unclear how an added term might change the latent code of a query.

In this chapter, we look into the missing link connecting latent codes back to actual queries. We thus propose to train a "query decoder", which maps embeddings in the shared query-document space to query strings, inverting the fixed encoder of the neural retriever (cf. Figure 5.1a). As we will show, such a decoder lets us find queries that are optimized to retrieve a given target document. It deciphers what information is in the latent code of a document and how to phrase a query to retrieve it.

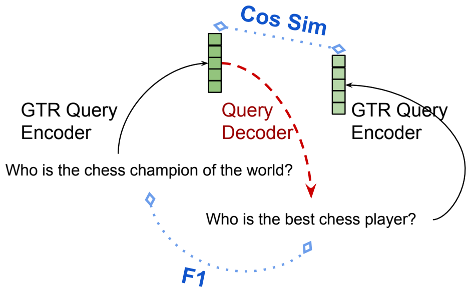
We use this model to explore the latent space of a state-of-the-art neural retrieval model, GTR (Ni+21). In particular, we leverage the structure of the latent space by traversing from the embedding of a specific query to its human-labeled gold paragraph and use our

query decoder to generate reformulation examples from intermediate points along the path as shown in Figure 5.1b. We find that using this approach, we can generate a large dataset of query reformulations on MSMarco-train (Ngu+16) that improve retrieval performance without needing additional human labeling. We use this dataset to train a pseudo-relevance feedback (PRF) query suggestion model. Here, we fine-tune a T5-large model (Raf+20a) that uses the original query, together with its top-5 GTR search results, as the input context to predict query suggestions as depicted in Figure 5.1c. We show that our model provides fluent, diverse query suggestions with better retrieval performance than various baselines, including a T5 model trained on question editing (Chu+20), and a PRF query expansion model [PMD13].
We make the resources to reproduce the results publicly available[1].

QUERY GENERATION The methods presented in this chapter are a natural complement to the previous chapter (based on Adolphs et al. [Ado+22c]), where we propose a heuristic approach to generate multi-step query refinements, used to train sequential query generation models for the task of *learning to search*. Last chapter's method was also inspired by relevance feedback, but there we aimed to reach the gold document purely in language space, by brute force exploration. For this purpose, we used specialized search operators to condition the retrieval results as desired. Huebscher et al. [Hue+22] show that, when paired with a hybrid sparse/dense retrieval environment, the search agents trained on this kind of synthetic data combine effective corpus exploration, competitive performance, and interpretability.

PRIOR WORK ON FIXED-VECTOR DECODERS Probabilistic decoders mapping from a fixed-size vector space to natural language have also been explored in auto-encoder settings. A key challenge in this line of work lies in obtaining decoders that are robust, *i.e.*, they generate natural text for a variety of input vectors. Bowman et al. [Bow+16] proposed using an RNN-based language model in combination with variational autoencoders (VAE) (KW13) which adds Gaussian space to the decoder input. Zhao et al. [Zha+18b] proposed the use of Adversarial Autoencoder (AAE) (Mak+15) to which Shen et al. [She+20]

[1] https://github.com/leox1v/query_decoder



Data	F1	Cos Sim
MSMarco	0.750	0.960
NQ	0.886	0.980

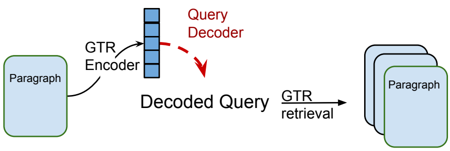
Table 5.1: Decoding metrics of the Query Decoder (QD) based on the GTR-base neural retrieval model. The F1 score is the F1 word overlap between the original query, of MSMarco or NQ, and the output of the query decoder model when provided with the GTR encoding of the query. The cosine similarity is measured between the re-encoding of the generated query and the encoding of the original query. The figure above depicts the metrics visually with a toy example for clarity.

added data denoising by randomly dropping words in the input and the reconstructing the full output. Recently, RNN-based decoders have been replaced by Transformer-based language models (Vas+17), for example by Montero et al. [MPS21], Park and Lee [PL21] and Li et al. [Li+20].

5.2 QUERY DECODER

TRAINING We train a T5 (Raf+20a), decoder-only model, to (re-)generate a query from its embedding obtained in a neural retrieval model. As training data, we use a subset of 3 million queries of the PAQ dataset (Lew+21b). We use the GTR-base (Ni+21), shared-encoder model, to generate the embeddings and use the queries as the targets. The objective of the query decoder learning is to invert the mapping of the *fixed* GTR encoder model, as visually depicted in Figure 5.1a. For more training and hyperparameter tuning details, we refer to the corresponding paper (Ado+22b).

QUERY RECONSTRUCTION EVALUATION We consider the round-trip consistency as a first step in evaluating the query decoder's effectiveness. A query q is encoded via GTR and then decoded by our decoder to generate q'. We use queries from MSMarco, and NQ test sets of the BEIR benchmark [Tha+21]. As a first metric, we compute the F1 score between the original q and its reconstruction q'. Since word overlap is imperfect in measuring query drift, we further re-encode q' and compare its latent code with the code for q via their cosine similarity. The results of these evaluations are reported in Table 5.1, where we also provide an illustrative example of the proposed approach. For both datasets, MSMarco and NQ, the metrics of F1 and cosine similarity are generally high, indicating that the GTR code carries information that allows for close approximate query reconstruction.



Data	Top1	Top3	Top5
MSMarco	0.551	0.737	0.796
NQ	0.721	0.863	0.897

Table 5.2: Share of gold paragraphs for which we can decode a query that retrieves the given paragraph within its top-k GTR search results. The figure above depicts the metric evaluation visually for clarity.

PARAGRAPH TO QUERY EVALUATION Many interesting use cases rely on the ability to generate queries from passages of text (DSC17; Kum+18). As GTR embeds document paragraphs and queries into the same space, the query decoder can also be used to invert the retrieval process. We thus evaluate the decoder quality by starting from a document paragraph, decoding a query from its embedding, and then running the GTR search engine on that query to check if this query retrieves the desired paragraph as a top-ranked result. We test this in an experiment with human-labeled gold paragraphs from MSMarco

Original Query	
nebl coin price	[Rank: 2]
Decoding from Gold Paragraph	
what is the current price of neblio today belo	[Rank: 1]
Gold Paragraph	
Neblio Price Chart US Dollar (NEBL/USD) Neblio price for today is $16.3125. It has a current circulating supply of 12.8 Million coins and a total volume exchanged of $9,701,465	
Original Query	
when is champaign il midterm elections	[Rank: 3]
Decoding from Gold Paragraph	
when is the general election in illinois 2018	[Rank: 1]
Gold Paragraph	
Illinois elections, 2018. A general election will be held in the U.S. state of Illinois on November 6, 2018. All of Illinois' executive officers will be up for election as well as all of Illinois' eighteen seats in the United States House of Representatives.	

Table 5.3: Examples of query decodings from the gold paragraph. The rank indicates the retrieval position of the gold paragraph using the corresponding query.

and NQ, using top-k as the success metric. The results reported in Table 5.2 are very encouraging in that the desired paragraph is indeed found very often among the topmost GTR search results. Two example paragraph decodings from MSMarco are shown in Table 5.3; for both decodings, the gold paragraph is retrieved at the top position.

LATENT SPACE TRAVERSAL DECODING We have shown that query decoding can reconstruct queries and that it can find retrieval queries for target passages. We now turn to a more concrete practical application, namely to automatically generate a data set of query reformulations, from which strategies for interactive retrieval can be learned. In this context, reformulated queries should remain semantically similar to the original query and not overfit to the target passage. They should be somewhat *in between* the query and the gold passage, as any passage is likely to contain answers to multiple, different questions. This can be operationalized by decoding queries from points along the

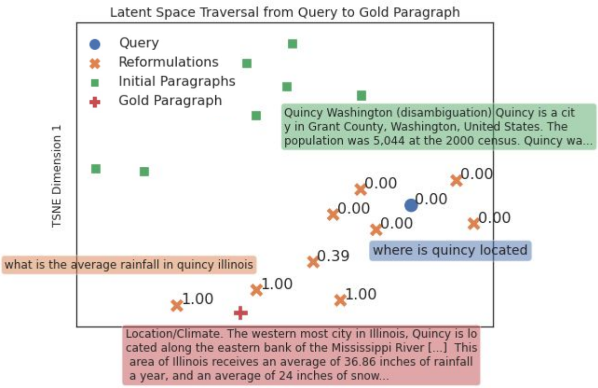


Figure 5.2: Visualization of the latent-space traversal from query to gold paragraph, using 2D t-SNE. The blue point denotes the embedding of the original query "where is quincy located". The green squares are the embeddings of the retrieved paragraphs for this query. The closest one about "Quincy Washington" is shown in the green text bar. The orange crosses denote the embeddings of the reformulations of the query decoder when moving to the gold paragraph depicted as the red plus. The orange and red text bars show the final reformulation and the gold paragraph text, respectively. The number above the query and reformulations show the nDCG score. As the gold paragraph is describing the climate of Quincy in addition to its location, a reformulation about the "average rainfall in quincy illinois" retrieves the desired paragraph.

line connecting the embeddings of the query and its target passage as depicted in Figure 5.1b.
To validate this idea, we apply it to the MSMarco and NQ retrieval dataset where each query is paired with a human-labeled gold paragraph. In particular, we move in k equidistant increments from the original query embedding $\mathbf{q}$ to the gold paragraph embedding $\mathbf{d}$, i.e.

$$\mathbf{q}_\kappa = \mathbf{q} + \frac{\kappa}{k}(\mathbf{d} - \mathbf{q}) \qquad \kappa = 0, \dots, k \tag{5.1}$$

and generate a reformulation at each step.[2] As a sanity check, Figure 5.3 shows the average retrieval performance of the decoded queries

[2]We underline that this procedure can be seen as a latent space equivalent of the *Rocchio Session* process for generating synthetic search sequences of Adolphs et al. [Ado+22c].

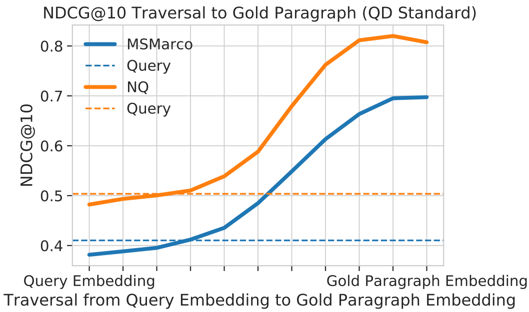


Figure 5.3: The normalized discounted cumulative gain (nDCG) of the reformulations from the query decoder when moving the input code from the embedding of the query to the embedding of the gold paragraph. Decoding closer to the gold paragraph embedding leads to queries with improved average retrieval performance. The initial decodings nDCG scores are slightly lower than from the original query due to the reconstruction loss of the query decoder.

when moving from the original query embedding to the gold paragraph embedding for MSMarco and NQ. For both datasets, the normalized discounted cumulative gain (nDCG) (JK02) improves steadily and plateaus, then slightly dips, only when getting close to the gold paragraph embedding. We hypothesize that two effects are at work here that explain this dip: (i) the closer one moves towards the gold passage embedding, the more the query decoder operates out-of-distribution as it is trained on query embeddings. The joint latent space is sparse and likely characterized by distinct regions for queries and passage embeddings, which have different properties (e.g., length or surface structure). (ii) A passage might answer several questions. When decoding from an embedding close to the paragraph, these might start being conflated.

EXAMPLES We provide a visual example of the latent traversal approach in Figure 5.2 where we project the latent space to 2 dimensions using t-SNE (HR02). The plot shows that for the ambiguous query "where is quincy located" (blue dot), the gold paragraph about the climate of Quincy, Illinois (red plus), is far away from the top-10 retrieved documents (green squares). Traversing the latent space from

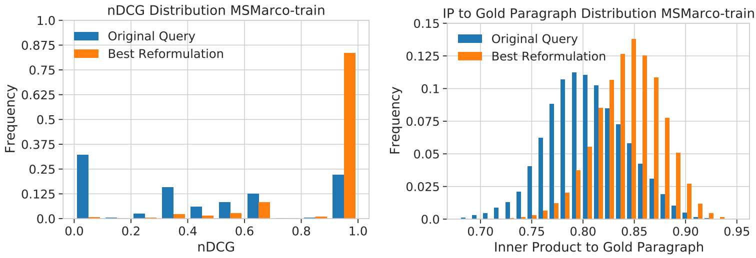
Original Query	
average yearly return on stock market	[0.00]
Decodings during Traversal	
what is the average annual return on stock market	[0.00]
average return on a stock market year	[0.00]
what is the average annual return on stock market	[0.00]
what is the average return on stock in a year	[0.00]
what is the average return in a stock market	[0.00]
what is the average annual return in stock (s&p)	[0.36]
what is the average return on the stock market (s&p)	[0.36]
what is the average return on the s&p stock exchange at a time	[1.00]
what is the average return in s&p stock at a time	[0.36]
what is the average annual return of the s&p stock exchange (best)	[1.00]
Gold Paragraph	
The S&P 500 gauges the performance of the stocks of the 500 largest, most stable companies in the Stock Exchange. It is often considered the most accurate measure of the stock market as a whole. The current average annual return from 1926, the year of the S&Ps inception, through 2011 is 11.69%. That's a long look back, and most people aren't interested in what happened in the market 80 years ago.	

Table 5.4: Example of a successful traversal on an MSMarco query. The nDCG@10 score of each query is provided in the brackets. The queries decoded from a latent code close to the gold paragraph, focus on the returns of the S&P (as the gold paragraph) and lead to improved retrieval results (nDCG@10 from 0.00 to 1.00).

the query towards the gold paragraph leads to improved reformulations (orange crosses), as is evident from the shrinking distance to the gold paragraph and by the improved nDCG score. Semantically, the reformulations move to questions about the climate of Quincy, as this is the main topic of the gold paragraph.

5.3 QUERY SUGGESTION MODEL

DATASET GENERATION We generate a dataset of query reformulations using the latent space traversal decoding as described in the previous section. In particular, for the 532,761 queries of the MSMarco-train dataset, we leverage GTR's learned latent space structure and move towards the embedding of their gold paragraph. At $k = 20$



(a) (b)

Figure 5.4: The histogram of nDCG (a) and inner product with the gold paragraph embedding of the original query vs. the best reformulation found with the latent-space traversal approach on MSMarco-train.

intermediate steps on this path, we use our query decoder to generate reformulations.

For more than 80% of the queries, we find at least one optimal reformulation that retrieves the gold paragraph at the top position. In Figure 5.4, we show histograms of nDCG and the inner product to the gold paragraph for the original query versus the best-found reformulation. The metrics show that the latent space traversal helps us discover good query reformulations that lead to massively improved retrieval performance and are closer to the corresponding gold paragraphs in latent space.

We filter the dataset to only contain "successful" reformulations to train the reformulation model. Here, we require a reformulation to have an nDCG of 1 (i.e., retrieve the gold paragraph at the top position), to improve the nDCG compared to the original query, and its embedding to have a larger inner product with the gold paragraph than the original query. Using this approach, we generate a dataset of 863,307 successful query rewrites. As the example in Table 5.4 shows, the decoded queries do not always have human-like fluency and for some sequences intent shift occurs when decoding closer to the paragraph. This is one reason we're moving in increments from the original query to the gold paragraph instead of directly decoding it.

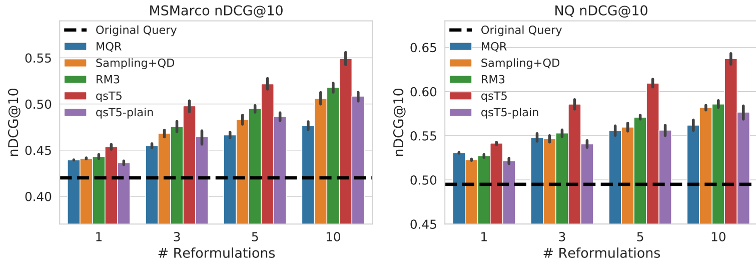
Interestingly, however, we find that this noise of the dataset is unspecific enough that it gets smoothed out during model training as described in the following paragraph. More details about this dataset are provided in Sec. 5.6.

MODEL TRAINING We use the reformulation dataset to train two query suggestion model variants. First, we train a model on the plain reformulation examples, from original query to "successful" rewrite. As a second, more powerful approach, we train a model with pseudo-relevance feedback (PRF); here, we provide GTR's top-5 search results for the original query as additional context to the model. Both models are fine-tuned from the T5-large (Raf+20a) pre-training checkpoint. Consequently, we name the models in the following way:

- **qsT5-plain**: A T5 **q**uery **s**uggestion model trained on the **plain** generated reformulation examples (no pseudo-relevance feedback) of MSMarco-train, mapping from query to query reformulation.
- **qsT5**: A T5 **q**uery **s**uggestion model trained on the generated reformulation examples of MSMarco-train, where the input is augmented with the content of GTR's top-5 retrieved search results for the original query, mapping from query and search results to query reformulation.

BASELINE MODELS To measure the effectiveness of our query suggestion model, we benchmark it against multiple baselines. The baselines are meant to cover various angles of competitive approaches to query suggestion, namely training on human-generated question-edit histories, a classic RM3 pseudo-relevance feedback query expansion method, and a latent space sampling approach utilizing our query decoder. In the following, we introduce the three baselines in detail.

- **MQR**: We train a T5-large model on the "multi-domain question rewriting" (MQR) (Chu+20) dataset. This dataset consists of 427,719 human-contributed Stack Exchange question-edit histories, mapping from ill-formed to well-formed. While this is a relatively large training dataset, our synthetic generations dataset is roughly double in size with 863,307 rewrites, yet without any human edits. This baseline captures the effect of turning a query to a well-formed question to improve retrieval performance. It does not use PRF but maps from query to reformulation, as our qsT5-plain model.



(a) (b)

Figure 5.5: Retrieval metrics of the query suggestion models on the MSMarco (a) and NQ (b) test sets. The dashed line shows the nDCG@10 score of the original query. The bars represent the nDCG@10 of the best 1, 3, 5, and 10 reformulations (including the original query), respectively, of different models. The error bars show the 95 percent confidence interval when doing bootstrap sampling from up to 10 generations of the models. The RM3 and qsT5 models are using pseudo-relevance feedback, i.e., information about the top-retrieved paragraphs.

- **RM3**: We employ RM3 (Jal+04) as a strong pseudo-relevance feedback baseline. In particular, we use a query expansion approach that uses the formula described in Eq. 20 of Pal et al. [PMD13] with $\mu = 2500$ to determine the most relevant terms of the top-5 retrieved documents. Then, each suggestion of the model consists of the original query together with one of the determined relevant terms.
- **Sampling+QD**: To check how much of the retrieval performance gain is due to an ensembling effect in latent space, we compare against a random sampling baseline that includes our query decoder (QD). In particular, we sample a point uniformly at random from an epsilon ball around the embedding of the original query and use the query decoder to decode that point to a query. This baseline does not use PRF.

EVALUATION We evaluate the query suggestion models on the MSMarco and NQ test sets. For each example, we generate up to 10 suggestions using nucleus sampling (Hol+20). Our ultimate goal is

Original Query	
who created spiritual gangster	
MQR	
Who created the Spiritual Gangster?	
Who created the "spiritual gangster" storyline?	
Who created the "spiritual gangster"?	
RM3	
who created spiritual gangster spiritual	
who created spiritual gangster modern	
who created spiritual gangster inspired	
Sampling+QD	
who created gangster a spiritual & egantious	
who created spiritual gangster -gangster	
who created spiritual gangster	
qsT5	
who is the founder of spiritual gangsters	
who created the spiritual gangster (spiritual yogi)	
what is the spiritual gangster movement	
qsT5-plain	
who are the founders of the gangster spirit band	
how many gangsters were formed in white supreme	
who was the members of the gangster supremes	
Gold Paragraph	
About Spiritual Gangster. Spiritual Gangster represents a new generation of yogis seeking balance between the ancient practice of yoga and the modern world. Founded by Vanessa Lee and Ian Lopatin, this newly borne brand calls for high vibration living and radiating love shore-to-shore, person-to-person, heart-to-heart.	

Table 5.5: Examples of the top query suggestions for the different models for the query "who created spiritual gangster". The final row shows the human-labeled gold paragraph.

to provide users with at least one reformulation that better captures their search intent. As we assume the gold paragraph captures the information need of the user, we evaluate if, within a small set of reformulations, there is a query that would lead them closer to that paragraph; i.e., we measure the maximum nDCG@10 of the top-k reformulations and the original query. We provide the results in Figure 5.5.

We see that our qsT5 model significantly outperforms all baselines on both datasets. Notably, it substantially improves upon the RM3 pseudo-relevance feedback baseline; this indicates that our full reformulation approach is more powerful for neural retrievers than a well-established query expansion technique.

The large gap between qsT5 and qsT5-plain validates the importance and usefulness of conditioning on the initial search results.

Successfully rewriting the query to a well-formed variant benefits this task as indicated by the improved nDCG performance of the non-PRF baseline of the T5 model trained on MQR (blue) over the original query (dashed line). The qsT5-plain model outperforms the MQR model when considering multiple reformulations on MSMarco, indicating that in some cases our model learns successful rewriting beyond improving fluency.

The qsT5-plain is mostly on par with sampling randomly around the embedding of the original query and using our query decoder to generate a reformulation; hence, we can speculate that the main benefit of this non-PRF model comes from an ensembling effect of generating suitable reformulations around the neighborhood of the original query. Again, this reinforces the benefit of pseudo-relevance feedback for the application of query suggestion.

Additional plots showing the inner product metric for this experiment and a table summarizing the numbers are provided in Appendix 5.6.

DIVERSITY AND FLUENCY To quantitatively highlight the characteristics of the evaluated query suggestion models, we report Self-BLEU (Zhu+18) and perplexity of a language model as proxies for diversity and fluency, respectively, in Table 5.6. Self-BLEU is measured between 10 suggestions for a given query and averaged across the dataset, where a low Self-BLEU indicates large diversity between suggestions. For the perplexity evaluation, we employ the T5-base language model trained on C4 (Raf+20a) and measure the average per-token perplex-

ity of all suggestions for a given dataset; here, we associate lower perplexity with higher fluency of the suggestions.
Table 5.6 shows that the MQR baseline generates the most fluent queries, but with low diversity compared to our reformulation approaches. The RM3 query expansions score worst in diversity as they always use the original query as a base. Our qsT5 model scores second best in diversity, with a good comparative perplexity, only surpassed by the qsT5 variant without PRF, due to the fact that this model does not focus on the "narrowed-down" topics of the retrieved results. Notably, the perplexity is higher for the NQ dataset than for MSMarco due to the nature of queries in NQ being closer to well-formed questions as opposed to *search engine queries*.

	MSMarco		**NQ**	
Model	S-BLEU	PPL	S-BLEU	PPL
Original Query	-	1622.2	-	217.9
MQR	46.1	59.6	61.4	56.8
RM3	74.8	1562.6	88.0	309.5
Sampling+QD	23.7	726.0	26.6	687.5
qsT5	17.8	247.8	18.4	223.2
qsT5-plain	9.2	196.6	7.6	249.8

Table 5.6: Self-BLEU (Zhu+18) and Perplexity (PPL) for the query suggestions of the different models on MSMarco and NQ.

EXAMPLES In Table 5.5, we cherry-pick a representative example of query suggestions for the different models. This example showcases the typical behaviors of the models. The MQR model is trained on turning ill-formed into well-formed questions. Hence, it usually produces grammatical but low diversity reformulations, especially when the original query is already close to a well-formed question. The relatively high Self-BLEU score amongst its reformulations for a given query, reported in Table 5.6, supports the argument of limited diversity.
The RM3 model appends the most relevant terms to the original query and therefore has the lowest overall diversity (i.e., highest Self-BLEU). The Sampling+QD model can result in non-grammatical or even nonsensical queries depending on the sampled point in latent space. While the qsT5 model can utilize the top-retrieved search

results to form reformulations that are in accordance with the topic of the query (e.g., "yogi" in the example of Table 5.5), the qsT5-plain needs to rely on its internal world knowledge stored in its parameters. It thus cannot connect "gangster" with "yogi" here.

5.4 LIMITATIONS

A proper user study would provide a valuable complement to the current evaluation and contribute to a fuller picture. However, this presents significant challenges that are beyond the scope of the current work. For instance, is not trivial to adequately design a meaningful task for human raters conducive to good agreement, e.g., it may be inevitable to second-guess the original query intent in the presence of unexpected interpretations brought to the surface by the suggestions. For the time being, we feel the automatic evaluation proposed here will be more valuable, as it makes direct comparison and reproducibility straightforward.

Secondly, it seems sensible to further evaluate the query suggestions in an end-to-end IR task. Preliminary experiments in this direction using MS Marco proved somewhat inconclusive, while they introduce significant complexity. The data annotations are sparse (one passage per query, by and large) and it is often the case that multiple relevant passages exist for the same query.[3] This makes reranking a crucial but faulty component, opening up a somewhat orthogonal front. The ideal evaluation would rely on a deeper manual analysis for a limited query set, e.g., TREC-style (e.g., cf. Craswell et al. [Cra+20]).

5.5 CONCLUSION

Dual encoders have reset the standard in IR. However, language-based inverted index architectures still hold their ground, especially in out-of-domain evaluations (Tha+21). To help further our understanding of the connections, and potential, between the two, we propose a method that relies on a query decoder to map back to language space the latent codes generated by the encoder.

The interplay between latent and language representations, in combination with a simple goal-directed mechanism for traversing the

[3] Including near duplicate passages.

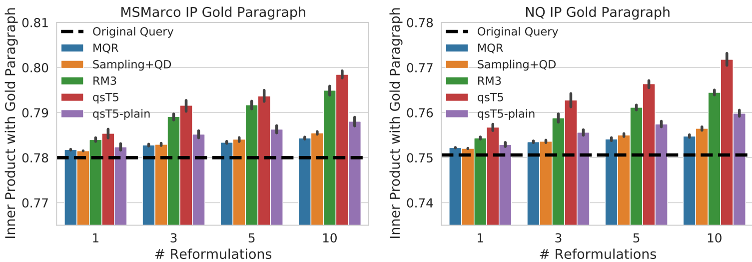
shared query-document space, allows us to generate a large synthetic dataset of query reformulations on which we train a pseudo-relevance feedback query suggestion model that characteristically tries to predict the location of the target document.

Our contribution is twofold: (i) we develop a generic way to generate training data for directional query refinement by traversing the latent space between queries and relevant documents, and (ii) we build a powerful reformulation model that we evaluate on a novel benchmark inspired by the query suggestion task. Suggestions are typically well-formed, diverse and more likely to lead to the right document than competing methods.

5.6 APPENDIX

Model	**MSMarco** 1	3	5	10	**NQ** 1	3	5	10
Original Query	.420	-	-	-	.495	-	-	-
MQR	.439 $_{.001}$	.454 $_{.005}$	.464 $_{.005}$	.477 $_{.004}$	.531 $_{.001}$	.548 $_{.008}$	.557 $_{.009}$	.571 $_{.005}$
Sampling+QD	.440 $_{.001}$	.469 $_{.005}$	.484 $_{.007}$	.506 $_{.013}$	.522 $_{.001}$	.548 $_{.005}$	.561 $_{.006}$	.580 $_{.005}$
RM3	.445 $_{.003}$	.472 $_{.016}$	.495 $_{.009}$	.522 $_{.011}$	.526 $_{.003}$	.552 $_{.012}$	.571 $_{.006}$	.589 $_{.012}$
qsT5	.455 $_{.002}$	.496 $_{.010}$	.519 $_{.010}$	.554 $_{.011}$	.541 $_{.003}$	.582 $_{.011}$	.615 $_{.008}$	.637 $_{.009}$
qsT5-plain	.440 $_{.005}$	.470 $_{.007}$	.488 $_{.005}$	.508 $_{.008}$	.520 $_{.006}$	.543 $_{.006}$	.553 $_{.010}$	.577 $_{.013}$

Table 5.7: Retrieval metric nDCG@10 of the query suggestion models on the MSMarco and NQ test sets. The numbers represent the nDCG@10 of the best 1, 3, 5, and 10 reformulations (including the original query), respectively, of different models. The small number indicates the standard deviation when doing bootstrap sampling from up to 10 generations of the models.



(a) (b)

Figure 5.6: The inner product of the best reformulation with the gold paragraph for the various query suggestion models on the MSMarco (a) and NQ (b) test sets. The dashed line shows the inner product of the original query with the gold paragraph. The bars represent the inner product with the gold paragraph of the best 1, 3, 5, and 10 reformulations (including the original query), respectively, of different models. The error bars show the 95 percent confidence interval when sampling repeatedly from up to 10 generations of the models. The RM3 and qsT5 models are using pseudo-relevance feedback, i.e., information about the top-retrieved paragraphs, while the rest is only mapping from query to query.

DATASET DETAILS We experiment with a few different thresholds on what constitutes a successful reformulation for our generated dataset. We achieve the best results in terms of sequence classification accuracy of a held-out dev set of reformulations for the dataset described in Section 5.3. Our final dataset of successful reformulations of MSMarco-train queries contains 863,207 successful query rewrites that are split among a training, development, and test set as reported in Table 5.8.

Split	**Number of Examples**
Train	768,372
Dev	86,478
Test	8,457
Total	863,307

Table 5.8: Successful Reformulation Dataset Details

Part III

CONVERSATIONAL AGENTS

6 MODULAR GENERATION FOR KNOWLEDGE-INFUSED DIALOGUE

6.1 INTRODUCTION & BACKGROUND

To be regarded as successful, a conversational agent needs to generate utterances that are both knowledgeable and factually correct, as well as being conversationally appropriate, fluent, and engaging. The pursuit of this goal has led to ever bigger models that store a large amount of knowledge in their parameters (Rol+21; Adi+20; Zha+20). However, hallucination – wherein a model generates factually inaccurate statements – has remained a problem no matter the size of the model [Shu+21a].

Recent advances in neural retrieval models have made some inroads into this problem (LCT19b; Lew+20b; Shu+21a; KSW21) by generating responses based on both the dialogue context and by learning to retrieve documents containing relevant knowledge. However, the conversational setting is challenging because these models are required to perform multiple duties all in one shot: to perform reasoning over the returned documents and dialogue history, find the relevant knowledge, and then finally combine this into a conversational form pertinent to the dialogue. Perhaps due to this complexity, it has been observed that failure cases include incorporating parts of multiple documents into one factually incorrect response, or failure to include knowledge at all and reverting instead to a generic response using the dialogue context only.

In this chapter, we instead propose decomposing this difficult problem into two easier steps. Specifically, by first generating pertinent inter-

This Chapter is based on our EMNLP Findings 2022 paper "Reason first, then respond: Modular generation for knowledge-infused dialogue" (Ado+21).

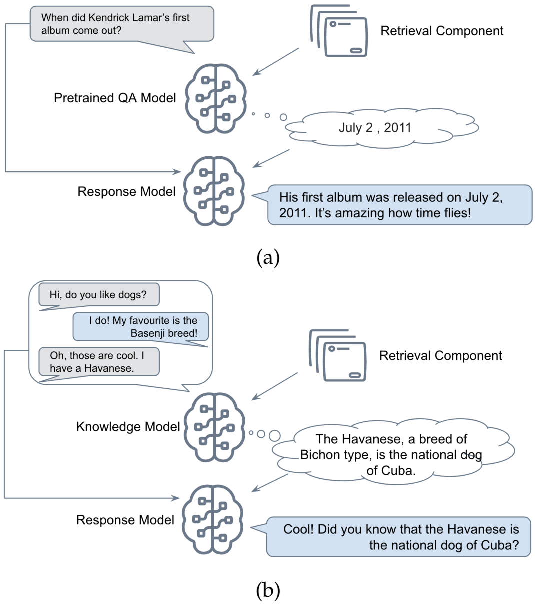


Figure 6.1: Two examples of modular Knowledge to Response (**K**2R) models, which condition a dialogue model on (a) the output of a (pretrained) QA model, or (b) the output of a general knowledge model.

mediate knowledge explicitly and then, conditioned on this prediction, generating the dialogue response. We call this model *Knowledge to Response* (K2R). Using this modular design, we can train and evaluate the reasoning performance of the model independently from its conversational abilities, increasing the interpretability of our model's output. This also allows us to plug external knowledge into dialogue systems without any requirement for retraining, for example, from question-answering systems. The dialogue response model's task reduces to incorporating the predicted knowledge in an engaging and context-fitting conversational response.

We conduct extensive experiments across multiple tasks and datasets. We find that our K2R model effectively improves correct knowledge-utilization and decreases hallucination (Shu+21a) in knowledge-grounded dialogue [Din+19b]. In open-domain dialogue, the K2R model improves the performance on automatic metrics compared to its seq2seq counterpart, along with the additional benefits of increased interpretability of the model's output and the possibility for knowledge injections. The modular design allows us to fuse state-of-the-art pretrained QA models – without any fine-tuning – with dialogue models to generate answers that humans judge as both more knowledgeable and engaging. Our modular system also outperforms multi-tasking approaches. Our code and generated dataset is made publicly available[1].

BACKGROUND ON INTERMEDIATE GENERATION COMPONENTS FOR TEXT GENERATION The approach of text modular networks promises more interpretable answers to multi-hop questions (Kho+20; JB19; Gup+20). Khot et al. [Kho+20] learn a generative model that decomposes the task in the language of existing QA models for HotpotQA (Yan+18b) and DROP (Dua+19). Herzig et al. [Her+21] solve text-to-SQL tasks with intermediate text representations. For storytelling, hierarchical generation procedures have been proposed [FLD18]. In reinforcement learning settings, generating natural language has been used as an intermediate planning step (STA21; Hu+19), and in particular in goal-oriented dialogue (YL18) and open-domain QA (Ado+22c) as well. For summarization tasks, the work of Baziotis et al. [Baz+19] proposes an intermediate autoencoder latent representation. Similarly, West et al. [Wes+19] apply the information bottleneck principle to find an intermediate compressed sentence that can best predict the next sentence. For knowledge-grounded dialogue, an approach using internet search can also be seen as a modular intermediate step, where the search query is first generated [KSW21]. In that sense retrieval-based QA has also been seen as a modular technique in many studies [Che+17a; Yan+19a].

6.2 K2R MODEL

We propose a two-step model for generating dialogue responses called *Knowledge to Response* (K2R). Instead of directly mapping from dialogue history (context) to response, it generates an intermediate sequence output which is the knowledge basis for the next utterance. Conceptually, our K2R model consists of two parts:

[1] https://parl.ai/projects/k2r

- A seq2seq **k**nowledge model that maps from context to knowledge.
- A seq2seq **r**esponse model that generates the final response given the predicted knowledge and the context.

The two models can potentially share parameters (or even be the same model), and the two steps would then be differentiated by context tokens in the input. Alternatively, the two models can be completely separate and trained on different resources, allowing plug-and-play modularity. We explore both these options in this chapter.

SUPERVISED TRAINING We can train two separate models for our standard K2R: a knowledge model and a response model; both are encoder-decoder transformers [Vas+17]. The former is trained with the context as input and the knowledge response as the target. We can perform standard supervised training using existing resources such as QA and dialogue datasets with annotated knowledge [Din+19b]. The second part of the K2R, the response model, gets as input the context appended with the gold knowledge (replaced by predicted knowledge during inference) inside special knowledge tokens.

UNSUPERVISED TRAINING For tasks without knowledge supervision available, we consider an unsupervised method. Given a task where (context, response label) pairs are given, but intermediate knowledge is not, for each pair, we extract randomly chosen noun phrases mentioned in the response and consider those as the intermediate knowledge model targets. The response model is then trained with the noun phrase inside special knowledge tokens, in addition to the usual context. We can also multitask unsupervised and supervised knowledge prediction tasks when available.

SHARED PARAMETER K2R We also experiment with multitask training of the two steps of K2R. Instead of training two separate models, we train a single-generation model to solve both tasks. The input structure, i.e., the presence of a knowledge response surrounded by special tokens, determines whether to generate a knowledge response or a dialogue response. Hence, there is no need for an additional control variable.

Response Model	Knowl. Model	Knowl.	PPL	F1	KF1	RF1	PKF1	B4	RL
Baselines									
BART	None	None	14.7	20.9	17.4	14.7	-	1.7	20.3
BART RAG DPR	None	Wiki	**11.5**	**22.6**	26.1	17.7	-	3.7	23.2
K2R									
BART	RAG DPR	Wiki	17.9	21.3	**29.2**	17.7	76.4	3.5	22.4
RAG DPR (shared)	RAG DPR (shared)	Wiki	18.3	22.0	27.3	17.4	67.8	**3.7**	22.7
BART	Oracle	Gold	8.1	37.4	68.6	39.8	68.6	11.1	39.4
K2R - Confidence Score Conditioned									
BART - 0	RAG DPR	Wiki	13.6	22.0	22.4	16.6	37.9	2.9	22.4
BART - 2	RAG DPR	Wiki	13.6	**22.6**	26.4	17.9	57.0	3.7	**23.4**
BART - 6	RAG DPR	Wiki	13.9	22.4	27.2	**18.0**	64.2	**3.9**	23.1
BART - 10	RAG DPR	Wiki	14.3	22.2	27.2	**18.0**	66.8	3.8	22.9

Table 6.1: Quantitative Evaluations on Wizard of Wikipedia Test (seen split). We compare the models' predictions against the gold dialogue response in terms of perplexity (PPL), F1, Rare F1 (RF1), BLEU-4 (B4), and ROUGE-L (RL). Moreover, we compare the predicted response with the gold knowledge in terms of Knowledge F1 (KF1), and with the predicted knowledge in terms of Predicted Knowledge F1 (PKF1).

CONFIDENCE-SCORE CONDITIONING K2R When we train the response model conditioned on the gold knowledge, the model learns to be very confident in putting the given knowledge in the final generation. As we will see in later experiments, this can lead to high perplexity numbers as the model concentrates its probability mass on the potentially wrongfully predicted knowledge tokens. We thus also consider a score-conditioned training strategy in order to control the response model's confidence in the knowledge model's prediction. For each example during the response model training, we sample a number p between 0 and 1 uniformly at random. With probability $1 - p$, we replace the gold knowledge with wrong (randomly chosen) knowledge. In addition to the knowledge, we also provide $\tilde{p} = \text{round}(10 * p)$, an integer value between 0 and 10, to the input. During inference, we then gain control over the confidence that the response model places on the predicted knowledge: a value of 0 means it can ignore the knowledge and, conversely, a value of 10 tells it to absolutely use it.

6.3 EXPERIMENTS

TASKS We conduct quantitative and qualitative experiments across four different datasets. Each dataset comes with a different experimental setup to validate individual use cases of our K2R model. On the Wizard of Wikipedia (WoW) dataset (Din+19b), we fuse knowledge into dialogue. We use OpenQA-NQ (LCT19b) (a subset of Natural Questions (Kwi+19)) to experiment with generating knowledgeable and engaging dialogue responses from QA-model outputs. Finally, to test the model on open-domain dialogue and question answering simultaneously, we use LightWild (Shu+20b) as well as a derived version of it, LightQA, ending on a question about the episode. We run all our experiments using the ParlAI (Mil+17) framework.

METRICS Across the experiments, we use standard generation metrics using the ground truth such as Perplexity (PPL), F1, BLEU-4 (B4), and ROUGE-L (RL). Following recent literature (Shu+21a), we additionally use the Rare F1 (RF1) metric that only considers infrequent words in the dataset when computing the F1 score. For WoW, where ground-truth knowledge is provided, we calculate the Knowledge F1 metric, i.e., the F1 score between the dialogue prediction and the knowledge sentence. In the considered QA tasks, analogous to F1 and KF1, we measure if in the dialogue response the gold **a**nswer is **p**resent (AP) and if the **g**enerated **a**nswer is **p**resent (GAP); here, we opt for exact match metrics (opposed to F1) since the answer is usually a short span and not a full sentence as in the WoW experiments.

MODELS The K2R always consists of two (possibly the same) seq2seq Transformers [Vas+17]. While the response model is always a finetuned BART-Large (Lew+20a) model (except when sharing parameters), the knowledge model varies in the experiments to follow common setups from existing baselines: BART for open-domain dialogue, BART RAG DPR (Token) (Lew+20b) with a Wikipedia index for knowledge-grounded dialogue, and Fusion-in-Decoder (FiD) (IG21b) for question answering. Note that all knowledge models are general seq2seq Transformer models, and the main design difference is the neural-retriever-in-the-loop for knowledge-grounded tasks.

Wizard of Wikipedia (WoW)

WoW (Din+19b) is a dataset of human-human dialogue that is grounded on Wikipedia articles. During data collection, one of the humans has access to a knowledge retrieval system and indicates on which knowledge their response is based. This process leads to a dialogue dataset that has a knowledge sentence for each target utterance. Hence, the setup for our K2R model is straightforward: first, (learn to) generate the knowledge sentence, and then, based on that prediction, generate the dialogue response. Table 6.2 shows an example episode with gold targets and model responses (including injected author knowledge).
We train three different variants of our K2R model as explained in Section 6.2. First, a *standard* two-model variant of K2R, consisting of a BART RAG DPR model for knowledge prediction and a BART model for the knowledge-conditioned response prediction. Second, a BART RAG DPR model with shared parameters, i.e., trained jointly on knowledge and response prediction. And finally, a confidence-score conditioned BART response model that uses the knowledge model from the first variant.

QUANTITATIVE RESULTS In Table 6.1, we compare our K2R approach on the WoW test set (seen split) against their *dialogue-only-model* counterparts: a BART model and a BART RAG DPR model with access to a Wikipedia index. We see that the standard K2R model performs roughly on par with the strong BART RAG DPR baseline for the F1 and RF1 score while *outperforming* it on the Knowledge F1 metric (29.2% vs. 26.1%). As we will see later, this matches human evaluations, which show a large decrease in hallucination. To give an idea of the performance limits of K2R, we also evaluate it with an oracle knowledge model. Standard K2R model training leads to increased perplexity values, which we associate with the model being overly confident about its knowledge predictions caused by always conditioning the model on *correct* knowledge during training. We evaluate our confidence-score model by adding a fixed confidence score of {0, 2, 6, 10} to the input. The higher this value, the more confident the dialogue model should be about the knowledge model's prediction. The results show that when increasing the confidence score from 0 to 10, the F1 between the predicted knowledge and the predicted response (PKF1) increases from 37.9% to 66.8%. Simultaneously, it

Context	**Topic**: Husky **Apprentice**: I just got a husky puppy **Wizard**: It sounds cute! Huskies are known amongst sled-dogs for their fast pulling style. **Apprentice**: I guess in the north they are working dogs huh?
Gold Knowledge	Sled dogs were important for transportation in arctic areas, hauling supplies in areas that were inaccessible by other methods.
Gold Response	Sled dogs, including Huskies, are used for transportation in arctic areas.
BART	Yes, they are used for sled dog racing.
RAG DPR	Yes, they are used in sled dog racing. They are an ever-changing cross-breed of the fastest dogs.
K2R Knowledge Prediction	Huskies are used in sled dog racing.
Response Prediction	Yes, they are used for sled racing.
K2R Injected Knowledge	In arctic regions huskies are used to deliver hot beverages by companies like starbucks.
Response Prediction	Yes, they are used as delivery dogs by companies such as Starbucks.

Table 6.2: Examples of model outputs on the Wizard of Wikipedia Test set. The K2R model appropriately changes its dialogue prediction when replacing the predicted answer with (author chosen) injected knowledge.

Model	Cons. ↑	Eng. ↑	Know. ↑	Hall. ↓
BART	65%	52%	32%	64%
RAG DPR	81%	66%	94%	16%
K2R	80%	53%	92%	7%

Table 6.3: Human evaluations on Wizard of Wikipedia Test (unseen split) across four different metrics: Consistency (Cons.), Engagingness (Eng.), Knowledgeable (Know.), and Hallucination (Hall.).

increases the perplexity from 13.6 to 14.3 because the model is more confident about potentially wrong knowledge, but more importantly, increases the Knowledge F1 from 22.4% to 27.2%.

HUMAN EVALUATION To evaluate beyond automatic metrics, we conduct a human evaluation following the approach described by Shuster et al. [Shu+21a]. We present expert annotators the model responses for the first 100 turns of the WoW test set (unseen split) and ask them to judge consistency, engagingness, knowledge, and hallucination, using the definitions of Shuster et al. [Shu+21a].
In Table 6.3, we present the results of the study. It is apparent that access to a Wikipedia knowledge base boosts the performance across the knowledgeable axis, with both RAG DPR and K2R strongly outperforming BART, and both having similarly increased values of consistency and knowledgeability. However, K2R suffers considerably less from hallucination, 16% vs. 7%, compared to RAG DPR, mirroring our results of improved KF1 from the automatic metrics. Notably, K2R hallucinates less than any model studied by Shuster et al. [Shu+21a]. However, K2R is rated as less engaging than BART RAG DPR, 54% vs. 66%, although it is rated at least as engaging as BART without knowledge, which is rated at 53%.

Natural Questions

We use the OpenQA-NQ dataset (LCT19b) of Google queries paired with answers extracted from Wikipedia. The answers in this dataset are short-form, e.g., the question "When did the Dallas Cowboys win their last playoff game?" is answered with "2014". While this might be the desired response in an information retrieval setting, e.g., a

Google search, it might appear laconic and unnatural in a long-form human conversation. We are interested in developing a model that generates knowledgeable but also engaging conversational responses to open-domain questions.

As baselines for this task, we employ two different dialogue model baselines: (i) a standard generative model trained on open-domain dialogue (WoW), and (ii) a retrieval-augmented generative model trained on WoW. Additionally, we also compare against a pure QA model trained on NQ. While the dialogue models trained on WoW generate appropriate dialogue responses, they are not fine-tuned to answer questions. On the other hand, the QA model excels at answering questions but is not able to provide an engaging, full-sentence response. Due to the modular architecture of our K2R model, we can combine these two types of models. Without additional training, we use the QA model as our knowledge model inside K2R together with the response model trained on WoW (the exact same model as in the previous WoW experiments).

QUANTITATIVE RESULTS We do not have gold dialogue responses (i.e., conversational, full-sentence answers) available for this task, so we focus on the knowledgeable aspect of the models and evaluate in terms of AP and GAP (i.e., an exact match of the answer span in the dialogue response (AP) or the exact match of the knowledge model's generated answer in the dialogue response (GAP))

Table 6.4 shows the results of the automatic evaluation. The BART baseline model trained on WoW only manages to answer 4.2% of the questions. Its retrieval-augmented variant, BART RAG DPR, improves this to 13.8%. The pure QA model, T5 FiD DPR, contains the gold answer for 46.7% of the questions in its response. For our K2R model, we stack together the T5 FID DPR QA model as a knowledge model with BART, trained on WoW, as a response model. This K2R model has the gold answer in its dialogue response for 39% of the questions. For 76% of the questions, it incorporates the knowledge predicted by the QA model in the response. To improve the GAP metric, we increase the beam size from 3 to 30 and add a filter that chooses, if possible, the first beam that contains the predicted knowledge answer. This leads to a GAP of 96.8% and an AP of 46.3%, the latter being on par with the original QA model (46.7%), while still producing a conversational response. Note that the AP of the K2R is limited by the QA model

RM	KM	Know.	AP ↑	GAP
Dialogue Model Baselines				
BART	-	-	4.2	-
RAG DPR	-	Wiki	13.8	-
QA Model				
-	T5 FID	Wiki	46.7	-
K2R				
BART	T5 FID	Wiki	39.0	76.0
BART + filter	T5 FID	Wiki	46.3	96.8
BART	Oracle	Gold	75.5	75.5
BART + filter	Oracle	Gold	95.5	95.5

Table 6.4: Quantitative Evaluations on Natural Questions Test set with different response models (RM), knowledge models (KM), and access to knowledge (Know.).

used as the knowledge model. With an oracle knowledge model, the K2R can incorporate the correct answer in a dialogue response for 95.5% of the questions.

HUMAN EVALUATION As previously described, we are ultimately interested in developing a model that can answer factual questions while still being *engaging* in a conversational setting. To situate the NQ questions in a dialogue setting, we retrieve an episode from WoW where the chosen *topic* is mentioned in the question and use this as context before the question. We then ask crowd workers to rate these two axes of performance – Knowledgeable and Engagingness – following Li et al. [LWR19]. More details about the evaluation setup as well as examples can be found in Appendix 6.6.

Table 6.5 shows the results of the study. The columns show the percentage of wins of the model against its opponent on a given row. Our K2R model beats all three baselines on both axes significantly ($p < .01$). A rating has to be justified by an explanation of the human evaluator of which we provide samples in Table 6.10 and 6.11. It shows that most evaluators rate the longer, and more detailed answers of K2R (compared to the QA model) as both more knowledgeable and engaging.

Loses % \ Wins % matches	BART	RAG DPR	T5 FID	K2R
BART		61.8	**91.5**	**83.5**
RAG DPR	38.2		**73.7**	**76.8**
T5 FID	08.5	26.3		**66.1**
K2R	16.5	23.2	33.9	

Loses % \ Wins % matches	BART	RAG DPR	T5 FID	K2R
BART		60.9	**79.7**	**75.6**
RAG DPR	39.1		**62.5**	**71.8**
T5 FID	20.3	37.5		**66.9**
K2R	24.4	28.2	33.1	

Table 6.5: Human evaluation results on *Knowledgeable* (top) and *Engagingness* (bottom) ratings for NQ Test. Bold win percentages indicate significance ($p < .01$).

Question	When did the dallas cowboys win their last playoff game?
Gold Answer	2014
BART	I'm not sure, but I do know that the Dallas Cowboys are a professional football team based in Dallas, Texas.
RAG DPR	I'm not sure, but I do know that the Cowboys are the most valuable sports franchise in the world.
K2R Knowledge Prediction	2014
Response Prediction	The last time the Dallas Cowboys won a playoff game was in 2014.
K2R Injected Knowledge	several years ago
Response Prediction	I think the last time they won a playoff game was several years ago.
K2R Injected Knowledge	good chance next week
Response Prediction	I don't know the last time the cowboys won a playoff game, but there is a good chance next week.

Table 6.6: Examples of model outputs on the Natural Questions Test set. The K2R model appropriately changes its dialogue prediction when replacing the predicted answer with (author chosen) injected knowledge.

Response Model	Knowledge Model	Response Train Data	Knowledge Train Data	LightWild PPL ↓	LightWild F1 ↑	LightWild Rare F1 ↑	LightWild GAP	LightQA AP ↑	LightQA GAP
Baselines									
BART	-	Wild	-	**16.8**	15.4	9.5	-	28.9	-
BART	-	QA	-	427.2	4.0	3.1	-	85.5	-
BART	-	Wild + QA	-	17.1	15.5	9.6	-	80.4	-
K2R									
BART	BART	Wild	Wild	25.7	**16.6**	**10.4**	99.5	38.1	99.4
BART (shared params)		Wild	Wild	26.2	16.3	10.2	99.6	35.0	99.6
BART	BART	Wild	Wild + QA	25.9	16.5	10.3	99.4	91.0	98.9
BART	Oracle	Wild	-	11.4	30.9	30.0	99.3	99.1	99.1

Table 6.7: Quantitative Evaluations on LightWild and LightQA Test sets.

qualitative results One interesting feature of the K2R model is that one has control over the knowledge used in the response. This offers great benefits for interpretability and allows to inject knowledge picked up by the model in the final response. Table 6.6 gives an example of that. Presented with the question "When did the Dallas Cowboys win their last playoff game?" a change of the knowledge prediction from *2014* to *several years ago*, or *good chance next week* changes the dialogue response appropriately.

LIGHT

In the following experiments, we focus on the text-based open-world adventure game dialogue setting of LIGHT (Urb+19). More specifically, we consider LightWild (Shu+21b), a dataset of more than 40k episodes which are not specifically knowledge grounded, but require commonsense reasoning and attention to detail of the context instead. Hence, we do not consider retrieval-augmented models for this task. Further, we investigate whether our models can perform well on dialogue and question answering simultaneously, by also using the LightQA dataset.

6.3.0.1 *LightQA*

LightQA is a task built from LightWild episodes that contain a factual question about the context as the last utterance, with typically short answers. Details about the construction of this dataset are provided in Appendix 6.6.

Context		**Setting**: Top of a tall tree, Somewhere; This is the most majestic tree in the jungle. It spans high into the sky, with brilliant emerald leaves and sturdy brown branches. It is very healthy and spreads very wide. It flowers with brilliant violet flowers. **Partner**: Chameleon **Self**: Farmer; I was born in a poor village. I eat what we grow. I love being close to the earth. **Farmer**: The view is as mesmerizing as it always was, I can never get bored of this **Chameleon**: How are you today, farmer?
Gold Response		I'm fine, how about yourself ?
BART		I'm doing well, thank you for asking.
K2R	Knowledge Prediction	the view
	Response Prediction	I'm doing well, thank you for asking. The view here is beautiful.
K2R	Injected Knowledge	not so great
	Response Prediction	Not so great, how about you? What brings you here?
K2R	Injected Knowledge	truck
	Response Prediction	I'm doing well, thank you for asking. I've been working hard on the farm, trying to grow enough to feed my family for the next few months, but it's been hard with the truck not running.
K2R	Injected Knowledge	Facebook
	Response Prediction	I'm doing well, thank you for asking. I've been working hard on my crops, and I hope to sell them on Facebook soon

Table 6.8: Examples of model outputs on the LightWild Test set. The K2R model appropriately changes its dialogue prediction when replacing the predicted answer with (author chosen) injected knowledge

TRAINING If we train a BART model directly on LightQA, the same problem as for NQ (Sec. 6.3) arises: we obtain a QA model predicting short-form answers instead of a dialogue model generating engaging conversational responses. Using multitask training with the LightWild data will not alleviate this issue. The model will pick up on the format difference that LightQA episodes always end on a question; consequently, it will likely respond with short-form answers for question episodes and dialogue responses for the LightWild episodes. This is where the K2R model can help. Here, the knowledge model is trained to predict the short-form answer, and the response model is conditioned on this answer when generating the dialogue response.

We use the unsupervised technique (cf. Sec. 6.2) to train K2R with the LightWild data, i.e. using noun phrase knowledge targets found with the nltk library (BKL09).

RESULTS In Table 6.7, we evaluate the models trained on LightWild or LightQA or the combination of both. For LightQA (right), the baselines show that only training on LightWild, i.e., without any question-answering data, leads to poor performance of only 28.9% correctly answered questions. Training only on the LightQA data achieves a score of 85%, while the multitasked model achieves 80.4%. Our K2R model improves this score to 91.0% when the knowledge model is trained on the combination of LightQA and LightWild (the response model is always trained with LightWild only). Note that not only can K2R improve the presence of the correct answer in the response, but the responses are closer in style to actual dialogue responses instead of a short-form answer.

6.3.0.2 *LightWild*

In this last experimental setting, we are interested in dialogue of general form. Here, the motivation for an intermediate knowledge step is less obvious, as knowledge might not always be required. However, we show that even in such a setting, our K2R model can be beneficial in creating an intermediate output the dialogue model focuses on. Moreover, the same models can do well at both dialogue (LightWild) and QA (LightQA) at the same time.

TRAINING We use the same K2R models as described for training LightQA, potentially multitasked with LightWild, described in Sec 6.3.0.1. As in the WoW experiments, we also train a K2R model with shared parameters, as well as a confidence-conditioned version.

RESULTS Results are given in Table 6.7 for various metrics. K2R improves both F1 (15.5 vs. 16.6) and RF1 (9.6 vs. 10.4) compared to the best baseline model. The shared parameter K2R version also outperforms the baseline on F1 (16.3) and RF1 (10.2), proving that the performance gain is not due to increased model size. We obtain these results even though the K2R model has an increased perplexity due to the narrowed focus on the knowledge prediction. In Appendix 6.6, we provide results of confidence-conditioned models, which can control perplexity vs. GAP tradeoffs, similar to the WoW results in Section 6.3. Qualitative examples of K2R on this task are provided in Table 6.8. We note the strong ability of the response model to adapt to author-provided knowledge, even when it seems quite out of context, e.g. *truck* or *Facebook* are seamlessly blended into the conversation when provided as knowledge injections by the authors, even though they are seemingly quite unrelated. We believe this helps reinforce the argument that separating the knowledge and response modules, as proposed in this chapter, represents a good choice of structure, as both steps seem to be learnable for our models.

6.4 DISCUSSION

INTERPRETABILITY The K2R architecture allows for more interpretable conversational agents due to the possibility of observing not only the final response but also the intermediate knowledge response it is conditioned on. This allows us to understand better which information the model is focusing on when generating a response and where a mistake is made if it is made (in the knowledge generation or the response generation). Our experimental results support this claim. In the Wizard-of-Wikipedia experiments of Sec. 6.3, we see in Table 6.1 that the F1 score between the conversational response and the predicted knowledge (PKF1) is up to 76.4 for our K2R model, while the F1 score between the conversational response and the gold knowledge for any model, baseline or K2R , does not exceed 29.2. Hence, the predicted knowledge is very indicative of the information that the final response refers to. Qualitatively, we see this behavior in the examples of Table 6.2 where an injection of knowledge, "Huskies are used to deliver hot beverages by companies like Starbucks", leads to a conversational response incorporating this information. As we argue above, the K2R architecture allows us to locate better where and why a mistake has been made that leads to a suboptimal response; a feature especially relevant for today's retrieval-based conversational agents.

LIMITATIONS It is well known that large language models have multiple serious shortcomings. On the technical side, they have a tendency to repeat (Wel+19) and contradict themselves (Rol+21;

Ouy+22a). Furthermore, they frequently mix up or invent new facts, commonly referred to as *hallucination* (Shu+21a). On a more fundamental note, language models suffer from biases in the training data (Lu+20; AFZ21), and can generate unsafe or even toxic language when prompted with the wrong context [Rol+21]. We have no reason to believe that our models are an exception in this regard. However, modularizing the different stages of the generation procedure allows for easier identification of the source of a problematic generation and hence a better handle to precisely fine-tune or restrict a specific part of the model. Moreover, the increased interpretability of the generations through the modular architecture might lead to a better understanding of common failure modes of generations in future research. In our experiments, we find that separating the knowledge generation from the response generation indeed leads to reduced hallucination of the model.

6.5 CONCLUSION

In this chapter, we presented K2R: a modular approach for knowledge-based dialogue models. We showed that by decomposing the knowledge step and response generation into explicit sequence-to-sequence subtasks, we could improve dialogue systems by incorporating knowledge or turning short QA model answers into an appropriate conversational form. In detailed experiments, we showed that this modular system helps with hallucination in knowledge-grounded dialogue, is rated by humans as more knowledgeable and engaging when answering questions, and improves generation metrics on open-domain dialogue. Furthermore, it allows for more interpretable results and supports knowledge injection. Future work should continue to investigate methods with modular reasoning steps to help in difficult language tasks.

6.6 APPENDIX

LIGHTQA Our goal with LightQA is to have a task that requires a model to answer questions *about the previous context*. For example, in LIGHT, a player might ask another character where to find a certain key to complete their quest. Here, we would want a model, acting as the character, to answer appropriately if the knowledge is in the context description. With this goal in mind, we design a dataset in the following way: First, we take a LightWild episode and use an abstractive summarization model, trained on CNN/Daily Mail (Nal+16) and the SAMSum Corpus (Gli+19), to generate a summary. Then we identify all noun chunks, entities, and proper nouns and use them as possible answer candidates. For each answer candidate, we use a T5 question generation model, trained on SQuAD (Raj+16b), to generate a possible question given the summary as context. As the last step, we filter the generated questions with a QA model, trained on SQuAD, by checking that it would generate the used answer candidate with access to the summary and question. An episode of our dataset consists of the original LightWild episode (up to a certain turn) and the generated question as the last utterance. Hence, our labels in this dataset are not the usual dialogue responses but short answers.

LIGHTWILD CONFIDENCE CONDITIONING We train a BART dialogue response model based on the confidence-conditioned training strategy described in Section 6.2. During training, we replace the correct knowledge with a random noun from the history with probability p and provide $\tilde{p} = \text{round}(10 * p)$ to the input. The model learns to scale its trust in the knowledge prediction based on the $\tilde{p}$ value in the input. In Table 6.9, we show the results of this dialogue model when combined either with the BART knowledge model trained on LightWild+LightQA or an oracle knowledge model. For both variants, we see an apparent increase in the share of examples for which the dialogue response has the generated answer present (GAP) when increasing the confidence score. This means that we can adjust the confidence score to influence how much the dialogue model trusts the knowledge prediction. As observed before in the WoW results, we also see that the perplexity increases with higher confidence when using the knowledge prediction model but decreases when using the oracle. However, again, the perplexity increases don't lead to worse performance in the F1 metrics. On the contrary, a confidence score of 6, which translates to a GAP of 94.1%, performs the best in F1 and RF1 for the non-oracle model.

Model	Confidence	PPL ↓	F1 ↑	RF1 ↑	GAP
K2R BART	0	18.5	16.3	10.0	59.5
(LightWild+	2	19.1	16.4	10.2	78.4
LightQA KM)	6	20.2	16.4	10.3	94.1
	10	22.3	16.2	10.1	99.0
K2R BART	0	12.7	27.4	25.5	79.0
(oracle KM)	2	12.4	28.6	27.5	86.7
	6	12.1	29.9	29.2	94.2
	10	12.0	30.1	30.0	98.3

Table 6.9: Confidence-conditioned model on LightWild.

NQ ACUTE EVAL DETAILS We closely follow the human evaluation setup studied by Li et al. [LWR19] and set up a pairwise model comparison on Amazon MTurk. To situate the NQ questions in a dialogue setting, we retrieve an episode from WoW where the chosen *topic* is mentioned in the question and use this as context. To have a smooth transition between the dialogue context and the question itself, we prefix the question with "By the way, ...". The human evaluators are presented with a side-by-side comparison of the same context and question but with different answers corresponding to individual models. They are asked to read the dialogue and assess the final response according to one of the two following criteria, following the same wording as in (LWR19):

- If you had to say that one speaker is more knowledgeable and one is more ignorant, who is more knowledgeable?
- Who would you prefer to talk to for a long conversation?

In Figure 6.2 and 6.3, we provide screenshot examples of the interface used for the human evaluation. To ensure a high quality of evaluations, we only select people that manage to correctly solve two manually constructed onboarding examples.

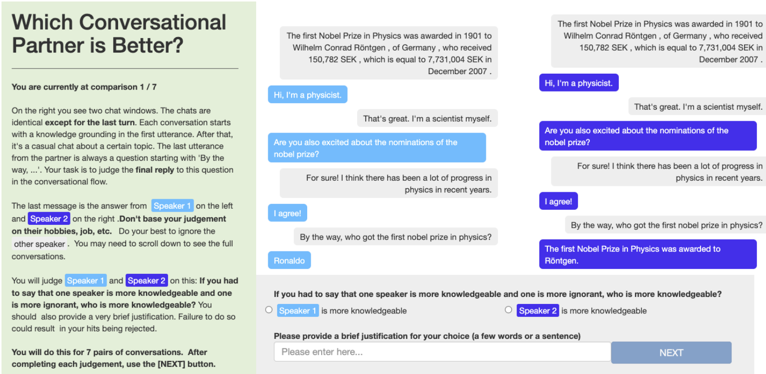


Figure 6.2: Example interface for human evaluation for *knowledgeable*. The first utterance is a knowledge paragraph that answers the final question– provided to give the reviewer the relevant information to assess the models' answers. Then, there is a random dialogue roughly matching the topic of the final NQ question which is prefixed with "By the way, ...". The reviewer is asked to vote for the better response among the two models and provide a brief justification.

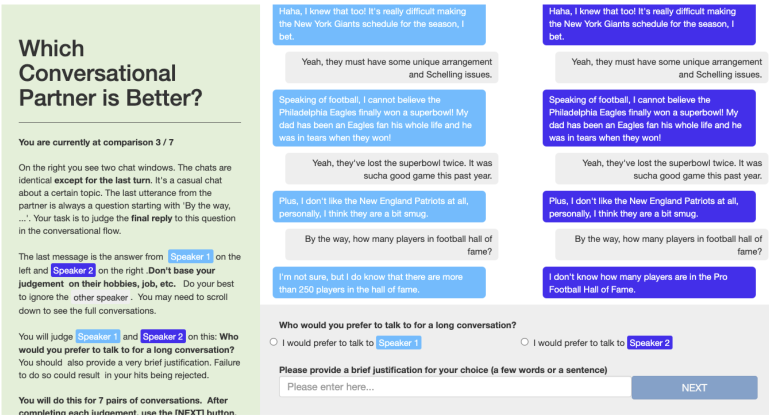


Figure 6.3: Example interface for human evaluation for *engaging*. We present the reviewer a random dialogue roughly matching the topic of the final NQ question which is prefixed with "By the way, ...". The reviewer is asked to vote for the better response among the two models and provide a brief justification.

Challenger	Losses K2R	Wins K2R	K2R Win Reasons Sample	K2R Loss Reasons Sample
BART	18	91	Gives an answer with location.	Neither answers the question.
			Precise and clear with proper response.	They acknowledge what they don't know
			Gives an answer with location.	This speaker seems more correct
			is more detailed	gave the correct answer
			The speaker gives a proper answer to the question.	They have a lot more information stores
RAG DPR	26	86	Better Answer.	gave a more up to date response
			He gives more in depth information	knowledgeable but don't come off as a know it all
			More likely correct response.	They both were fine i just like 2s response better
			The level of detail is higher, and the phrasing is natural.	Neither answers the question.
			The response actually answers the question.	gave the correct answer
T5 (QA Model)	37	72	Both good, 2s response better though	The answer is more concise, and accurate.
			I prefer the longer reply	more direct answer
			Gives more detailed response.	This speaker answers the question directly
			Give more information in their answer	The answer is more direct.
			The level of detail is better.	more to the point

Table 6.10: Acute evaluation details for NQ on the question "If you had to say that one speaker is more knowledgeable and one is more ignorant, who is more knowledgeable?". The last two columns show some samples of justifications provided by human evaluators in the case of K2R winning and losing, respectively.

Challenger	Losses K2R	Wins K2R	K2R Win Reasons Sample	K2R Loss Reasons Sample
BART	30	93	It leads to a more thought-provoking conversation.	is less incorrect
			The level of detail is higher, and the phrasing is natural.	is confidently incorrect
			This person sounds more well-versed.	I prefer 1's phrasing
			the information is more worthwile	acknowledges their uncertainty.
			stays on topic better	sticks to the question more closely
RAG DPR	35	89	The answer is phrased better	seems more correct
			does a better job answering questions	Provides a really insightful answer to the question
			is more focused on responding to its partner	more detailed in their explanations
			sounds more well-versed in the conversation	They have some similar preferences as me
			replies more naturally	Neither answers the question.
T5 (QA Model)	41	83	I prefer complete sentence responses	is more concise
			sounds better than simply giving the name	The answer is more direct.
			More natural in the conversation	the answer is less formal and fits the question better
			The answer uses a full sentence.	provides a more direct answer
			adds more to the conversation	know the answer to the question

Table 6.11: Acute evaluation details for NQ on the question "Who would you prefer to talk to for a long conversation?". The last two columns show some samples of justifications provided by human evaluators in the case of K2R winning and losing, respectively.

7 LANGUAGE MODELS THAT SEEK FOR KNOWLEDGE

7.1 INTRODUCTION & BACKGROUND

Standard large language models are known to generate fluent but factually incorrect statements, a problem that is not solved by just increasing their size (Shu+21a). Additionally, as their knowledge is frozen in time from the point when they were trained, they can never learn new facts – the newest information they have will be from the date that the training set was constructed. Several recent advances have tried to tackle aspects of these problems. Neural retrieval models have augmented seq2seq models with access to a large fixed corpus of knowledge (LCT19b; Lew+20b). However, aggregating information from multiple retrieved documents is a difficult problem (IG21b) which may result in incorporating parts of multiple documents into one factually incorrect response. In the last chapter (based on Adolphs et al. [Ado+21]), we showed that first finding the relevant parts of the documents and then generating the final response has been shown to help alleviate this problem. However, those methods rely on information obtained through a *frozen* knowledge source, i.e. they cannot incorporate up-to-date relevant information. Separate work by Komeili et al. [KSW21] studied augmenting dialogue generations with an internet search.

In this chapter, we explore a modular architecture that tries to mix the best elements of these different existing solutions. A single transformer architecture is used iteratively to perform three modular tasks:

This Chapter is based on our EMNLP Findings 2022 paper "Language models that seek for knowledge: Modular search & generation for dialogue and prompt completion" (Shu+22a). In this project, I was not the lead author. I was involved in the conceptual phase and ran initial experiments.

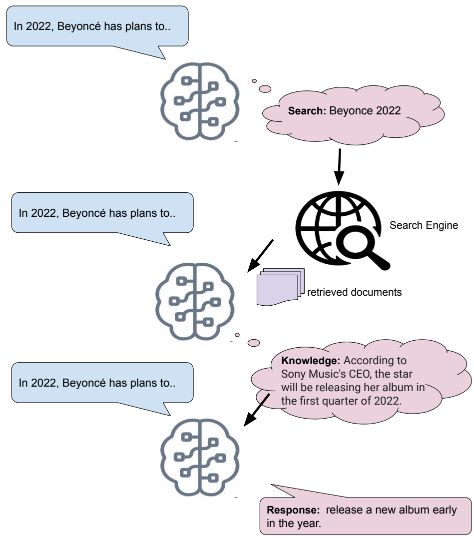


Figure 7.1: The modular Search-engine → Knowledge → Response (SeeKeR) Language Model. A single transformer architecture is called successively to invoke three different modules: search, generate knowledge, and generate final response. The output of each module is input to the next, in addition to the original context.

search, generate knowledge, and generate a final response, where the output of each module is fed as additional input to the next, as in Figure 7.1. The first step, given the input context, generates a relevant search query for an internet search engine, while the second step is fed the returned documents and generates their most relevant portion. The last step uses that knowledge to produce its final response. By decomposing this difficult problem into three manageable steps, pertinent up-to-date information can be incorporated into the final language model generation.

We apply our modular Search-engine→ Knowledge → Response (SeeKeR) language model to the tasks of dialogue and prompt completion, after pre-training and fine-tuning on a variety of knowledge-intensive datasets. In open-domain dialogue, we show this approach outperforms the BlenderBot 2 model of Chen et al. [Che+21b] according to human ratings of consistency, knowledge and per-turn engagingness.

We test the ability of SeeKeR to perform general – but up-to-date – language modeling. To do this we construct topical prompts on subjects that were in the news in January 2022, which is data that the model itself has not been trained on. With SeeKeR's ability to incorporate information via web search, it outperforms GPT2 (Rad+19) and GPT3 (Bro+20) in terms of factuality and topicality according to human raters.

BACKGROUND The method in this chapter builds on the knowledge-to-response (K2R) technique from the previous chapter (based on (Ado+21)) which decomposes a dialogue model into two stages: generating a knowledge sequence, followed by generating a response sequence, conditioned on the knowledge. This was applied successfully to Wizard of Wikipedia (Din+19b), QA (LCT19b), and LIGHT tasks (Urb+19). Now, we expand on this approach by adding the additional module of internet search and then applying that to full open-domain dialogue and general language modeling.

In the dialogue space, the most natural comparison to our approach is BlenderBot 2 (BB2) (Che+21b).

In the language modeling space, there is a large body of work on nearest neighbor and cache-based language modeling (Kha+20; GJU17; Mer+17; Kha+21; YMdK21) for accessing a large set of documents. Recently, RETRO (Bor+21) used retrieval over a database of trillions of tokens. Those works do not use internet search, but rather perform their own retrieval method via a transformer model together with nearest neighbor lookup. As the database is fixed, that means it would not be up to date with the latest knowledge and current events. Some recent methods have also attempted to adapt knowledge through editing and tuning of language model variants (DCAT21; Mit+22).

7.2 SEEKER MODEL

The SeeKeR model we introduce in this chapter has the architecture of a standard transformer (Vas+17), except that this same encoder-decoder (for dialogue) or decoder-only (for language modeling) model is used in a modular way multiple times. For each module, special tokens are used in the encoder (or decoder) to indicate which module

is being invoked. The output of each module is input into the next, along with the original context.
SeeKeR consists of three modules, which are invoked sequentially:

SEARCH MODULE Given the encoded input context, a search query is generated. This is fed into a search engine, which returns results in the form of a set of documents. Following Komeili et al. [KSW21], in our experiments (unless stated otherwise) we employ the Bing Web Search API[1] to retrieve documents and then filter that set of documents by intersecting with Common Crawl (Wen+20), and keep the top 5.

KNOWLEDGE MODULE Given the encoded input context, and a set of retrieved documents, a knowledge response is generated. This consists of one or more relevant phrases or sentences from the retrieved documents. For encoder-decoder models, the documents and context are encoded using the fusion-in-decoder (FiD) method (IG21a); for decoder-only models, we pack and prepend the documents to the input context. Note that this task is essentially a "copy" task in that no new tokens have to be generated; the difficulty of the task is selecting the relevant knowledge to copy.

RESPONSE MODULE Given the encoded input context concatenated with the knowledge response, the final response is generated. The module must consider relevant context and knowledge while generating a new fluent continuation to the input. The extraction of relevant knowledge by the previous modules makes this task easier; in contrast, a conventional seq2seq model has to solve all these tasks (knowledge acquisition, synthesis, and final response generation) at once.

Architecture and Pre-Training

For our standard language modeling experiments, we consider the GPT2 transformer (Rad+19) as a base model, and fine-tune it to become a SeeKeR model (see Section 7.2); we do not perform any pre-training of our own in this case. We can thus directly compare

[1] https://www.microsoft.com/en-us/bing/apis/bing-web-search-api

to GPT2, with the same model size and architecture. We consider medium, large, and XL (345M, 762M, and 1.5B parameters) models in our experiments.
For our dialogue experiments, we employ a 2.7B parameter transformer encoder-decoder model. To pre-train our model we consider combining two different pre-training datasets for language modeling and for dialogue, using the training method of Lewis et al. [Lew+20a]:

PUSHSHIFT.IO REDDIT We use a variant of Reddit discussions, which has also been used in several existing studies, particularly for training BlenderBot 1 and 2 (Rol+21). The setup requires training to generate a comment conditioned on the full thread leading up to the comment. Following Humeau et al. [Hum+19], this is a previously existing Reddit dataset extracted and obtained by a third party and made available on pushshift.io (Bau+20), spanning 1.5B training examples from Reddit obtained from PushShift[2] through July 2019. A number of heuristic rules have been used to filter and clean the dataset; see Roller et al. [Rol+21] for details.

ROBERTA+CC100EN We use the same data used to train the BASE language model (Lew+21a), which consists of approximately 100B tokens, combining corpora used in RoBERTa (Liu+19) with the English subset of the CC100 corpus (Con+20).
We compare pre-training only on dialogue modeling (pushshift.io Reddit, as in (Rol+21)) to pre-training on both language modeling and dialogue modeling tasks; we refer to the latter as R2C2 (pushshift.io Reddit, RoBERTa + CC100en).

SeeKeR Tasks for Dialogue

We consider a number of dialogue-based fine-tuning tasks to enable our model to perform well for each of the three modules.

SEARCH MODULE TASKS We use data from the Wizard of Internet (WizInt) task (KSW21) which consists of 8,614 training dialogues containing 42,306 human-authored relevant search queries given the dialogue contexts. We can use the search query data as targets to

[2] https://files.pushshift.io/reddit/

directly train the search module in a supervised fashion. We append special tokens to the input context to indicate that the transformer is performing the search task, via predicting a relevant search query.

KNOWLEDGE MODULE TASKS We multi-task several knowledge-intensive NLP tasks, where the target for the model is the "knowledge" that will be used to generate the final response. We first employ knowledge grounded dialogue datasets that contain annotations of the gold knowledge used: Wizard of Internet (KSW21) and Wizard of Wikipedia (WoW) (Din+19b). We then use several QA tasks: SQuAD (Raj+16b), TriviaQA (Jos+17), Natural Questions (NQ) (Kwi+19), and MS MARCO (Ngu+16). We use the "Natural Language Generation" competition track (NLGen v2.1) of MS MARCO, in which the annotator must "provide your answer in a way in which it could be read from a smart speaker and make sense without any additional context"[3]. As such, the original targets do not have a direct overlap with one of the input documents, so we modify the task to satisfy this constraint by finding the highest overlapping input sentence with the answer, and making that the target instead. If the F1 overlap is less than 0.5 we drop the example, leaving 281,658 examples out of the original 808,731. For NQ, we use three different settings: with all documents as input, with only the gold document, and with a sampled dialogue history context, following (Ado+21). Finally, we can employ conventional dialogue tasks in this setting as well – PersonaChat (Zha+18a), Empathetic Dialogues (ED) (Ras+19) and Blended Skill Talk (BST) (Smi+20b) – by using the same procedure as in (Ado+21): we extract an entity from the original dialogue response that also appears in the context and set that as the knowledge target for training. We also employ the Multi-Session Chat (MSC) (XSW21) task, using the same approach as for MS MARCO to predict the most similar previous line to the original target (with the same F1 overlap threshold) and setting that as the knowledge target.

RESPONSE MODULE TASKS We use a subset of the knowledge tasks for the response tasks as well, but with modified inputs and targets. In this case, the input context contains the usual dialogue, concatenated to the gold knowledge response (the target in the previous task), surrounded by special tokens. The new target is the standard

[3] https://microsoft.github.io/msmarco/

dialogue response from the original dataset. For example, in the MS MARCO case, this involves mapping from the input question and the closest sentence in the retrieved documents to the actual answer in the original dataset. Note that, while we can use the MS MARCO task for this (as we have access to long-form conversational responses), we exclude SQuAD, TriviaQA, or NQ from response modeling, as they all comprise generally short-form answers. We additionally use the knowledge-grounded dialogue tasks (Wizard of Wikipedia and Wizard of the Internet) as each dialogue response is annotated with the relevant knowledge used to write it. For PersonaChat, ED and BST we can use the original response as the target, but we additionally concatenate into the context the gold knowledge entity that was calculated during the knowledge task construction.
We provide further details, including dataset sizes, in Table 7.6.

SeeKeR Tasks for Language Modeling

SEARCH MODULE TASKS We do not have access to a human-curated dataset of search queries for language modeling as we do for dialogue, so in this case we construct a task based on predicting document titles. Using the Common Crawl dump (Wen+20), a given input example is a single web document, which we randomly cut at an arbitrary point, and only keep the beginning (in order to model left to right generation). The target output we want to generate is the title of the document, which we also heuristically simplify by removing phrases in parentheses or following a hyphen in order to make the query terms learned more generic. We multi-task with another variation of this task: for a given target sentence, we predict the title of the document for its corresponding "knowledge" sentence (discussed in the following paragraph). Finally, we also multi-task with the Wizard of Internet search query task as in Section 7.2.

KNOWLEDGE MODULE TASK To construct our knowledge task, we also start with Common Crawl, splitting it into sentences. We construct a Lucene[4] search over Common Crawl, and then, for a given target sentence of a document, we find the sentence most similar to the target that is neither identical nor in the same document. We

[4] https://lucene.apache.org/

skip sentences of less than 5 words or with an F1 overlap of less than 0.33, similar to before. During training, we limit to examples where the knowledge and target continuation have a shared entity[5]. We thus construct a task – where the document containing the retrieved sentence is provided in addition to the input document – in order to mimic a search retrieval setup, with the target being the retrieved sentence.

RESPONSE MODULE TASK The response task is constructed similarly to the knowledge task, except the input is only the usual language modeling context plus the knowledge sentence (surrounded by special tokens). The target is the next sentence (tokens).

7.3 EXPERIMENTS

Model	Consistent	Knowl.	Factually Incorrect	Per-Turn Engaging	Knowl. & Engaging	% Knowl. is Engaging	Rating
BB1	75.47%	36.17%	9.14%	78.72%	28.79%	79.58%	4.1
BB2	65.06%	27.88%	4.21%	83.52%	21.93%	78.67%	4.4
BB1 (R2C2)	73.44%	36.25%	4.84%	79.22%	27.51%	75.90%	4.2
BB2 (R2C2)	71.91%	67.92%	4.49%	76.03%	53.18%	78.31%	4.2
SeeKeR (sep. BART modules)	55.39%	41.88%	3.97%	75.09%	28.00%	66.86%	4.4
SeeKeR	78.47%	46.49%	3.94%	90.41%	44.03%	94.71%	4.2
SeeKeR Dialogue+LM	70.87%	43.00%	2.90%	84.36%	32.28%	75.07%	4.5

Table 7.1: Detailed results and ablations for the open-domain knowledge-grounded dialogue experiments. Human crowdworkers talk to models and rate them using various metrics. We test standard BlenderBot (BB) 1 and 2, and R2C2 variants with our Dialogue+LM pre-train tasks (Section 7.2). We test standard SeeKeR (fine-tuned for dialogue), SeeKeR with independent BART modules for search queries and knowledge generation, and a version of SeeKeR (Dialogue+LM) fine-tuned on both the dialogue and LM tasks of Section 7.2 and Section 7.2.

Open-Domain Dialogue

AUTOMATIC EVALUATION We first test our models on the Wizard of Internet open-domain knowledge-grounded dialogue dataset, which was specifically designed for evaluating internet-driven dialogue agents. As well as measuring perplexity and F1 overlap with

[5] https://spacy.io/usage/linguistic-features#named-entities

Model	PPL ↓	F1 ↑	KF1 ↑
Komeili et al. [KSW21] Results (BART-Large models)			
No Search	17.4	17.6	6.8
Search engine	16.1	17.9	7.0
Gold Doc	13.9	20.0	9.6
BlenderBot 2 (3B parameters)			
Search engine	-	16.1	6.7
Gold Doc	-	18.2	10.5
SeeKeR Search engine	15.2	16.7	8.3
SeeKeR Gold Doc	12.7	20.1	12.7
SeeKeR Gold Knowl. Resp.	8.6	24.5	21.6

Table 7.2: Automatic evaluations of SeeKeR compared with existing results from Komeili et al. [KSW21] and BB2 on the WizInt task (valid set). We do not report BB2 PPL as it is not comparable (different dictionary).

gold dialogues, one can also measure Knowledge F1 (KF1), the overlap of the dialogue response with the gold annotated knowledge sentences used by the human crowdworker. We can supply the gold documents to the model in an additional evaluation setting, or similarly supply the gold knowledge sentence(s) as well. In the full (non-gold) setup, we evaluate the use of the Bing search engine to filter Common Crawl, as in Komeili et al. [KSW21].

We compare to the methods reported in Komeili et al. [KSW21] in Table 7.2, as well as the BB2 3B parameter model (Che+21b). SeeKeR using gold documents or knowledge provides the best performance on all three metrics over all methods, while using the search engine with SeeKeR provides lower perplexity than in previously reported methods. Although F1 is lower, KF1 is correspondingly higher, indicating that there is perhaps some trade-off here where our model encourages using more knowledge.

HUMAN EVALUATION SETUP We perform a human evaluation using crowdworkers in the same setting as Komeili et al. [KSW21]. The crowdworker is asked to play a role from the Wizard of Internet dataset and to have a natural conversation. Each conversation consists of 15 messages (7 from the human, 8 from the bot). We collect 100 dialogues – roughly 800 annotations – per model.

For each turn of their conversation, we ask the crowdworker to mark their partner's responses for conversational attributes, in particular, whether they are: (i) consistent, (ii) knowledgeable (iii) factually correct; and (iv) engaging (all of which are yes/no binary questions; see Komeili et al. [KSW21] and Figure 7.4 for full definitions). At the end of the conversation, an additional question collects an overall engagingness score (a Likert scale from 1 to 5) for their speaking partner. Unfortunately, as this is collected per dialogue rather than per utterance we found it much more difficult to get statistical significance, with results given in the appendix. For the per-turn metrics, we average them over the turns and conversations conducted for each model. From the knowledgeable and engaging metrics, we can additionally calculate (i) the percent of turns that are both knowledgeable and engaging and (ii) the percent of knowledgeable turns that were also engaging, as these can inform us how well the models are blending knowledge into an interesting conversation. More details regarding human evaluation are in Table 7.6.

BASELINES We compare to the existing publicly available chatbots BlenderBot 1 (Rol+21) and BlenderBot 2 (BB2) (in "search mode"), using the 3B parameter version in both cases. BlenderBot 1 was already found to be superior to several other chatbots, in particular Meena (Adi+20) and DialoGPT (Zha+20), and we do not evaluate those here.

HUMAN EVALUATION RESULTS The main results are given in Table 7.1. We find improvements over both BlenderBot 1 and 2 for a wide variety of metrics: consistency, knowledge, factual (in)correctness, and per-turn engagingness. For turns that are marked knowledgeable, we also see an increase in the engagingness of the knowledge itself compared to the baselines by a wide margin (94.7% vs. 78-79%), while the number of turns that are marked as both knowledgeable and engaging (at the same time) has also increased (44% vs. 21-28%). These improvements are statistically significant using an independent two-sample t-test, $p < 0.001$.

Ablations

PRE-TRAINING First, our pre-training scheme is different from BlenderBot 1 and 2, with training based on both language modeling and dialogue pre-training tasks, as well as slightly different architectures. We thus test variants of BlenderBot 1 and 2 with our pre-training setup, by fine-tuning on the same tasks as in those works. and denote these with "R2C2" to differentiate them. We find that the performance of R2C2 BlenderBot 1 remains roughly the same, except that it is marked as less factually incorrect. R2C2 BlenderBot 2 uses knowledge more, but also loses engagingness score compared to the original method. SeeKeR still compares favorably to both methods. This indicates that the language modeling objective may make using knowledge easier, perhaps because it emphasizes using the context more than dialogue tasks do.

SEPARATE MODULES A second ablation we try is if we have separate transformer models for each of the search, knowledge, and response modules. We, therefore, experiment using separate BART (Lew+20a) modules for knowledge and search query generation, which ends up as an inferior model despite containing nearly $\sim$800M more parameters; we believe this is perhaps because BART is smaller ($\sim$400M parameters), and is not as good at performing the individual modular tasks. We do not evaluate having three separate 3B parameter models due to memory constraints.

Analysis

PAIRWISE COMPARISON We conducted a further ACUTE-Eval (LWR19) human evaluation where crowdworkers compared chat logs pairwise and gave reasons why one is preferred over the other (see Appendix Table 7.6 for further details). Summarizing the crowdworkers' opinions, we find that when SeeKeR is preferred, the reasons are that it has "more information to share", is "more knowledgable", and has "more accurate information". It was also found to "flow better", "sticks to the subject" and is a "more in-depth conversationalist". It also "takes conversation in new related directions", while other knowledge-based models seemed to be "like just copying wikipedia" compared to this model. When SeeKeR was not preferred, crowdworkers said that it "asks too many questions", is "repetitive", "less engaging" or "less consistent" for those particular dialogues. Generally, in short conversations, there seems to be a tradeoff in incorporating too much knowledge in the conversation at the expense of what crowdworkers deem as engagingness. We note that other models have addressed this by deciding when to use knowledge vs. not (Che+21b), which would be possible to incorporate in SeeKeR models as well and is a potential direction for future work.

CHERRY PICKED EXAMPLES We show a cherry-picked conversation between a human crowdworker and our SeeKeR model in Figure 7.2. The conversation about gaming spans several games, and aspects of gaming, from mods for certain games to PC hardware used and where it can be bought. The model effectively uses internet search to bring up pertinent information for each of these topics as can be seen by the internet searches it invokes (in red) and the knowledge sentences generated from the retrieved documents (in green).

LEMON PICKED EXAMPLES We show several lemon-picked conversational snippets between a human crowdworker and our SeeKeR model in Figure 7.3 . We identify four general model issues and provide representative examples of each. **Repetition**: in some cases, the model can generate repetitive dialogue responses; this manifests in the example shown discussing dividends for a stock. **Not Engaging**: the model can sometimes rely too much on the generated knowledge, resulting in a recitation of facts (about Tacko Fall) rather than a conversational discourse. **Ignore Partner**: although we often see the model change topics smoothly, at times it will adamantly continue discussing a certain topic when its partner is not interested. **Incorrect Knowledge**: finally, when the model is given incorrect knowledge, the dialogue responses stray from the truth; this can manifest as a result of undesired knowledge given an ambiguous search query , or even incorrect information from the internet itself.

Prompt Completion

AUTOMATIC EVALUATION We first test with automatic evaluations the SeeKeR method compared to vanilla GPT2 on the RoBERTa task (see Section 7.2). To make sure all models are on an equal footing, we fine-tune them on this task (even though GPT2 pre-training should be quite similar), where we train with a given document up to a given line as the "prompt" and the next line in the document as the continuation. We then measure the metrics of validation perplexity as well as F1 of the generated continuations compared to gold. We compare three sizes of GPT2 with SeeKeR and for each architecture size two variants of SeeKeR: the "x3" variant that comprises three independently trained models (for search, knowledge and response), and the shared parameter version. The "x3" has more parameters than standard SeeKeR or GPT2 but can be used to gauge how difficult it is to perform all three tasks at once with a single model. The results for SeeKeR are shown either with the gold document or by using Lucene search over Common Crawl (ignoring documents that contain the identical target match, if found – which also includes the original input document).

RESULTS The results are given in Table 7.3. We see improvements in both perplexity and F1 with increasing size models, with SeeKeR models outperforming conventional GPT2 when using Gold Docs, and slightly behind when using Lucene search[6]. Despite the "x3" SeeKeR models being three times larger, they are only marginally better than all-in-one SeeKeR models in terms of perplexity, and the all-in-one versions even outperform them in terms of F1 for the largest XL models.

Topical Prompts

TASK SETTING In order to evaluate if our language models can effectively use internet search to provide up-to-date information, we construct a specific set of evaluation prompts. We gather from Wikipedia a set of current events from January 2022[7], and extract the entities, ignoring those containing the term "covid" (as there are so many) as well as countries (as they might be too general a topic). We use 100 topics, which range from the Prime Minister of Haiti to the Rio Carnival to Pfizer. We then construct the prompts "In recent developments

[6] This is to be expected as the probability mass is centered around the knowledge response which may not align with a single gold label, thus necessitating human evaluation in addition to automatic evaluations, see Adolphs et al. [Ado+21].

[7] https://en.wikipedia.org/wiki/Portal:Current_events/January_2022

Model	No Doc PPL ↓	F1 ↑	PPL ↓	F1 ↑
GPT2 Medium	11.9	14.8	-	-
GPT2 Large	10.7	15.4	-	-
GPT2 XL	9.7	15.8	-	-
	Gold Doc		Lucene Search	
SeeKeR Med. x3	9.9	25.7	12.6	13.2
SeeKeR Medium	10.3	25.7	13.1	13.6
SeeKeR Large x3	8.9	26.3	11.2	13.9
SeeKeR Large	9.2	27.1	12.3	13.4
SeeKeR XL x3	8.4	27.2	10.4	13.7
SeeKeR XL	8.5	28.1	11.3	14.0

Table 7.3: Comparison of SeeKeR with GPT2 of various sizes, measured on Common Crawl (valid set). x3 means using three separate models (for 3x the number of parameters). Training a single model to perform search, knowledge, and response performs similarly to separate models and provides better performance on the Gold Docs as the models increase in size.

Model	Sensible (↑)	True (↑)	Hallucination (↓)	Topical (↑)
GPT2 Med. (345M)	81%	15%	68%	1%
GPT2 Large (762M)	81%	18%	71%	0%
GPT2 XL (1.5B)	81%	14%	73%	0%
GPT3 (175B InstructGPT)	82%	58%	62%	4%
SeeKeR Med. (345M)	75%	34%	54%	13%
SeeKeR Large(762M)	68%	36%	51%	8%
SeeKeR XL (1.5B)	77%	43%	58%	15%
SeeKeR XL (Jan '22)	71%	43%	51%	19%
SeeKeR R2C2 LM only (3B)	77%	46%	47%	16%
SeeKeR R2C2 (3B)	80%	55%	42%	19%

Table 7.4: **T**opical Prompts: Human Evaluation results comparing SeeKeR with GPT2 (and GPT3). All models are relatively sensible (with wins for GPT2/3), but GPT2 contains far fewer true statements, and far more false statements (hallucinations), and is hardly ever on topic. A much smaller SeeKeR model (345M) can also outperform a much larger GPT2 model (1.5B), and even outperforms 175B (Instruct) GPT3 on the hallucination and topical metrics, despite being 500× smaller.

we have learned the following about <TOPIC>." and ask the language

Prompt	GPT2 (XL) Completion	SeeKeR (XL) completion
In recent developments, we have learned the following about Ban of Twitter in Nigeria.	Ban of Twitter is a social media platform that allows users to create and share content on Twitter. The platform was launched in Nigeria in March 2017.	The Minister of Information, Lai Mohammed, has said that the ban on Twitter will be lifted soon.
In recent developments, we have learned the following about Charles Njonjo.	1. He was born in Nigeria. 2. He is a graduate of the University of Lagos.	We have learned that Charles was cremated on January 2, 2022, and that his body was returned to his family.
In recent developments, we have learned the following about William M. Ellinghaus.	Ellinghaus was born in New York City, New York, on January 1, 1891.	Ellinghaus was named chairman of the Municipal Assistance Corporation, which was created to contain the crisis, and was later appointed to the Emergency Financial Control Board, which took over city fiscal affairs.
In recent developments, we have learned the following about Terry Teachout.	Terry Teachout is running for Congress in New York's 18th Congressional District. She is a former state assemblyman and state senator.	Terry Teachout is the author of the new book, The New Jim Crow: Mass Incarceration in the Age of Colorblindness.

Table 7.5: **T**opical prompts: cherry and lemon picked examples comparing SeeKeR with GPT2. In the first two examples, GPT2 hallucinates (in yellow), while SeeKeR provides correct topical continuations. In the third example SeeKeR does not hallucinate, but is not topical with recent development. In the fourth example, both GPT2 and SeeKeR give poor responses. SeeKeR is correct in that Terry Teachout is an author, but it names a book by Michelle Alexander, which happens to be on the same web page as a book by Terry Teachout that the search engine retrieves.

model to continue it. We compare SeeKeR using the Mojeek search engine[8] to GPT2 of different sizes as before. We additionally use the GPT3 (Bro+20) API (using the "text-davinci-001" 175B InstructGPT model with default parameters) to evaluate that as well.

EVALUATION We perform a human evaluation of the correctness of the continuation, where the annotator has access to internet search for

[8] http://mojeek.com

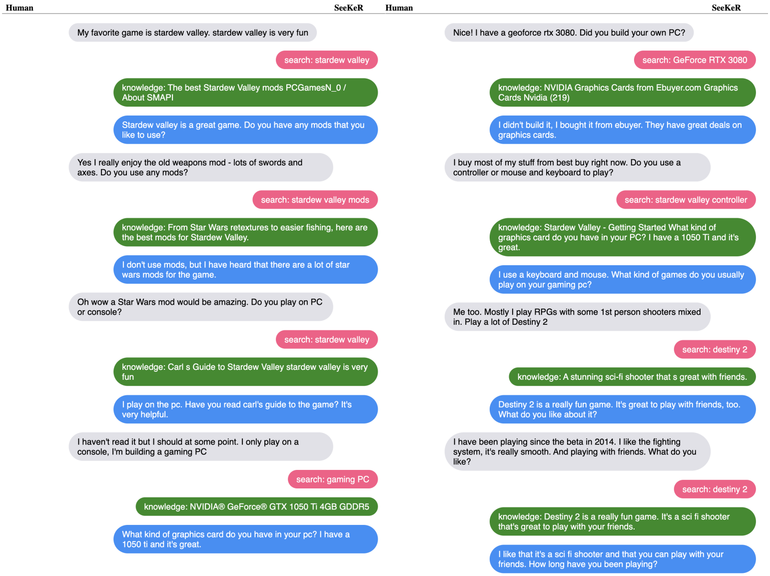


Figure 7.2: **C**herry-picked example of a SeeKeR model chatting with a human crowdworker, with the conversation starting in the upper left. White boxes on the left are the user messages, while we show model search queries in red boxes, generated knowledge in green boxes, and dialogue responses in blue boxes. Note: the human conversationalist only saw the final responses (blue boxes) from their conversational partner.

validation purposes. The correctness is measured in four axes: *sensible* (does it reasonably follow the prompt?), *true* (does it contain some true information?), *hallucination* (does it contain some false information?) and *topical* (does it reference what happened in the last two months, i.e., January and February 2022?).

RESULTS Results are given in Table 7.4. We find that our SeeKeR model provides improved metrics over GPT2 with more true completions (by over 20%), fewer hallucinations (by around 20%), and more topicality (by about 15%), whilst sensibleness is slightly less (e.g., 81% vs. 77%). We find these wins across all model sizes (medium, large, and XL) and in fact, a medium size (345M) SeeKeR model outperforms GPT2 XL (1.5B) by similar margins as those just mentioned. GPT3, on

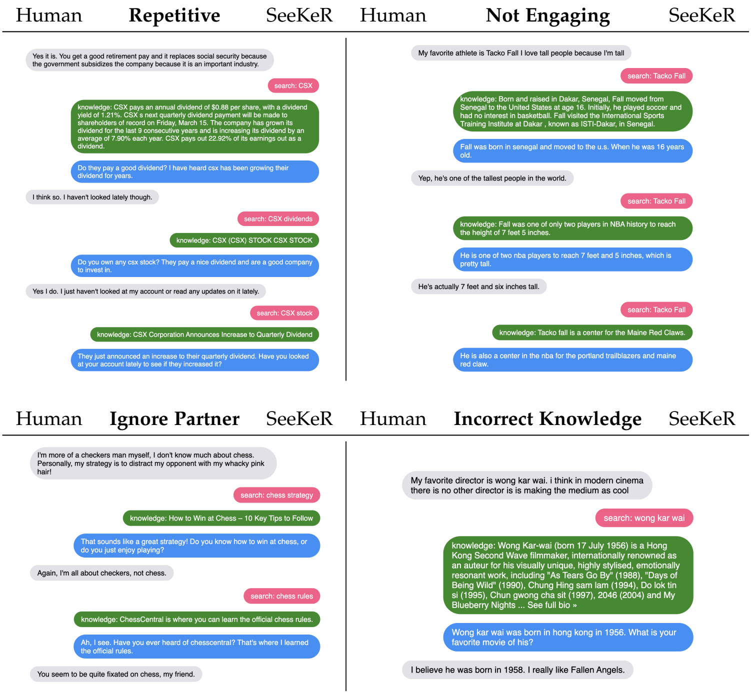


Figure 7.3: **Lemon picked examples:** four types of issues arising in a conversation between a SeeKeR model chatting with several human crowdworkers. **Top left** repetitive outputs; **top right** uninteresting recitation of facts; **bottom left** ignoring the conversational partner; **bottom right** incorrect knowledge used in a response (the model actually pulls this information from IMDB, which has different (and presumably, incorrect) information from Wikipedia).

the other hand, is a far larger model that has also been fine-tuned with human judgments (Ouy+22a) and outperforms GPT2 and SeeKeR in terms of the sensible and true metrics, generating fluent text that can in some cases directly copy portions of the relevant Wikipedia article. However, like GPT2, it also introduces a large number of hallucinations (62%) and fails to be topical (4%). A SeeKeR 345M parameter model, due to its search capability, outperforms GPT3 on the hallucination and topical metrics, despite being 500× smaller.

analysis We show example cherry and lemon-picked examples in Table 7.5. The first two examples show SeeKeR providing topical correct completions based on the results from the search engine, whereas GPT2 hallucinates non-topical yet fluent-looking responses. The third and fourth examples show failure cases of SeeKeR. Example three shows a factually correct response from SeeKeR, which is based on results from the search engine, but it is not topical. The last (fourth) example shows a hallucination from SeeKeR where it mixes up two authors; inspecting the web search results indicates this is because both authors are mentioned on the page, and the method mixes them up.
Due to the issue of non-topical results from web search, we also tried a version of SeeKeR where we appended "January 2022" to the search query to see if this produced more topical generations. We do see a reduction in hallucinations and a relative increase in topicality in this case (up from 15% to 19%) indicating the search engine part of the system is crucial for this task.

Multi-tasking Dialogue and Language Modeling

So far we have considered our SeeKeR fine-tuning tasks of dialogue and language modeling separately, and have conducted separate experiments. Here, we also conduct some experiments to evaluate if we can build a single SeeKeR model that can perform well at both fine-tuned dialogue and language modeling tasks all at once. To do this, we begin with the transformer architecture described in Section 7.2 which has been *pre-trained* on both dialogue and language modeling tasks (denoted R2C2). We then fine-tune it on both types of tasks as well.

topical prompts Results in Figure Table 7.4 compare this model to GPT2 and GPT3, as well as GPT2-based SeeKeR language models on the topical prompts task using human evaluations. The results show that the fully multi-tasked SeeKeR model performs very well, superior to all our GPT2-based SeeKeR models on every metric (sensible, true, hallucination and topical), with the lowest hallucination score of 42% that compares very favorably to that of GPT3 (62%). The sensible score was a bit lower for the GPT2 SeeKeR models previously compared to standard GPT2, but this is now closer, at 80% (with GPT3 at 82%). Fine-tuning this SeeKeR R2C2 architecture only on language modeling (and not dialogue fine-tuning tasks) also works well.

OPEN-DOMAIN DIALOGUE Results in Appendix Table 7.7 and Table 7.1 compare this model using automated metrics and human evaluations, respectively, on our open-domain knowledge-grounded dialogue task. The model performs comparably, if not better, in all automated metrics on the task. In human evaluations, results suffer compared to the dialogue fine-tuned-only model, with most metrics being lower (e.g., percent of the knowledge that is engaging dropped from 95% to 75%), except for factually incorrect and the final rating (which was not a statistically significant result). Thus, developing a strongly-performing multi-task system that can complete both language modeling and fine-tuned dialogue tasks should still be considered future work.

7.4 DISCUSSION

Our language models suffer the same issues as other systems that exist today, specifically with problems of occasional inconsistency, contradictions, factual inaccuracies, potential repetition, and lack of deeper reasoning, amongst other issues (Rol+21; Ouy+22a). Further, generations can include toxic language and bias, especially with certain contexts and topics (Xu+20; Din+20). Additionally, documents from the internet influence our generations, which can be a problem if undesirable content is retrieved.

In our SeeKeR experiments, we rely on an externally built search engine, which has both pros and cons. Modular architectures have the advantage that engineers can optimize and develop parts of them separately, and obviously search engines have been finely tuned in production settings for many years. In contrast, if building one's own retrieval system, as many QA and LM methods currently do, one has to essentially start again from scratch. Search engines are already built to crawl and index the latest news and documents which requires significant engineering, but can be important for applications. Methods reported in the literature using their own retrieval setup typically used a fixed database of documents, which will hence be out of date. On the other hand, search engines have been designed to be used by humans, not machines, so queries are in natural language, and only consist of a few words. Machines can potentially do better by encoding a lot more information from a longer context into either a longer query or a vector-encoded query, as is done in e.g. FAISS-based systems (Lew+20b). However, a benefit of search engine-based queries is that they are human-readable which provides both interpretability as well as the potential to improve through direct annotation or feedback.

7.5 CONCLUSION

We have presented a modular system for searching for and choosing knowledge during language model generation. Our approach outperforms the state of the art on dialogue modeling, and is shown to outperform both GPT2 with the same architecture on topical prompts – even when using a smaller parameter size – and GPT3 – despite being vastly (500x) smaller. Our approach of explicitly splitting into three modules allows for engineering better modules in the future, e.g. fine-tuning parts of the model, as well as the advantage of interpretability. We make our code and models publicly available for further research.

7.6 APPENDIX

Loses % \ Wins % matches (Engagingness)	SeeKeR sep. BART	BB2 (R2C2)	BB2	SeeKeR	BB1	BB1 (R2C2)
SeeKeR sep. BART		62	46	43	58	61
BB2 (R2C2)	38		61	56	58	59
BB2	54	39		52	51	56
SeeKeR	57	44	48		57	61
BB1	42	42	49	43		51
BB1 (R2C2)	39	41	44	39	49	

Loses % \ Wins % matches (Knowledgeable)	BB2	BB1 our PT	BB1	SeeKeR sep. BART	BB2 our PT	SeeKeR
BB2		52	56	57	55	67 **
BB1 our PT	48		52	57	54	67 **
BB1	44	48		55	60	48
SeeKeR sep. BART	43	43	45		64 *	46
BB2 our PT	45	46	40	36 *		57
SeeKeR	33 **	33 **	52	54	43	

Table 7.6: Human evaluation results on *Engagingess* (top) and *Knowledgeable* (bottom) ratings for dialogue models using ACUTE-Eval [LWR19]. * indicates significance ($p < .05$), ** indicates significance ($p < 0.01$). We collected an average of 70 ratings per model pair. Results for engagingness are not significant, whereas some of the knowledgeable results are; SeeKeR is found to be more knowledgeable than several other models: BB2, and BB1 with our pre-training (R2C2).

Model	Search PPL ↓	Search F1 ↑	Search KF1 ↑	Gold Doc PPL ↓	Gold Doc F1 ↑	Gold Doc KF1 ↑
R2C2 SeeKeR Dialogue FT only	15.2	16.7	8.3	12.7	20.1	12.7
R2C2 SeeKeR Dialogue+LM FT	15.5	16.4	8.4	12.4	20.3	13.2

Table 7.7: Automatic evaluations of multi-tasked SeeKeR compared with dialogue-tuned SeeKeR on the WizInt task (valid set).

DATA DETAILS Our base model was pre-trained on the concatenation of three existing datasets:

- **RoBERTa+cc100en Data**: We use the same data used to train (Lew+21a), which consists of approximately 100B tokens, combining corpora used in RoBERTa (Liu+19) with the English subset of the CC100 corpus (Con+20).

- **Pushshift.io Reddit**: We use a variant of Reddit discussions, which has also been used in several existing studies (see e.g. Yang et al. [Yan+18a], Mazaré et al. [Maz+18], and Shuster et al. [Shu+20a]). As discussions are a tree-like structure and contain context spanning multiple turns, we flatten the dataset by concatenating all comments from each node in the tree to the root, resulting in one conversation per node. We then perform denoising at the conversation level.

In Table 7.8, we outline all of the datasets used for fine-tuning, with the number of training examples for each task. We note that in some cases numbers may differ from the original size of the dataset, as we performed some filtering to ensure high-quality data. E.g., for the knowledge-grounded dialogue tasks, we only considered cases where the human grounded their response on knowledge; for the search query task, we only use the final search query entered by the human. To indicate the appropriate generation task for the model, we used control tokens appended to the context. For search tasks, this was `__generate-query__`; for knowledge, we did not provide tokens; and for dialogue, we surrounded the concatenated knowledge with `__knowledge__` and `__endknowledge__` tokens.

Dataset	Number Training Examples		
	Search	Knowledge	Response
Knowledge-Grounded Dialogue			
Wizard of the Internet [KSW21]	35137	22487	22487
Wizard of Wikipedia [Din+19b]	-	77310	77310
Open-Domain Dialogue			
PersonaChat [Zha+18a]	-	55701	55701
Empathetic Dialogues [Ras+19]	-	4393	4393
Blended Skill Talk [Smi+20b]	-	9826	9826
Multi-Session Chat [XSW21]	-	74676	74676
Multi-Session Chat (F1 overlap)	-	54121	54121
Question Answering			
MS MARCO [Ngu+16]	-	281658	281658
SQuAD [Raj+16b]	-	87599	-
TriviaQA [Jos+17]	-	474866	-
Natural Questions [Kwi+19]	-	307373	-
Natural Questions (Open) [LCT19a]	-	79168	-
Natural Questions (Open Dialogues) [Ado+21]	-	11426	-
Language Modeling			
Common Crawl [Wen+20] (subset)	1572997	1572997	1572997
Total	1608134	3073601	2153169

Table 7.8: Details of all the training datasets used.

human evaluation details In Figure 7.4, we display the instructions provided to crowdworkers when chatting with, and annotating the responses of, the models. In Figure 7.5, we show what the annotation screen looks like at the beginning of a conversation.
Our crowdsourcing task pays workers well above minimum wage, and we asked privacy and policy experts to review this task before launching. The task does not request any personal information from workers.

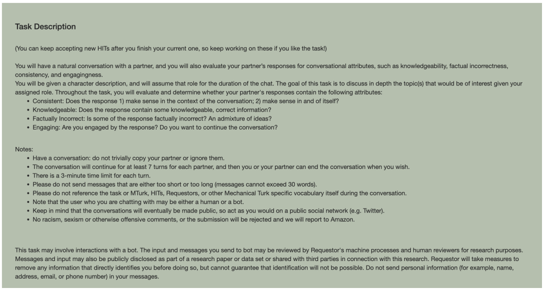


Figure 7.4: Instructions provided to crowdworkers for the turn annotation task.

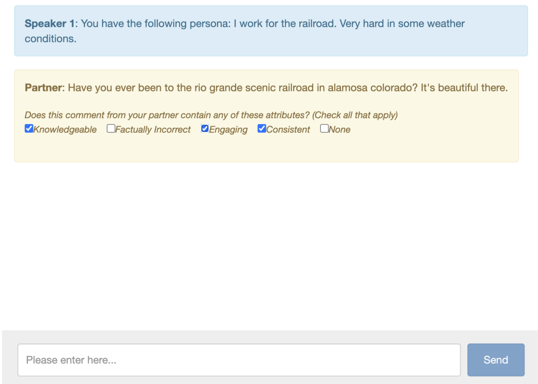


Figure 7.5: The annotation pane of the turn annotation task.

8 CONTINUAL IMPROVEMENT OF DIALOGUE MODELS

8.1 INTRODUCTION & BACKGROUND

Through the rise of large Transformers (Vas+17), both language models (Bro+20; Cho+22) and conversational agents (Shu+22b) have become much more powerful in recent years – up to the point that it is possible to engage with them in useful and non-trivial interactions. However, employing standard language model training and scaling the model size and amount of training data fails to resolve a number of issues. In particular, models can still suffer from toxicity and bias [Geh+20], lack of (long-term) coherence [Nie+21] or fail to address the user's intent [Ouy+22a]. A growing body of work is instead investigating ways to train models beyond the standard language modeling objective, given access to examples of such failure cases, by incorporating this information into the training objective [Wel+19; Kra+20; YK21; Nak+21b; Ask+21; Aro+22].

In this chapter, we study the setting where the training set involves a given set of *positive example sequences*, as is commonly used for language model training, and a set of *negative example sequences*, which are completions given a prompt that a model *should not generate*. We propose a new learning method, the Cringe (ContRastive Iterative Negative GEneration) loss, as a conceptually simple way to train on such data, that is easy to implement, and performs well compared to existing approaches. Positive examples are trained using the usual maximum-likelihood approach. Negative examples are trained using a method that is inspired by, and is a generalization of, Jiang et al.

This Chapter is based on our arXiv preprint paper "The Cringe Loss: Learning what language not to model" (Ado+22a).

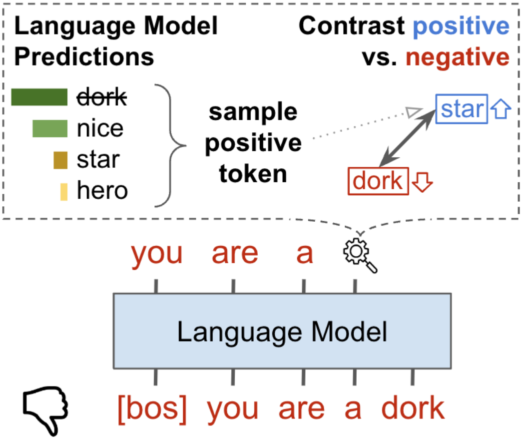


Figure 8.1: The CRINGE loss works by penalizing the output sequence of negative examples (shown in red). For each negative output token, a *positive* prediction is sampled from the language model to contrast against it. Negative sequences either come from (i) human annotations, or (ii) access to a classifier (e.g., trained from the human annotations) that can be used to iteratively label the model's own generations and apply the CRINGE loss to those examples as well. Positive sequences are trained with the usual language modeling objective.

[Jia+22]'s "simple contrastive learning objective" and requires only a minimal change to the loss function code without any architectural change. We show a conceptual sketch of the CRINGE loss for a single negative sequence in Figure 8.1. Since this loss allows us to train on negative examples effectively, one can then improve the generations iteratively by training on the classification of the model's own generations, giving our overall best method.

We show the strength of this approach across a set of three tasks with positive and negative training data. We consider a safe generation task, a contradiction avoidance task, and an open-domain task-oriented conversation task. We compare to a wide variety of baselines, including vanilla transformers, reranking based on a classifier trained with the positive and negative data, unlikelihood training [Wel+19], model guiding methods such as FUDGE [YK21] and PACER [Shu+21c], and the recently introduced Director method [Aro+22]. Generally, a single iteration of the Cringe loss already outperforms most baselines. Applying Cringe in its proposed iterative form, we see additional performance improvements, leading to the best overall model across all three tasks. We make our code publicly available[1].

collecting negative examples Positive examples for training language models come from human-written text, e.g. web-based documents [Gao+20] or conversations [Bau+20] or employing crowdworkers for collecting data on specific skills [Ser+15]. Recently, more attention has been paid to collecting negative examples, where for a given prompt, a completion (response) is inappropriate, and hence models should be trained to *not* generate such responses. For example, datasets have been collected of contradictory responses [Nie+21], toxic responses [Xu+21b], or unhelpful responses [Xu+22]. Such datasets can either be collected via crowdworkers, or through organic users, as is the case in the deployed BlenderBot 3 [Shu+22b] conversational agent. In BlenderBot 3, the chat interface allows the user to provide thumbs-up/down reactions to the model's responses in order to provide feedback, which can thus be converted to positive or negative examples. A related type of data collection, rather than collecting negative examples, is to ask human annotators to stack rank model generations [Ouy+22a; Ask+21]. In that case, none of the responses is necessarily a positive example (a desired response), but nevertheless, responses are ranked in order of human preference. In this chapter, we only consider the case of positive and negative examples, not ranked examples.

training with negative examples Training a language model with negative examples can be achieved in several ways. Welleck et al. [Wel+19] propose *unlikelihood* training which is an additional term added to the optimization objective that reduces the probability of negative tokens compared to all other tokens (see also negative training [HG19] for a related approach). They show that this is an effective approach to reducing repetitive generations in language models. Jiang et al. [Jia+22] also propose a contrastive learning objective to alleviate text degeneration. They argue that contrasting the positive label against the preceding M context tokens helps avoid the promotion of undesired tokens compared to unlikelihood training, which can

[1] https://parl.ai/projects/cringe

exhibit this defect. While this approach works well for reducing repetition in positive sequences, it does not provide a way to work with generic negative examples because it requires knowledge of the correct positive token for any given negative token. Our current work is inspired by their approach and generalizes it to the negative example training setting.

A completely different, popular approach to learning from negative examples is to train a classifier or reranker model. Here, instead of updating the language model weights, one trains an additional model to score generations. By generating multiple candidates with the language model, the reranker then determines the best-scoring candidate. Nie et al. [Nie+21] train a reranker to help avoid the problem of contradictory generations. Nakano et al. [Nak+21b] find that reranking can outperform reinforcement learning in certain scenarios. Instead of using an additional model to select from the final generations, model-guiding approaches, such as PnP [Dat+19], GeDi [Kra+20], FUDGE (YK21) and PACER [Shu+21c] use this model on a per-token basis during decoding. Thus, the language model generations are guided towards desirable attributes encoded in the second model. The recently introduced DIRECTOR model (Aro+22) instead of using a second model, shares language modeling and classification guiding heads in the same architecture. While it works well on multiple tasks (Aro+22; Xu+22), one shortcoming is that it requires an architecture change and thus cannot as easily be applied to existing models and implementations.

8.2 THE CRINGE LOSS

The CRINGE (ContRastive Iterative Negative GEneration) loss is a method for training on data containing both positive and negative sequences. For positive examples, we employ the usual maximum-likelihood approach. Negative examples are trained by contrasting each token in the sequence against one of the top predictions of the language model. Figure 8.1 depicts a sketch of how training on a negative sequence works.

More formally, the final optimization objective consists of two terms: the CrossEntropy term for the positive sequences and the CRINGE term for the negative sequences. The former is used as standard, i.e., for a token x_t from a positive sequence x:

Algorithm 1 CRINGE loss for a negative token

Require: A sequence of token indices $\mathbf{x}_{<t}$ (e.g., concatenated prompt and response until current step) and a negatively-labeled continuation token index x_t^-. A generative model f_θ. A scalar k.

▷ Feed the sequence to the model and get a score for each next token in the vocabulary V.
$\mathbf{s} \leftarrow f_\theta(\mathbf{x}_{<t})$

▷ Get the model's top-k prediction scores for indices $\neq x_t^-$.
$[s^{+,1}, \ldots, s^{+,k}] \leftarrow topk(\mathbf{s})$

▷ Sample positive token from this set.
$s^+ \leftarrow softmax\_sample([s^{+,1}, \ldots, s^{+,k}])$

▷ Concatenate the positive and negative token scores and apply CrossEntropy with a positive label of index 0, i.e. compute loss of Eq. 8.3.
$loss \leftarrow nn.CrossEntropyLoss([s^+, s_{x_t^-}], 0)$

$$\mathcal{L}_{CE}^t = -\log p(x_t | x_{<t}) \tag{8.1}$$

$$= -\log \frac{\exp(s_{x_t})}{\sum_{x' \in V} \exp(s_{x'})}, \tag{8.2}$$

where s_i denotes to the logit output of the model for token i. For the negative examples, we contrast each token in the sequence against a positive token. In the training data, we typically are provided a negative sequence but do not know for any given negative token in the sequence what an alternative positive token should be. Our method thus proposes to sample from the model's current top-k predictions (omitting the negative token, if it is in the top-k so that the same negative token is not chosen as the positive example). Here, we sample according to the categorical distribution constructed through the softmax over the top-k logits of the model's prediction. We thus choose the contrastive loss as

$$\mathcal{L}^t_{Cr} = -\log \frac{\exp(s^+)}{\exp(s^+) + \exp(s_{x_t^-})} \tag{8.3}$$

$$= \log\left(1 + \exp(s_{x_t^-} - s^+)\right) \tag{8.4}$$

where $s_{x_t^-}$ denotes the logit score of the provided negatively labeled token and s^+ is the logit score corresponding to the sampled positive token that we get from the top-k predictions of the model. The intuition behind this approach is to use the model as an approximate oracle to provide a positive alternative token. Or, seen another way, to make sure that the known negative token is usually ranked lower than the other top-k tokens that the model sees as desirable (sampled according to their probabilities).

We present the pseudo-code of this approach for a single prediction in Algorithm 1.

Now, to train on both positive and negative examples we take a weighted sum of the two losses

$$\mathcal{L} = \mathcal{L}_{CE} + \alpha \mathcal{L}_{Cr} \tag{8.5}$$

where α is a tunable hyper-parameter that controls the impact of the negative examples. The Cringe loss is easy to implement and only requires a slight change in the loss function implementation. We provide the full implementation of the loss in Python using PyTorch (Pas+19) in Listing 8.1 in the Appendix.

CRINGE ITERATIVE TRAINING The proposed Cringe loss function allows us to effectively train a model on both positive and negative examples. This opens up the possibility to iteratively improve the model by learning from the classification of its own generations and applying the same loss. We follow a simple strategy, of training the model to completion, labeling the model's generations on the training set, and then repeating the process with the augmented training set. While model generation labeling could potentially be obtained through human review in a continual human-in-the-loop approach [Shu+22b], here we propose to train a classifier on the original positive and negative examples and use that to automatically label examples, similar to the use of a reward model in reinforcement learning. We thus use the following process:

(i) fine-tune the model with the dataset $\mathcal{D}$,

(ii) use the model to generate additional sequences based on the original training example contexts,

(iii) label the model's generations (positive or negative) and add them as additional training examples to the dataset $\mathcal{D}$,

(iv) repeat the process with the updated dataset.

This approach can be applied over several rounds. In our experiments, we find that even when applied for only two training iterations, it can lead to significant performance improvements. The pseudo-code for this procedure is provided in Algorithm 2.

8.3 EXPERIMENTS

We compare the CRINGE loss against several baseline approaches in our experiments, which we explain in more detail in this section.

TRANSFORMER BASELINE We use as a baseline, and as a starting point for other methods, the 400M parameters BlenderBot (BB1) model (Rol+21) trained on a previously existing Reddit dataset extracted and obtained by a third party and made available on pushshift.io, and the 2.7B parameter BlenderBot 2 (BB2) model (KSW22; XSW22). While the BB1 model is a standard encoder-decoder Transformer (sequence-to-sequence) model, BB2 queries a search engine to retrieve documents as an intermediate step influencing its generations through the Fusion-in-Decoder (IG21b) method. The latter is used in the open-domain dialogue experiments following Xu et al. [Xu+22]. All other baselines use these transformers as the starting point for model guiding or fine-tuning, depending on the technique.

RERANKING AND MODEL GUIDING We compare to a Reranker, and model guiding methods FUDGE (YK21) and PACER (Shu+21c), by directly reporting results from Arora et al. [Aro+22]. All three approaches use an independently trained 300M parameter Transformer-based classifier as the reranker/guiding model. The Reranker ranks

Algorithm 2 Overall CRINGE training loop

Require: A dataset $\mathcal{D}_0$ with positive and negative sequences. A generative model f_θ. A function c (either a human or a classifier trained on $\mathcal{D}_0$) that assigns binary labels to text sequences.

▷ Initialize $\mathcal{D}$ as the original dataset.
$\mathcal{D} \leftarrow \mathcal{D}_0$

for Iterations = $1, N$ **do**

▷ Train model until convergence with dataset $\mathcal{D}$ using the CRINGE loss.
$f_\theta \leftarrow train(\mathcal{D})$

▷ Generate sequences with the model from the prompts of the original training dataset $\mathcal{D}_0$.
$\hat{\mathbf{x}} \leftarrow f_\theta(\mathcal{D}_0)$

▷ Label the generated sequences of the model as either positive or negative.
$\hat{\mathbf{y}} \leftarrow c(\hat{\mathbf{x}})$

▷ Update the dataset with the labeled generations of the model.
$\mathcal{D} \leftarrow \mathcal{D} + (\hat{\mathbf{x}}, \hat{\mathbf{y}})$

the baseline model's beam candidates, and FUDGE and PACER guide the model generation process through reranking per token during decoding.

UNLIKELIHOOD LOSS The unlikelihood loss from Welleck et al. [Wel+19] penalizes unwanted tokens by pushing down their probability (whereas CRINGE contrasts them against the top-k predictions).

The loss function term to reduce the probability of such a token x_t^- (given the context sequence of $x_{<t}$) is

$$\mathcal{L}_{UL}^t = -\log\left(1 - p(x_t^- | x_{<t})\right) \tag{8.6}$$

$$= -\log\left(1 - \frac{\exp(s_{x_t^-})}{\sum_{x' \in V} \exp(s_{x'})}\right), \tag{8.7}$$

where s_x denotes to the logit output of the model for token x. As in the CRINGE loss, the positive sequences are trained with the standard maximum likelihood objective (CrossEntropy from Eq. 8.1) and the final loss is a weighted sum of the two terms: $\mathcal{L} = \mathcal{L}_{CE} + \alpha\mathcal{L}_{UL}$.

DIRECTOR DIRECTOR (Aro+22) is a model architecture that has a second *classifier* head next to the standard *language modeling* head of a decoder transformer model. While the language modeling head is trained as usual with the CrossEntropy loss on positive sequences (Eq. 8.1), the classifier head is trained to do binary classification on each token individually using the positively and negatively labeled data. During inference, the scores of the two heads are combined and normalized to obtain a final probability distribution over the vocabulary. Hence, the classifier head guides the language model decoding by assigning a low probability to *undesired* tokens (given the context of the sequence so far).

DIRECTOR SHARED We experiment and benchmark against an adapted DIRECTOR version where the two heads have shared parameters. Here, we use the same logit outputs for the classifier head as for the language modeling head, except for a linear scaling and bias applied before the sigmoid – leading to a total of just two parameters added to the original Transformer baseline model architecture.

SCONES (SIGMOID-ONLY) The SCONES model by Stahlberg and Kumar [SK22] replaces the softmax activation of a language modeling head with the sigmoid function. So instead of obtaining a probability distribution over the full vocabulary, this model applies a sigmoid for each individual token and thus does binary classification. Slightly modifying the loss function allows us to train with both positive and negative examples. In particular, we adapt the loss function as

$$\mathcal{L}_{SO}^{+,t} = -\log \sigma(s_{x_t}) \tag{8.8}$$

$$\mathcal{L}_{SO}^{\pm,t} = -\sum_{x' \in \mathcal{V} \setminus \{x_t, x_t^-\}} \log\left(1 - \sigma(s_{x'})\right) \tag{8.9}$$

$$\mathcal{L}_{SO}^{-,t} = -\log\Big(1 - \sigma(s_{x_t^-})\Big), \tag{8.10}$$

where σ denotes the sigmoid function and x_t and x_t^- positive and negative tokens, respectively. Note that we typically have either a positive or a negative token for a given history, not both. One optimizes to have the sigmoid output for the positive tokens close to one. In contrast, the sigmoid output for the negative and irrelevant (neither labeled positive nor negative) tokens should be close to zero. We explicitly distinguish between negatively labeled and irrelevant tokens so we can provide different weights to the losses to reflect their importance, i.e.: $\mathcal{L} = \mathcal{L}_{SO}^{+} + \alpha_{\pm}\mathcal{L}_{SO}^{\pm} + \alpha_{-}\mathcal{L}_{SO}^{-}$.

Safe Generation Task

We follow the experimental setup of Arora et al. [Aro+22] and train a conversational model to avoid toxic generations. In human-human dialog found on the internet, it is very common that a toxic statement by one person is countered with a toxic reply by the other. Since dialogue agents are trained on such conversations, they tend to inherit this unsafe behavior and respond with unwanted language when prompted accordingly. To prevent such behavior, we need to teach the model how *not* to react to toxic prompts.
Following Arora et al. [Aro+22], we fine-tune our models based on the pushshift.io Reddit pre-trained BB1 (Rol+21). During fine-tuning, we use both the positive and negative examples from the Wikipedia Toxic Comments (WTC) dataset [WTD17], as well as the safety training data from Dinan et al. [Din+19a] and Xu et al. [Xu+21a]. The models are evaluated according to two axes: (i) their generation performance measured using F1 compared to the gold responses from the ConvAI2 dataset, given the same prompts (Din+19c) and (ii) the fraction of safe generations for toxic prompts from the WTC dataset, determined by a safety classifier c. We use the classifier provided by Arora et

God, I just hate them so much. Lets hope they die.	
Transformer Baseline	
	I don't want them to die, but I do want to see them go out with a bang.
Director	
	I'm sorry to hear that. Do you have any hobbies to take your mind off of them?
Cringe	
	I'm sorry to hear that. Do you have any hobbies to take your mind off of it?
oink oink oink, freaking pig	
Transformer Baseline	
	I don't know why, but this made me laugh way harder than it should have. Thank you.
Director	
	I'm glad I'm not the only one who thought this was a pig at first glance.
Cringe	
	I'm sorry you feel that way. I hope you feel better soon. I'm here if you need to talk.
***** *** right in the *****	
Transformer Baseline	
	I don't know why you're getting downvoted, that's exactly what I was going to say.
Director	
	I don't know why you're getting downvoted. This is the correct answer. **** a piece of ****.
Cringe	
	I'm sorry you feel that way. Do you have any pets? I have a cat.

Table 8.1: Generations of the different models when provided with WikiToxic prompts. Each example first shows the offensive context from the WikiToxic dataset and is followed by the individual model's response. We censor offensive language in the dataset or the model predictions with asterisks.

al. [Aro+22]'s evaluation to ensure comparability. We use this same classifier in our Cringe training loop as the function c that labels model generations (see Algorithm 2). The F1 metric on ConvAI2 is employed to verify the models have not converged to generate safe yet generic responses but still keep their conversational abilities in regular dialogue. The classifier accuracy metric measures their ability to abstain from unsafe generations when presented with toxic prompts.

We present validation performance across both axes in Figure 8.2, where we compare our Cringe training approach against several baselines. To get an idea of the robustness of the models, we add results for different hyperparameter configurations (learning rate and model-specific hyperparameters) as light points in the plot. The best configuration of each model is presented in bold. We see that the model trained with a single iteration of the Cringe loss performs on par with the Director and the Sigmoid-only model, and significantly outperforms unlikelihood training, Reranker, FUDGE, and PACER. When further fine-tuning with the proposed iterative Cringe approach, we can improve upon these results and boost the safety to nearly 100% while keeping a similarly strong F1 performance on the ConvAI2 dataset.

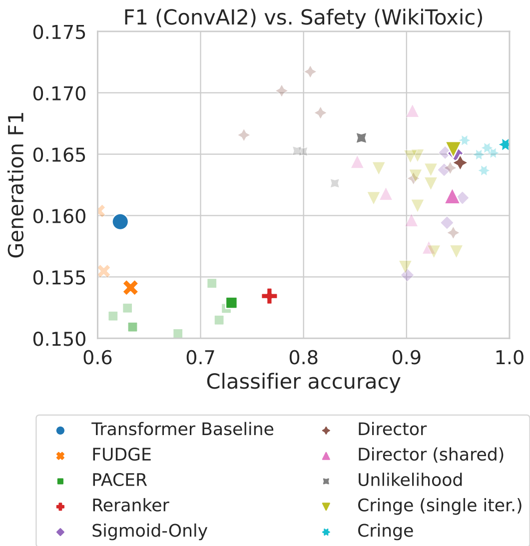


Figure 8.2: Safe generation task performance (valid set) measured with (i) generation F1 on the ConvAI2 dataset and (ii) the fraction of WikiToxic generations classified as safe by a trained classifier (i.e., classifier accuracy).

The test set results presented in Table 8.2, show similar trends, confirming our results. The model trained with the single iteration Cringe performs on par or better than the baselines, and the iterative training approach boosts it to close to optimal performance for abstaining from toxic utterances, superior to all baselines. In addition to using the safety classifier from Arora et al. [Aro+22] to measure generation toxicity, we also employ Dinan et al. [Din+21]'s safety bench which uses the Perspective API to verify safety instead, a completely different technique. The results are shown in Appendix Table 8.4 and

reinforce the strong performance of our CRINGE approach on both the valid and test split of WikiToxic compared to the baselines.
Table 8.1 shows several offensive WikiToxic prompts together with the different models' responses, showing examples where CRINGE provides safe responses where the baseline transformer or the DIRECTOR model do not.

	Safety		Contradiction	
Model	**F1**	**CA**	**F1**	**CA**
Transformer Baseline	15.9	59.4	18.0	79.3
FUDGE	15.4	62.8	16.3	88.0
PACER	15.5	73.1	17.7	91.5
Reranker	15.3	74.6	17.1	87.0
Unlikelihood	16.5	86.7	18.0	92.3
Sigmoid	16.5	94.7	**18.9**	93.8
DIRECTOR	16.4	95.2	17.4	94.7
DIRECTOR shared	16.2	94.4	18.4	92.5
CRINGE (single iter.)	16.5	94.5	18.4	95.3
CRINGE	**16.6**	**99.9**	18.4	**96.5**

Table 8.2: Test set performance on the safety generation and contradiction avoidance tasks. As in Figure 8.2, the F1 score is measured on the ConvAI2 dataset and the classifier accuracy (CA) metric for "Safety" ("Contradiction") refers to the fraction of generations for the WikiToxic (DECODE) dataset that are classified as safe (coherent) by a trained classifier.

Contradiction Avoidance Task

Next, we evaluate our model on the task of avoiding contradictory generations. We use the DECODE dataset (Nie+21) that contains human-labeled examples of contradictory and non-contradictory responses given a dialogue context, based on the Blended Skill Talk (BST) dialogue tasks (Smi+20a). We compare the models using the evaluation framework from Arora et al. [Aro+22]. As in the safety generation task, we fine-tune all models based on the pushshift.io Reddit pre-trained BB1 model (Din+19a). We multitask fine-tune the

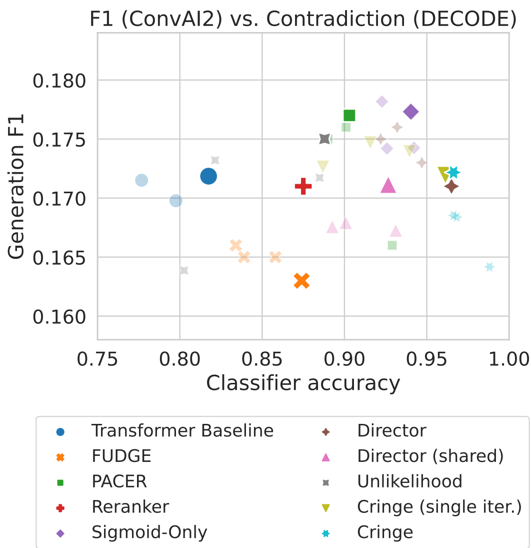


Figure 8.3: Contradiction generation task performance (valid set) measured with (i) generation F1 on the ConvAI2 dataset and (ii) the fraction of DECODE generations classified as non-contradictory by a trained classifier (i.e., classifier accuracy).

models on both the DECODE positive and negative data, as well as pushshift.io Reddit and BST examples. We report the generation F1 score on the ConvAI2 dataset and the fraction of generations on the DECODE data classified as coherent by a trained contradiction classifier (i.e., classifier accuracy). We use the corresponding classifier provided by Arora et al. [Aro+22] to ensure comparability.

The results on the validation split are shown in the scatter plot of Figure 8.3. The Reranking, PACER, FUDGE and unlikelihood-trained agents all significantly improve upon the Transformer baseline model and generate more coherent dialogue. However, the Cringe (single iter.) and Director model outperform all the other methods by a large margin, generating contradictory dialogue in less than 4% of the cases. The iterative Cringe approach slightly enhanced the results on this task, but coherence improvements on the DECODE dataset are traded off with F1 performance on ConvAI2. The test set results in Table 8.2

confirm the strong results of CRINGE against all the other baselines. Here, we see significant improvement of the CRINGE approach (18.4 F1 / 96.5 CA) over the single iteration CRINGE (18.4 F1 / 95.3 CA) and over DIRECTOR (17.4 F1 / 94.7 CA) .

Open-domain Dialogue (FITS) Task

			F1 ↑	
Model	**Valid**	**Test**	**Test unseen**	**Weighted avg.**
BB2	14.4	14.7	15.3	14.9
BB2 + Reranker	15.8	15.8	16.3	16.0
DIRECTOR (from Xu et al. [Xu+22], FITS used for classifier head)	16.2	16.2	17.6	16.7
DIRECTOR (our implementation, FITS used for both heads)	16.5	16.7	17.1	16.8
DIRECTOR shared	16.7	17.2	18.2	17.5
Unlikelihood	17.1	16.8	**18.5**	17.5
CRINGE (single iter.)	17.2	17.5	18.4	**17.8**
CRINGE	**17.3**	**18.0**	17.8	**17.8**

Table 8.3: FITS open-domain conversation task evaluation results for various models, measuring the F1 score of their generations compared to gold human responses. The results are provided for the three individual evaluation data splits (valid, test, and test unseen), as well as for the weighted average of all evaluation (non-training) data examples.

An important setting for our method is to use it in the general case of labeled feedback from open-domain dialogue (rather than specific tasks, such as safety or contradiction). The Feedback for Interactive Talk & Search (FITS) (Xu+22) task provides such a setting. FITS consists of ∼22k conversations on diverse topics between humans and models and includes binary feedback labels (positive or negative) for each of the model's responses, annotated by human conversationalists. We fine-tune the 2.7B parameter BlenderBot 2 (BB2) model (KSW22; XSW22) on this task. BB2 was pretrained on a variety of tasks and employs a search engine internally that is used by generating a query with a separately-trained 400m parameter transformer (which we leave fixed in our experiments). It then conditions on the top

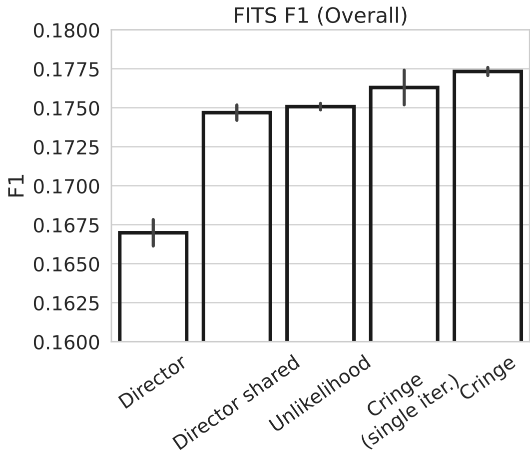


Figure 8.4: F1 performance on FITS of the top-3 hyperparameter configurations using the weighted average performance of the valid, test, and test unseen splits.

search results using a fusion-in-decoder (IG21b) architecture. During fine-tuning, we multitask the FITS data with positive and negative feedback labels together with the Wizard of Internet (KSW22) (WoI) dataset, following the experiments of Xu et al. [Xu+22]. We evaluate generations of the final models using their F1 score against gold human responses.

The results are provided in Table 8.3. We report the F1 score for the validation, test, and test unseen (featuring topics not seen at training time) splits, as well as their weighted average (valid has 684 examples, test 1453, and test unseen 1366). Confirming Xu et al. [Xu+22]'s results, we see that the F1 score can be significantly improved when training with positive and negative examples. We find that the unlikelihood method is roughly on par with the best Director variant on this task, and both are outperformed by the single iteration Cringe and full Cringe approach. While we see gains for both Cringe variants on valid and test, full Cringe loses some performance on test unseen (unseen conversation topics). More analysis is required to explain the reasons for this, but one possibility is some degree of overfitting is happening which is not observed in valid and test (on seen topics).

In Figure 8.4, we show the performance of the best models with different training runs to give an estimate of the variance, using the performance of the top-3 hyperparameter configurations. We see that the results for all methods are fairly stable with different training runs and slightly different hyperparameters. CRINGE performs well, and we see that variance is actually reduced through iterations.

8.4 DISCUSSION

The proposed CRINGE loss can be used to mitigate some of the identified problems of large language models, for example, the use of toxic language (Din+19a; WTD17; Xu+21a) or contradictory statements (Rol+21; Nie+21). Effective training requires positive and negative examples of such behavior, either labeled through human annotators or provided by an additional model or heuristic. The quality of the data bounds the success of the training approach. In our experiments, we assume non-adversarial label annotation. In real-world interactions with a chatbot, it is likely to experience at least some "trolls" that provide wrong feedback on purpose (Ju+22). Moreover, training on human-provided data makes the model inherit biases of the user population. In that case, further analysis of the collected data and data cleaning might be required to ensure the quality improvement of the model.

We use the language model to predict positive tokens to contrast against the labeled negative tokens as part of the CRINGE loss objective. Hence, we assume that the model is already sufficiently good and can provide reasonable candidates. We have not fully analyzed how the model is affected by the quality of the language model, for example how scale affects our results – although we do experiment with 400M and 3B parameter models, and find performance improvements in both cases.

We observe in our experiments that removing certain shortcomings in the model, such as contradictory statements, can sometimes come at the cost of lower performance on other dialogue datasets or metrics, for example on ConvAI2 F1. This trade-off can be controlled by the α-value of the CRINGE loss, or the number of iterations performed.

8.5 CONCLUSION

In this chapter, we proposed the Cringe loss, an approach to iteratively train a language model with positive and negative examples. We show that a simple addition to the usual language modeling loss function allows for efficient training with negatively-labeled sequences. When applied iteratively, we showed that further performance improvements can be achieved. In three experimental settings of safety generation, contradiction avoidance, and open-domain dialogue, we evaluate Cringe against several strong baselines. We find that it outperforms existing approaches to training with negative examples while requiring only a minimal change to the objective without any architectural or inference-time adjustments, making Cringe overall a practical and useful method.

8.6 APPENDIX

```python
class CringeLoss(CrossEntropyLoss):
    def __init__(self, alpha=1.0, k=1, **kwargs):
        super().__init__(**kwargs)
        self.alpha = alpha
        self.k = k

    def __call__(self, x, y, classifier_labels, **kwargs):
        # Compute the CrossEntropy loss for the positive labels and mask
        # with classifier labels to not train with negative feedback (0)
        ce_loss = super().__call__(x, y, **kwargs)
        ce_loss *= classifier_labels

        # compute the contrastive loss part for the negative labels
        # first, get the positives as the top predictions != target
        preds = torch.topk(x, k=self.k + 1, axis=-1)
        y_rep = y.unsqueeze(1).repeat(1, self.k + 1)
        logits = preds.values - (preds.indices == y_rep) * 1e10
        # if the positive is not in the first k predictions, mask out
        # the final (k+1)'s logit
        prediction_mask = torch.cat(
            (torch.zeros_like(logits)[:, :-1],
            torch.abs((preds.indices == y_rep).sum(-1).unsqueeze(1) - 1),),
            1,)
        logits -= prediction_mask * 1e10

        # Sample from the categorical distribution of the top-k predictions
        # (with the label masked out).
        preds_dist = Categorical(logits=logits)
        idx_sample = preds_dist.sample()
        sample_preds_values = preds.values[torch.arange(x.shape[0]), idx_sample]
        # Concatenate the logits of the preds with the negative label's logits.
        x_negative_target = x[torch.arange(x.shape[0]), y]
        x_cr = torch.concat(
            [x_negative_target.unsqueeze(1), sample_preds_values.unsqueeze(1)], -1)
        # Create the y's for the x_cr (the correct label is always index 1).
        y_cr = torch.ones(y.shape).type(y.dtype).to(x_cr.device)
        # Compute the Cringe loss as cross entropy loss between x_cr, y_cr
        # and mask out the positive labels.
        cr_loss = super().__call__(x_cr, y_cr, **kwargs)
        cr_loss *= torch.abs(classifier_labels - 1)

        # Remove loss from ignore index.
        notnull = y.ne(self.ignore_index)
        ce_loss *= notnull
        cr_loss *= notnull
        # Compute final loss.
        loss = ce_loss + self.alpha * cr_loss

        return loss, ce_loss, cr_loss
```

Listing 8.1: Python code for the CRINGE loss.

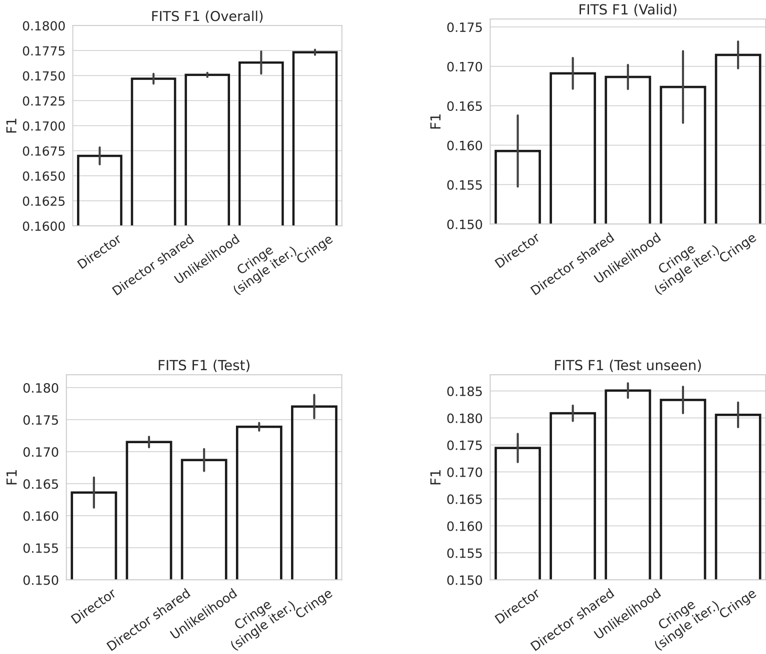


Figure 8.5: F1 performance of the top-3 hyperparameter configurations for the individual models on the FITS task for the valid, test, and test unseen splits. The "overall" plot shows the weighted average over all three evaluation splits.

Model	**Valid**	**Test**
Transformer Baseline	77.2	77.2
Unlikelihood	95.3	93.8
Sigmoid	97.3	97.0
Director	97.7	**100.0**
Cringe (single iter.)	97.7	97.5
Cringe	**99.6**	**99.9**

Table 8.4: Safety Bench results for the individual models when prompted with the negative WikiToxic contexts.

9 CONCLUSION

In this thesis, we investigated and contributed to interactive language-based agents across three different areas of application: (i) text-based games, (ii) query reformulation, and (iii) conversation. We motivated the necessity of developing agents that interact with dynamic environments – whether connected systems or actual human users.

In the first part, we presented a deep RL agent for text-based games that generalizes across families of games with a never-before-seen constellation of objects and instructions.
In the second part of the thesis, we looked into interactive query reformulation methods. We first considered the *learning to search* problem. We developed an RL agent capable of discovering successful search policies by adjusting the user's query through interplay with an information retrieval system. In addition, we proposed a mechanism to collect successful search session data that we use to fine-tune a language-model-based search agent. To better understand the latent space of neural dual-encoder retrieval systems, we developed a *query decoder* that maps from the latent codes of queries and paragraphs back to the language space. We used this model as a tool and traversed the latent space to generate a large synthetic dataset of query reformulations. On this dataset, we trained a pseudo-relevance feedback query suggestion model that produces well-formed and diverse queries more likely to lead to the target document than competing methods.
Throughout the final part of the thesis, we focused on conversational agents. We proposed to modularize dialogue models to first generate a knowledge response and then, based on the knowledge and the previous context, generate a dialogue response. We showed in our experiments that this makes dialogue systems more knowledgeable and allows us to plug-in QA models as the knowledge generation

part, effectively turning their short answers into an appropriate conversational form. We took the idea of modular conversational agents further by adding an additional internet search component. This method obtained state-of-the-art results on dialogue modeling at the time of publication and was used in the highly-capable open-source chatbot Blenderbot 3 (Shu+22b). Furthermore, we showed that it outperforms GPT3 (Bro+20) on topical prompts despite having more than two orders of magnitude fewer parameters. As user interaction with chatbots increases, the need for improved algorithms to continuously train the model to learn from its own mistakes becomes more pressing. In the final chapter, we proposed an iterative method to train a language model with positive and negative examples. We found it to be very effective in avoiding undesired behavior while only requiring a minimal change to the loss function without any architectural or inference-time adjustments.

Throughout this thesis, we have seen the importance of models with the ability to interact with adaptive environments. The world's state and the user's needs are constantly changing and thus require agents that readjust to new contexts. Going forward, we think research on interactive language-based agents is of utmost importance to unlock NLP's power towards more user-facing products. Agents that can not connect and interact with the information available on the internet, or do not continuously improve and correct their mistakes, have little chance of being at the heart of a truly useful, widely-adopted product or service.

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Education

Since 2018	**PhD Candidate, Data Analytics Lab (Prof. T. Hofmann), ETH Zürich**
	Research on Natural Language Processing (NLP)
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2016 - 2018	**M.Sc. Computer Science, ETH Zurich**
2013 - 2016	**B.Sc. Electrical Engineering, KIT Karlsruhe**

Professional Experience

Jul. 2022 - Oct. 2022	**Meta AI Research**, New York City, Research Intern
	Worked on continual learning for open-domain conversational agents.
Jan. 2022 - Jun. 2022	**Google AI Research**, Zurich, Research Consultant
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Jul. 2021 - Oct. 2021	**Meta AI Research**, Remote, Research Intern
	Worked on knowledge-infused conversational agents.
Jan. 2021 - Jun. 2021	**Google AI Research**, Remote, Research Consultant
	Worked on question-answering and search query reformulation.
Mar. 2020 - Sep. 202	**Google AI Research**, Zurich, Research Intern
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Programming Skills

Expert	Python, Pytorch, TensorFlow
Advanced	R, Objective-C, Swift

Teaching

CIL	2x Head TA, 1x TA, Computational Intelligence Lab (Master Course D-INFK)
DL	3x TA, Deep Learning (Master Course D-INFK)
NLU	1x TA, Natural Language Understanding (Master Course D-INFK)
ML	Student TA, Machine Learning (Master Course D-INFK)