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Deep CNNs and Adversarial Regularization for Fatigue Damage Failure Prediction of Concrete Anchors

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1 Introduction

Fatigue experiments present with large scatter even for identical specimens tested under controlled laboratory conditions. It has long been known that variations in the mechanical behavior of fatigued metals occur, such as hardening or softening and variations on the shape of hysteresis curves. In order to incorporate measurements in the fatigue life prediction of concrete anchors, a fully data-driven model, using load-displacement and acceleration data, was trained to predict directly the remaining cycles to failure for anchors embedded in cracked concrete loaded in variable amplitude fatigue.

2 DenseNets & Adversarial Regularization

Four experiments with identical variable amplitude block-loading conditions were performed. All experiments fail either on the anchor head or expansion cone neck as shown in Fig.1. In order to exploit effectively the variation of features in multiple scales, a deep network with dilated convolutions was used. In order to facilitate the flow of gradients from the layers closer to the output to the ones closer to the input, the output features of each convolutional layer are appended to the input features of all subsequent layers (after appropriate padding). This constitutes a so-called **DenseNet** [1] architecture.

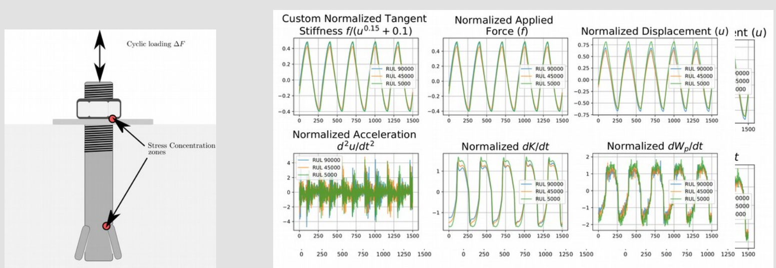

Fig. 1. Left: Schematic of the anchor used and stress concentration zones. **Right:** Example of inputs to the network. The potentially useful features may present in multiple scales.

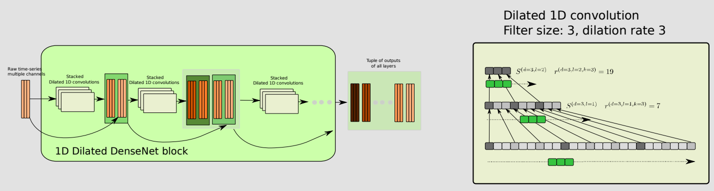

Fig. 2. Left: DenseNet block. The outputs of the convolution filter of each layer, are appended as input to each subsequent layer. Interestingly, due to feature reuse, DenseNets have fewer parameters than typical convolutional neural networks. **Right:** Stacked Dilated convolutions. Dilated convolutions allow for fast growth of the receptive field of a convolutional network while at the same time perform better in representing multi-scale features.

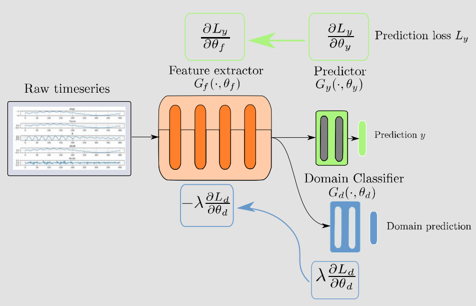

Fig. 3. Schematic of the domain adversarial training procedure. The procedure can be implemented in a single training loop, by reversing the back-propagated gradients from the domain classifier.

The raw data of the experiments are expected to have biases that are not related to the predictive task, but occur only on a given experiment. In tandem with the **predictive network**, a **domain classifier** trained to detect which experiment each data-point belongs to by using the same features, which are the outputs of a **feature extractor network.** By training the feature extractor to ''*fool"* the domain classifier and at the same time extract useful features for the predictive network we achieve removing some bias from the extracted features. This constitutes a **domain adversarial** training procedure [2]. A schematic of the network is shown in Figure. 3.

3 Results

In Figure 4 a comparison of the predictive performance for models trained with and without domain adversarial regularization is performed. Data from 3 experiments are used for training and a held-out experiment is used for evaluation.

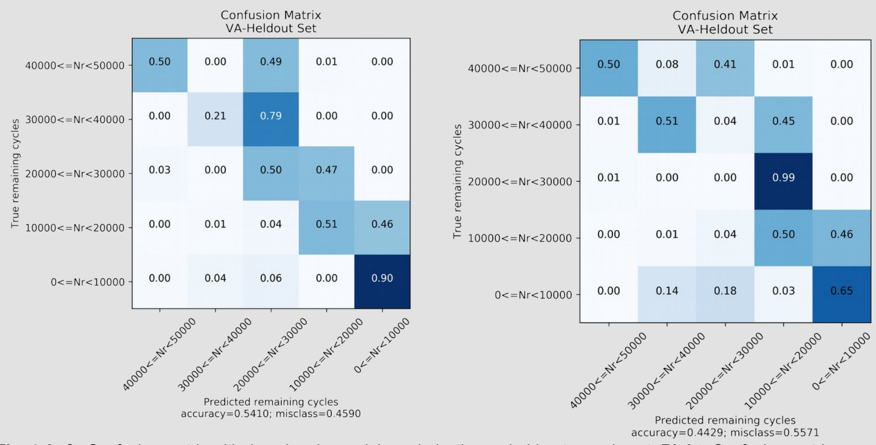

Fig. 4. Left: Confusion matrix with domain adversarial regularization on held-out experiment. **Right:** Confusion matrix without domain adversarial regularization.

3 Conclusion

Some encouraging results on machine learning for remaining fatigue life prediction were achieved. The employed techniques are expected to have wide applicability to other time-series classification problems where potential biases are expected due to small number of experiments. This is a over-arching problem related to the use of experimental data for predictive model construction using machine learning.

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6 References

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