Learning From Differences

Oliver Linger

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Supervisor: Dr. Derek Bridge

Department of Computer Science

University College Cork

Abstract

Declaration of Originality

In signing this declaration, you are confirming, in writing that the submitted work is entirely your own original work, except where it clearly attributed otherwise, and that it has not been submitted partly or wholly for any other educational award.

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2. With respect to my work: none of it has been submitted to any educational institution contributing in any way to an educational award.

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Literature Review

In recent years, the application of neural networks in regression tasks has garnered significant attention within the realm of machine learning and artificial intelligence. Applying neural networks to regression tasks has become a common practice within the machine learning community [2]. Traditionally, supervised learning approaches entail presenting datasets described by features alongside their corresponding expected values to the artificial neural network (ANN), facilitating the learning process aimed at predicting these expected values.

However, inspired by case-based reasoning, which involves solving new problems by adapting solutions from old ones [3], researchers have developed new predictive ensemble models based on the principles of case-based reasoning (CBR). These principles involve retrieving the most similar case(s), reusing the case(s) to attempt to solve the problem, revising the proposed solution if necessary, and retaining the new solution as part of a new case [4].

Researchers have posited the potential advantages of deviating from this conventional paradigm by training neural networks on differences between sets of features to predict differences between values. This departure from the traditional approach underscores a shift towards a more nuanced understanding of the learning process, emphasizing the exploration of alternative methodologies to enhance the efficiency and efficacy of neural network training. Additionally, it aims to provide more transparency within the learning process to offer insights into the black box that is a neural network.

2.1 KNN + ANN for Regression, utilizing (CBR)

In recent years, the exploration of alternative methodologies for enhancing the performance of neural networks in regression tasks has attracted considerable attention within the machine learning community. One such innovative approach, inspired by the principles of case-based reasoning (CBR), involves training neural networks to predict differences between values based on differences between sets of features.

This departure from the conventional supervised learning paradigm aims to leverage the inherent advantages of learning from differences, potentially leading to more interpretable and efficient models. The study under consideration [1] gives a systematic factorial study conducted to investigate the efficacy of this approach across various datasets and experimental conditions. The study's findings suggest that neural networks trained on differences demonstrate comparable or even superior performance to those trained using traditional methods, while requiring significantly fewer epochs for convergence. In this section of the literature review, we consider the utilization of case-based reasoning for regression tasks, with a specific focus on the implementation of KNN (K-Nearest Neighbors) and ANN (Artificial Neural Network) frameworks.

2.1.1 Learning From Differences Paper

The paper by [1] introduces the innovative concept of training a neural network based on the disparities between a base case and its closest neighbors. Titled "A Factorial Study of Neural Network Learning from Differences for Regression" [1], the study aims to present novel learning methodologies geared towards enhancing performance and fostering a more interpretable learning process. The research evaluates three model variations: a benchmark neural network, a learning from differences model, and an augmented learning from differences model incorporating the original context. The context here refers to the base case, from which differences with its nearest neighbors are calculated.

According to [1], the study's key findings underscore a significant increase in accuracy when incorporating contextual information in the learning process. Moreover, comparable or superior results were achieved with fewer training epochs compared to the basic neural network. This enhancement is attributed partly to the broader training dataset that encompasses neighbors greater than 1. Notably, the paper advocates for a hybrid approach, combining learning from differences with direct feature-based learning, which yields superior results.

The graphical representations in the paper highlight a distinct trend: rapid attainment of high accuracy levels with the learning from differences method, particularly when contextual information is included. Conversely, the basic neural network requires a substantially larger number of epochs to achieve comparable accuracy, if not worse. This disparity suggests the efficiency of the learning from differences approach.

In conclusion, the paper suggests a marginal performance enhancement and a substantial reduction in training epochs through the adoption of the differences method and inclusion of contextual information. However, it is crucial to acknowledge the time overhead associated with retrieving and training using similar cases.

Despite its contributions, the paper falls short in adequately addressing classification and exploring additional variations of the learning from differences model beyond context inclusion. Incorporating original values for the base case in the generated differences dataset provides a valuable framework for understanding the observed disparities. While the model with contextual inclusion demonstrates slight improvements over the base model in learning from differences, a more comprehensive examination of the methodology is warranted for further refinement and enhancement.

2.2   KNN + ANN for Classification

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7.3 Experiment 3: Glass Dataset Classification

7.4 Experiment 4: Raisin Dataset Classification

7.5 Experiment 5: Car Safety Dataset Classification

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Results

Bibliography

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