Investigations on the Logical Tensor Networks and Proposed Possible Application Extension

PROPOSER

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INTRODUCTION

As humans, we process strong reasoning and problem-solving abilities. For a long time, researchers are trying to build intelligent systems that can mimic human brains[3]. The current implementations of neural networks have shown their ability of fast learning and processing unstructured data, such as images, audio, and texts[5]. However, despite their learning ability, neural networks require a large amount of labeled data and lack interpretability[5], that is, they predict "what the result is" instead of "why this is the result." This is where the symbolic system sheds light on. Symbolic systems are good at logical reasoning and interpretability to obtain explainability[6]. Based on these, the combination of neural networks and symbolic systems, Neuro-Symbolic (NS) system, integrates the strengths and bridge the gap between the two systems to achieve effective and interpretable learning and reasoning.

MODEL UNDER INVESTIGATION

In this project, I will investigate the Logical Tensor Networks (LTN), an NS system encoding first-order logic in deep tensor networks to represent and learn data relationships[4]. It has been shown to produce powerful results in querying, learning, and reasoning, including efficiently solving tasks such as regression, classification, and query answering[1].

METHODOLOGIES AND EVALUATION

In the investigation part, I will modify the PyTorch implementation of LTN[2] and apply it to new (one or more) datasets for classification/regression problems. The goal here is to show the effectiveness of LTN in solving such tasks as was suggested. In addition, simpler and classical machine learning methods will be applied on the same datasets as a comparison of LTN, such as K-nearest neighbors, logistic regression, and support vector machine (SVM). Measurements such as average least squares error function, receiver operating characteristic (ROC) curve, and confusion matrix will be used to evaluate and compare the results produced by these multiple models/methods.

The completeness of this project is expected to be determined by:

1. Successfully build the LTN model for chosen datasets;
2. Apply classical methods on the datasets;
3. Evaluate the prediction results by the specified measurements and show the metrics data (ex. ROC curve);
4. Compare and summarize the performance of the specified models/methods.

If time permits, the project will also explore the application extension of the current LTN model on text analysis to predict emotions considering there is no existing work on applying LTN in emotion analysis.

TIMELINE

(1) March 21 - April 1: modify current LTN to apply it on new datasets;
(2) April 2 - 8: apply classical methods on the datasets and compare results;
(3) April 9 - 21: write report for the above work and start working on the model application of extension;
(4) April 22 - 28: finish and revise the report.

REFERENCES

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