A Study on the Neural Attention for Symbolic Reasoning Architecture

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Abstract

Integrating hard constraints on neural network outputs is a very sought after capability that will guarantee the sanity of the predictions with respect to domain knowledge. Most of the existing approaches either fail to provide a robust framework that supports different tasks or constraints or they try to impose the constraints during training time which does not guarantee the correctness of the inference. In this regard we have decided to study the NASR (Neural Attention for Symbolic Reasoning) architecture advanced by Samsung AI (Cornelio et al., 2023). Their proposed pipeline adds a symbolic reasoning module capable of correcting prediction errors and a neural attention module that directs the reasoning effort on potential errors while keeping the rest of the outputs unchanged.

1 Introduction

1.1 Problem Statement

The primary objective of our project is to address the challenges faced by deep learning architectures, particularly in handling problems that involve non-trivial symbolic reasoning. Specifically, we study a way to improve the ability of neural networks to adhere to hard symbolic constraints during the generation of model outputs, an issue prevalent even in domains such as image processing.

1.2 Motivation for Project

The motivation behind choosing this project stems from the observed limitations of deep learning architectures in handling tasks requiring symbolic reasoning. The inability to impose hard symbolic constraints on model outputs, even in typical deep learning applications like image processing, hinders performance and erodes public trust in AI. The paper's goal is to bridge this gap by exploring neuro-symbolic integration methods.

1.3 Summary of Approach

We attempt to replicate the findings of Cornelio et al. (2023) in their research paper Learning Where and When to Reason in Neuro-Symbolic Inference. The proposed approach, named Neural Attention for Symbolic Reasoning (NASR), combines the efficiency of a neural solver with the precision of a symbolic solver. By utilizing a dual-step process, the researchers first employ the neural solver to complete a task and subsequently delegate the symbolic solver to correct any errors. The Mask-Predictor efficiently decides which subset of neural predictions should undergo revision by the reasoning engine.

1.4 Contributions of Each Member

- **Radu G. Buzas:** Created the project presentation and worked on porting the codebase to Google Colab.
- **Andrei B. Nicula:** Fixed the installation guide and worked on porting the codebase from a Linux CUDA hardware accelerated enviroment to a Windows non-CUDA environment.

1.5 Related Research

Previous works in this domain, such as those by Xu et al. (2018), Yaqi et al. (2019), Li et al. (2019), and Wang and Pan (2020), primarily focused on neuro-symbolic learning, applying constraints in the loss function during training. However, the issue of ensuring constraints are met during inference remained under-addressed.

2 Approach

We started by watching Cristina Cornalio's presentation from NeSy 2023 as a soft introduction to the subject matter before delving in and carefully examining the chosen paper in order to understand the theoretical principles presented.
After getting a bit more comfortable with our new knowledge we went through their git repository to try and replicate their experiments. It's here where we ran into a bit of trouble. It appears that their code was developed to run in a Linux environment using an Nvidia GPU for hardware acceleration. We managed to port most of their codebase to run in a Windows environment without an Nvidia GPU by disabling Linux specific parallelization and moving the workload from the GPU to the CPU.
After implementing those fixes we appended some must needed information to their installation guide, information on how to solve the errors arising from the project's dependency's. Finally we created our own github repository with the modified project and guide.
The experiment we have analysed is the solving of visual sudoku. The first step was to generate new random datasets, unfortunately due the hardware limitations of the local machine used only the "multiple_sol" dataset was generated, the outlier giving the abnormally bad performance described in the paper. The elpased time to generate this dataset using prolog, as opposed to backtracking, was 12 minutes.
Now we are able to train and test out every individual component of the visual sudoku solver, starting with the Perception part of the Neuro-Solver to the Mask Predictor and finally the whole NASR Pipeline with or without RL.
Comparing the NASR pipeline to our baseline prolog symbolic solver we observe that on the worst dataset the pipeline withou RL falls short with an accuracy of 67.6% compared to our baseline accuracy of 69.6%. However enabling RL gives us a significant boost to performance reaching 75.6%.

Sudoku Solver	Accuracy	Test Time
NASR without RL	67.6%	16s
NASR with RL	75.6%	18s
Baseline	69.6%	51s

3 Limitations

A clear limitation is the longer inference time. Compared to other neural models, NASR is slowed down by the symbolic engine. There's no assurance that all errors will be correctly detected by the Mask-Predictor module. Additionally, due to the neural nature of the transformer, unpredictable behavior could occur. The ensemble cannot be trained with the use of back-propagation, since the symbolic solver is most like not differentiable. The use of SCD (stochastic gradient descent) may prove more efficient than the use of reinforcement learning.

4 Conclusions and Future Work

Overall I think we did a good job comprehending the research, running the described experiments and confirming the results presented in the paper.
We could've tried changing the training methods with the hope of further optimizing every part of the pipeline. In hindsight it would've been really interesting to find an original experiment that could have been solved efficiently by using the NASR pipeline but in all honesty it's hard to achieve that level of dedication and effort while juggling other projects, undergraduate thesis and maybe a part-time job.
The integration of hard constraints in neural networks is a really fascinating topic, not to mention its usefulness or importance, that we both thoroughly enjoyed studying about.

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