Project Proposal

Administrivia

Team Name: **A.K.A**

Team Members:

1. Kedar Sedai
2. Aayam Neupane
3. Akshay Rai Priyadarshi

Problem Statement

The concept of logical reasoning and machine learning combined in a way that benefits both is presented in the article. While the machine learning model can learn to perceive facts in basic logic from data, the logical reasoning model may employ symbolic domain knowledge to fix erroneously perceived facts. To address this concept, the authors suggest a brand-new technique known as abductive learning. The new framework does not require predefined rules for logical reasoning or ground-truth labels for the facts in primitive logic. Instead, it leverages logical abduction to bridge the gap between symbolic knowledge and sub-symbolic data as well as how to jointly optimize the logical reasoning and machine learning models..

The paper also emphasizes on how to integrate logical reasoning and machine learning in a way that benefits both. The idea is to let the machine learning model learn from data how to recognize facts with primitive logic, while the logical reasoning model can use symbolic domain knowledge to rectify incorrectly perceived facts and help the machine learning models perform better. Moreover, without requiring predetermined rules for logical reasoning or ground-truth labels for the facts of basic logic, how to optimize both the machine learning and logical reasoning models simultaneously.

Research Questions

1. How can we develop a framework for the abductive learning approach that integrates logical abduction and machine learning to enhance reasoning and perception tasks?
2. What are challenges and potential solutions for seamless integration of machine learning with logical learning in future AI systems?

Justification

Why NeSy AI?

Why should this problem be solved with a neuro symbolic approach? Benefits, drawbacks.

The advantages of both paradigms (machine learning and logical reasoning) may be combined with the neurosymbolic approach, machine learning can manage ambiguous and sub-symbolic data, while logical reasoning can use symbolic knowledge to accomplish deductive inference.

The neurosymbolic method can facilitate reciprocal improvement: From data, machine learning can learn to recognize facts with basic logic; logical reasoning can rectify incorrectly seen facts and offer feedback for enhancing the machine learning models.

The neurosymbolic technique can accomplish superior generalization and adaptation. While machine learning can draw conclusions from sparse data and apply them to many tasks, logical reasoning can extend to new scenarios and adjust to shifting conditions.

Some potential drawbacks of the neurosymbolic method are:

- The neurosymbolic approach may be computationally expensive: The integration and communication of logical thinking and machine learning may be difficult and expensive due to their disparate representations and optimization techniques.
- Evaluating the neurosymbolic method might be challenging: It can be challenging and subjective to compare and validate machine learning and logical reasoning as they may use various performance metrics and criteria.

Intellectual Merit

How does this project extend the state of the art?

This effort advances the state of the art by putting forth a unique framework for the mutually advantageous integration of machine learning and logical reasoning. Abductive learning is a framework that bridges the gap between sub-symbolic perception and symbolic reasoning through logical abduction and consistency optimization. The authors show that, in contrast to current neural network models, their framework can concurrently learn to recognize symbols and deduce unknown mathematical operations from pictures of handwritten equations. In order to do further tasks requiring combined perception and reasoning, the authors also demonstrate how adaptable their framework is and how it may include different symbolic AI approaches like constraint logic programming. A novel approach to attaining human-level learning capacity is investigated by this study.

Broader Impacts

Why is solving this problem broadly impactful to science and/or society?

Perception and Reasoning Integration: Abductive learning fills the gap between logical reasoning and machine learning (perception). It allows machines to execute tasks that need both perception (interpreting sub-symbolic input) and reasoning (using symbolic knowledge) by smoothly merging these two paradigms.

Human-Like Problem-Solving: Human-like problem-solving requires the capacity to combine perception and logic. Abductive learning simulates how people inadvertently combine these skills while learning new things or making decisions in the actual world.

Proposed Methodology

1. Describe the concept of the target and primitive concepts:
    - Decide which target idea you wish to understand first. This could be a task involving a particular pattern, connection, or categorization.
    - Next, deconstruct the issue into its most basic elements. These are the essential components that comprise the target notion. When interpreting handwritten equations, for instance, the fundamental notions may consist of symbols such as "+," "-," "x," and integers.
2. Provide a Domain Knowledge Base:
    - Use first-order logical clauses to build a knowledge base. The problem domain's constraints, rules, and structure are explained in these clauses.
    - The learning process is guided by the knowledge foundation. It helps limit the search space and takes into account the domain knowledge already in place.
3. Set up a Machine Learning Model from Start:
    - Select a machine learning model (decision tree, neural network, etc.) that is suitable for mapping the basic symbols to input data (pictures of handwritten equations, for example).
    - Use labeled data to train this model (where the labels match the primitive symbols).
4. Logical Abduction for Knowledge Inference:
    - Abduction is a type of reasoning in which, given observable evidence (input data) and prior information (knowledge base), we deduce the most plausible explanation (hypothesis).
    - In this instance, abduction is used to deduce a knowledge model that characterizes the idea of interest. This model integrates the domain knowledge base with the learnt perception model (from the machine learning stage).
5. Managing Inconsistencies:
    - Disparities between the knowledge base and the perception model might cause abduction to fail.
    - Use consistency optimization if there is any discrepancy. This entails changing the pseudo-labels that the machine learning model generated.

- Look for a heuristic function that can detect and fix any inaccuracies in the pseudo-labels.

6. Iterative Refinement:
    - Apply the updated pseudo-labels to retrain the machine learning model.
    - Iteratively repeat the abduction procedure until convergence or a predetermined limit is reached.
    - Both the perception model and the knowledge model are improved with each iteration.
7. Feature Transformation and Decision Model:
    - Utilizing the derived knowledge models as relational features, convert the training data into binary feature vectors.
    - Since we are working with handwritten equations, learn a decision model that can manage noise generated by subsampling.
8. Generalization and Adaptation:
    - Assess how well your abductive learning framework works with larger equations and other assignments.
    - Show that the knowledge that has been learnt can adapt to new situations and generalize beyond the training set.

Expected Results

The project on abductive learning aims to show that the suggested method can execute both fully functional first-order recursive logic reasoning and sub-symbolic machine learning at the same time. The intended outcome is to demonstrate, more precisely, that: Abductive learning framework can outperform the comparative approaches in learning the perception model and the knowledge model from the handwritten equation decipherment tasks.

Modern deep learning models cannot generalize to longer equations or adjust to diverse tasks as the abductive learning framework can since it uses the acquired perception and knowledge models.

The extended n-queens issue may be solved using the flexible abductive learning framework, which can also combine several symbolic AI approaches as constraint logic programming.

Also, in the process, we learn to use symbolic AI techniques in experiments which could help us with future developments and contributions.

References:

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