Artificial Intelligence and Autonomous Systems 096208 - Abstract Submission

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1 Field of Research

Our project aims to predict search progress utilizing Graph Neural Networks (GNNs). Following previous work, we define search progress as the fraction of the total search effort that has already been expended. More formally, given a search algorithm A and a heuristic search problem P, the search progress of algorithm A solving problem P after expanding $Gen_A(P)$ nodes with $Rem_A(P; Gen_A(P))$ remaining nodes to be expanded is defined as:

$$Prog_A(P) = \frac{Gen_A(P)}{Gen_A(P) + Rem_A(P; Gen_A(P))} \tag{1}$$

Meaning - the fraction of the total search effort that has already been expended.

We hypothesis that GNNs can learn the underlying structure of the search space, and predict search progress more accurately than previous methods.
Our intuition is that the receptive field of a search node can be used to predict search progress, as the size and qualities of these nodes might help determine whether we are in some plateau of search, closer to the goal, etc. As previous work has shown promise in predicting search progress based on features with deep learning methods such as LSTMs, we are interested in exploring the potential of GNNs in this domain.

2 Literature Review

3 Work Domain

Our project will be practical, focusing on creating aduquate datasets and training GNNs to predict search progress. We aim to create our own simple dataset of Blocksworld problems in STRIPS Fikes and Nilsson [1971], and use the A* search algorithm with different heuristics to solve them. We will then train a GNN to predict search progress based on the search nodes expanded by the A* algorithm.

4 Work Outline

The following is a rough outline of our project:

Algorithm 1 Sampling Blocksworld Instance

Input: Number of blocks n

Output: Blocksworld instance

1: Initialize n blocks
2: Sample two permutations $p_1 = (i_1, i_2, \ldots, i_n)$ and $p_2 = (j_1, j_2, \ldots, j_n)$ of $1, 2, \ldots, n$.
3: Sample two binary vectors $b_1, b_2 \in \{0, 1\}^n$.
4: In the initial configuration, place block i_1 on the table. For every $k = 2, 3, \ldots, n$, place block i_k on block i_{k-1} if $b_1[k] = 1$, otherwise place it on the table.
5: In the goal configuration, place block j_1 on the table. For every $k = 2, 3, \ldots, n$, place block j_k on block j_{k-1} if $b_2[k] = 1$, otherwise place it on the table.

1. Create a dataset of Blocksworld problems. An instance of the Blocksworld problem consists of a set of blocks, initial and goal configurations of the blocks. The goal is to move the blocks from the initial configuration to the goal configuration using legal moves. We hope that by sampling initial and goal configurations randomly uniformly, we will get a diverse set of problems that will be challenging for the search algorithm. We refer the reader to Algorithm 1 for a method to efficiently sample Blocksworld instances.

2. Implement the A* search algorithm with different heuristics to solve the Blocksworld problems. Possible options considered at this stage are the h_{max}, h_{add}, and h_n heuristics, where h_n is the number of blocks that are not in their correct position.

3. Running the A* algorithm on the Blocksworld problems, we will collect the labeled data for our GNN - for each node we expand, we will record the search progress.

4. Train a GNN to predict search progress based on the search nodes expanded by the A* algorithm. We will use the PyTorch Geometric library to implement the GNN.

5 Research Goals

Reasonable Results We expect that the GNN will be able to predict search progress more accurately than previous methods. We hope for improved or comparable results to the previous methods mentioned on Sudry and Karpas [2022]. Maybe we will implement the previous methods and compare them to our GNN, but this is not guaranteed.

Interpretability We hope that the GNN will be able to learn the underlying structure of the search space and provide insights into the search progress. We will analyze the GNN's predictions and try to understand what it has learned.

Generalization We hope that the GNN will be able to generalize to new Blocksworld problems that it has not seen before, with a varying number of blocks. Within time constraints, we find it reasonable to limit the scope of our project to Blocksworld problems and A* search.

References

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