Artificial Intelligence and Autonomous Systems 096208 - Abstract Submission

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1 Field of Research

In this project, we aim to predict search progress utilizing Graph Neural Networks (GNNs). Predicting search progress is a challenging problem in the field of heuristic search, as it requires understanding the underlying structure of the search space. It is also a useful tool for temporal planning and scheduling, as it can help estimate the time required to solve a problem.

Previous work including learning in planning problems primarily consisted of heuristic estimations and focus on the speed of the search. Recently, a study by Sudry and Karpas [2022] showed that deep learning methods such as LSTMs can predict search progress, based on extracted features from the search nodes induced by the guided search algorithm.

This work expanded the field of progress estimation techniques, which traditionally relied on exact functions in the search space, such as heuristic values and expanded nodes Thayer et al. [2012]. It showed deep learning methods can surpass earlier baselines and generalize to new problems, based on the obseravtion that heuristic searches, especially with common search algorithms, domains or heuristics, behave similarly.

In our work, we plan to take this a step further and explore the potential of GNNs in predicting search progress. We hypothesize that GNNs can learn the underlying structure of the search space and predict search progress more accurately than previous methods.

2 Literature Review

Traditionally, there are two main approaches to predict search progress: offline and online methods. Offline methods are based on the analysis of the search space **??**, while online methods are based on the search nodes expanded by the search algorithm **??**. Recently, a study by Sudry and Karpas [2022] showed that deep learning methods such as LSTMs can predict search progress based on extracted features from the search nodes induced by the guided search algorithm.

Learning in search has been studied in the past, with a focus on modeling the environment and the actions of the agent **??**. As search algorithms induce a graph of search nodes, it is natural to consider the use of GNNs in this domain. GNNs have been shown to be effective in learning the structure of graphs and predicting properties of nodes in the graph **??**. We believe that GNNs can be used to predict search progress based on the search nodes expanded by the search algorithm.

3 Work Domain

Our project will be practical, focusing on creating adequate datasets and training GNNs to predict search progress.

We will opt to find a small enough domain for our project to be feasible, yet complex enough to be learnable by the GNN. Our work will be based upon either an existing dataset of planning problems or a dataset we will create ourselves. We will then use the A* search algorithm with different heuristics to solve these problems and collect labeled data for the progress prediction task. This specialized data, accessible in Python for deep learning frameworks, is our project's first contribution.

We will then train a GNN to predict the search progress of a node in the search graph, based on the sequence of nodes expanded by the A* algorithm - the *search history*. We will use the PyTorch Geometric library to implement the GNN.

4 Work Outline

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

Matan Sudry and Erez Karpas. Learning to estimate search progress using sequence of states. In *Proceedings of the International Conference on Automated Planning and Scheduling*, volume 32, pages 362–370, 2022.

Jordan Thayer, Roni Stern, and Levi Lelis. Are we there yet?—estimating search progress. In *Proceedings of the International Symposium on Combinatorial Search*, volume 3, pages 129–136, 2012.