Motion Planning Transformers: Finding Search Regions in 2D Mazes

Ish Mehta
Georgia Tech
Atlanta, GA
imehta34@gatech.edu

Toluwanimi Delano
Georgia Tech
Atlanta, GA
tdelano3@gatech.edu

Aaditya Anugu
Georgia Tech
Atlanta, GA
aanugu3@gatech.edu

Karthik Ramamoorthy
Georgia Tech
Atlanta, GA
kramamoorthy8@gatech.edu

Team Name: **Dream Deep Learning Team**

1. Introduction

Recent strides being made in autonomous robotics has led to researchers putting more emphasis on fast and efficient motion planning algorithms. A popular choice for these are sampling-based motion planning algorithms (SMP) [9]. Such algorithms aim to construct a path by generating trees or graphs by randomly sampling points from start location to goal location, with one of the most popular algorithms being Rapidly Exploring Random Trees (RRT) [6]. While these work quite well, there is a major issue with them. They do not scale well in terms of computation with increasing environment sizes. Previous efforts have been made to restrict the search space for generating the shortest path [1], but these methods are based on robot kinematics which make them hard to generalize. There are other efforts based on convolution neural networks and multi layer perceptrons however these are heavily dependent on environment sizes. Thus, we need an algorithm that can scale with the map size, while still maintaining reasonable computation times. Over the last few years, we have seen applications of transformer based models [10] in natural language processing are able to scale efficiently and deal with high dimensional data simultaneously. Thus, in this project we will try to re-implement the Motion Planning Transformer (MPT) [3]- a transformer based model to help reduce search space in 2-dimensional environments for SMP algorithm.

2. Approach

We will be implementing a methodology that restricts the search space of the RRT algorithm on two different datasets, one of which being a maze, and the other a space densely packed with random objects of varying shapes. The architecture will be heavily inspired by the MPT paper [3]. In this paper the authors first use a Convolutional Neural Net to extract features of the map, and then use a transformer to encode the features to a latent space. We then use a pixel-wise classifier which produces a probabilistic regions which creates a sub-space in the map where the RRT algorithm can then operate. To generate the ground truth paths, we take a similar approach to [3] where we will use open source code for a random path finding algorithm such as RRT on all our maps. There will be many different evaluation metrics to determine how well our experiment performed. The first one will be to see the overlap between the ground truth restricted region and the predicted restricted region, on a validation set. Another metric would be the reduction in time for the RRT algorithm to complete.

3. Related Works

There are prior papers that have gone about making motion planning algorithms for robots more efficient. One such approach is using dynamic planning networks (DynamicMPNet) [4] where the authors discuss simulating a Dubins car in order to surpass the performance of pre existing models for accuracy. In [7] the authors explore the idea of making improvements to ROS Navigation by using using Behavior Trees, STVL(spatio-temporal voxel layer), TEB(timed elastic band) controller, DWA(dynamic window approach), and multi-sensor fusion network to improve robot navigation. These changes that were implemented in Navigation2 allowed for more versatile and accurate robot navigation, and this system has even already been tested extensively. In [5], Leveraging Experience with Graph Oracles(LEGO) is an algorithm that uses Conditional Variational Auto-encoder(CVAE) to predict roadmaps for paths and can find the bottlenecks in paths to create more efficient path finding. LEGO's technique of considering specific problems like navigating through small or awkwardly shaped regions with the use of roadmaps is a significant improvement to path finding algorithms. However, the main problem with these approaches is they assume a fixed size input environment map and often require redefining network architectures and retraining for different map sizes.

4. Datasets

For this project, we will working with 2 datasets. Our first dataset will be generated using the *maze-dataset* [2] package. This package was primarily built for the maze-transformer interpretability project and includes a variety of maze generation algorithms, including randomized depth first search, Wilson's algorithm for uniform spanning trees, and percolation. Our second dataset which we might use is from a MathWorks example notebook [8] which consists of 400,000 different paths in 200 maze map environments.

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