

Clearance for Manipulators

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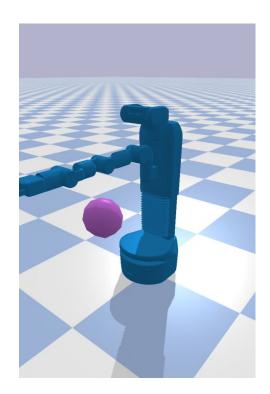
Problem Description

- Motion planning requires efficient distance computations to ensure safe navigation and collision avoidance
- Traditional planners like RRT* struggle with computational efficiency, especially for robots with many degrees of freedom (e.g., 8-DOF Fetch robot).
- Clearance calculations are slow, impacting real-time planning.



Objective

Leveraging learning-based methods to optimize distance calculations for asymptotically optimal planners like RRT*.



Dataset Collection

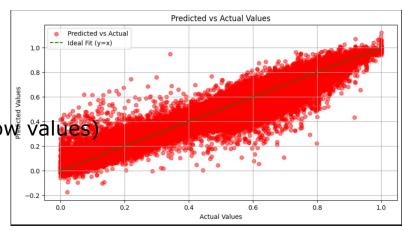
- Each sample includes 8 robot joint states and 6/12 obstacle parameters, with ground truth min distances calculated using PyBullet.
- Collected more than 15 million samples using multiple WPI Turing Machines.



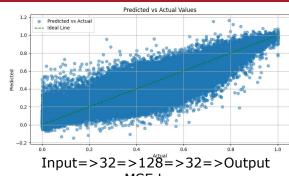
Neural Network Architecture (1 Obstacle)

- Input: 8 Joint Values + 6 Obstacle Parameters
- Hidden Layers: 2 layers with 1400 neurons each, followed by ReLU activation and 1% Dropout
- Output: Single neuron to estimate minimum distance
- Dataset Size: 5 Million
- Loss Function: Weighted MSE Loss

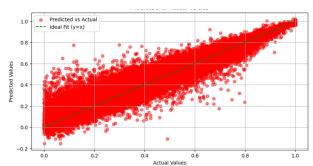
 (Penalises more on wrong predictions for low values
- Learning Rate: 1.7495e-04
- Test samples with relative error:
 - **•** > 0.1 12.94%
 - > 0.2 5.32%



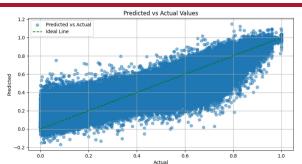
Other Tested Model Architectures



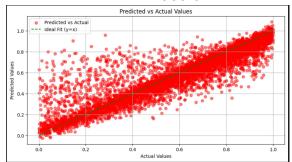
Input=>32=>128=>32=>Output MSE Loss LR: 3e-03



Input=>64=>128=>512=>128=>64=> Output MSE Loss LR: 6e-05



Input=>16=>64=>16=>Output
Weighted MSE Loss
LR: 1.7495e-04

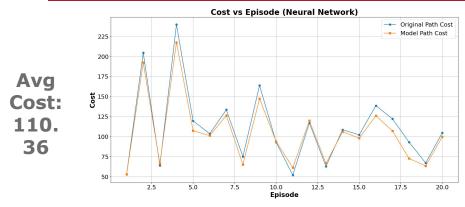


Input=>64=>64=>Output MSE Loss

LR: 2e-04

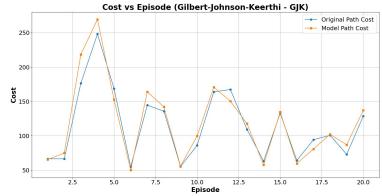
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Results - RRT* with 1 obstacle

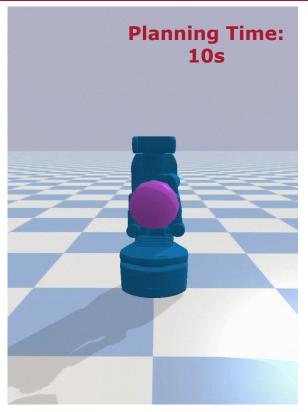


Number of States in Tree using NN: 202

Avg Cost: 114. 98



Number of States in Tree using GJK: 160



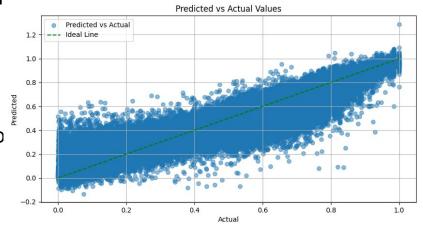
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Neural Network Architecture (2 Obstacles)

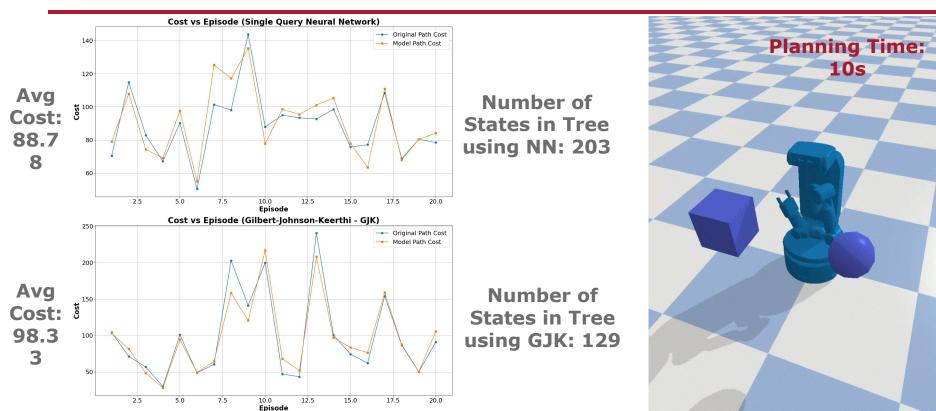
- Input: 8 Joint Values + 12 Obstacle Parameters
- Hidden Layers: 2 layers with 1400 neurons each, followed by ReLU activation and 1% Dropout
- Output: Single neuron to estimate minimum distance
- Dataset Size: 10 Million
- Loss Function: Weighted MSE Loss
 (Penalises more on wrong predictions for lo
- Learning Rate: 1.7495e-04



- **•** > 0.1 16.88%
- **•** > 0.2 10.78%



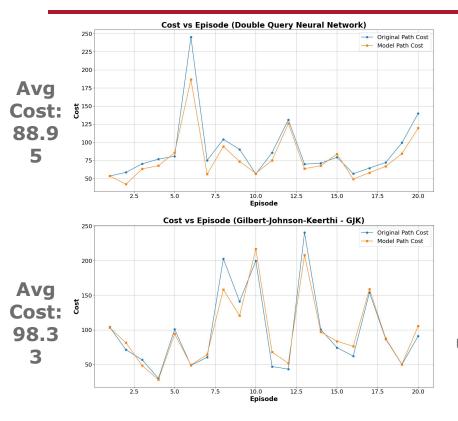
Results - RRT* with 2 obstacles - Single Call



*Limitation: Our model struggles to predict small values correctly

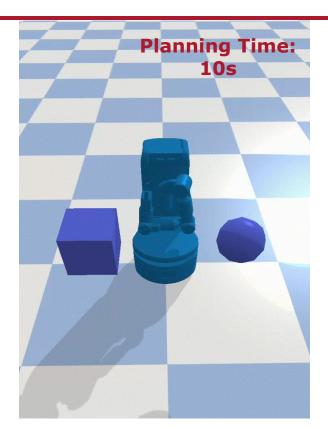
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Results - RRT* with 2 obstacles - Multi Call



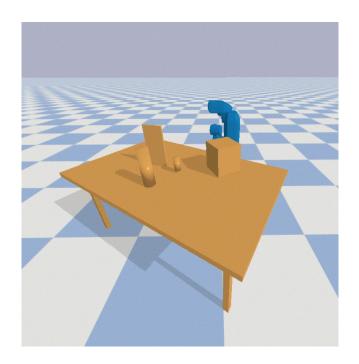
Number of States in Tree using NN: 153

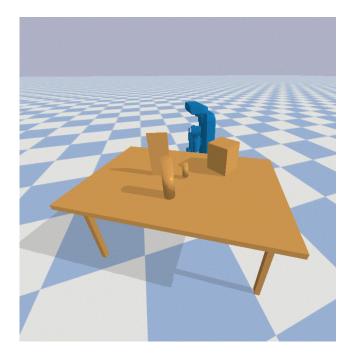
Number of States in Tree using GJK: 129



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Table Scene





Acknowledgement

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References

- [1] N. Das, N. Gupta, and M. Yip, "Fastron: An online learning-based model and active learning strategy for proxy collision detection," 2017. [Online]. Available: https://arxiv.org/abs/1709.02316
- [2] J. C. Kew, B. Ichter, M. Bandari, T.-W. E. Lee, and A. Faust, "Neural collision clearance estimator for batched motion planning," 2020. [Online]. Available: https://arxiv.org/abs/1910.05917
- [3] Elpis Lab, "Grapeshot Motion Planning Framework," https://github.com/elpis-lab/grapeshot/tree/master, 2024, accessed: Nov. 04, 2024.
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Thank You!

