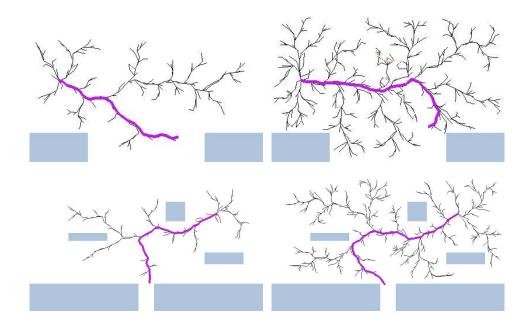
# Learning Based Sampling For RRT\* Algorithm



EECS 545 - Final Project Li Chen, Yue Du, Yeyang Fang, Daiyao Yi, Xuran Zhao

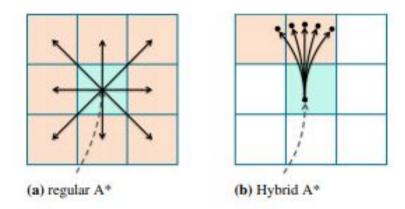
#### Introduction

- Traditional RRT\* path planning includes uniform sample in the planning space. This results in long converge time.
- We proposed a learning based sampling method for RRT\* planning to get a faster planning performance.



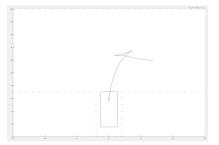
#### Data generation

We used hybrid A\* to generate the training data. It can generate a smooth path in a given 2-D space for vehicles.

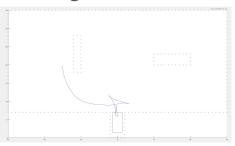


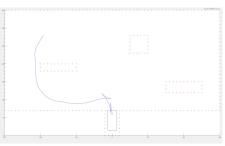
#### Data generation

We considered four scenarios to generate the training dataset of the network.





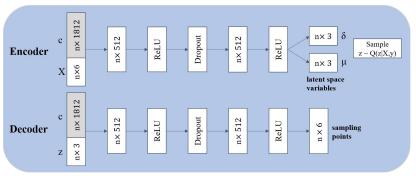




| No. | Obstacle? | Dimension | Scenario         | Trajectory Generated | Data Generated |
|-----|-----------|-----------|------------------|----------------------|----------------|
| 1   | No        | 20m x 30m | Reverse Parking  | 154                  | 2310           |
| 2   | No        | 13m x 30m | Parallel Parking | 138                  | 2055           |
| 3   | Yes       | 35m x 60m | Reverse Parking  | 1001                 | 15015          |
| 4   | Yes       | 35m x 60m | Reverse Parking  | 507                  | 7605           |

#### Conditional Variational Autoencoder (CVAE)

- Contains encoder Q(z|X,c) and decoder P(X,z|c)
  - o z latent space variables
  - $\circ$  X sampling points (  $X = \begin{bmatrix} x & y & \theta & \dot{x} & \dot{y} & \dot{\theta} \end{bmatrix}$  )
  - o c conditions, in our case maps and initial/end points



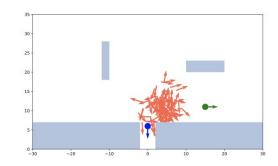
• Maximizing:

$$||x - f(z, y)||^2 - D_{KL}(\mathcal{N}(\mu(x, y), \Sigma(x, y)) || \mathcal{N}(0, I))$$

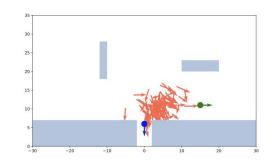
Loss Function:  $L = L_{recon} + \omega L_{KL}$  ( $\omega$  - weighting parameter)

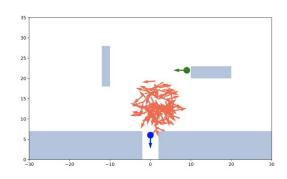
#### Sampling Learning - Orientation Improvements

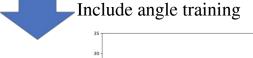
$$X = \begin{bmatrix} x & y & \theta & 0 & 0 & 0 \end{bmatrix}$$

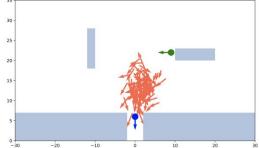


$$X = \begin{bmatrix} x & y & 0 & cos(\theta) & sin(\theta) & 0 \end{bmatrix}$$

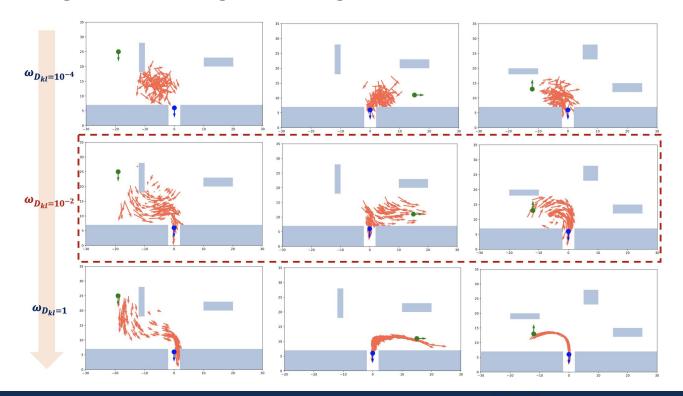




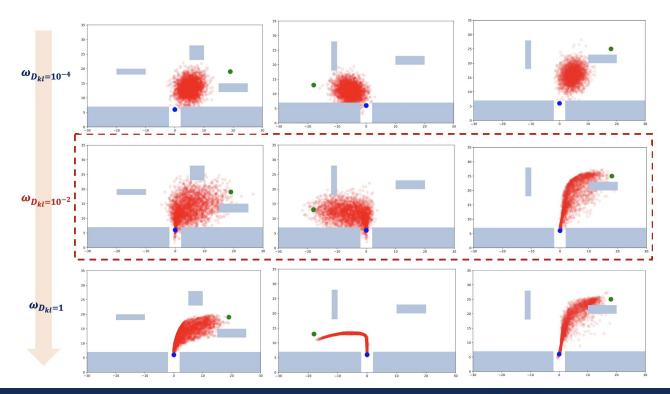




## Sampling Learning - Weighted Loss



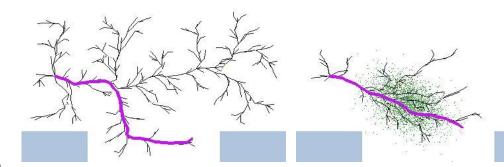
#### Sampling Learning - Weighted Loss

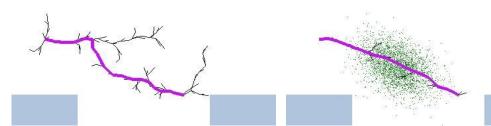


## Simple map

#### CVAE

• Average forward time: 0.0127s



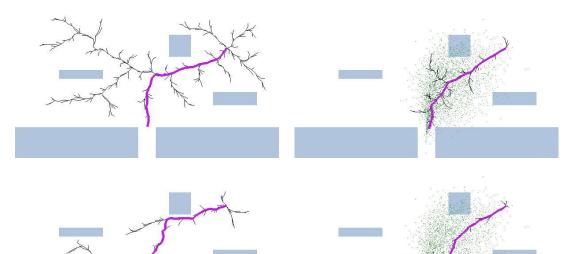


|            | # nodes    | # nodes   |          | elapsed(s) |           | path_len (x0.1m) |  |
|------------|------------|-----------|----------|------------|-----------|------------------|--|
|            | random     | learnt    | random   | learnt     | random    | learnt           |  |
| RRT*       | 251.5629   | 244.4267  | 3.6873   | 3.5150     | 265.2073  | 221.5089         |  |
|            | (119.9123) | (90.5567) | (3.8788) | (2.5824)   | (28.8045) | (10.4951)        |  |
| biRRT* (o) | 93.03      | 48.57     | 0.2290   | 0.0819     | 257.7198  | 228.9368         |  |
|            | (23.6036)  | (5.2093)  | (0.1084) | (0.01397)  | (20.3302) | (6.8773)         |  |

## Complex map

#### • CVAE

• Average forward time: 0.0127s



|            | # nodes    | # nodes   |           | elapsed(s) |           | path_len (x0.1m) |  |
|------------|------------|-----------|-----------|------------|-----------|------------------|--|
|            | random     | learnt    | random    | learnt     | random    | learnt           |  |
| RRT*       | 492.23     | 135.2     | 28.0249   | 2.4032     | 317.2249  | 260.7166         |  |
|            | (137.0647) | (28.8119) | (16.4521) | (0.9523)   | (37.1870) | (9.1753)         |  |
| biRRT* (σ) | 156.32     | 70.56     | 1.7625    | 0.5296     | 340.8630  | 280.5843         |  |
|            | (45.5480)  | (11.7760) | (0.9827)  | (0.1635)   | (55.2340) | (11.2468)        |  |

## Thank you! Q&A



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