The report for Challenge 3

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1 Exercise one: Evaluate a Rule-based Agent

1.1 video submission

All videos for exercise 1 can be found at:

https://drive.google.com/drive/folders/1hmy64HHtFuYDw6TSVIYygMToBfybegJl?usp=sharing

1.2 result evaluation

Evaluation Metric	Value
collision rate	0.28
out of road length	0.0
distance _to_route	0.06
incomplete route	0.27
running time	0.79
final score	0.278

Table1: final evaluate results for PID method

```
policy_type: 'basic'
model_path: ''
model_id: 0
results_folder_path: ''
obs_type: 0

target_speed: 30

# parameters for PID
dt: 0.1 # 0.25
lateral_KP: 6 # 2
lateral_KI: 0.00144
lateral_KD: 3 # 1.40625
longitudinal_KP: 0.099 # 0.09
longitudinal_KI: 0.001 # 0.00144
longitudinal_KD: 1 # 1.40625
max_steering: 2.0
max_throttle: 2.0

train_episode: 2000
eval_in_train_freq: 1
save_freq: 10
buffer_capacity: 10000
buffer_start_training: 100
```

Figure 1: Basic agent configuration settings

2 Exercise two: Train a SAC Agent in Ordinary Scenarios

2.1 plot the episode reward during training

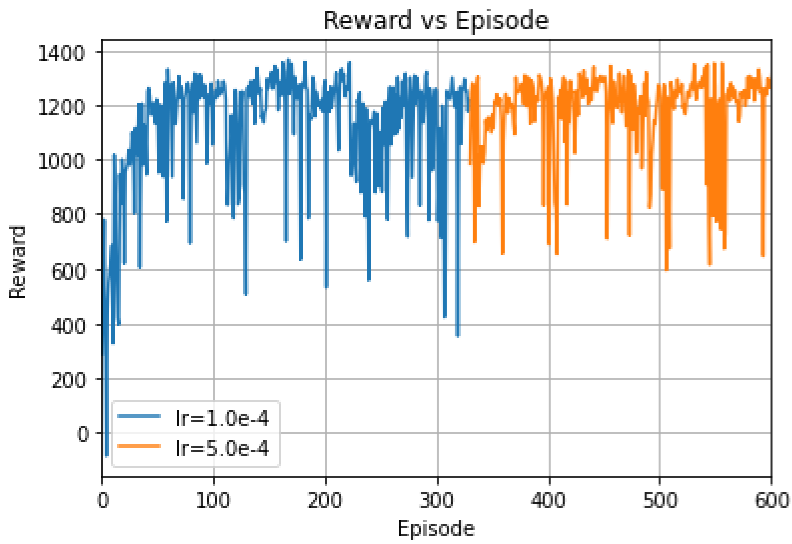

Figure2: Episode reward figure for SAC agent training. 600 episodes in total

3 Exercise three: Evaluate the Trained Agent

3.1 video submission

All videos for exercise 3 can be found at:
https://drive.google.com/drive/folders/1hmy64HHtFuYDw6TSVIYygMToBfybegJl?usp=sharing

3.2 evaluation table

Evaluation Metric	**Value**
collision rate	0.12
out of road length	0.51
distance _to_route	0.17
incomplete route	0.07
running time	0.59

final score	0.196

Table2: final evaluate results for Trained Agent in Safety-critical Scenarios

3.3 results comparison

Histogram:

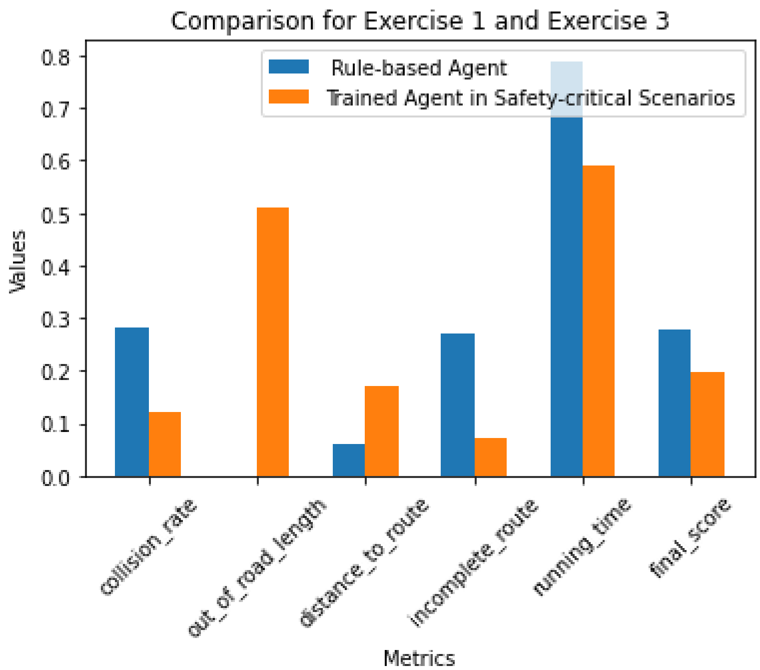

Figure 3: PID and SAC agent metric comparison

Discussion:

The tuning of the PID agent for exercise 1 turned out to be quite difficult. We used trial-and-error for the most part to try and get the best performance from this agent. The most difficult tasks ended up being ones that involved turning at the intersection, where in some of the scenarios the car would simply stop moving or slow down to a very low speed, causing it to not finish the route. It also had trouble avoiding obstacles at high speeds, something which the sac trained model was able to do much better. We tested very large values for both longitudinal and lateral PID, and scaled them down to a more reasonable behavior.

The sac model training got up to the required 1200 reward in less than 100 episodes using the default parameters. We modified the learning rate from 5e-4 to 1e-4 after ~320 episodes in order to do some fine-tuning since the reward was already fairly high. In the end, we tested the sac agent after 601 episodes, but its performance wasn't good (the final_score for this agent was ~0.450). We decided to test the agent at other points in its training and found that the best performing one was at 299 episodes. This sac agent was able to perform the right and left turns that the PID model got stuck at, while also being able to avoid obstacles by turning to the right (this isn't ideal for scenarios 4-7 since it meant the car was driving on the curb instead of the road). Even though the sac agent wasn't trained on safety-critical scenarios, it was able to outperform our PID agent on these tasks. However, the sac agent did show some bad driving, it seemed to have a preference for driving on the middle of the road, or between lanes.

From figure 3, we can see that the SAC model was able to avoid collisions much better than the PID agent, but it also spent longer driving out of the road, when it drove on the curb to avoid a leading car). It also had a higher distance to route because of its driving outside of its intended lane.