Learning-Enabled Autonomous Driving via AWS DeepRacer

TEXAS STATE UNIVERSITY

REU Site: Research Experiences for Undergraduates in Edge Computing (REUEC)

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What is AWS DeepRacer?

AWS DeepRacer is a 1/18th scale full-autonomous racing car which utilizes reinforcement learning models to learn driving habits. The car uses cameras in order to view the physical track and a reinforcement model to control throttle and steering. The performance of this device can also be tested within simulation.

Figure 1. AWS DeepRacer Physical Car

Training a Model

AWS DeepRacer uses a variety of software to train, evaluate, and deploy reinforcement learning models for both simulation and real life application.

Models are highly configurable based on a variety of categories such as:

- Hyperparameters
- Tracks
- Reward Function
- Training Time
- Race Type
- Action Space
- Training Algorithm

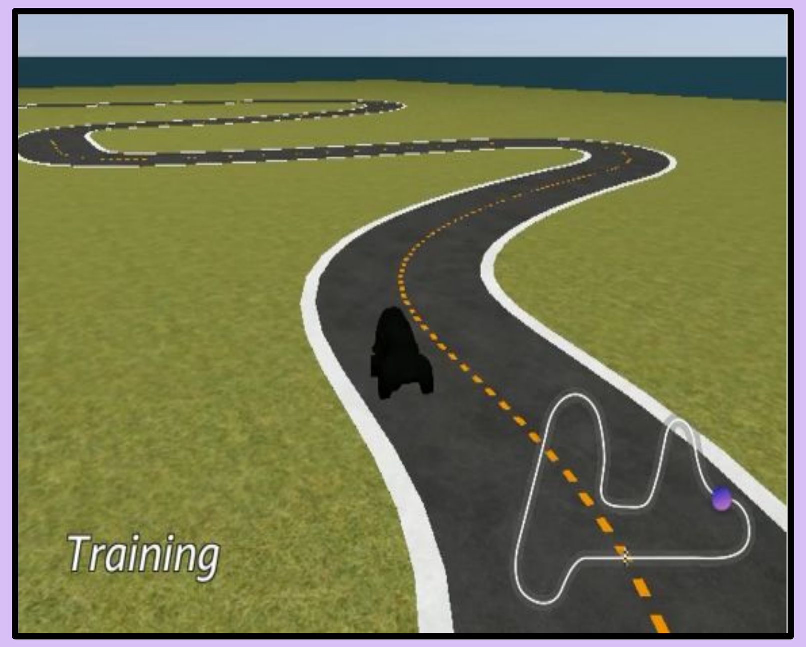


Figure 2. Training a Model in Simulation using Robomaker

Simulation Experiment

Objective - Investigate the training behavior to design a multipurpose model capable of performing well any track or environment.

Procedure - Three Models were trained and evaluated to compare their performances based on the amount of tracks and training order.

Model S1: Trained to perform on a single track
Model S2: Trained with a dataset of 10 different tracks in sequential order
Model S3: Trained with a dataset of 10 different tracks in a randomized order to eliminate biases within training

Results -

- All three models showed similar evaluation results
- The randomized approach, Model S3, slightly improved performance when training with multiple tracks
- The pre-trained Model S3, was able to perform well on tracks not present in the original training dataset.
- This experiment successfully demonstrated a model that was able to perform well in a variety of different circumstances

Training Approaches Compared

	Average Time	Average Reward
Single Track Model	57.7s	702
Sequential Model	63.4s	581
Randomized Model	62.4s	624

Figure 3. Training Approaches Compared

Single Model Approach vs. Multi-Track Approach on an Unknown Track

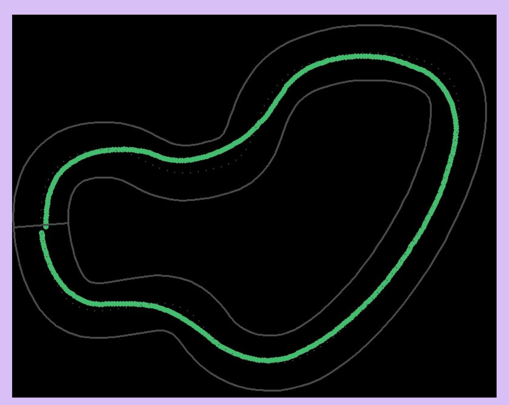


Figure 4. Single Track Evaluation

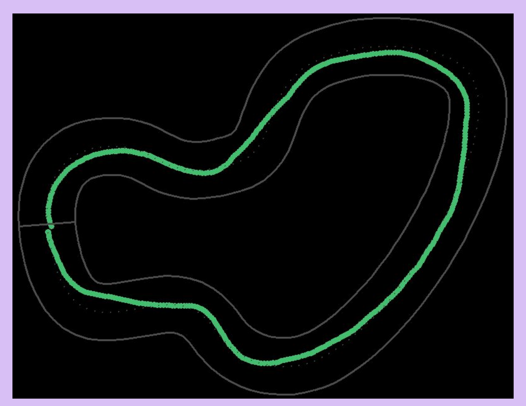


Figure 5. Multi-Track Evaluation

Evaluation on an Unknown Track

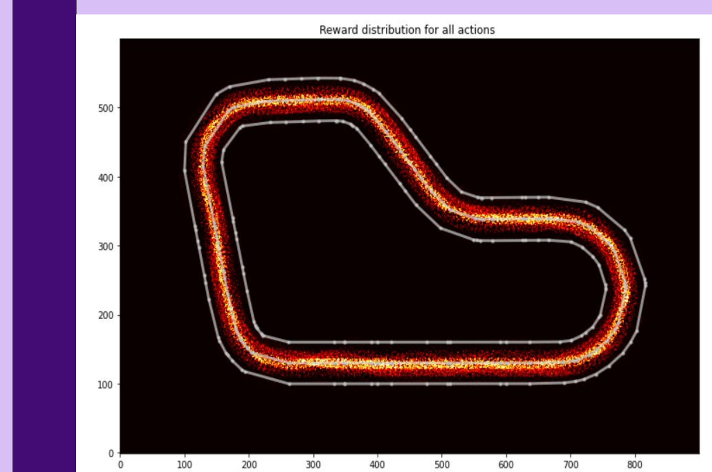
	Average Time	Average Reward
Single Track Model	26.9s	328
Randomized Model	27.2s	312

Figure 6. Evaluation on the 2019 Championship Track (Unknown to the Model)

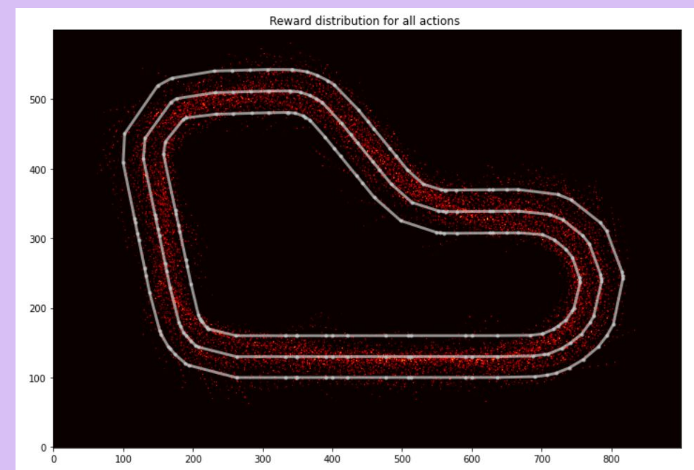
Specialized Models

Model P1: Heavily incentivized to stay within the two borders
Model P2: Identifies waypoints and then implements *Pure Pursuit* algorithm to figure out curvature needed to move car from current waypoint to goal waypoint.
Model P3: Model uses geometry to guide car to the intersection of a generated circle and direction of front wheels.

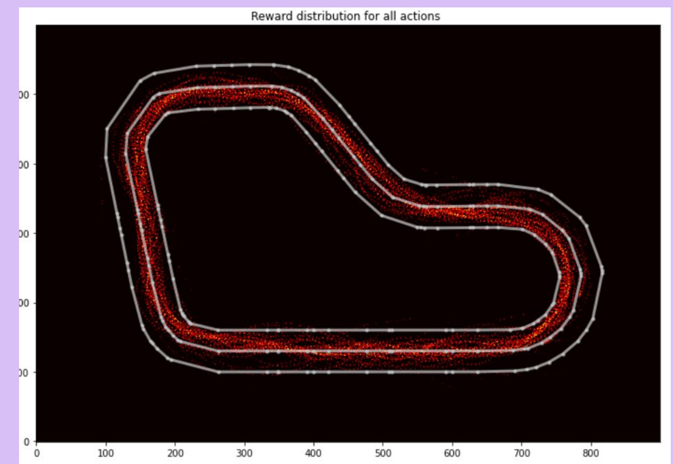
Heatmaps



Model P1



Model P2



Model P3

Physical Environment

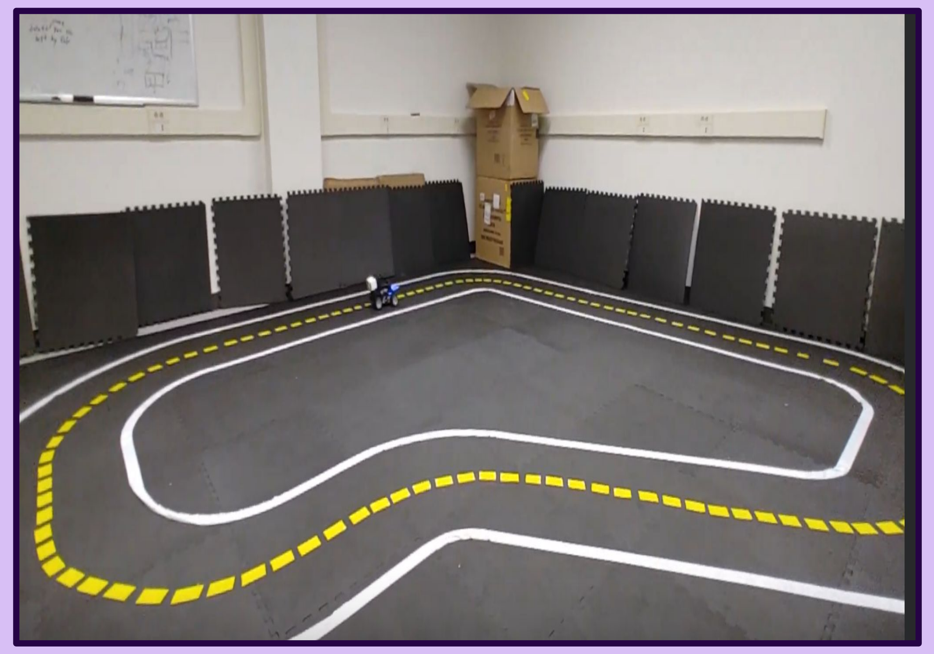


Figure 7. Physical Track at Texas State University, based on Re:Invent 2018

Conclusion

- Set up Local Simulation at TXST
- Constructed Specialized Models
- Built a custom physical environment at TXST.
- Bridged the Sim2Real gap