MaxQ

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AWS DeepRacer

AWS DeepRacer is an autonomous 1/18th scale race car designed to test RL models by racing on a physical track. Using **cameras to view the track** and a reinforcement model to control throttle and steering, the car shows how a model trained in a simulated environment can be transferred to the real-world.

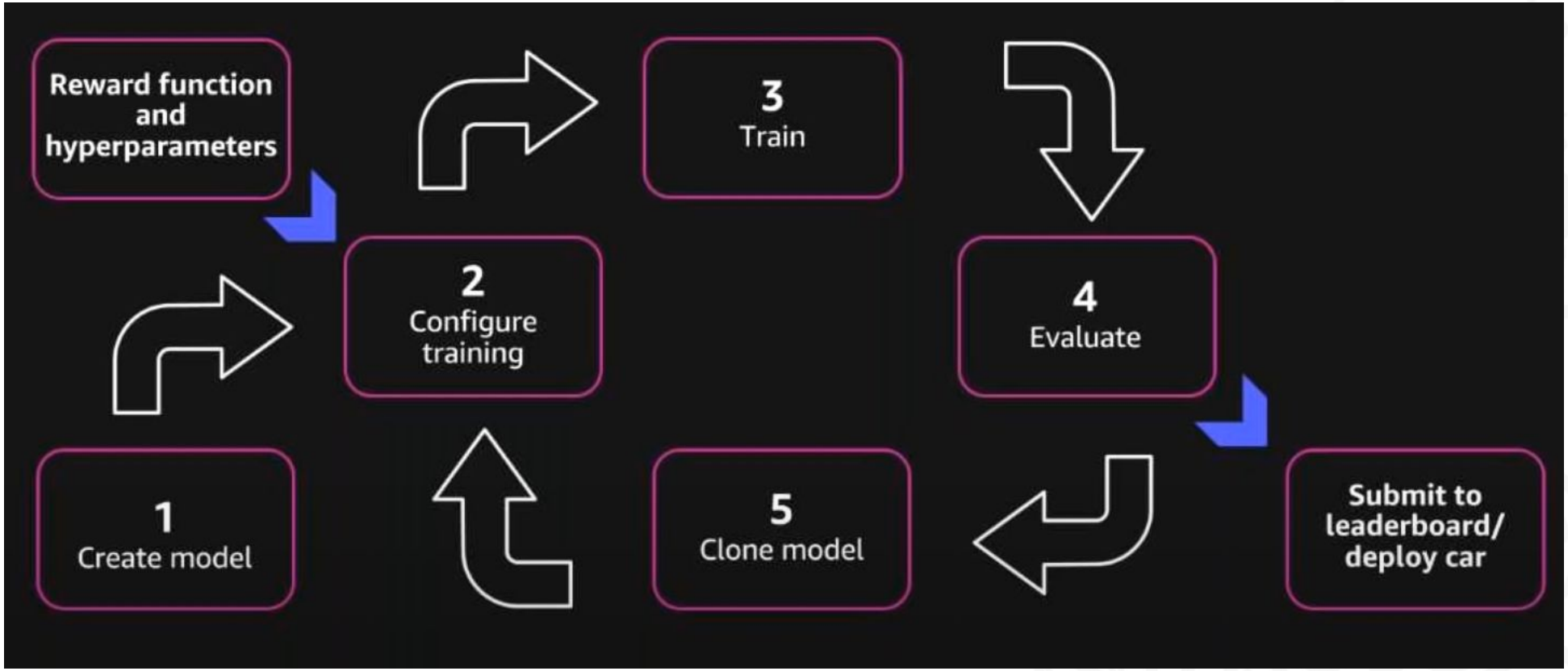
State space: The image fed through the camera mounted the vehicle's front

Action space: Discrete vs. continuous

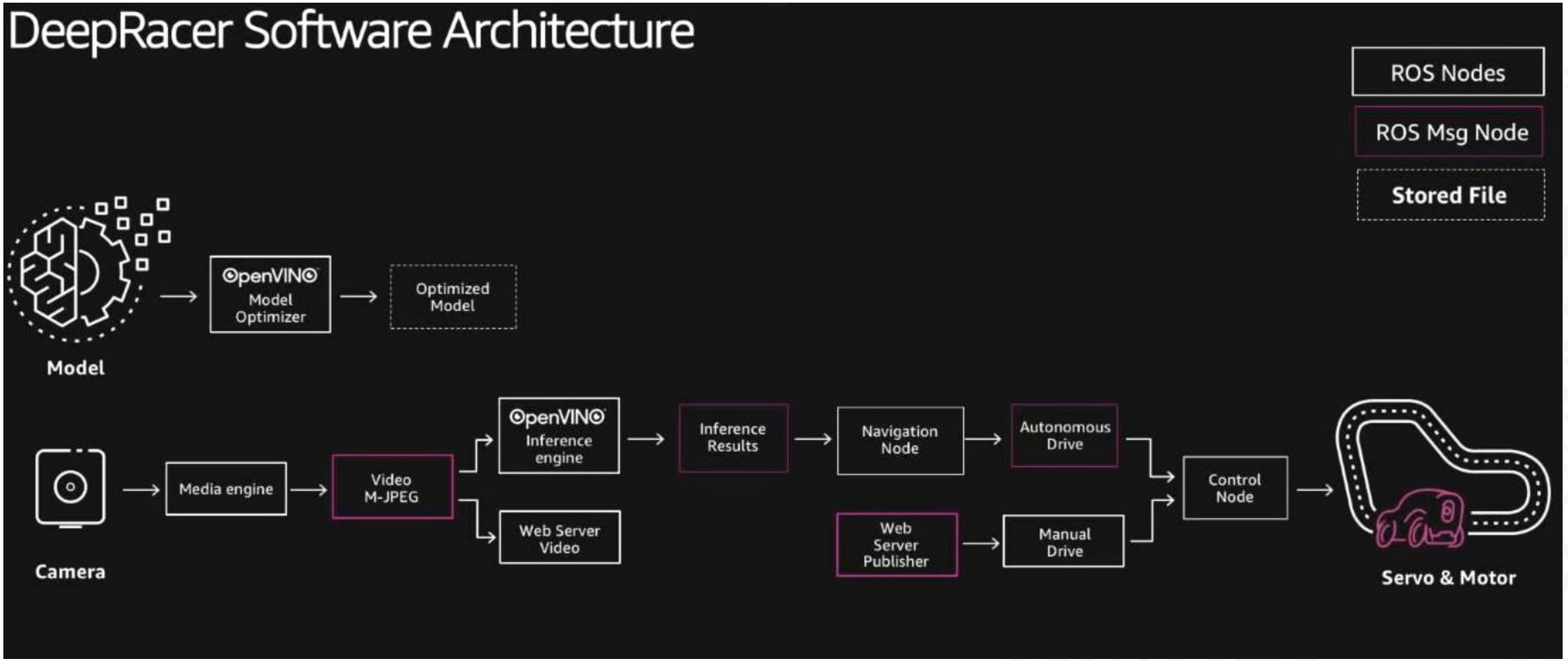
Reward function: Custom rewards given based on type of action

Input params considered:

all_wheels_on_track	*-flag to indicate if the agent is on the track*
track_width	*-width of the track*
distance_from_center	*-distance in meters from the track center*
waypoints	*-list of (x,y) as milestones along the track center*
closest_waypoints	*-indices of the two nearest waypoints.*
heading	*-agent's yaw in degrees*
speed	*-agent's speed in meters per second (m/s)*



https://www.youtube.com/watch?v=X_Jm8bMklHc&ab_channel=AWSOnlineTechTalks



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Pre-Contest optimal model

No change in hyperparameters

Speed: min:0.5 & **max:** 1 m/s

Action space: Continuous

Trained on: re: Invent 2018

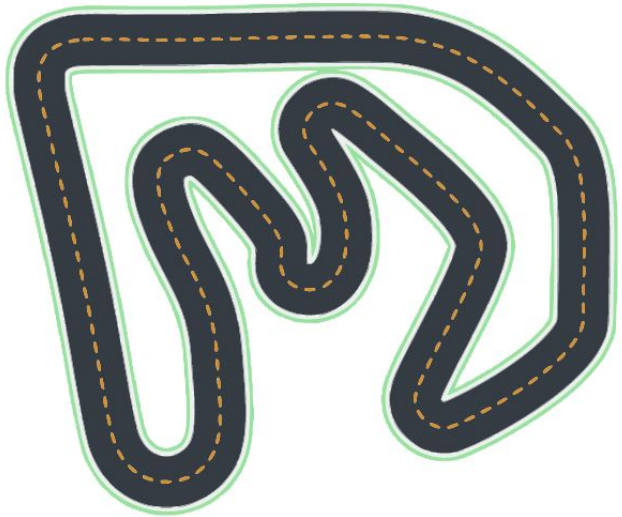
Training hours: 5 hours

Reward formulation:

Performance on complex tracks

Vivalas Speedway

Inspired by a historic Las Vegas track of yesteryear, the Vivalas Speedway is the second longest, and most difficult track to be released in 2021. 5 consecutive opposing hairpins are framed in by the Vivalas Loop perimeter; a modified oval full of high speed straightaways primed for passing and all out speed. Which racers will go all in and gamble it all for the jackpot?



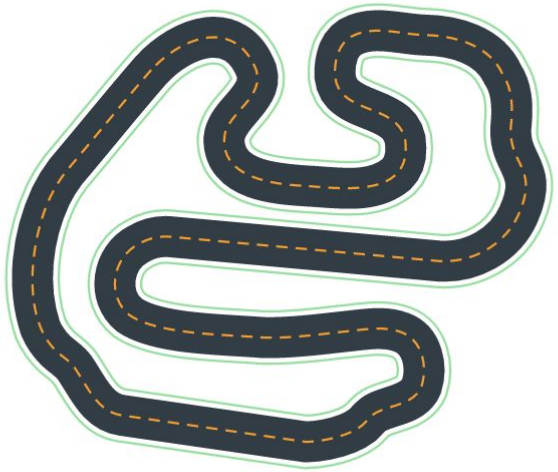
Evaluation results

Trial	Time (MM:SS.mmm)	Trial results (% track completed)	Status
1	01:30.662	100%	Lap complete
2	01:30.865	100%	Lap complete
3	01:08.934	76%	Off track
4	01:29.466	100%	Lap complete
5	01:02.465	69%	Off track

Performance on complex tracks

Rogue Raceway

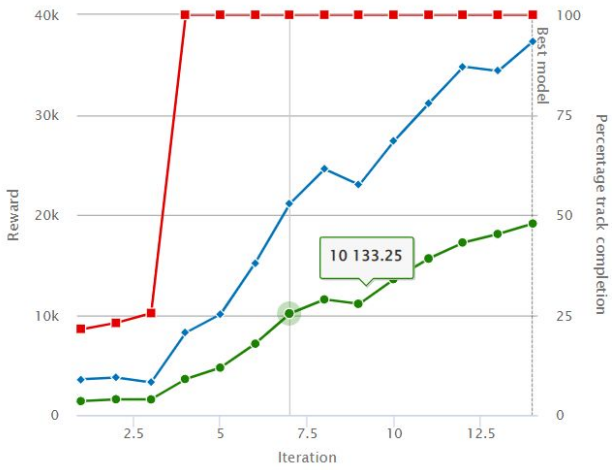
Named in honor of the 2021 DeepRacer Championship Cup winner, Sairam Naragoni, the Rogue Raceway boasts a variety of sweeping turns and drag strips for a worthy training challenge.

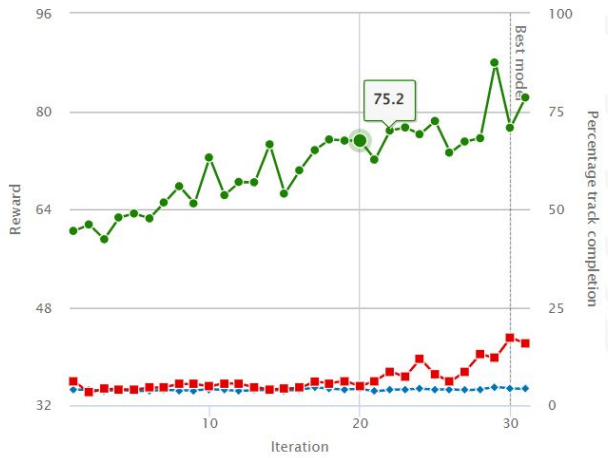


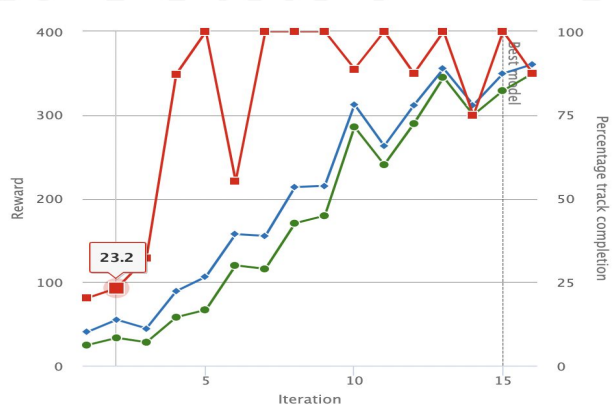
Trial	Time (MM:SS.mmm)	Trial results (% track completed)	Status
1	01:38.724	100%	Lap complete
2	01:40.396	100%	Lap complete
3	01:38.534	100%	Lap complete
4	01:39.203	100%	Lap complete
5	01:40.591	100%	Lap complete

Experimented models:

	Action space	Speed	Training hours	Major changes
Model 1:	Continuous	[0.5 : 1.5]	3 hours	# Decreased throttle while steering
Model 2:	Discrete[22 actions]	[0.5 : 3]	1 hour	# Reward for **progress** parameter
Model 3:	Continuous	[0.5 : 1]	4 hours	#Speed Incentive & Straightness

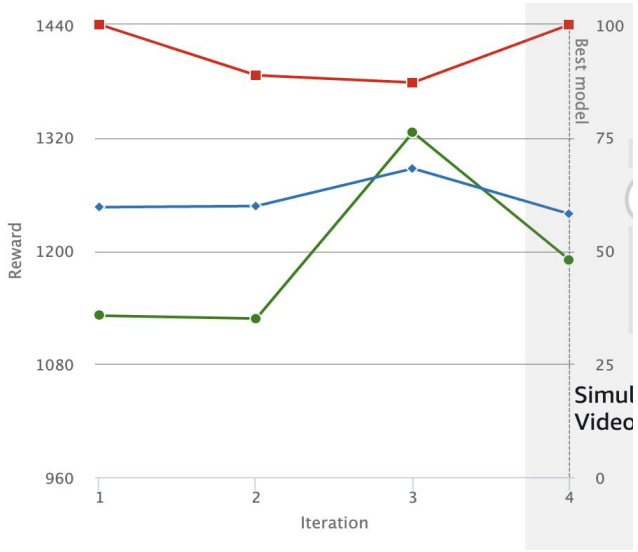


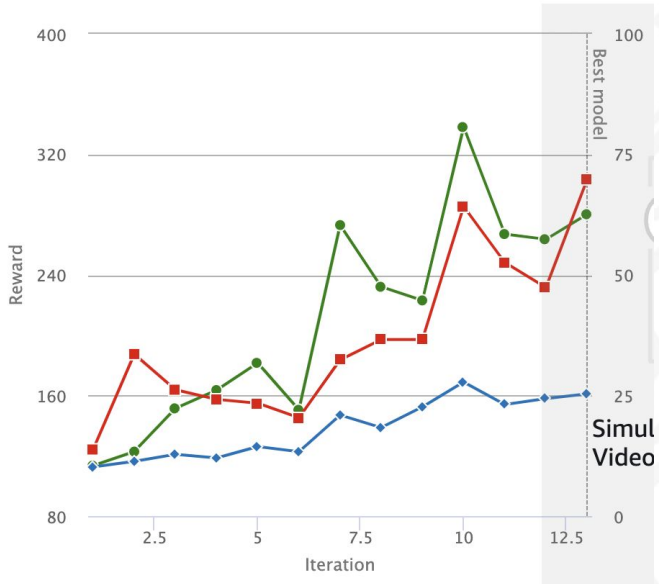




Experimented models:

	Action space	Speed	Training hours	Major changes
Model 4:	Discrete[15 actions]	[0.5 : 3]	5 Hours	# closer to center line
Model 5:	Discrete	[0.5 : 1.5]	2 Hours	# 15-20 actions space(_clone)



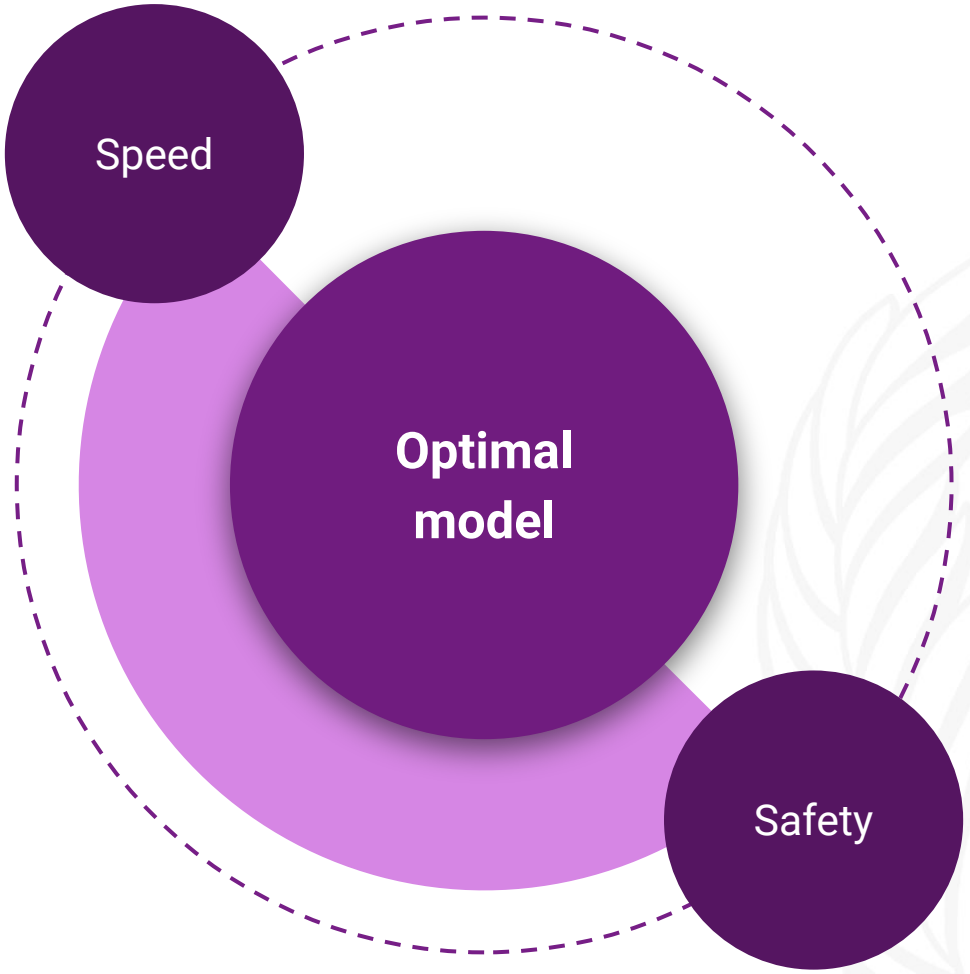


Observations

1 *Continuous action space*

Speed: 0.5 - 2 m/s 2

3 *Corner prediction strategy*


Speed
Optimal model
Safety

Final optimal model

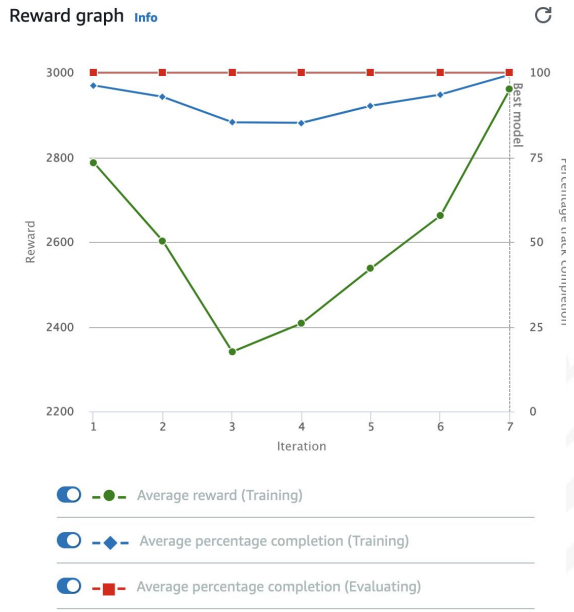
No change in hyperparameters

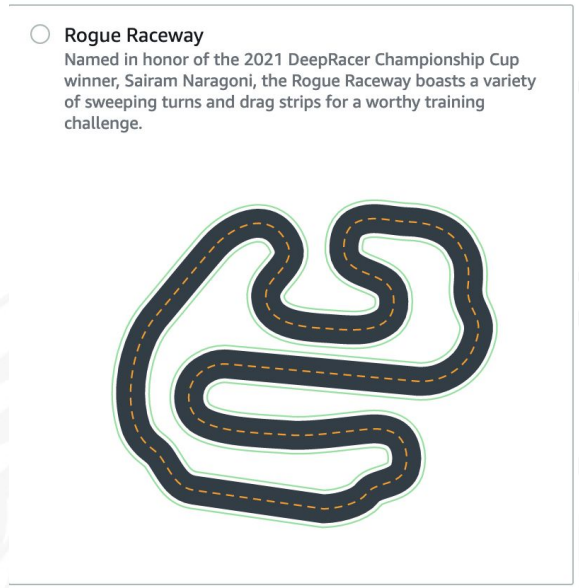
Speed: min:0.5 & **max:** 2 m/s

Action space: Continuous

Trained on: re: Invent 2018

Training hours: 12 hours





Method of evaluation

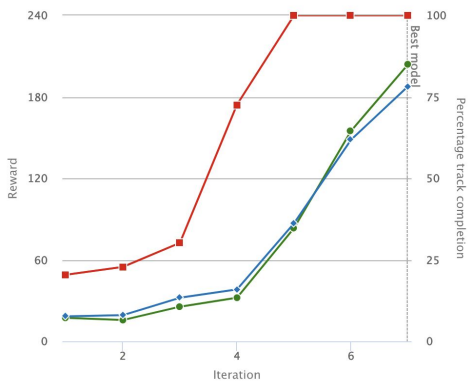
- We made decisions on completion rate on challenging tracks and not community races .
- The best lap time will always be the lap completed without resets.

Evaluation results

Trial	Time (MM:SS.mmm)	Trial results (% track completed)	Status
1	00:18.664	28%	Off track
2	00:18.071	28%	Off track
3	00:17.801	28%	Off track
4	00:05.600	8%	Off track
5	01:04.603	100%	Lap complete

Final Model Development

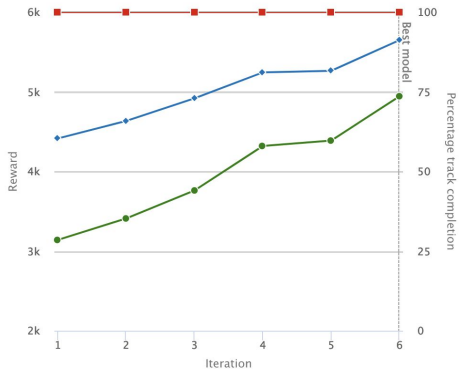
1m/s



1hr

- Basic Reward Function
- Only Line Markers

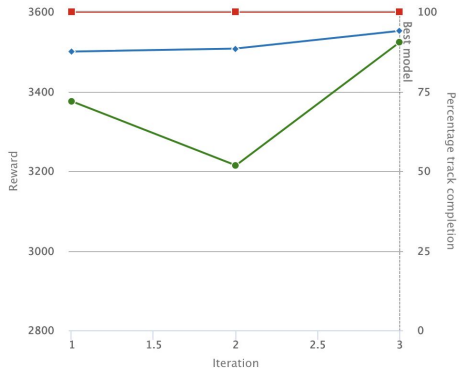
1m/s



4.5hrs

- Added zig-zag steering penalty
- Added low speed penalty
- Added corner perception
- Evaluation on multiple complex tracks gives 100% percent completion.

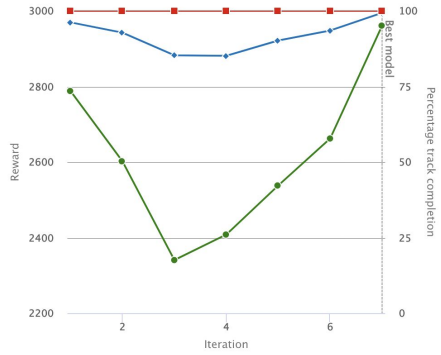
1.5m/s



2.5hrs

- Adjusted thresholds.
- Increased speed to 1.5m/s
- Evaluations on few complex tracks gives 100 % completion result

2m/s



4.5hrs

- Increased speed to 2m/s
- Evaluation shows higher incompletion rate on even moderate tracks.

Elements of the reward function

On Track Reward

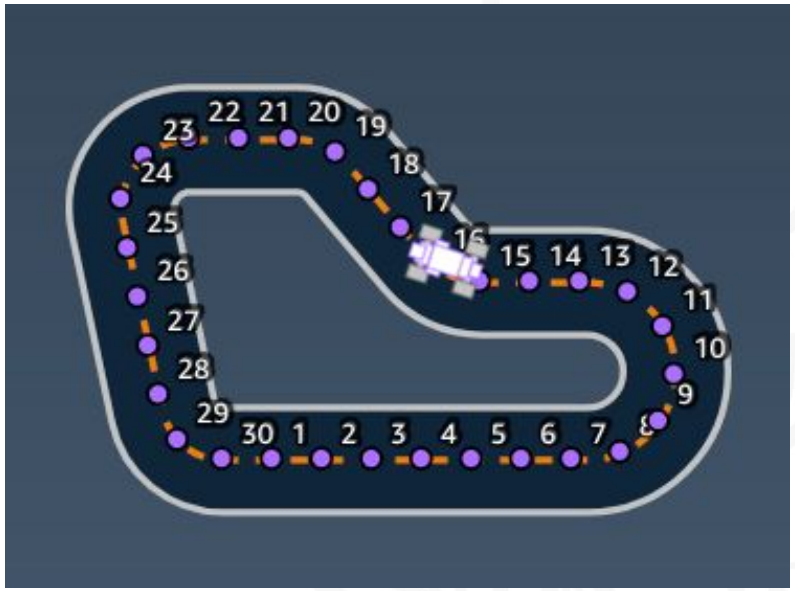
```
def road_wheels(reward,on_track):
    if not on_track:
        reward = 1e-3
    else:
        reward = 10
    return reward
```

Center vehicle Reward

```
def center_vehicle(reward,track_width,distance_from_center):
    marker_1 = 0.1 * track_width
    # Give higher reward if the car is closer to center line and vice versa
    distance_from_border = abs(0.5*track_width-distance_from_center)

    if distance_from_center <= marker_1:
        reward *= 1.5
    if distance_from_border >0.1:
        reward *=2
    else:
        reward *=0.5
    return reward
```

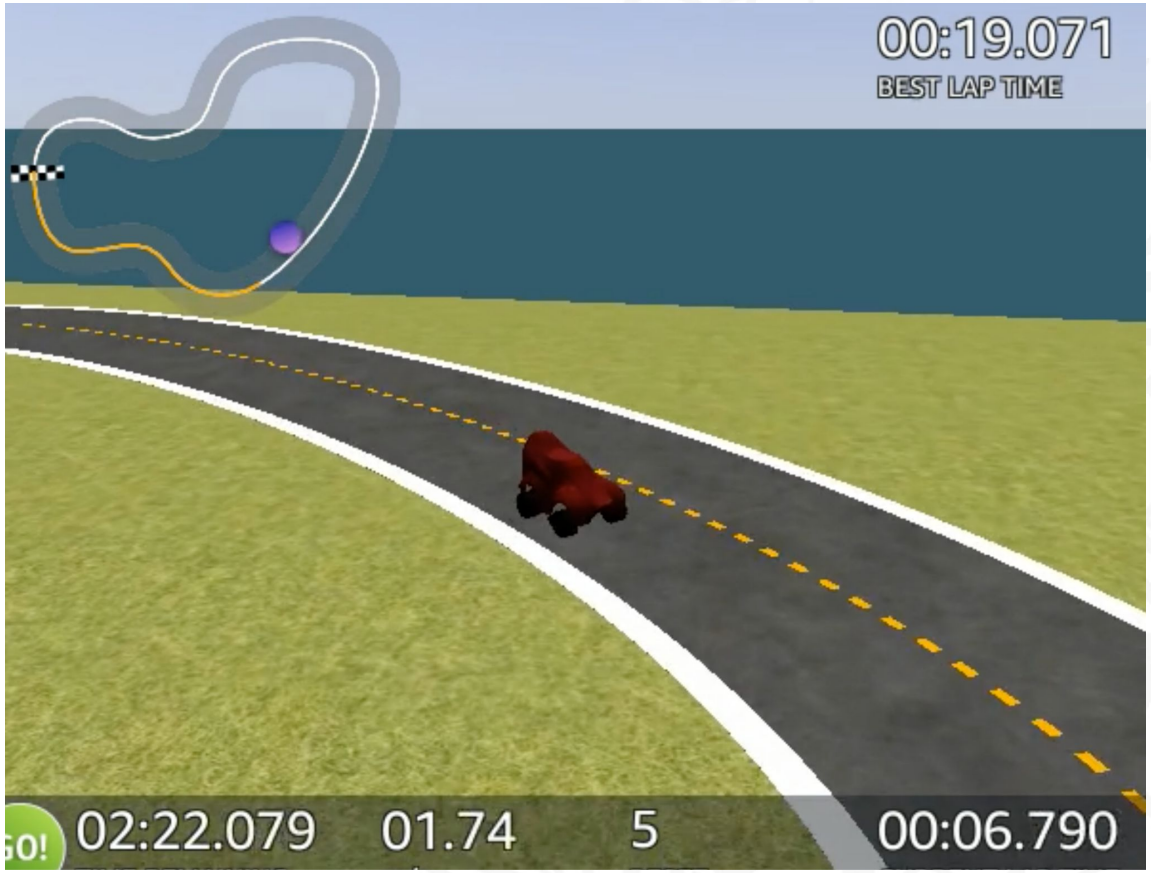
Zig-zag steering penalty

```
def steer_vehicle(reward,waypoints,closest_waypoints,heading):
    next_point = waypoints[closest_waypoints[1]]
    prev_point = waypoints[closest_waypoints[0]]


    track_direction = math.atan2(next_point[1] - prev_point[1], next_point[0] - prev_point[0])
    # Convert to degree
    track_direction = math.degrees(track_direction)


    direction_diff = abs(track_direction - heading)
    if direction_diff > 180:
        direction_diff = 360 - direction_diff


    DIRECTION_THRESHOLD = 10.0
    if direction_diff > DIRECTION_THRESHOLD:
        reward *= 0.5

    return reward
```



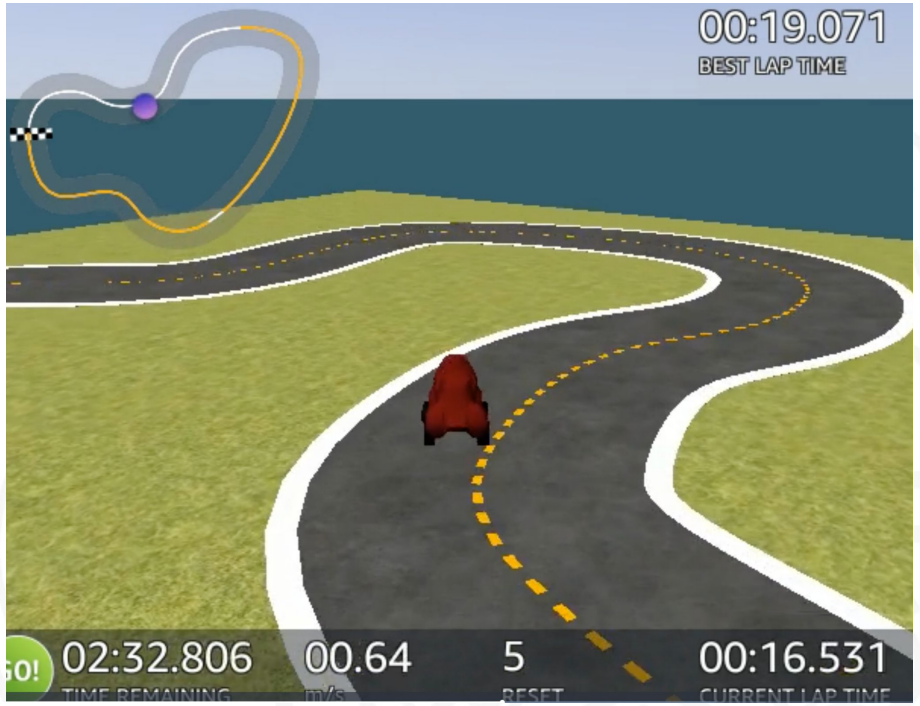
Low speed penalty

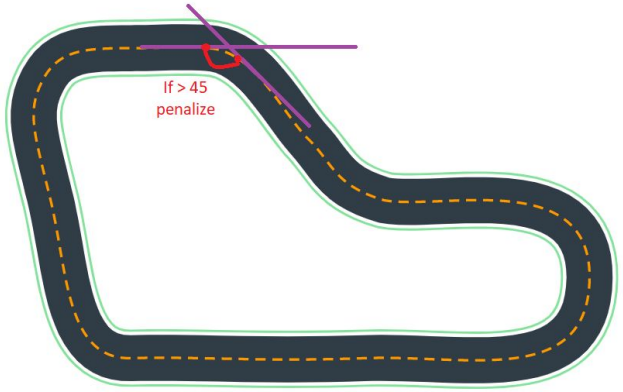
```
def accel(reward,speed):
    speed_fraction = speed/MAX_SPEED
    reward /= (1/(speed_fraction))
    return reward
```



Corner Overspeed Penalty

```
def prempt(reward,waypoints,closest_waypoints,speed):
    for_point = waypoints[min(len(waypoints)-1,closest_waypoints[1]+3)]
    bak_point = waypoints[closest_waypoints[0]+1]


    track_direction = math.atan2(for_point[1] - bak_point[1], for_point[0] - bak_point[0])
    # Convert to degree
    track_direction = math.degrees(track_direction)


    direction_diff = abs(track_direction - heading)
    if direction_diff > 180:
        direction_diff = 360 - direction_diff


    DIRECTION_THRESHOLD = 45.0
    if direction_diff > DIRECTION_THRESHOLD and speed>0.8:
        reward *= 0.5
    return reward
```





Reasons for choosing continuous action space.

- For small action spaces , we were able to create a safe model that complete challenging tracks 100% of the time.
- It is better option to incentivize desired behavior for specific points on any challenging track .
- Smoother changes in speed and steering ,accurately depicting real life conditions.

Disadvantages of choosing continuous action space.

- Takes a big amount of time to train good models when you increase action space.

Improvements:

- Decrease focus on completion rate on challenging tracks and focus on speed on easier tracks
- Maximum speed could be increased to 4 m/s
- Different steering range, lowering the steering angle could lessen the amount of resets.
- Discrete action space with lower steering range, could be explored to lessen training time.