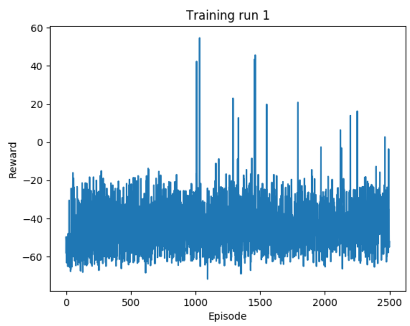
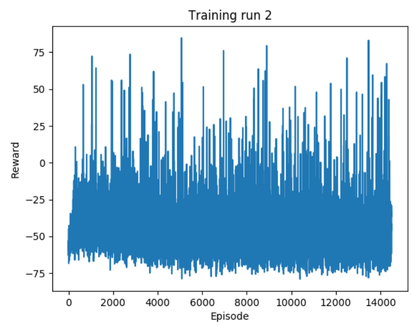
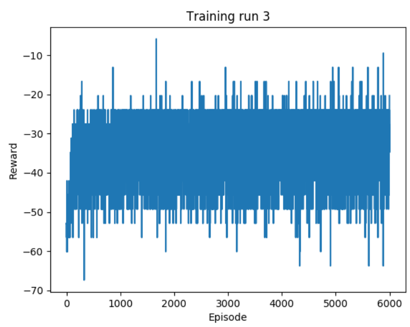
1 Experiments and Results

1.1 Q-Learning







Run	discount rate	learning rate	epsilon	epsilon decay	epsilon floor
1	0.99	0.01	0.05	N/A	N/A
2	0.99	0.01	0.9	0.99	0.01
3	0.99	0.01	0.9	0.99	0.01

We first ran Q-Learning against the full problem with the state (96x96x4 RGB) given by the environment. This quickly ran out of memory. We introduced thresholding, binarization, downsampling, and bitpacking to reduce this memory usage greatly.

Training run 1 was against an 84x96 binary state. The issues we encountered in this run helped inform subsequent experiments. There is no learning apparent in its results, as the agent performs similarly to an agent randomnly walking.

We hypothesized that the single largest issue was too large of a state space. For the second training run, we downsample the state, grabbing every fourth pixel, to produce a 21x24 state. We also introduce epsilon decay and an epsilon floor. This training run also performed poorly, though it does appear to achieve a reward above -20 with more consistency.

We hypothesized the state space was still too large, so we began working on a constant track across episodes in training run 3 to reduce it. The results are more consistent than the previous runs. Even though runs 1 and 2 have some higher rewards, this is a result of "lucky" tracks rather than learning, so this is still an improvement. We also observe that the car does learn to accelerate down the initial straightaway, though this learning is reflected poorly in the collected data. This supports our hypothesis that the state space was too large, as we began to observe real learning.

2 Difficulties

The car is unable to make the first left turn. Each episode is also long, making training slow, making the turning problem worse.

3 Next steps

We must find a way to let episodes complete quicker, possibly by removing rendering steps. Implementing replacing traces can also speed up training. A slower epsilon decay may help the car to take turns. We can downsample further to 12x12 to reduce the state space even more; we can also reduce the action space. This will speed up learning. We can introduce a hueristic to guide exploration - on random choice in e-greedy policy, choose to turn left or right based on presence of the track on the left or right side of the screen.