Implement a basic driving agent

In your report, mention what you see in the agent's behavior. Does it eventually make it to the target location?

The basic driving agent achieves the target in around 20% of the times. So it is just luck dependence if the car could reach the destination point.

Identify and update state

Justify why you picked these set of states, and how they model the agent and its environment.

The main work is done by planner, so if agent sticks with navigation that suggested by next_waypoint it will easily reach the destination. But in this case the idea is to be able gather more rewards and as a result needs to find a different ways. So just the next_waypoint is not enough, degree of freedom is huge and Q function may never convergence. To avoid that needs create more states that will increase the alternative routes and reduce the close loop options. To do that, all agent's surround could be used (start location, current coordinates, final location, deadline, possible actions (those that not breaking the law). Using all these in state will precise the agent's route and reduce faults. But amount of all the states' possible options is too big – the exercise is limited by 100 trials. The best candidate is sense that provides 4 options:

1. Planner navigation – **next waypoint** is the important anchor in the agent state;
2. There are a lot of states' components could be used like time, location, sense, but we are limited by exercise for relative fast learning that should be accomplished in 100 trials. The best candidate is **sense**.
3. Action made by agent – this is the main point, if action is a same as a next_waypoint the Q value will be high, otherwise – low. There are possible exclusions due to random moves.

The state like (agent location, time to deadline, destination) very attractive but to learn all states requires a lot of time. For example, deadline is changing from 25(40 sec) to 0. That means all states should be multiplied by 40.

On the other hand, sense + next_waypoint + action will very promise and optimistic to learn it faster.

Implement Q-Learning

What changes do you notice in the agent's behavior?

- Car started reach the destination frequently.
- Started follow the rules;
- Amount of rewards was increasing;
- Amount of moves increased as well;

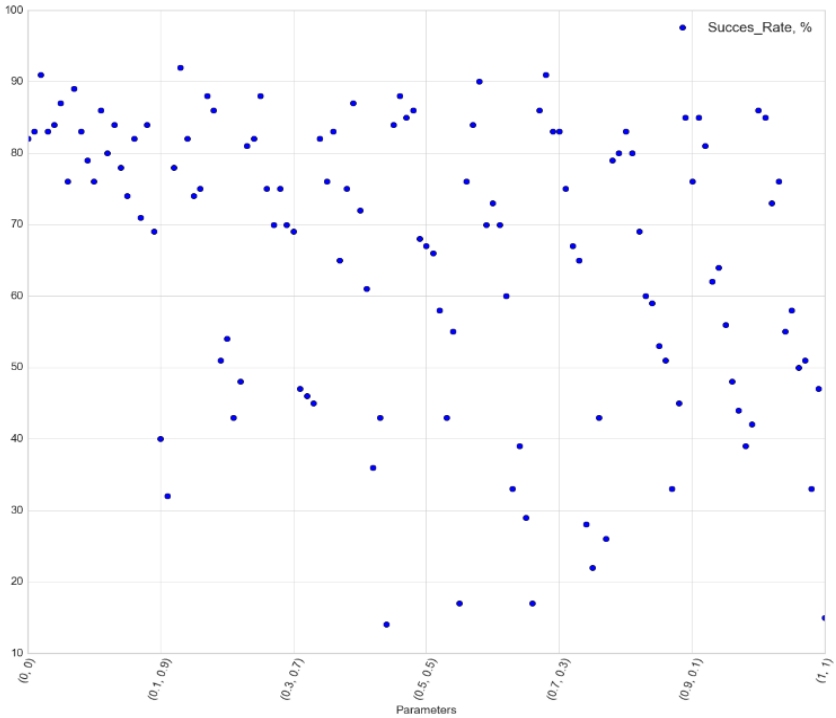
Enhance the driving agent

Report what changes you made to your basic implementation of Q-Learning to achieve the final version of the agent. How well does it perform?

1. The sense of dummy cars are coming from the right was removed from the state. It is not playing any role according to US traffic rules.
2. Counting the actions that following the rules, otherwise Environment prevents the agent move (chooseAction in a code), it reduced amount of penalties also;
3. Ran the different Alpha and Gamma (see appx below), but in actual there are a lot of combinations:

Alpha	Gamma	Success Rate, %	Rewards
0.2	0.1	92	3228
0	0.2	91	3270
0.7	0.1	91	3149.5
0.6	0.2	90	3203
0	0.7	89	2960
0.2	0.5	88	3023.5
0.3	0.2	88	3147
0.5	0.1	88	3323.5
0	0.5	87	3209
0.4	0.5	87	3101.5
0.1	0	86	3159
0.2	0.6	86	3311
0.5	0.3	86	3129
0.7	0	86	3144
1	0	86	3115.5
0.5	0.2	85	3177.5
0.9	0	85	3210
0.9	0.2	85	3100.5
1	0.1	85	3207

Rewards should be dividing by 100



Success rate (reached/trials) is not a good criteria, because the because it takes a time to learn. Wiki says to increase learn rate Alpha should be high. Success Criteria in this exercise is 7 out of last ten moves and a lot of combinations are possible.

So it's hard to say what the best, a lot is of depends on starting point, but it gave the idea of the good Alpha-Gamma pairs, and the bad also:

Alpha	Gamma	Success Rate, %	Rewards
0.9	0.8	44	3256.5
0.2	0.9	43	3143.5
0.4	0.9	43	2952
0.5	0.8	43	3005.5
0.7	0.9	43	2979
0.9	1	42	2877.5
0.1	0.9	40	2982
0.6	0.8	39	3053
0.9	0.9	39	3063.5
0.4	0.8	36	3257.5
0.6	0.7	33	2957.5
0.8	0.9	33	3008
1	0.8	33	2888.5
0.1	1	32	2982
0.6	0.9	29	2765
0.7	0.7	28	3065.5
0.7	1	26	2949.5
0.7	0.8	22	2764
0.5	1	17	2641.5
0.6	1	17	2734
1	1	15	2885
0.4	1	14	2580

As well the starting Q-table value is very important, I found that '-1' is doing great job. Epsilon value important also - too big, will lead to a lot of random movements, too small – algo will sticky to next_waypoint

then amount of rewards will decrease. Finally, following Wiki recommendation, alpha was chosen 0.7 and GAMMA = 0.1. I didn't see any benefits of using dynamic (time dependence) Alpha and Gamma.

So, as a result the code produces Q-table that successfully passing the last 10 moves in average 9 wins.

Does your agent get close to finding an optimal policy, i.e. reach the destination in the minimum possible time, and not incur any penalties?

No, because planner gives the minimum time and Q-table in a good chance can achieve it in a same time. In general time is higher, because of randomallity that implemented.

All point of the Q learn is to produce a best **short** way to the destination. The decision on what is the best is higher value from the Q-table for the next action. Q-table doesn't know the endpoint and agent is led by planner. In the beginning agent spends more time of doing nothing (action – None is the best action defined by Q-table) but then Q-table gets worth values and agent starts moving (this is why to set default value to -1 is important – just push agent to move somewhere). And after it learns more and more and finally gets the right point if action = next_waypoint then it's the best action. But greedy policy is stays and sometimes agent makes movements out of Q-table. This is good in the beginning – during the learning, but later is disturbs. Yes, it helps to achieve the rewards, but in this case safe and fast 'reach destination' driving is required. In this case Q-table cares to be stick to planner. To reach the max rewards and safe driving SARSA should be used, but it requires much more learning resources and not be 100% achieve the project goal.

Reference:

https://github.com/studywolf/blog/tree/master/RL

Appendix – TEST of different Alpha and Gamma:

Alpha	Gamma	Success Rate, %	Rewards
0.2	0.1	92	32.28
0	0.2	91	32.7
0.7	0.1	91	31.495
0.6	0.2	90	32.03
0	0.7	89	29.6
0.2	0.5	88	30.235
0.3	0.2	88	31.47

0.5	0.1	88	33.235
0	0.5	87	32.09
0.4	0.5	87	31.015
0.1	0	86	31.59
0.2	0.6	86	33.11
0.5	0.3	86	31.29
0.7	0	86	31.44
1	0	86	31.155
0.5	0.2	85	31.775
0.9	0	85	32.1
0.9	0.2	85	31.005
1	0.1	85	32.07
0	0.4	84	31.885
0.1	0.2	84	32.835
0.1	0.7	84	32.72
0.5	0	84	31.7
0.6	0.1	84	30.915
0	0.1	83	33.24
0	0.3	83	32.8
0	0.8	83	32.7
0.4	0.2	83	31.26
0.7	0.2	83	31.665
0.7	0.3	83	32.28
0.8	0.2	83	31.505
0	0	82	31.725
0.1	0.5	82	31.96
0.2	0.2	82	33.3
0.3	0.1	82	32.755
0.4	0	82	31.76
0.3	0	81	32.6
0.9	0.3	81	32.26
0.1	0.1	80	32.465
0.8	0.1	80	29.99
0.8	0.3	80	32.355
0	0.9	79	30.12
0.8	0	79	32.16
0.1	0.3	78	30.81
0.2	0	78	32.285

0	0.6	76	32.5
0	1	76	31.96
0.4	0.1	76	30.435
0.6	0	76	32.61
0.9	0.1	76	31.895
1	0.3	76	32.035
0.2	0.4	75	32.5
0.3	0.3	75	31.68
0.3	0.5	75	32.325
0.4	0.4	75	32.765
0.7	0.4	75	32.52
0.1	0.4	74	33.11
0.2	0.3	74	31.9
0.6	0.4	73	31.185
1	0.2	73	32.385
0.4	0.6	72	33.66
0.1	0.6	71	32.545
0.3	0.4	70	29.755
0.3	0.6	70	30.165
0.6	0.3	70	32.015
0.6	0.5	70	31.89
0.1	0.8	69	33.48
0.3	0.7	69	32.19
0.8	0.4	69	32.81
0.5	0.4	68	30.865
0.5	0.5	67	31.795
0.7	0.5	67	32.805
0.5	0.6	66	33.4
0.4	0.3	65	32.62
0.7	0.6	65	31.475
0.9	0.5	64	31.985
0.9	0.4	62	30.765
0.4	0.7	61	31.605
0.6	0.6	60	30.72
0.8	0.5	60	32.075
0.8	0.6	59	30.97
0.5	0.7	58	32.425
1	0.5	58	30.97

0.9	0.6	56	31.685
0.5	0.9	55	32.555
1	0.4	55	30.445
0.2	0.8	54	30.465
0.8	0.7	53	33.43
0.2	0.7	51	31.99
0.8	0.8	51	30.855
1	0.7	51	30.44
1	0.6	50	31.21
0.2	1	48	28.72
0.9	0.7	48	29.55
0.3	0.8	47	30.815
1	0.9	47	31.025
0.3	0.9	46	29.355
0.3	1	45	29.32
0.8	1	45	30.13
0.9	0.8	44	32.565
0.2	0.9	43	31.435
0.4	0.9	43	29.52
0.5	0.8	43	30.055
0.7	0.9	43	29.79
0.9	1	42	28.775
0.1	0.9	40	29.82
0.6	0.8	39	30.53
0.9	0.9	39	30.635
0.4	0.8	36	32.575
0.6	0.7	33	29.575
0.8	0.9	33	30.08
1	0.8	33	28.885
0.1	1	32	29.82
0.6	0.9	29	27.65
0.7	0.7	28	30.655
0.7	1	26	29.495
0.7	0.8	22	27.64
0.5	1	17	26.415
0.6	1	17	27.34
1	1	15	28.85
0.4	1	14	25.8