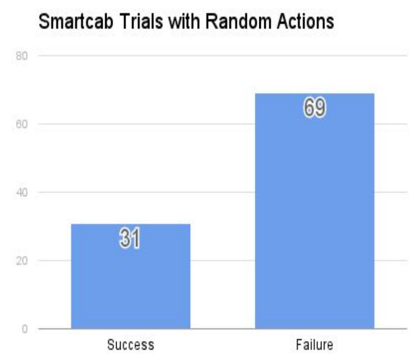
QUESTION: Observe what you see with the agent's behavior as it takes random actions. Does the smartcab eventually make it to the destination? Are there any other interesting observations to note?

When taking random actions the smartcab does sometimes reach the destination. With 100 trials the smartcab arrived at the destination 31 times. Arriving about one out of three times seems pretty high considering we are just taking random actions. One interesting observation is that the world is is bounded to a fairly small area with Smartcab wrapping around to the other side if proceeding beyond the bounds. This explains why we have such a high success rate even with taking random actions since the bounds keep the Smartcab from wandering too far away from the destination.



Another note is that failures are due to a hard cap on the deadline at -100. If allowed to roam indefinitely the Smartcab would eventually randomly land on the destination, especially since we are working with such a small bounded world.

QUESTION: What states have you identified that are appropriate for modeling the smartcab and environment? Why do you believe each of these states to be appropriate for this problem?

I chose the following to use as parameters for modeling the smartcab state:

State Parameter	**Possible Values**
next_weightpoint	Left, Right, Forward
light	Red, Green
oncoming	None, Left, Right, Forward
left	None, Left, Right, Forward
right	None, Left, Right, Forward
deadline	**Omitted to reduce state space**

Some of these inputs could be condensed, for example *oncoming* could be condensed to True or False, however we could be limiting the agent's ability to learn some traffic rules. One such rule would be that it is okay to go right on red if there is nobody going forward from the left. Because of this I chose not to condense those inputs.

Even though deadline is removed from the state, it is still there implicitly because the smartcab does not get the large reward if not reaching the destination on time.

Another discarded idea was to condense light and inputs to contain right of way logic in the following way.

waypoint	Left, Right, Forward
ok_right	True, False
ok_left	True, False
ok_forward	True, False

=>

waypoint	Left, Right, Forward
ok_waypoint	True, False

This would drastically reduce the state space, however it would also be imposing those logic rules onto the learner and making the smartcab less able to adapt to different environments such as foreign countries where the rules are different.

OPTIONAL: How many states in total exist for the smartcab in this environment? Does this number seem reasonable given that the goal of Q-Learning is to learn and make informed decisions about each state? Why or why not?

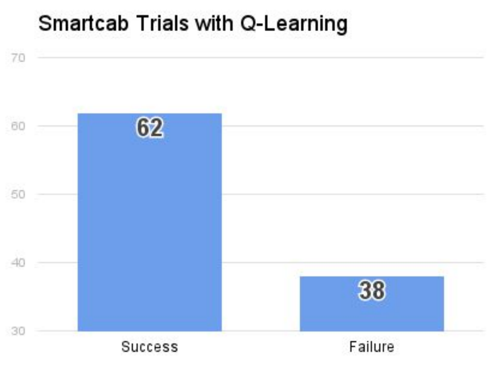
The total number of states is the combination of all of the state parameters: next_weightpoint x light x oncoming x left x right = 3 x 2 x 4 x 4 x 4 = 384

There are 384 total states given the chosen state model.

With 384 states we have 384 x 4 = 1536 possible Q values, however when running a trial it seems unlikely that we need to know every value. A lot of those states will have negative reward, and since Q-Learning will guide the smartcab mostly to positive rewards, we will never see many of those states. Considering this, I believe 384 is a reasonable number to allow Q-Learning to make informed decisions.

QUESTION: What changes do you notice in the agent's behavior when compared to the basic driving agent when random actions were always taken? Why is this behavior occurring?

We now see many more successes than the agent that performed random actions, but we still have a lot of room to improve the model parameters given 38 trials failed. One note is that If we did a 1:1 comparison with not enforcing the deadline, then the Q-Learning Smartcab is able to reach the destination in 98-100% of the trials.



Given the improved behavior over random actions we can infer that the Q-Learning Smartcab is able to estimate expected reward from transitions and find a policy that considers these rewards.

QUESTION: Report the different values for the parameters tuned in your basic implementation of Q-Learning. For which set of parameters does the agent perform best? How well does the final driving agent perform?

To test performance against different parameter combinations, I implemented a basic grid search. For evaluating performance I chose look at the success rate among the final 10 trials in a set of 100 trials. This way we are not penalizing a good parameter tune if it does a lot of learning early on, but does well in the final trials. Similarly, a parameter tune could do well early on but never improve on itself.

The grid search was then repeated to make sure the algorithm performed well among many sets of trials. (100 x 100 trials). Results in the table are averaged from all trials. Best parameters are highlighted in green.

Epsilon	**Alpha**	**Gamma**	**Initial Value**	**Mean Reward per Trial**	**Success Rate (%)**
1/(t+1)	**1/(.8*ln(t+2))**	**0.9^t**	**1**	**22.201**	**99.3**
1/(t+1)	**1/(.8*ln(t+2))**	**0.8^t**	**1**	**22.312**	**99.1**
1/(t+1)	**1/(ln(t+2))**	**0.8^t**	**1**	**22.3215**	**99.0**
1/(t+1)	**1/(.8*ln(t+2))**	**0.9^t**	**10**	**22.328**	**98.9**
1/(t+1)	**1/(ln(t+2))**	**0.9^t**	**1**	**22.1365**	**98.6**
1/(t+1)	**1/(ln(t+2))**	**0.9^t**	**10**	**22.318**	**98.4**
1/(t+1)	**1/(ln(t+2))**	**0.8^t**	**10**	**22.595**	**98.2**
1/(t+1)	**1/(.8*ln(t+2))**	**0.8^t**	**10**	**22.4195**	**98.0**
1/(ln(t+1)+1)	**1/(ln(t+2))**	**0.8^t**	**1**	**22.104**	**96.0**
1/(ln(t+1)+1)	**1/(.8*ln(t+2))**	**0.8^t**	**0**	**21.834**	**95.3**
1/(ln(t+1)+1)	**1/(.8*ln(t+2))**	**0.9^t**	**1**	**22.4385**	**95.3**
1/(ln(t+1)+1)	**1/(.8*ln(t+2))**	**0.8^t**	**1**	**22.1525**	**95.2**
1/(ln(t+1)+1)	**1/(ln(t+2))**	**0.9^t**	**1**	**21.9755**	**95.0**
1/(ln(t+1)+1)	**1/(ln(t+2))**	**0.9^t**	**10**	**22.0485**	**94.6**
1/(ln(t+1)+1)	**1/(.8*ln(t+2))**	**0.9^t**	**0**	**22.0245**	**94.4**

1/(ln(t+1)+1)	**1/(ln(t+2))**	**0.8^t**	**10**	**22.0695**	**94.4**
1/(ln(t+1)+1)	**1/(.8*ln(t+2))**	**0.9^t**	**10**	**22.2185**	**94.3**
1/(ln(t+1)+1)	**1/(.8*ln(t+2))**	**0.8^t**	**10**	**22.2835**	**94.1**
1/(ln(t+1)+1)	**1/(ln(t+2))**	**0.9^t**	**0**	**22.033**	**94.1**
1/(ln(t+1)+1)	**1/(ln(t+2))**	**0.8^t**	**0**	**22.067**	**92.9**
1/(t+1)	**1/(ln(t+2))**	**0.8^t**	**0**	**9.879**	**37.5**
1/(t+1)	**1/(.8*ln(t+2))**	**0.8^t**	**0**	**9.7895**	**36.8**
1/(t+1)	**1/(.8*ln(t+2))**	**0.9^t**	**0**	**9.1685**	**33.5**
1/(t+1)	**1/(ln(t+2))**	**0.9^t**	**0**	**8.4895**	**29.9**

QUESTION: 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? How would you describe an optimal policy for this problem?

For our applications here I think the optimal policy could be defined such that the smartcab does not run any red lights, does not get into any accidents, and makes it to the destination on time.

To determine If my agent is making traffic violations, I implemented a simple counter for each time the agent gets a negative reward. Again only the final 10 trials were considered for evaluating performance, and averaged over 100x100 trials.

Average Number of Penalties per Trial	**Mean Reward**	**Average Success Rate**
0.2217	22.32745	99.3%

On average we incurred 0.22 penalties per trial, and from the high success rate we can infer that the agent is reaching the destination in minimal time. From those metrics I believe my agent is close to finding an optimal policy.