***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?*

1. **Prior** to implementing the random choice among possible actions `(None, 'forward', 'left', 'right')`, the red car stayed in place. This makes sense, because previously the action for each iteration was always `None`.
2. **After** implementing the random choice among possible actions, as expected, the car began to move, and yes, it eventually makes it to its destination (but usually not before the deadline expires)
3. After listening to the lectures on Q-Learning, I admit I **expected** for the car to reach its destination "better" (e.g. more directly) on subsequent iterations, but then I noticed `# TODO: Learn policy based on state, action, reward`, and realized that learning will come later.
4. It's a little hard to tell, but it also appears like the agent is, at this point, doing wrong things (e.g. disobeying traffic laws in ways that are likely to bring harm to itself and others). From what I could tell in `environment.py`, such harmful actions are classified as `Invalid Moves`, and result in a `reward` of `-1.0`. There were definitely a few `rewards` of `-1.0` in the simulation.
5. So, at this point, it seems like we've successfully given movement to an actor which is likely to (unintentionally) inflict harm. Yikes!

***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?*

1. Many, but not all, of the elements in `inputs` (that is, in `self.env.sense(self)`) are important for modeling the**smartcab** and its environment.

    i. The state of the light (e.g. `red, green`) is required to know whether the desired next action is presently allowed.
    ii. Similarly, the location and heading of other cars is important for knowing whether or not our `agent` needs to adjust its desired heading. Without knowing this information, our `agent` will be unable to perform **collision avoidance**.

    iii. However, it's important to note that the information provided by `right` is redundant to the information provided by`light`. Specifically, if the `light` is `green`, then traffic which is to the smartcab's `right` should yield to the smartcab in all circumstances (i.e. should not turn `left` or go `forward`, because their light is `red`, and it should only turn `right` when there is no traffic going `forward` from its `left`).

    In reality, it is perhaps paramount for a smartcab to pay attention to whether there is traffic to its right. Actors in the wild don't always yield (e.g. sometimes turn right into a far left lane to miss traffic from the left, sometimes turn right without noticing traffic from the left), and a smartcab shouldn't ignore the possibility of a collision when right-of-way dictates that none should occur.
    Nevertheless, for the purposes of this exercise, it is appropriate to assume that other actors will obey traffic laws at all times. That being the case, information about cars to the smartcab's `right` is **redundant**, and is therefore not an appropriate state to consider.

2. Additionally, it is practically important to include `self.planner.next_waypoint()`, since the reinforcement provided by`Environment.act()` considers whether the action taken is or isn't the action which `RoutePlanner.next_waypoint()`expects.

    In one sense, we want the smartcab to have access to all of the information it's being graded on, so that it can learn for itself the way to get the best grade.

In another, broader sense, reinforcement learning is a *slow* process, unless feedback can be provided fairly regularly during the process. To use an analogy, it's going to take someone a long time to learn the rules of football if you only tell them 'good job' after every game they play, hide the scoreboard from them, and don't let them know when they or anyone else got a penalty. Accordingly, we can imagine that grading the smartcab according to `RoutePlanner.next_waypoint()` as injecting domain knowledge into our Q-Learning algorithm (where it *should* go, except in certain circumstances). Certainly we hope that the smartcab will improve on this suggestion (specifically, by not crashing into other cars or disobeying traffic signals), but this frequent feedback is crucial to rapidly developing a sensible policy.

3. It is neither practical nor desirable, however, to include the `deadline` as a state about which the smartcab should care. Firstly, if the deadline only reaches to 20, then the **size** of the state space increases by a factor of 20. This means that it will take 20 times as long to explore the state space, and therefore ~20 times as long to converge to a sensible Q-Learning policy. Secondly, it's unclear what information the `deadline` would be conveying to the smartcab beyond the information that's already conveyed by merely missing the deadline; should it behave differently when the `deadline`value is smaller? Should it start disregarding traffic laws in order to reach its destination? That's probably not the result we would want here, and so it would be inapproriate to includ `deadline` in the state vector.

***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?*

1. From mere permutations of the `inputs` vector, there are 64 distinct states. This is because there are two states for`light`, and four for each of `oncoming` and `left` (specifically, `None`, `forward`, `right`, and `left`). (Note from the above question that `right` is being ignored, as it contains only redundant information). Also, from`RoutePlanner.next_waypoint()`, there are three additional, distinct states (`right`, `left`, and `forward`).

   Accordingly, there are a total of **192 distinct states** in this smartcab environment.

```
{'next_waypoint': 'forward', 'green', 'oncoming': None, 'left': None}
{'next_waypoint': 'left', 'red', 'oncoming': None, 'left': 'left'}
{'next_waypoint': 'right', 'red', 'oncoming': 'right', 'left': 'forward'}
```

2. This high number of states seems correct for the `agent` to have a full understanding of the intersection and its possible next actions. Without an understanding this full, it seems unlikely that a **smartcab** would be able to explore alternative routes in case the chosen one is blocked.

   - For instance, consider a smartcab approaching a red light, and intends to turn right at the intersection. If another car approaches the intersection from the smartcab's left and intends to go forward, the smartcab must correctly ascertain that it must wait for the car to pass, even if the smartcab can legally turn right from a red light after having stopped first.
   - Even though there are 192 distinct possible states, many of these states are invalid, since they would cause an accident even in the absence of the smartcab. However, even strange accidents happen occasionally, so while the likelihood of many of the potential states is low, it's not zero, so the smartcab can't assume they'll never occur.

***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?*

1. Previously, the smartcab was only taking random actions, and unfortunately no mechanism was in place to choose better on subsequent trials. Now, however, although the smartcab begins by taking random actions (many of which are invalid), by the third or fourth trial, the number of invalid actions approaches 0, and the smartcab appears to take a fairly direct route to the destination.

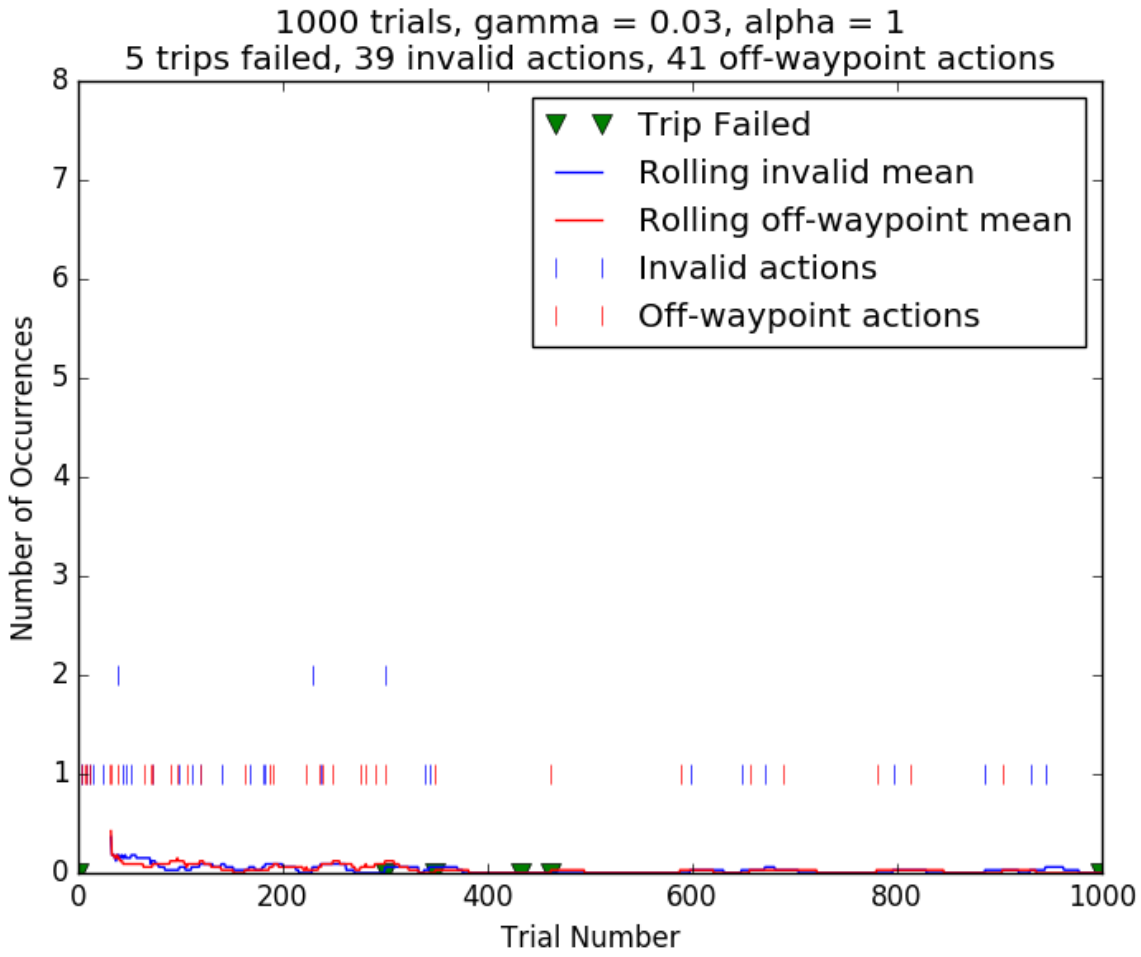
   In short, this is because the smartcab is seeking rewards and remembering consequences, and the rewards have been constructed in a way that leads to the observed behavior. In more depth:

   i. The smartcab is determining its state (i.e. suggested next move, the color of the traffic light, and the location and heading of nearby cars).
   ii. The smartcab is updating its Q-table (think of it like its memory for all scenarios) with the expected reward for any of the actions it could take in the current state (i.e. `left`, `forward`, `right`, or remain stationary). If the smartcab hasn't been in this state before, it assigns the actions a high reward, so that it explores things it doesn't know well yet.
   iii. The smartcab takes the action with the highest Q-value in its table for this state. It breaks ties randomly, because there isn't a sensible way to break them systematically.
   iv. After having acted, the smartcab again determines its state and updates its Q-table, except this time it doesn't care about any one action in particular, but rather about whether there is some high-Q action available to it now. (In essence, it knows it can make decisions later, but it's wondering if the last action it took it to a land of meaningful opportunity, and updates the value of that previous decision accordingly).
   v. As discussed above, there are 192 distinct states, and 4 possible actions for each of these states. Accordingly, it takes a while for the Q-table in this simulation to converge to consistent, optimal behavior.

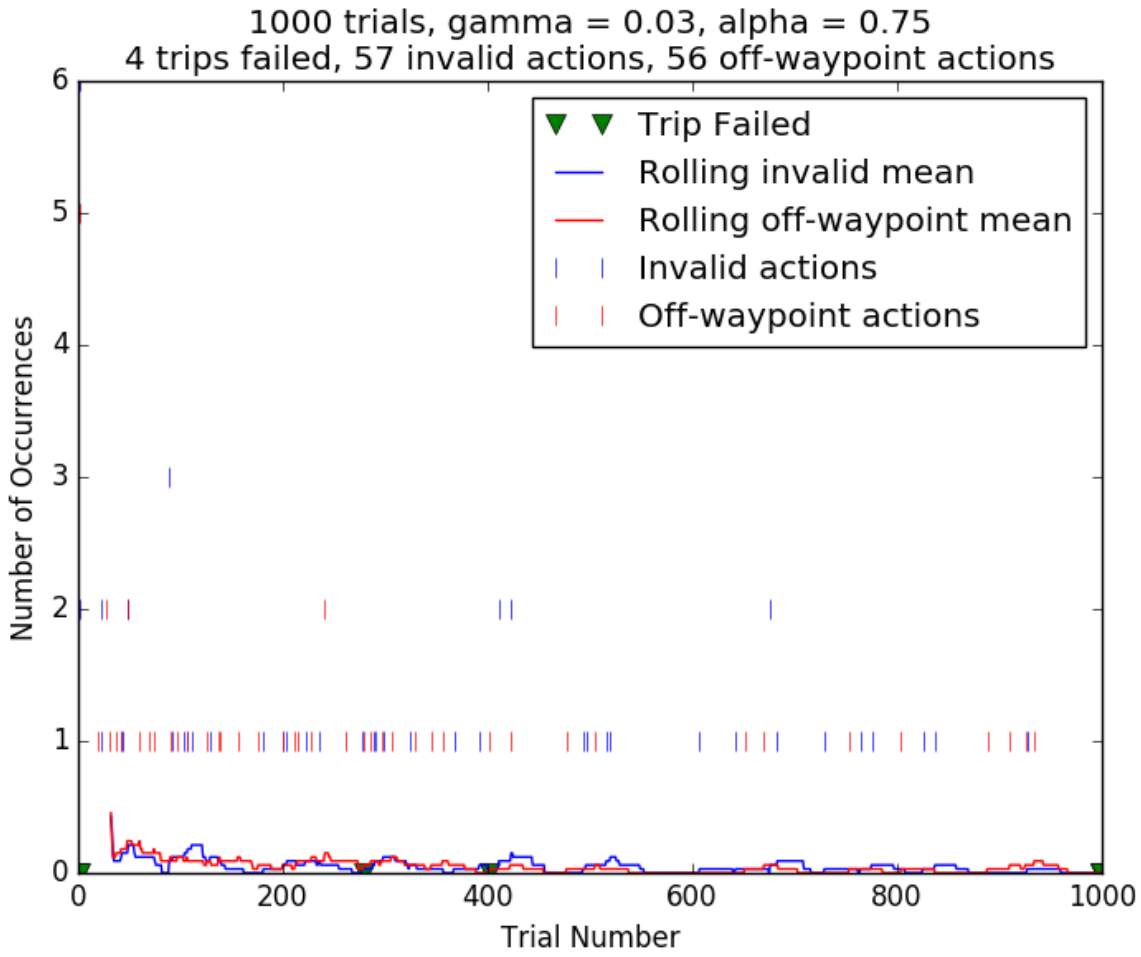
2. Interestingly, by the 7th or eighth trial (though perhaps sooner), the smartcab develops a tendency to loop, and never remains at an intersection. While comical, this is probably also not an ideal policy in the abstract, since it's wasteful of gas, increases wear on the vehicle, and greatly confuses the passengers. However, perhaps that behavior can be eliminated by tweaking variables in the Q-Learning algorithm.

***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?*

1. `epsilon`, interestingly enough, was not used (discussion follows).
2. `alpha` was dynamic in this algorithm, always being the inverse of the number of times the Q-Learning algorithm had encountered the current state-action pair. Thus, initially, alpha is 1, then 0.5, then 0.33, etc. for a particular state in which that action has already been chosen. This has the effect of replacing `epsilon`'s simulated annealing effect, as over time, the learning rate "cools" just the same, though by a different calculation. For comparison, static `alpha` values were used as below:
   i. For a static `alpha` of 1, the difference in performance between a dynamic `alpha` is negligible.

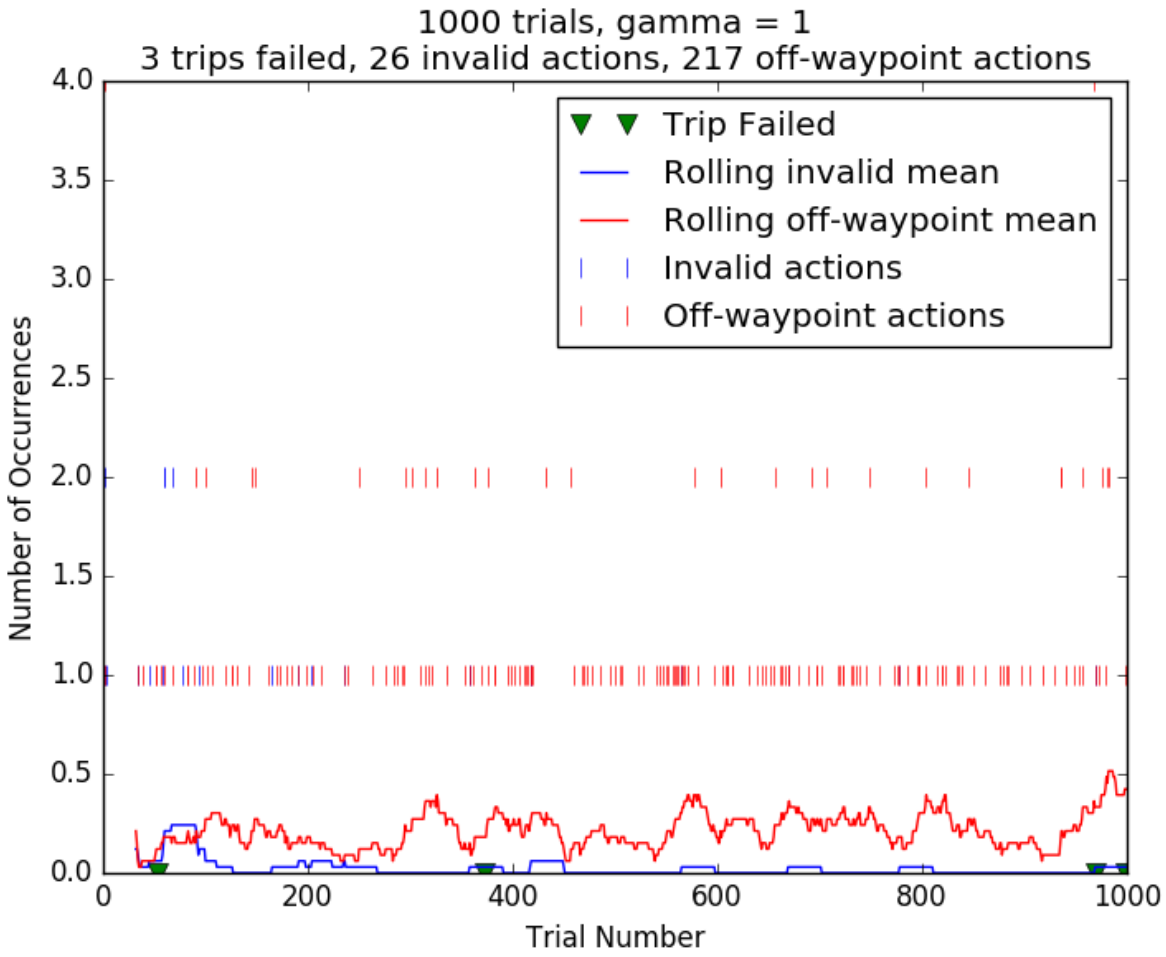


ii. For a static `alpha` of 0.75, the number of invalid and off-waypoint actions increased somewhat.



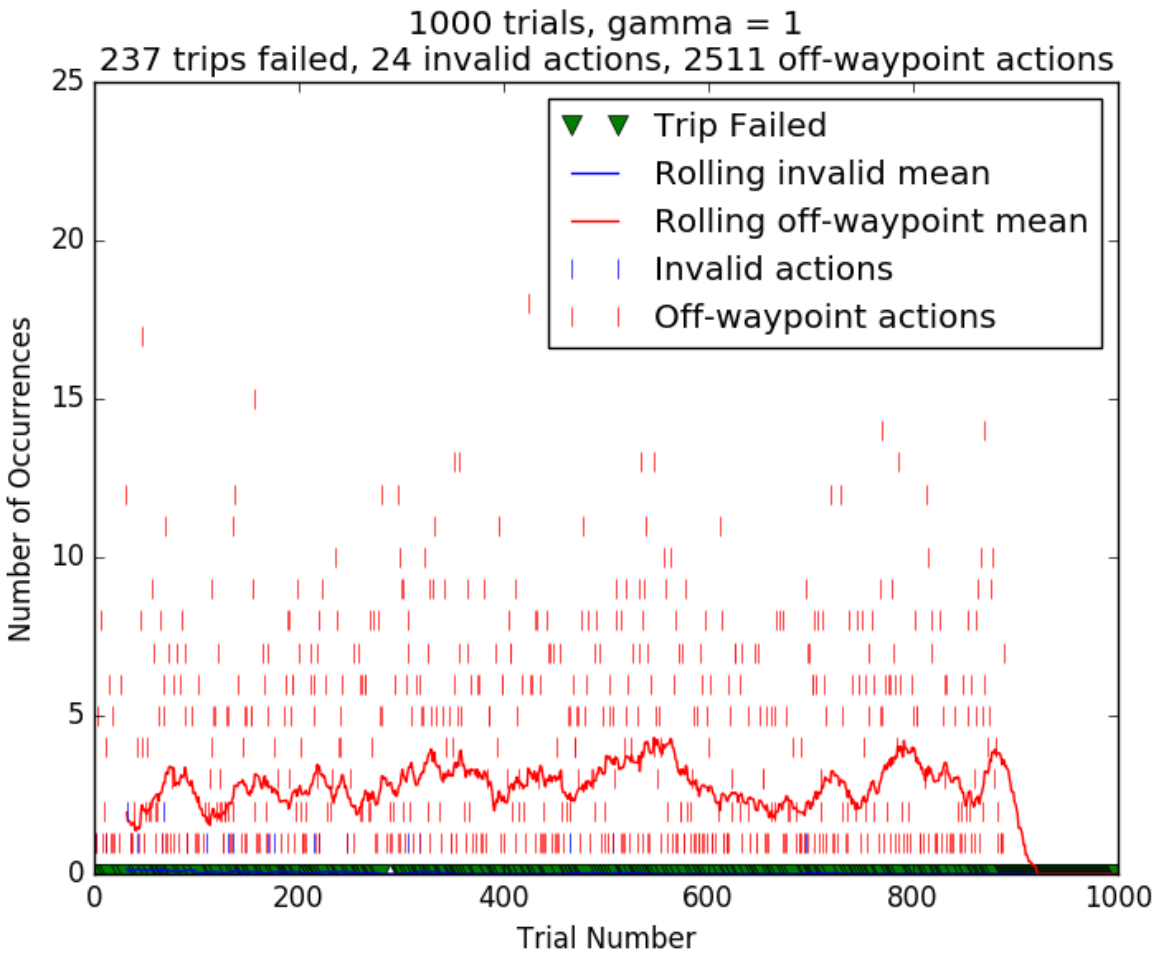
iii. This trend continued as `alpha` decreased to 0.5, 0.25, 0.1, 0.02, and 0.01.

3. `gamma` (as hinted by the graphics above) was `0.03`. This is primarily an attempt to suppress the "looping" tendency identified in the question above. Interestingly, a `gamma` this low still allowed the smartcab to "learn" a good driving policy within a few trials.
    i. At a `gamma` of 1, the smartcab's behavior tends depend on its very early encounters. Sometimes, it reaches the target fairly frequently, but it takes unnecessary actions.

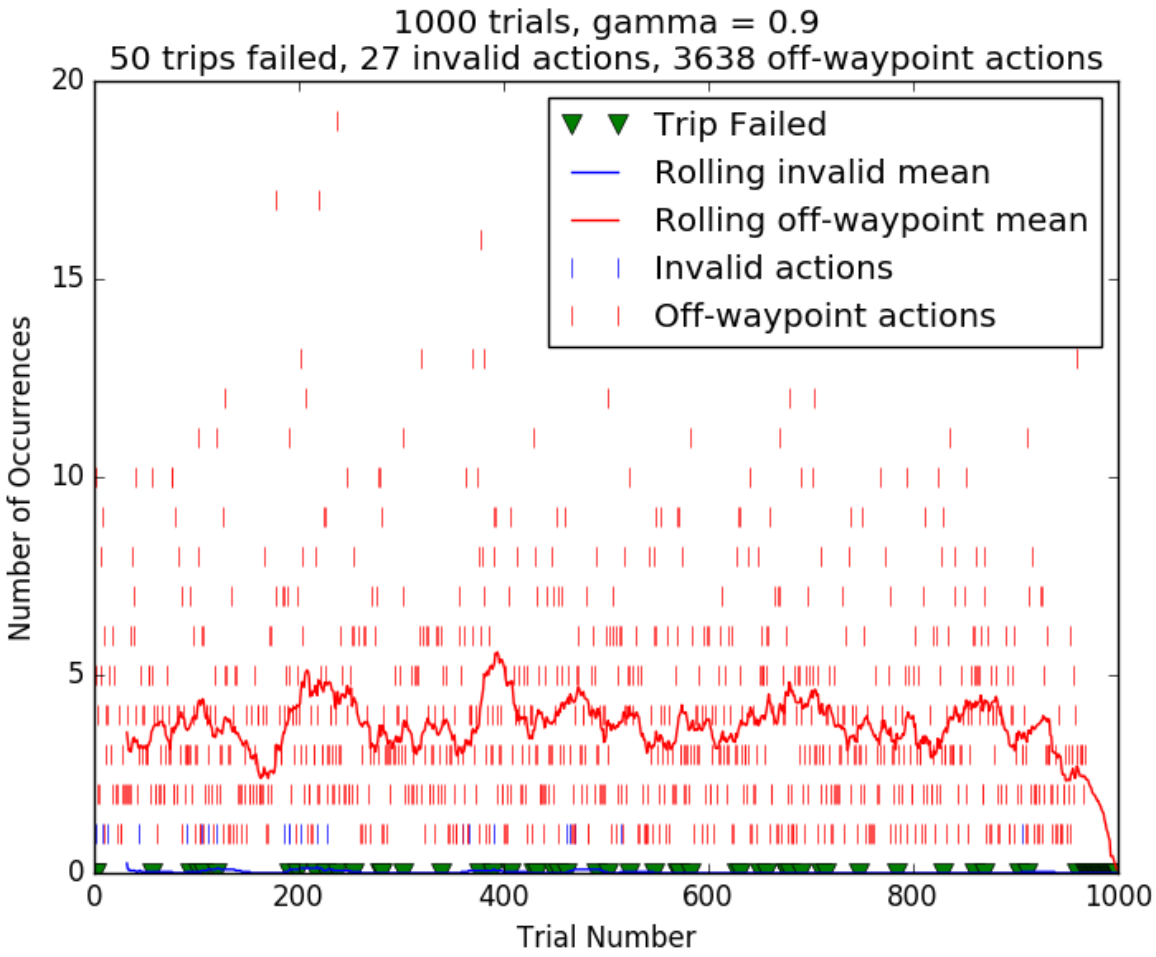


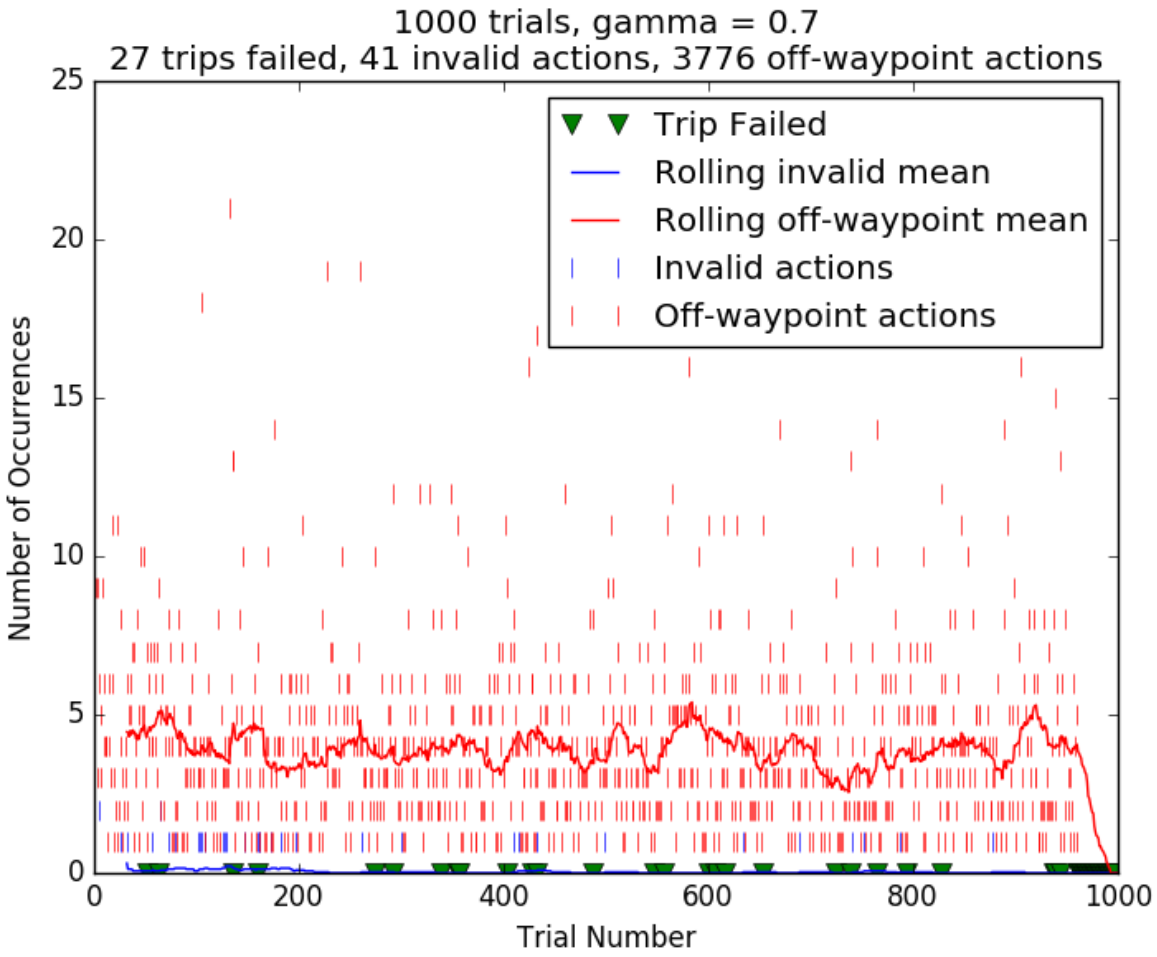
At other times, it prefers taking many unnecessary actions, and reaches the target far less

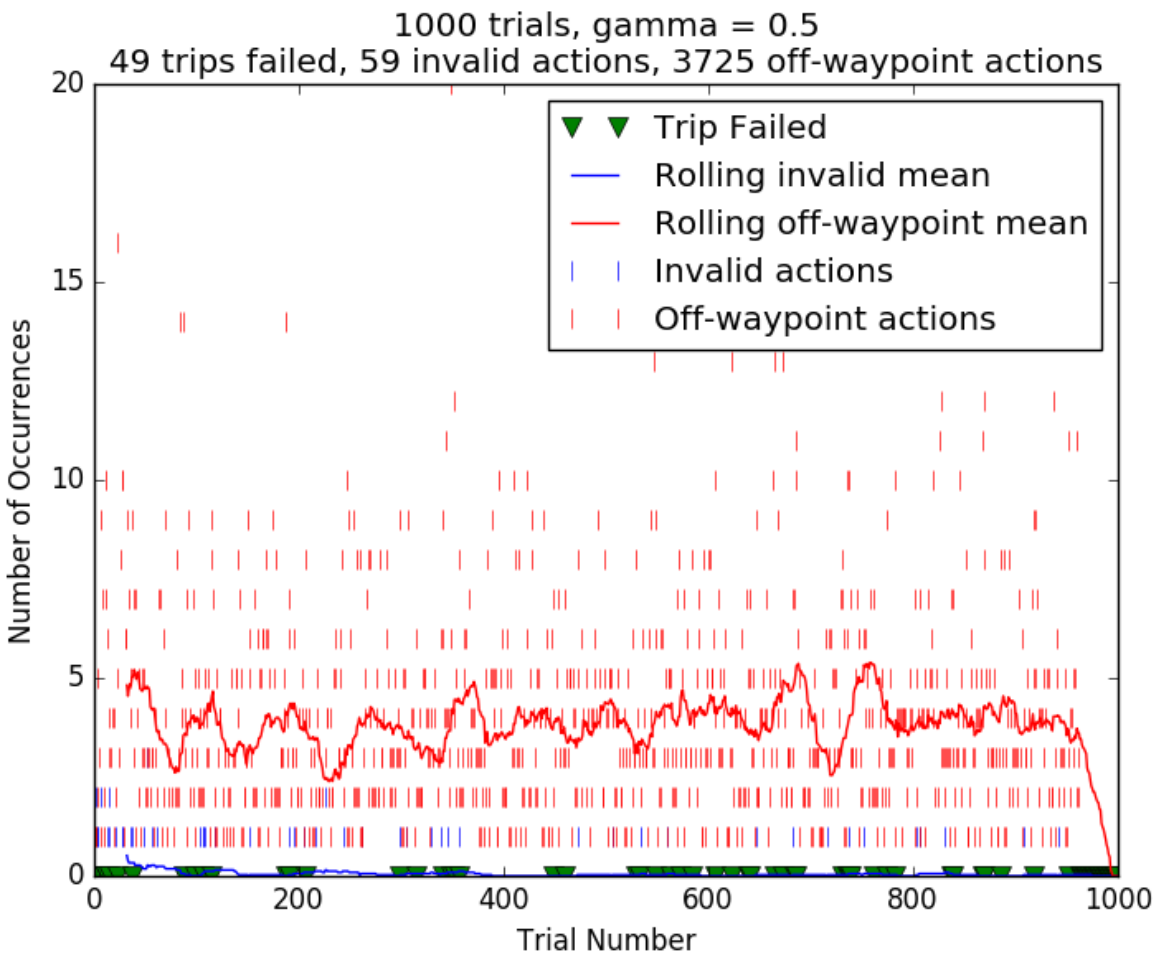
frequently.

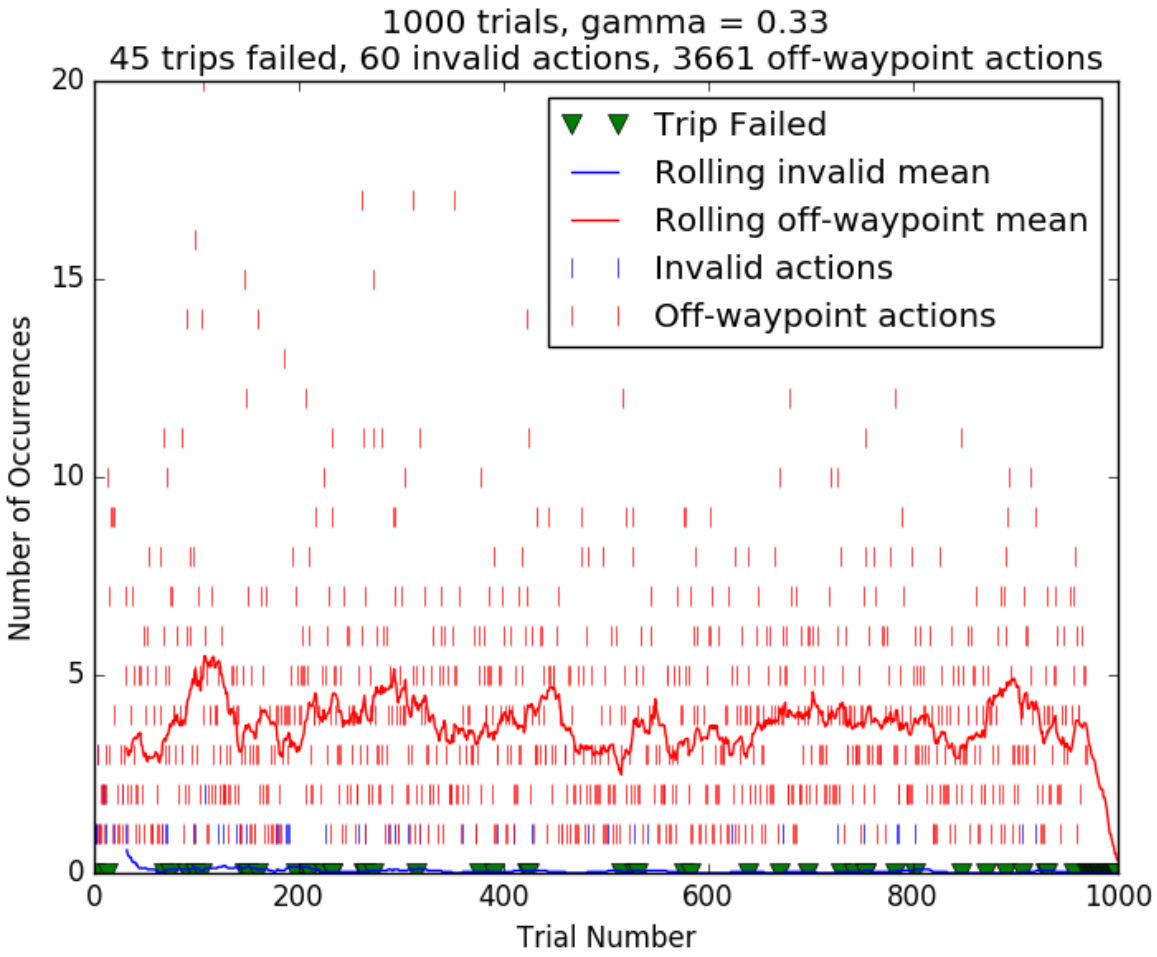


ii. For `gammas` between 0.9 and 0.2, the car very quickly favors looping, and thus takes many unnecessary actions.

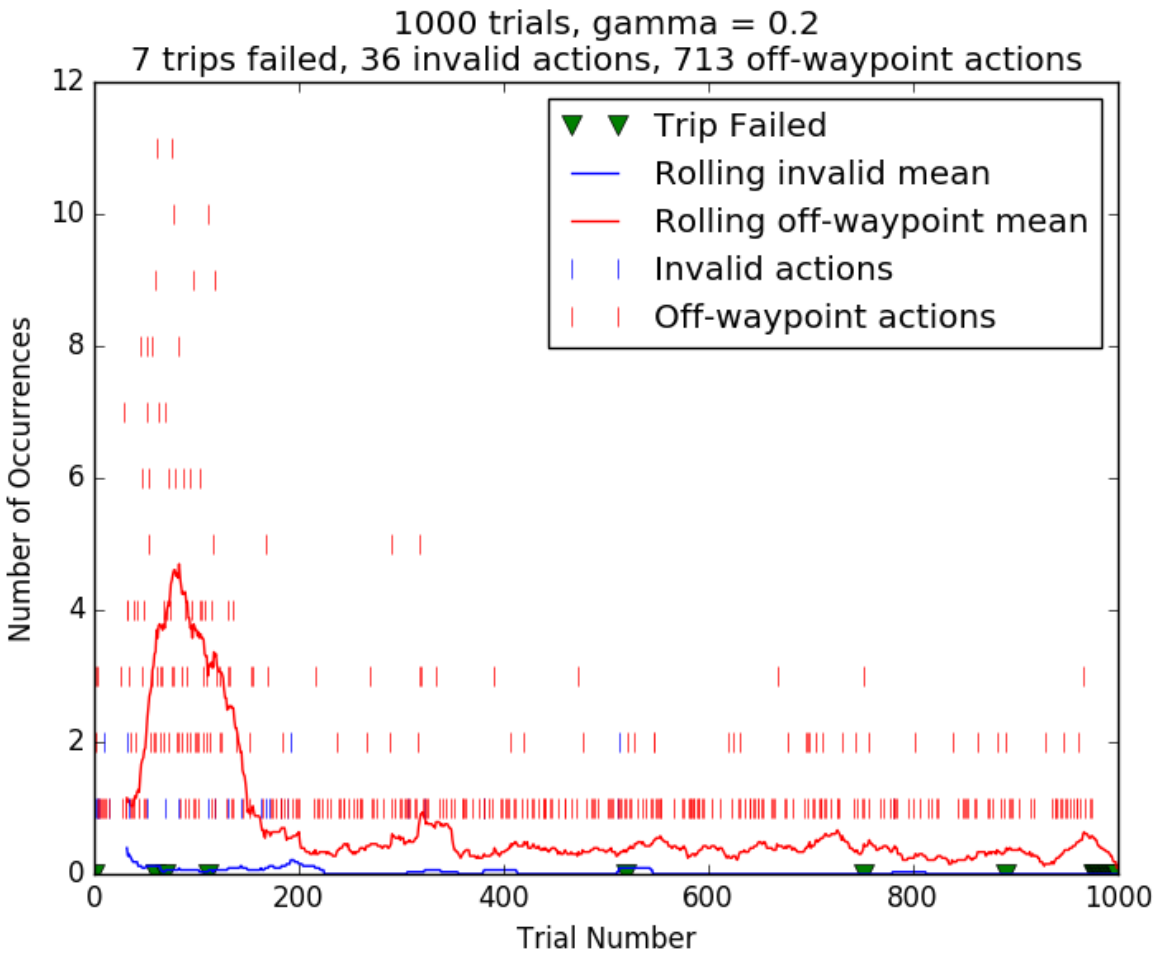

1000 trials, gamma = 0.9
50 trips failed, 27 invalid actions, 3638 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
5
10
15
20
0
200
400
600
800
1000


1000 trials, gamma = 0.7
27 trips failed, 41 invalid actions, 3776 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
5
10
15
20
25
0
200
400
600
800
1000

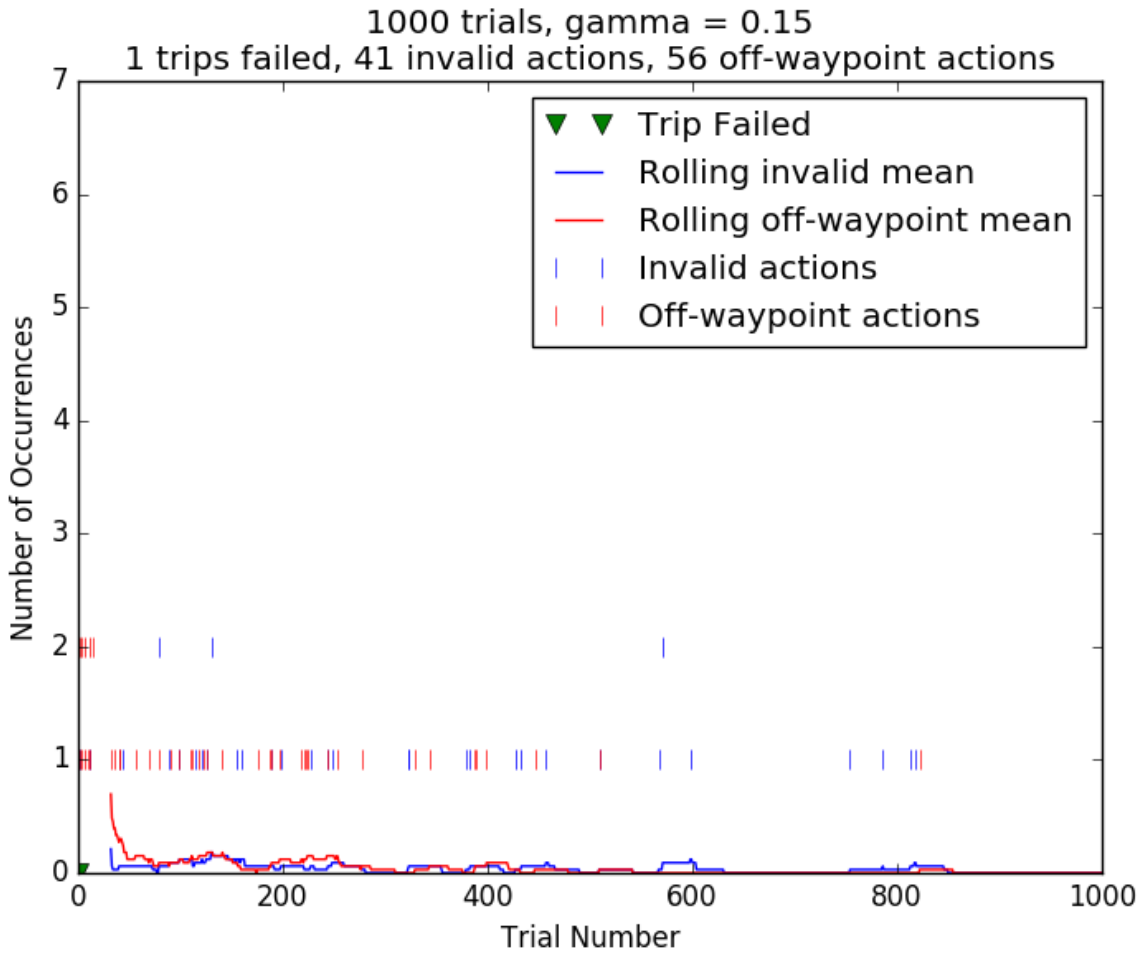

1000 trials, gamma = 0.5
49 trips failed, 59 invalid actions, 3725 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
5
10
15
20
0
200
400
600
800
1000

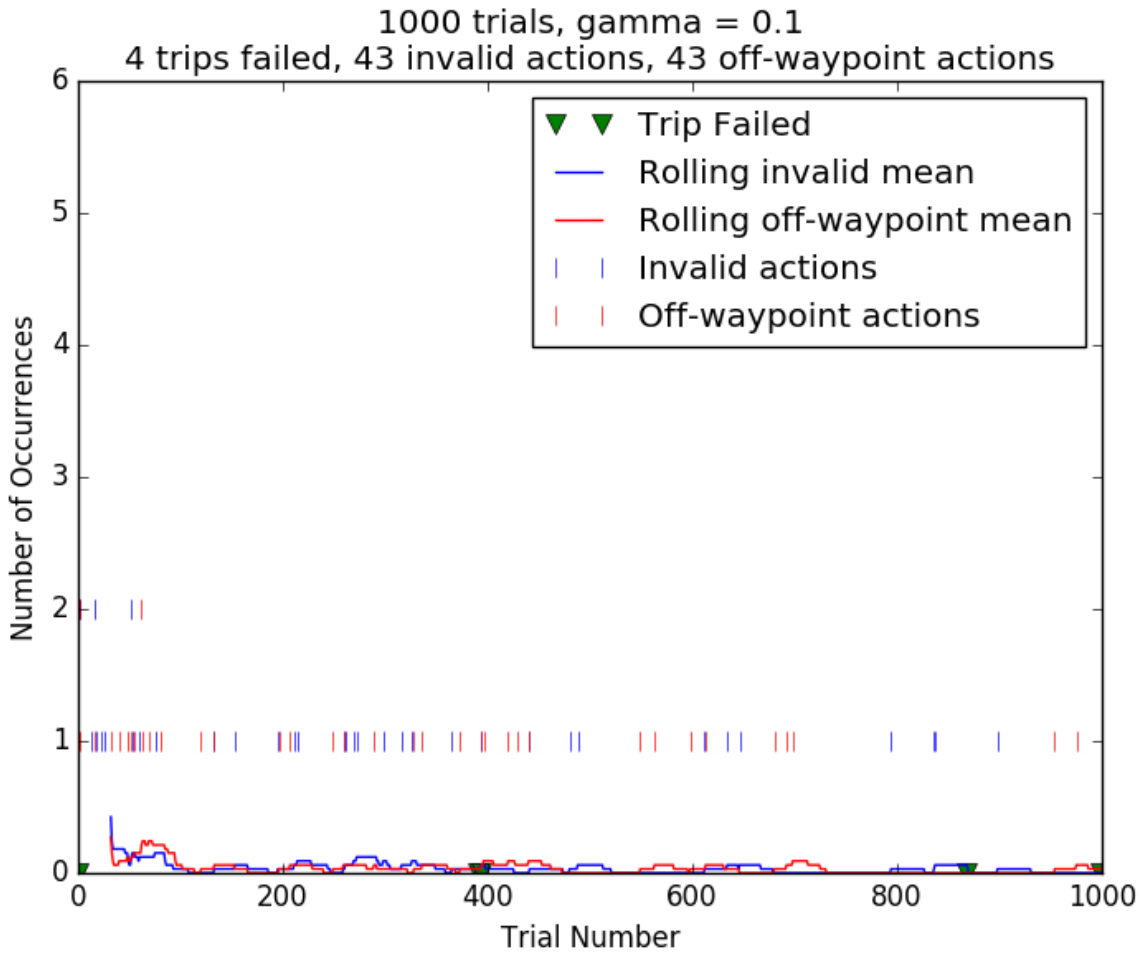

1000 trials, gamma = 0.33
45 trips failed, 60 invalid actions, 3661 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
5
10
15
20
0
200
400
600
800
1000

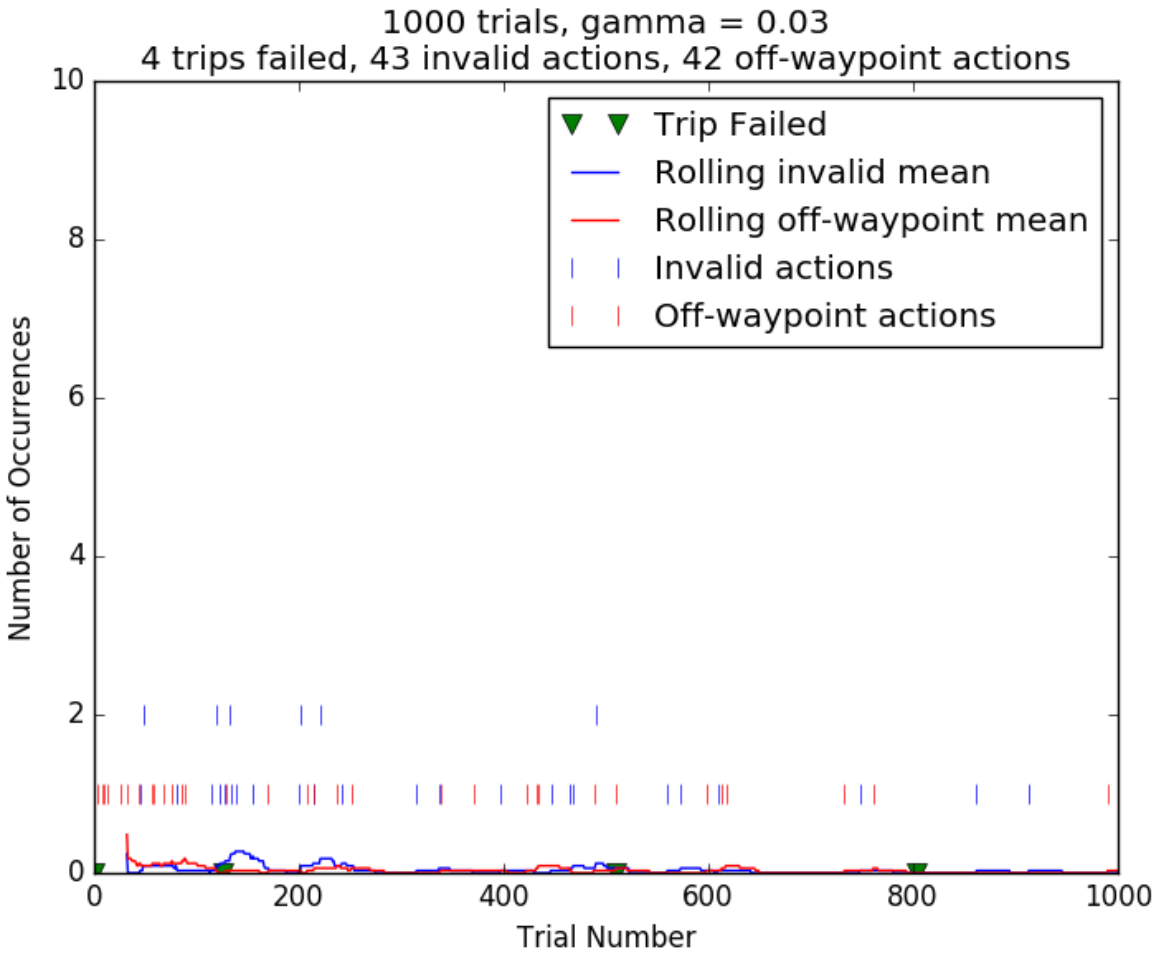
iii. At a `gamma` of 0.2, the tendency to loop begins to diminish.

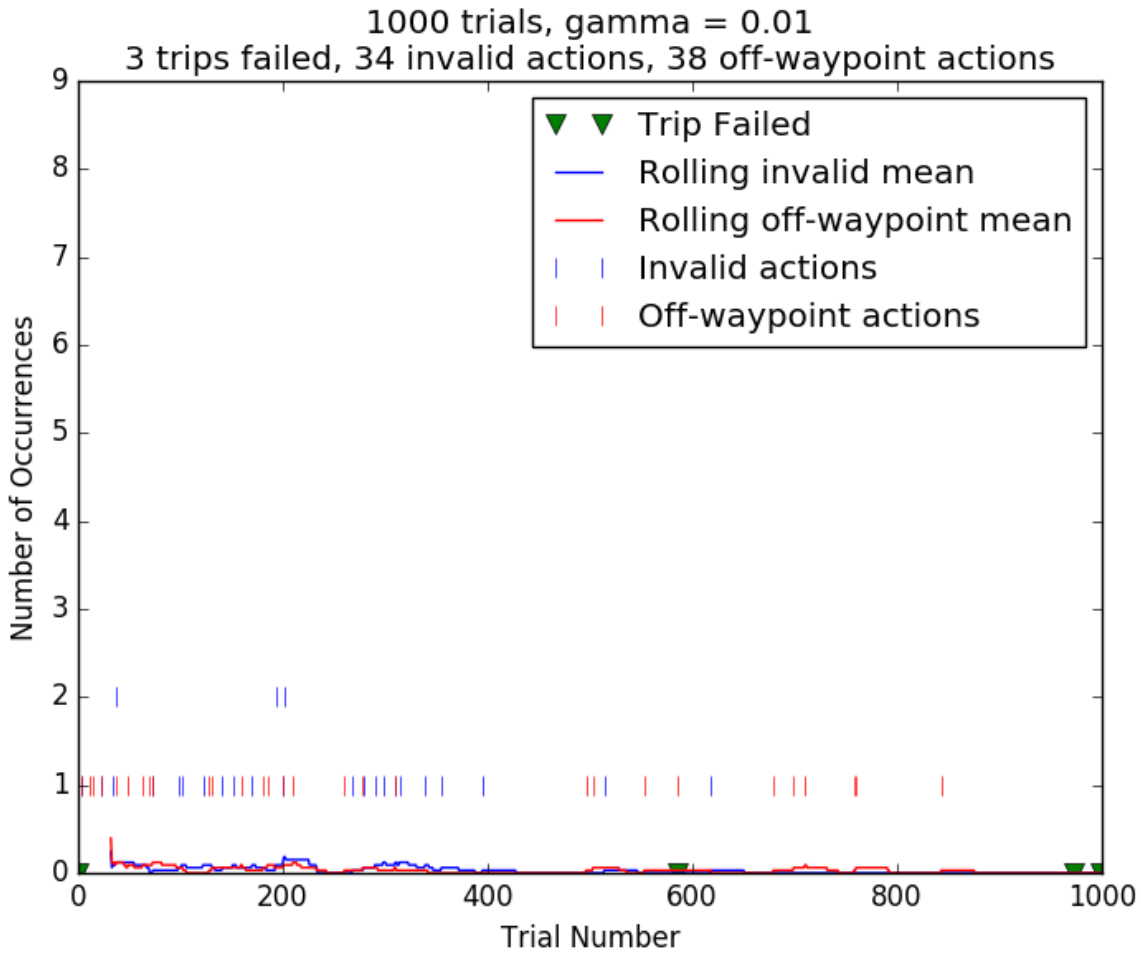


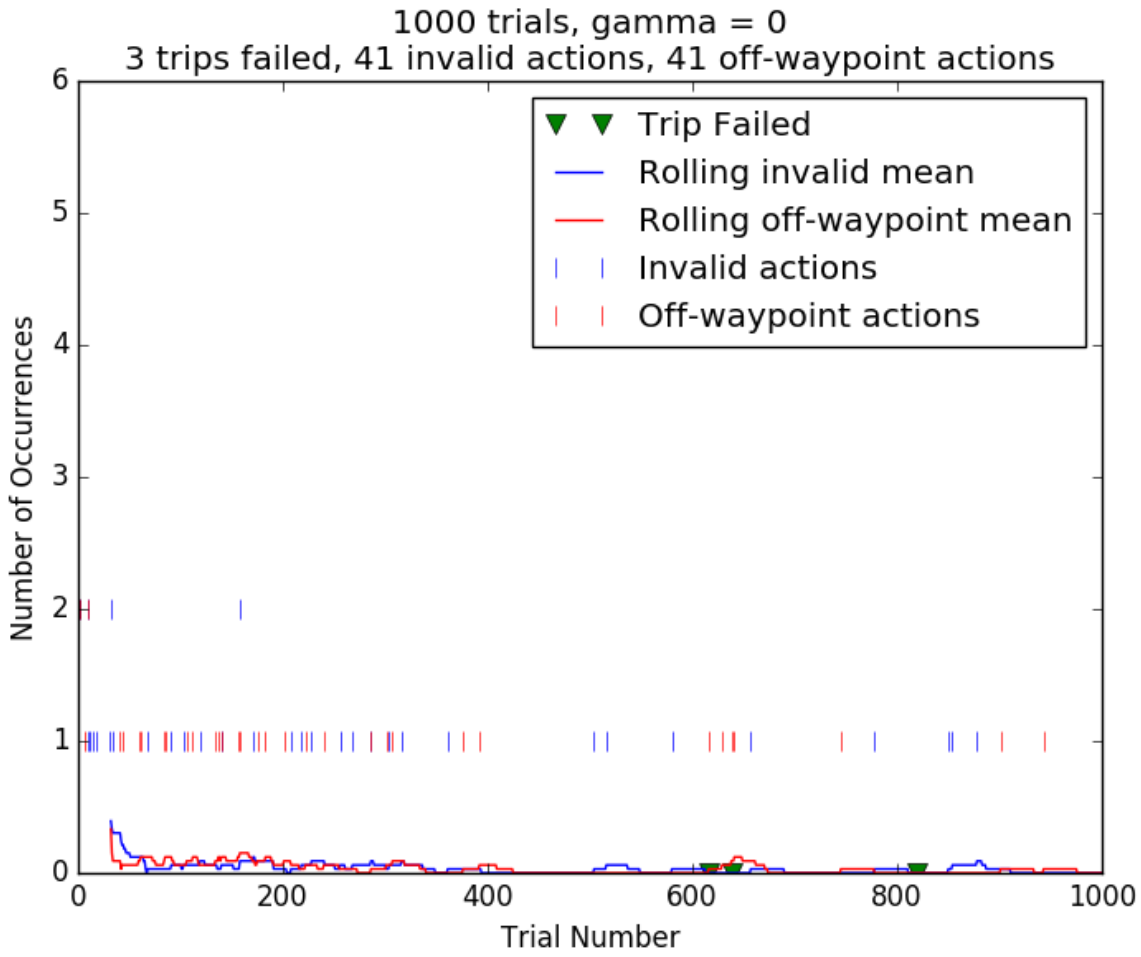
iv. For `gammas` between 0.15 and 0, there is no noticeable difference in behavior. Taking unnecessary actions and taking invalid actions are minimized.


1000 trials, gamma = 0.15
1 trips failed, 41 invalid actions, 56 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
1
2
3
4
5
6
7
0
200
400
600
800
1000


1000 trials, gamma = 0.1
4 trips failed, 43 invalid actions, 43 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
1
2
3
4
5
6
0
200
400
600
800
1000


1000 trials, gamma = 0.03
4 trips failed, 43 invalid actions, 42 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
2
4
6
8
10
0
200
400
600
800
1000


1000 trials, gamma = 0.01
3 trips failed, 34 invalid actions, 38 off-waypoint actions
Trip Failed
Rolling invalid mean
Rolling off-waypoint mean
Invalid actions
Off-waypoint actions
Number of Occurrences
Trial Number
0
1
2
3
4
5
6
7
8
9
0
200
400
600
800
1000



4. The resulting driving agent prefers to identify a straight-line (Manhattan) path and follow it to the destination. This agent does not opportunistically divert to side streets when it finds itself at a red light (the "looping" behaviour discussed aboved). This agent obeys traffic signals, but occasionally acts in a way that would **cause a collision** with other vehicles on the roadway (yikes!). The success rate of this agent rapidly approaches 1.0 over 100 trials.
5. The occasional collisions, I assert, are because of a low number of trials relative to the probability of encountering any given other-vehicle configuration. Since encountering other vehicles is relatively rare, the smartcab doesn't have time in only 100 trials to learn not to ram into them.
6. By increasing the number of trials to 1000, the smartcab eventually encounters enough other-vehicle state-action pairs to "learn" the correct actions to take in those cases.

***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?*

1. To me, an **optimal policy** is one that mirrors Asimov:
    i. The smartcab never collides with another vehicle or allows another vehicle to collide with it,
    ii. it never disobeys traffic laws, and
    iii. it always reaches its destination, so long as doing so is consistent with the above two.
2. The resulting agent quickly approaches, but does not quite achieve, an optimal policy.
    i. After the first few trials, the agent generally attempts to head toward the destination along the straight-line Manhattan path.
    ii. For the next hundred or so trials, the agent will occasionally encounter other vehicles. As it encounters other vehicles rarely, it is uncertain of the action it should take in these cases. This usually results in collisions.

    iii. After the next few hundred trials, the agent has learned enough about other vehicles to avoid running into them most of the time.
    iv. However, it bears mentioning that collisions never fully go away, and neither do off-waypoint actions.
3. While none of the `alpha` or `gamma` values used in this exercise resulted in the above **optimal policy**, when `alpha = 1` and `gamma = 0.03`, the smartcab came the closest to the optimal polocy. In those trials, over 1000 runs, only about 3-4 trips were failed, only about 40 invalid actions were taken, and only about 40 off-waypoint actions were taken. These rates place it well below human drivers in terms of performance, so such an actor should *definitely* not be set loose on the roads. Nevertheless, it is an impressive accomplishment for such a simple algorithm to produce.