CSC 549 - Advanced Topics in Artificial Intelligence

Deep Reinforcement Learning

Programming Assignment 3

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Contents

1 Code Usage

This is a quick description of each of the files and how to use them.

- basis.py - Useless. Meant to be a parent class to fourier and polynomial basis, but I didn't follow through very well with it.
- fourier_basis.py - Generates the coeffecient matrix and has an apply function that will apply the basis to the input.
- make_images.py - After sarsa_lambda.py makes the numpy arrays and saves them to results, make_images will read those in to generate the matplotlib pyplot figures for the writeup.
- mc.py - This is the simulation for the mountain car. If you run this file directly, it will render an animation to represent what the mountain car is doing. You can change between animate and animate2 in the main function, but that's not particularly helpful, especially since animate2 does not have the offset to make the bottom of the mountain at the proper spot.
- polynomial_basis.py - Hypothetically correct, but actually using it is impractical because it makes the episodes very very slow.
- render.py - This is a scratch file that I play around with to test things like how the parameters affect the performance. Currently it's set to test a few variations of gamma.
- numerical_analysis.py - This is a scratch file that I play around with to test things like how the parameters affect the performance. Currently it's set to test a few variations of gamma.
- sarsa_lambda.py - This is the most interesting file! This one will do a bunch of runs, average them, save the results to files for make_images.py to make images for. For your sanity I recommend lowering the contants at the top of the file.

  Parameters:

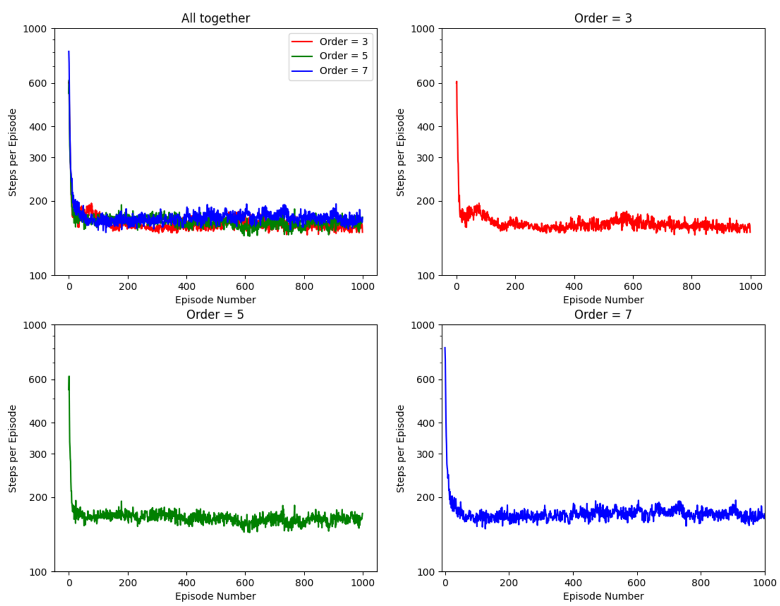
  - "--animate" - Will run the algorithm with an animation running. Plays 250 frames each time (instead of stopping with the episode). I recommend having a run that you save the agent's weights at least once. Note that this only does the fourier basis with an order of 3.
  - "--save-res" - Used to save the number of steps in an episode to files for plotting learning curves.
  - "--save-w" - Used to save the average of the weights at the end of all of the runs.
  - "--load-w" - Used to load saved weights. If not found, will throw an error and exit with -1.

The ideal run cycle for your interests should be something like:

```
$ python3 sarsa_lambda --save-w
   <... various output ...>
$ python3 sarsa_lambda --load-w --animate
```

2 Required answers

1. Learning curves, $\epsilon = 0.03$:



Note that while alpha is contast, it is not a scalar. Alpha was set in accordance to what the research paper had their alpha, which is determined by the c vector of the basis:

$$\vec{\alpha} = \frac{0.001}{||\vec{c}||_2}$$

This graphic shows the learning curves for orders $3, 5, 7$ and $\gamma = 1, \lambda = 0.9$, where λ is the trace decay rate and γ is the discount factor.

Based off of these graphics, it seems that the agent learns the environment ridiculously quickly. I suspect that is just by nature of what a near perfect solution may be (which is to just move in the direction of the velocity). The agent consistently gets under 200 steps per episode after about 5 episodes, which I admit is rather suspeicious but I can't see anything wrong with it, I just think it's a very easy problem for the agent.

Anyway, to do some numerical analysis (specifically on an order of 3), it would seem the standard deviation after it's learned the solution is about 8 steps, with a mean of 161 steps per episode. This is very neat, and tells me that a little under 70% of the time the agent can finish the episode in 161 ± 8 steps!

The fastest episode (min of steps per episode) was 145 steps, and the maximum after the 25th episode was 195.45 (remember that this is averaged over 100 runs).

You can find more detailed information by looking at 'numerical_analysis.py', if you so desire.

In hind sight, averaging the information over 100 runs then doing this analysis somewhat ruins the point of the standard deviation...

2. Surface plot of the value function. I show the surface plot of all three value functions here, but they look very similar.
   You can look in "make_image.py" for details on how these images are made.

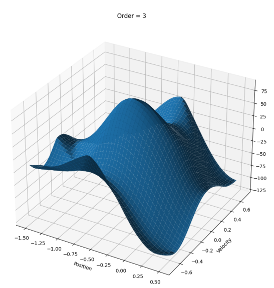


Figure 1: Order = 3

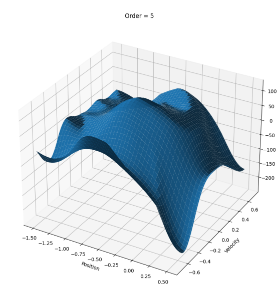


Figure 2: Order = 5

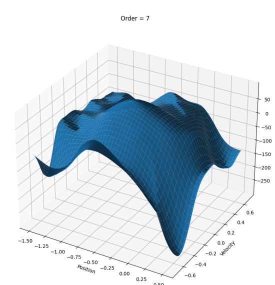


Figure 3: Order = 7

I will point out that it looks different from the Sutton and Barto value function plots. However, I'm confident that this is due to the face that these are rendered from an agent that is using a fourier basis. This can be seen in the nature of the curves, where there is a lightly visible periodic nature to the curves on both dimensions (which you can better see if you render it yourself and use the pyplot 3d figure to rotate them around and see what's going on). I at one point had a bug in my code where instead of calculating the value with the mesh on the proper state space, the state space was much too large. I didn't save any of the images, however it was very apparent the periodic nature of the bases from that.

Also if you just read through the paper to figure out how it works it's easy to know what's going on. The agent just learns what weights to associate with what cosine coefficients (not quite the right word but just the c array in fourier_basis.py) are most relevant. Obviously by learning those the output is going to look similar to a cosine wave. Actually it is very similar to when you do a fourier series of a function (such as with sound processing) and whenever there's a proper signal at a frequency there's a spike there in the output. Very cool.

3. (a) What would happen in $\gamma < 1$ and the solution was many steps long? When gamma is less than 1, the episodes just don't want to finish. I tested this with a gamma of .99 it finished a little slower than normal, but when I did 0.98 it got through very few episodes. It's also worth noting that with $\gamma = 0.99$, the was much more variance in the episode length.

   My guess at what is going on is that the gamme being lower messes with the accuracy of the Q values as well as slowing the propogation of the reward throught the state actions space. This seems to conflict to some degree with how the z vector is propogating the reward after getting a reward, but with how the gamma is applied, it seems to make sense. Running through the algorithm on a whiteboard to try to figure out what is going on did not elucidate the answer to the question to me, so this is my best guess.

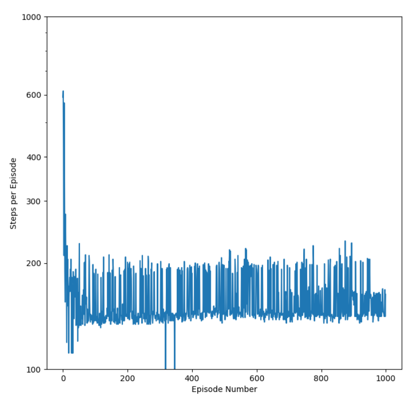


Figure 4: $\gamma = 1$

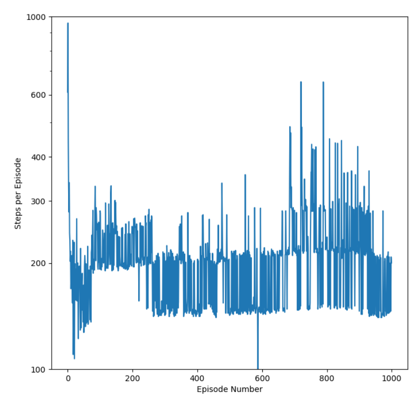


Figure 5: $\gamma = .99$

   (b) What would happen if we had a zero step cost and a positive goal reward, for the case where $\gamma = 1$, and the case where $\gamma < 1$?

   - After testing this myself, for some reason after the first episode it just didn't want to finish. It had gotten to nearly a million steps before I stopped it from running. My guess at what is going on: After the first episode (which was finished by choosing completely random actions), it only gleaned enough information to know that when it was on the right side of the bottom it was able to get positive reward by moving rightward.
     This caused the agent to dislike moving left. Thus it would get as far up the hill as it could, but then once it started moving

backwards it was essentially applying the brakes until it hit the bottom, where it would start again (since the exploration chance is too low, it never broke free from this). When compared against a negative reward for every action taken, even if the agent had started along the path of only trying to go right, it would have eventually given the state-action values enough negative values for low rightward velocities (and even negative velocities) that it realizes it needs to try going to the left first (which I'm fairly certain is what was always happening, even when it was initially choosing randomly, because when I made the change the first episode usually takes around 40000 steps. That is significantly greater than the average starting episode length of barely greater than 1000).

The negative step cost apparently does wonders for teaching the agent; however I wasn't able to learn much about how gamma affects learning since regardless of the reward function having a gamma of less than 1 just makes the agent refuse to learn, apparently.

- When $\gamma < 1$, the agent did nothing different. Identical results.

3 Code base

This section inlvolves my notes on the code involved in this assignment. It won't give you any value, however it will help me to gain a better understanding of what I've done.

3.1 Mountain Car

I won't fully describe the code here, it is simple and you can read about the algorithm in Sutton and Barto's Introduction to Reinforcement Learning on page 245.

The basics is that it is meant to simulate an underpowered vehicle that needs to travel up the hill.

It simulates being underpowered by involving a cos with the x position when you apply force to the vehice. Underpowered is also accomplished by bounding the velocity to rather low values.

The hill, counter-intuitively, is actually centered at roughly $\frac{-\pi}{2}$. To make it exactly $-\frac{\pi}{2}$, you would need to replace the 3 in $\cos 3 * x$ with a π. The reason this is counter intuitive is that it seems the cosine would indicate where the hill is, but remember that it is actually to calculate how to manipulate the new velocity after applying a force. When you have the position of $\frac{-1}{2}$, it gives the $\cos 3 * x$ a result of 0, which means it doesn't subtract anything from how the force would affect the new velocity. You may think that it wouldn't do what you want it to on certain positions since cosine has both negative and positive outputs, but this actually makes it work out even better (especially with the forces applicable including -1 and 1, which would make the signs work together in a way that makes sense in a simulation).

3.2 Bases

These are wild! Basically the concept with having a fourier basis is that you're doing a kind of fourier series on the state (where action is considered a part of the state in my implementation; an alternative would be to have several weight vectors for each possible action, like what Jonathan mentioned he did when I was discussing the project with him). What this is basically doing is having the agent learn which "harmonics" are most relevant to the agent to be able to figure out what it needs to do. There's a neat trick that the paper describes where they realized they can cut the expansion in half since the problem is "symetric", which I don't quite understand but I'm guessing that it is based in the fact that the simulation space is centered around a point (which was described in the paper) and would be just as valid to have the goal on the left bound as the right.

3.3 Sarsa Lambda

I don't have much insight to add that wasn't taught in the textbook or lectures.

The gist if it is that the agent is learning weights for the basis function instead of the Q values for each state action pair, which does not scale well with continuous state (and action) spaces. There's an eligibility trace, $\vec{z}$, that helps the agent to more accurately update the weights when it gets a good reward (0 in this case).

Sadly despite my best attempts I cannot quite figure out how the linear algebra was derived. I am unable to follow what the motivation is behind many of the calculations beyond being able to guess at what is going on (such as $\vec{w}^T \times \vec{x}$ would be applying weights to the "input", to use terms I'm familiar with).