Reinforcement Learning: Midterm Project

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Contents

1 Introduction

In the course of this class, one of the primary reinforcement learning algorithms we have studied is $TD(\lambda)$. In this report, we will review and attempt to implement portions of Richard Sutton's 1988 paper called Learning to Predict by the Methods of Temporal Differences. Our focus will be an implementation of the $TD(\lambda)$ algorithm and the reproduction of figures 3, 4 and 5 from the paper.

2 Temporal Differences

In this section, I will attempt to give a quick overview of how Temporal Difference Learning algorithms work and what advantages they might have over other algorithms. A major advantage that TD procedures have is the ability to be implemented incrementally. This gives the algorithms advantages over other methods like supervised learning since they require far less computational power.

A confusing part of the paper was the introduction of the variable ω. ω stands for the a vector of modifiable weights. This ω helps us keep track of the changes through the incremental sequences. A sequence is a change in state off the mdp that we are attempting to model. After each sequence we observe, we will generate an observation $\Delta\omega_t$. This process can be observed in the following equation, which was equation one in the paper.

$$\omega \leftarrow \omega + \sum_{t=1}^{m} \Delta\omega_t \tag{1}$$

$TD(\lambda)$ is a class of TD procedures that make greater alterations to more recent predictions. In particular, we know that $TD(\lambda)$ will consider exponential weighting with recency. $TD(\lambda)$ is given by equation 4 from the paper which is stated below.

$$\Delta\omega_t = \alpha(P_{t+1} - P_t) \sum_{k=1}^{T} \lambda^{t-k} \nabla_\omega P_k \tag{2}$$

3 Experments Replicated

3.1 Overview of Bounded Random Walk Problem

The experiments were conducted on a simple dynamical system that generates bounded random walks. Bound random walks take random steps either left or right until the sequence hits a boundary. The movements left or right are both equally probable in our example. We describe the possible states will the letters $A - G$. The bounds can be arbitrary, but for this example the left side will be A, and the right side is G.

3.2 Expirement Data

Sutton's paper gives good instructions on how to construct the training sets, however he is ambiguous on certain details. In order to replicate the experiment, I randomly generated 100 training sets, each containing 10 sequences. A sequence is the set of states that the mdp will go through until the mdp ends at a bound. For example, the following is a sequnce, DEFEDEDEFG. The much longer string DEFEDCDEFEFEDEFEDEFEDCDCDCBCDCDCBCDEDCBA would be considered a sequence as well. For these experiments, Sutton does not state a limit to the length of a sequence, or a minimum for the sequence.

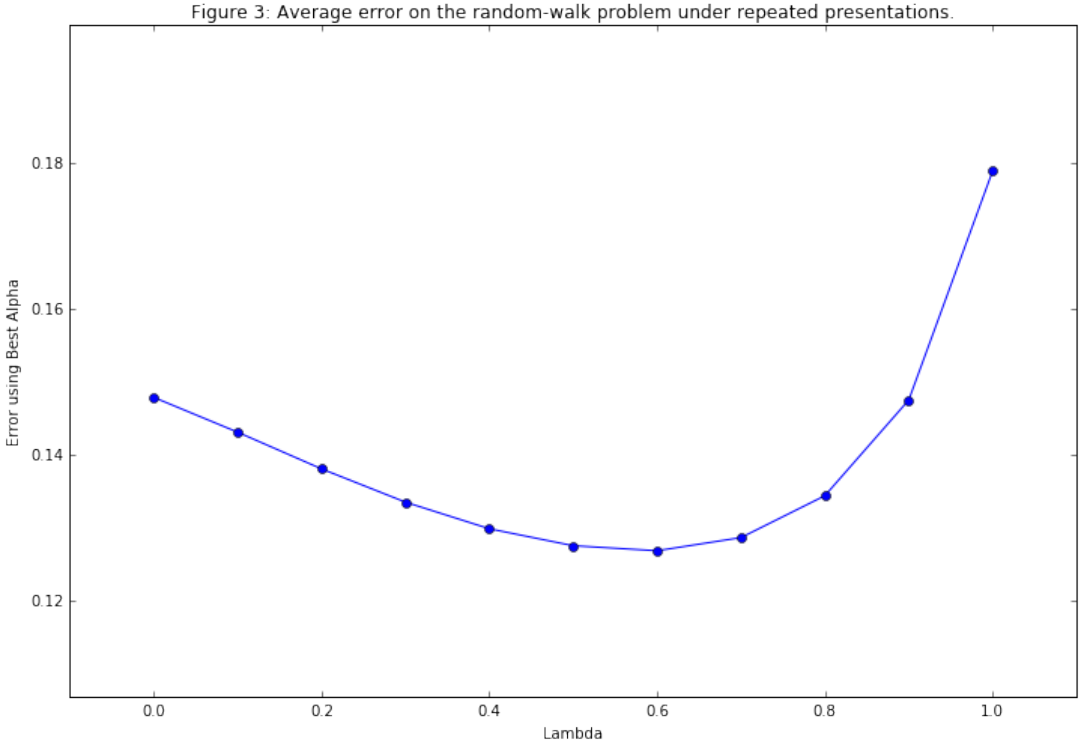
Now as I explained above, $TD(\lambda)$ makes greater alterations to more recent predictions. We know from equation 4, that the exponent on lambda will get large as we get farther along in the sequence. Now in the case of $TD(1)$, we know that 1 rasied to any power is 1. So in that case every member of the sequence would be weighted the same. So would a distribution of training sets with longer sequences effect our results?

3.3 Experiment 1

We used the training sets described above for experiments one. But, we do not update the weight vector after each sequence as indicated by our equation (1). Instead, we perform what the paper calls the repeated presentations training paradigm. We keep iterating through the training set until we no longer see a change in $\Delta\omega$. Once we converge, we will get the RSME error between our weights and the ideal weights. The ideal weights are $[\frac{1}{6}, \frac{1}{3}, \frac{1}{2}, \frac{2}{3}, \frac{5}{6}]$.

3.3.1 Figure 3

The following is our replication of Figure 3. This graph shows the average RMSE error over the 100 test cases versus the increasing value for lambda. We assume that the weights are initially set with random weights.

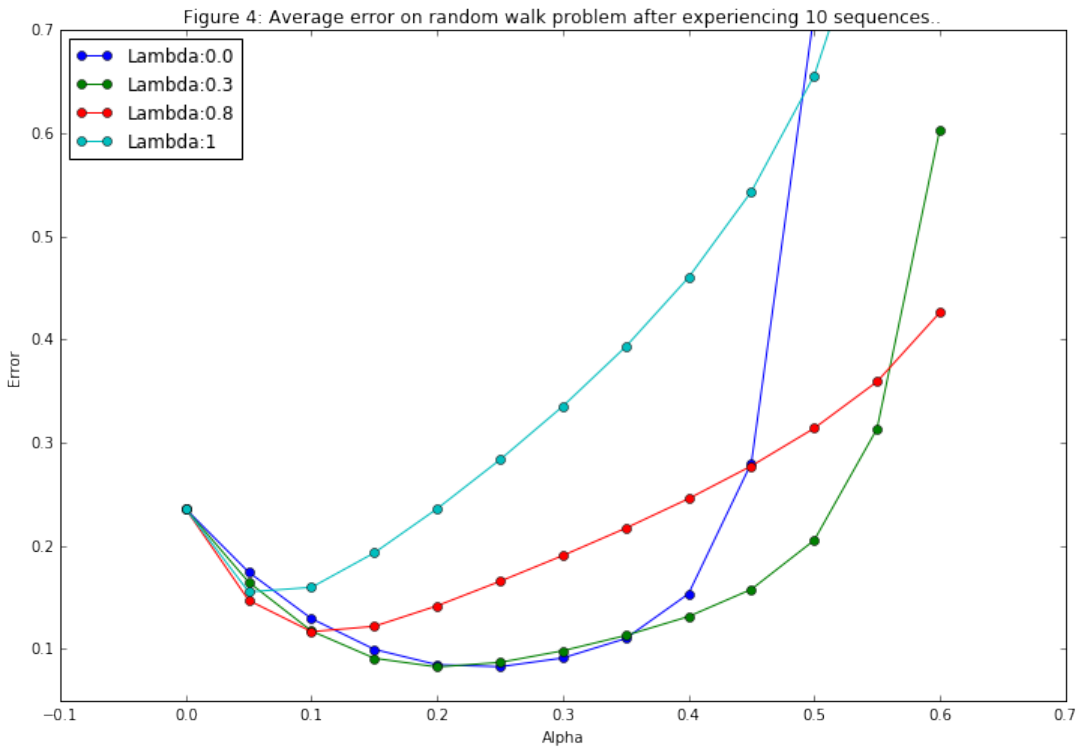


3.4 Experiment 2

The second experiment will examine the learning rate when we only view the training set exactly once. We only show each training set only onces, and weights are updated like the equation (1). We also use a range of alpha values, instead of defaulting to 0.01 like in experiment one. We also will default the value of ω to $[0.5, 0.5, 0.5, 0.5, 0.5]$.

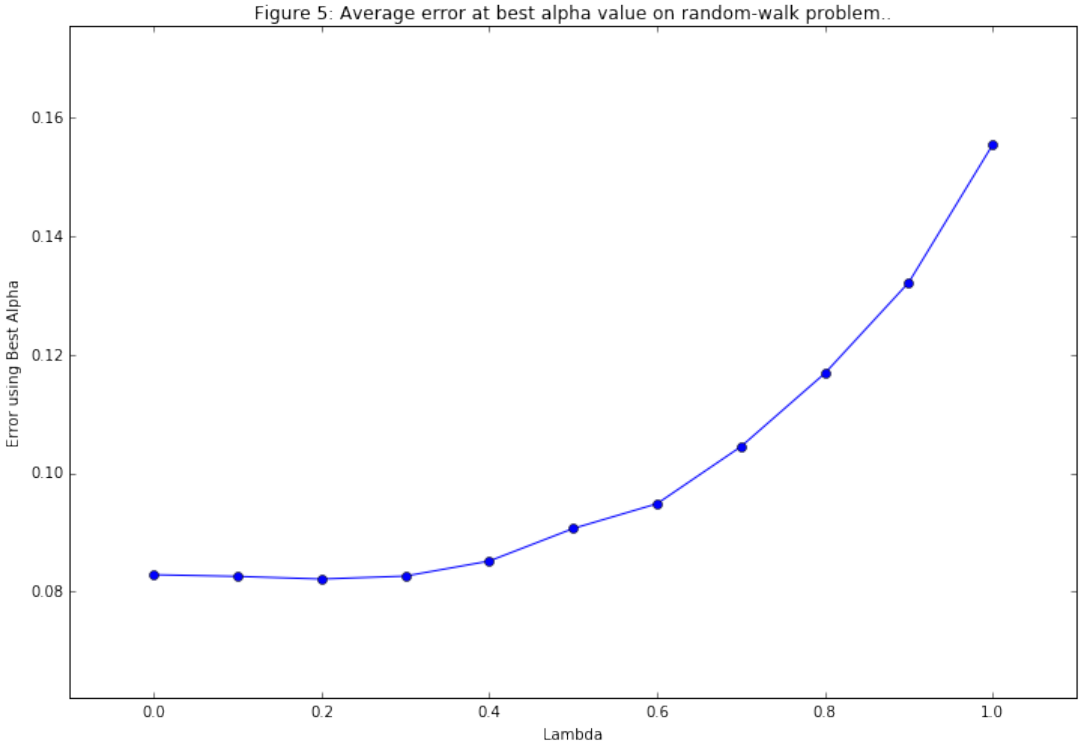
3.4.1 Figure 4

The following is our replication for figure 4. This figure shows the average error on a random walk after experiencing 10 sequences, or one training set. The $\lambda = 1$ is the Widrow-Hoff supervised-learning procedure.



3.4.2 Figure 5

THe following is our replication of Figure 5 from the paper. This figure shows the best error level achieved for each λ value. We pulled the best lambda values from the data of figure 4 to yield the lowest error for that lambda value.



4 Conclusion

4.1 How well do our results match the Paper?

We were significantly happy with our results even if our results where not exact. We could easily observe the trends in figures 4, 5, and 6. Are their signficant differences in our Results compared to the Paper? Yes, we did observe some differences.

Figure 3 was probably our most accurate graph when concerning change in error as compared to the paper. However, our std was only around 0.02 for each iteration. we do notice a small in error in from 0.0 to 0.6 then a more signficant rise toward the end.

For figure 4, we notice while alpha is smaller our graph is more accurate. We do have very large error for $\lambda = 1$, and $\lambda = 0$ for $\alpha > 0.5$. However, we are happy that the increases in error as α is increased are in sync with the paper. $\lambda = 1$ increases first, followed by $\lambda = 0.8$, then $\lambda = 0$ and finally $\lambda = 0.3$.

The last figure we will examine is figure 5. We also had slightly better error results for each value of lambda, as compared to our paper. For example, we can see our value at $\lambda = 0$ has an average error of 0.08 compared to 0.11. If you look at $\lambda = 1$, we received an error around 0.16 compared to arround 0.21 for the paper. In general, I am happy that we achieved a simlar slope of the graph as compared to the paper.

4.2 Any pitfalls observed trying to replicate the experiment from the paper?

There was considerable confusion for me to implement experiment 1. I initially implemented that expirement as what eventually became experiment 2. I also had trouble picking a correct α for experiment 1. I initally thought that 0.10 was a small α, however I actually got convergence once I picked 0.01.

4.3 What steps did you take to overcome those pitfalls?

I generally got through any pitfalls by trial and error. We needed a small alpha value in experiment one, otherwise we wouldn't converge. We would get very large differences between the weights.

4.4 What assumptions did you make, and why?

We made a couple major assumptions. We do not believe that a minimum or maximum length of a sequence is set by the paper. However, we do believe it is reasonable to assume a random distribution of lengths.

For inital values, there was some leeway as Sutton didn't explictly state some of those values. We assumed that $\Delta\omega$ is initally set to $[0, 0, 0, 0, 0]$. Also in experiment one, I assumed that the ω vector could be set to random weights [0 - 1].

Are these assumptions justified? I would believe so. We generally needed to make some guesses to make the algorithm even work. I think Sutton would have told if the length of a sequence was specfic. $\Delta\omega$ should start out at $[0, 0, 0, 0, 0]$, otherwise the algorithm might not converge.