Machine Learning Engineer Nanodegree

Capstone Project

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August 4th, 2017

I. Definition

Project Overview

This project will attempt to teach a computer (reinforcement learning agent) how to play blackjack and beat the average casino player. Blackjack [1] also known as twenty-one, is the most widely played casino banking game in the world. It is a comparing card game between a player and dealer, meaning players compete against the dealer but not against other players. Mathematicians have been researching Blackjack for over 60 years [2] because of its simple rules, its inherent random nature, and the abundance of "prior" information available to an observant player [3].

Problem Statement

The aim of this project is to produce a Blackjack strategy that will earn more than the average casino player.

Blackjack Rules for this project

Blackjack is a card game where the goal is to obtain cards that sum to as near as possible to 21 without going over. They're playing against a fixed dealer.
Here are the rules of the game:

Face cards (Jack, Queen, King) have point value 10. Aces can either count as 11 or 1, and it's called 'usable' at 11. This game is placed with an infinite deck (or with replacement). The game starts with each (player and dealer) having one face up and one face down card.

The player can request additional cards until they decide to stop or exceed 21 (bust). After the player sticks, the dealer reveals their facedown card, and draws until their sum is 17 or greater. If the dealer goes bust, the player wins. If neither player nor dealer busts, the outcome (win, lose, draw) is decided by whose sum is closer to 21.

The reward for winning is +1, drawing is 0, and losing is -1.

Strategy

A reinforcement learning technique, Q-learning, will be used to solve this problem. A Q-table is built for all state-action pairs and after taking an action at the end of each round of the game, its corresponding entry in the Q-table is updated based on the reward received. The learning process is stopped when the agent has sufficiently explored the environment.

At this point, we would have the optimized Q-table which is the strategy the agent has learned to play blackjack.

Metrics

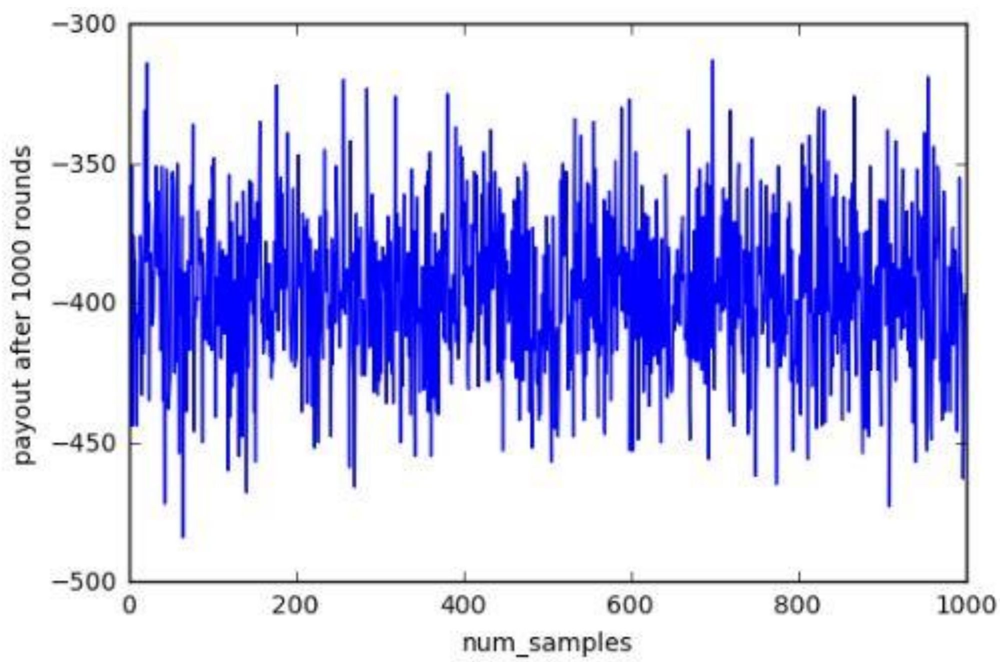
As there is a payout awarded at the end of each round of the game, it is the obvious choice as a performance metric. To compare the performance of different strategies, these strategies should be applied over a large number of rounds to get close to their true payouts. Hence, the average payout after 1000 rounds of the game repeated 1000 times will be used to compare the simulated performance of the average casino player and that of the trained agent.

II. Analysis

Data Exploration

This project will make use of Open AI Gym's Blackjack environment.

The actions and corresponding payouts of the average casino player are simulated using the Open AI blackjack environment mentioned above. Each round, either hit or stick is chosen at random. Over 1000 rounds, the average payout was found to be around -400 as seen below.




```
Average payout after 1000 rounds is -395.943
```

average payout after 1000 rounds for average player

Algorithms and Techniques

Decaying epsilon-greedy Q-learning will be used to solve this problem as the number of states is reasonably small.
- Possible values of sum of agent's cards [2, 21] = 20 - Face up card of dealer [1, 10] = 10 - Player has usable card [0, 1] = 2

Size of the state space is 400.

The agent maintains a Q-table which contains an entry for each state and the corresponding Q values for each action possible. When in a particular state of the environment, the agent looks up the maximum Q value for that state and takes the corresponding action. If a state is being reached for the first time, the Q value for each action of that state is initialized to 0 and the action in this case is random as all Q values for the new state are 0. The Q values are then updated based on the reward obtained from the environment using the below formula [4].

$$Q(s_t, a_t) \leftarrow \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \left(\overbrace{\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}}^{\text{learned value}} - \underbrace{Q(s_t, a_t)}_{\text{old value}} \right)$$

Q = Q(1-alpha) + alpha(reward + discount utility of next observation)

Learning rate (alpha)

The agent has to learn based on the reward for a particular action and the learning rate determines how much the agent learns. As can be seen above formula, *alpha*=0 will make the agent not learn anything while *alpha*=1 will make the agent consider only the most recent information [4].

Discount factor (gamma)

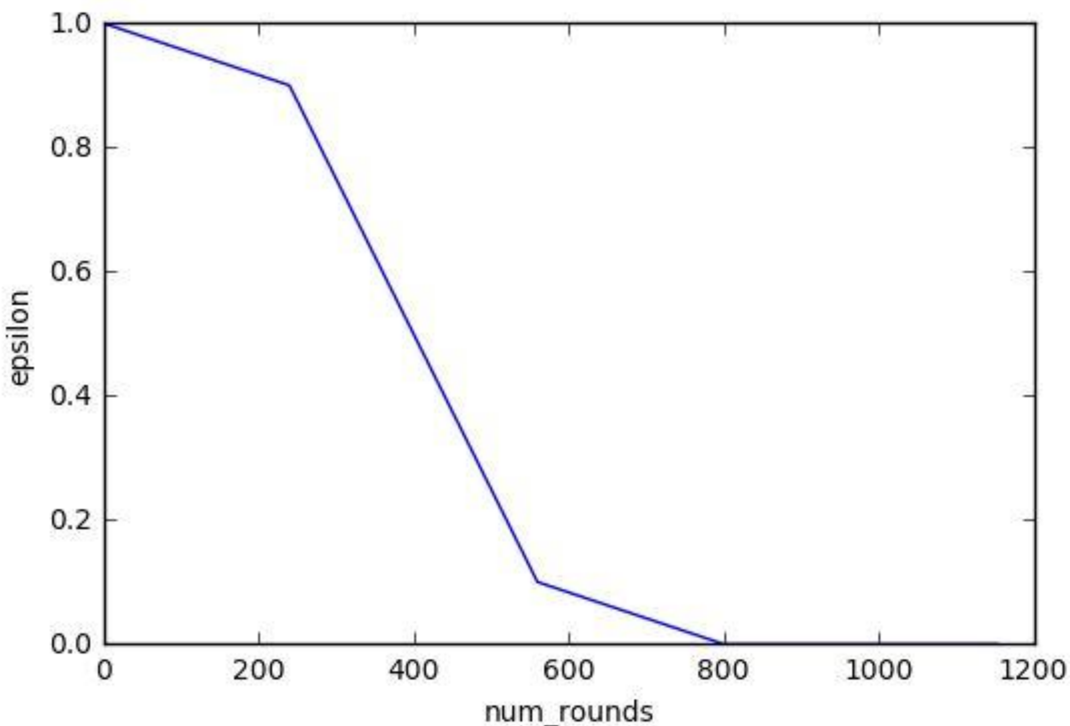
The discount factor *gamma* determines the importance of future rewards. A factor of 0 will make the agent "myopic" (or short-sighted) by only considering current rewards, while a factor approaching 1 will make it strive for a long-term high reward [4].

Exploration factor (epsilon)

To ensure the agent learns enough about the environment, it has to explore the environment enough. *epsilon* determines how much the agent explores by forcing the agent to take a random action with probability *epsilon*. This ensures the agent reaches new states it hasn't learned to reach before. However, as the agent learns enough about the environment, it has to minimize exploring and thus a decaying value of *epsilon* is used. Its value should remain high enough for a while so the agent can sufficiently explore the environment before reducing slowly to a *tolerance* value. Once epsilon reaches this tolerance value, the exploration stops and the learning is also stopped by making *alpha* 0.

Number of episodes to train

This is a parameter I added to easily tweak the rate of decay of *epsilon* depending on the number of episodes used to teach the agent. *epsilon* drops to 90% of its initial value in the first 30% of `num_episodes_to_train`. *epsilon* then drops to 10% of its initial value in the next 40% of `num_episodes_to_train`. *epsilon* finally becomes 0 in the final 30% of `num_episodes_to_train`. Here 0 is the tolerance value at which we stop the learning process of the agent by setting *alpha* to 0. *epsilon* value decays like in the below graph when the `num_episodes_to_train=800`.



epsilon_decay

Benchmark

Assuming the average player uses no strategy and makes a random choice each time (most likely while drunk), the payout at the end of 1000 rounds is simulated in the Open AI environment. This would be the benchmark against which the trained agent in this project will be compared. This exact scenario was simulated above and the benchmark value was found to be -395.9.

III. Methodology

Data Preprocessing

As the Open AI blackjack environment already provided data in a format suitable to be used with the Q-learning algorithm discussed above, no data preprocessing is necessary.

Implementation

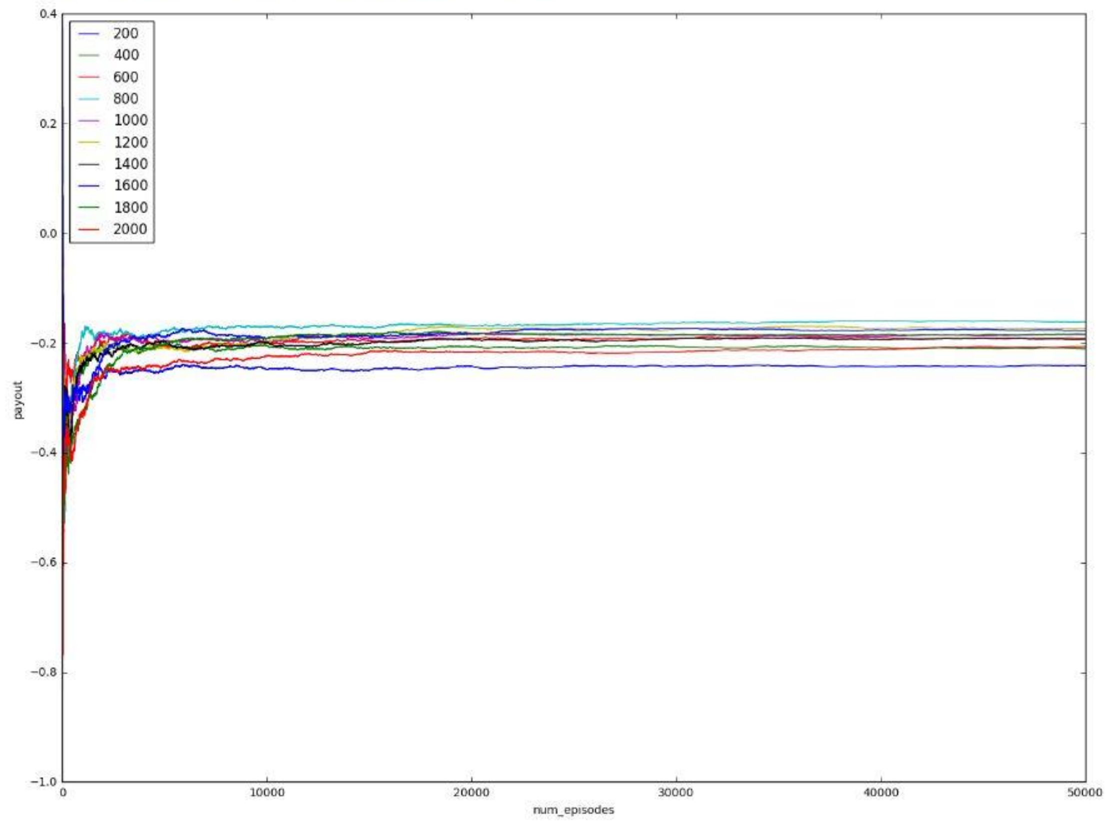
The algorithm described above in the **Algorithms and Techniques** section is implemented using Python. The code for this is provided in the accompanying jupyter notebook.

The Agent can be created by passing the environment and the parameters discussed above. It has a `update_parameters()` function which updates *epsilon* and *alpha* at the end of each action. There is a `choose_action()` function that determines which action to take based on the *epsilon* and the values in the Q-table. This action results in a payout from the environment passed on to the agent's `learn()` function which updates the Q values in the table.

Refinement

Only one custom parameter (`num_episodes_to_train`) was tweaked and suitable choices were made for the others. Initial value of *epsilon* was chosen to be its maximum value of 1. *alpha* was chosen to a common value of 0.5 and the discount factor *gamma* was chosen to be 0.2 to keep the agent short-sighted as most of the rounds finish in one, two or three states. The optimum value for `num_episodes_to_train` was searched over a list of values and chosen to be 800 based on below image. This is because the average payout is highest for this value.

```
Average payout after 1000 rounds after training for 200 episodes is -241.18
Average payout after 1000 rounds after training for 400 episodes is -210.5
Average payout after 1000 rounds after training for 600 episodes is -191.04
Average payout after 1000 rounds after training for 800 episodes is -161.44
Average payout after 1000 rounds after training for 1000 episodes is -184.24
Average payout after 1000 rounds after training for 1200 episodes is -172.62
Average payout after 1000 rounds after training for 1400 episodes is -192.8
Average payout after 1000 rounds after training for 1600 episodes is -177.08
Average payout after 1000 rounds after training for 1800 episodes is -184.14
Average payout after 1000 rounds after training for 2000 episodes is -206.22
```



Search for optimum value of num_episodes_to_train

IV. Results

Model Evaluation and Validation

The agent is created using the parameters chosen above and the simulations are run 1000 times - each time for 1000 rounds of the game. The agent learns for the first 800 rounds and makes its decisions during the remaining simulations based on its final Q-table.

The learned model achieves an average payout per 1000 rounds of around **-125** and doing so over a large number of simulations proves the robustness of the model as such a large sample tests the model thoroughly. However, the payout over 1000 rounds of the game is likely to vary a significant amount due to the inherent randomness of the game.

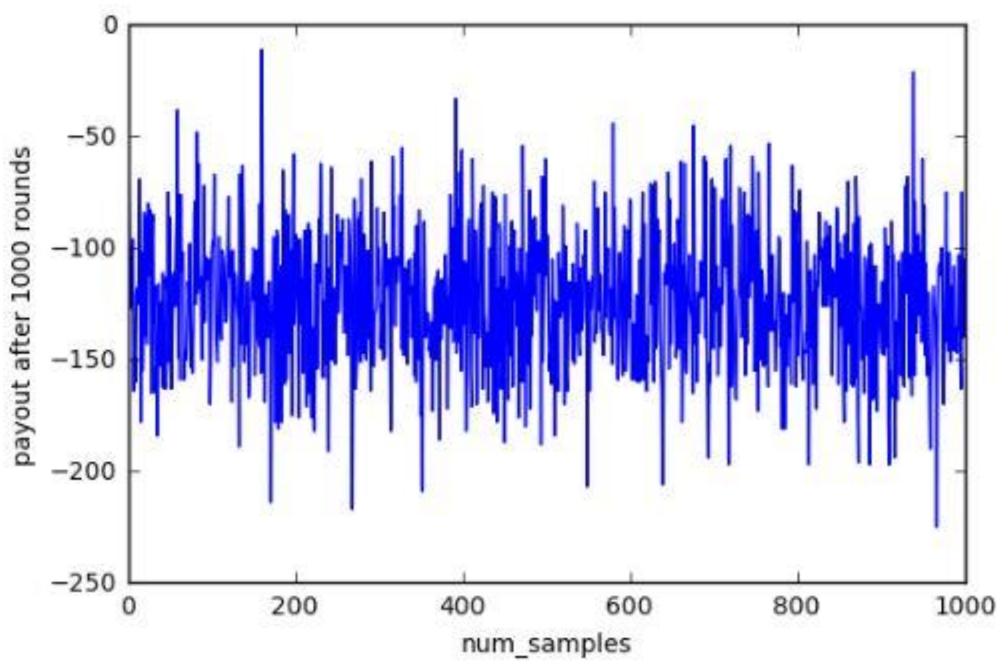
Justification

Over 1000 rounds, the average payout was found to be much higher than the benchmark -400 with a value of around -125. This is a significant increase in the payout and proves that the agent has learned to satisfactorily play the game much better than the average casino player.

V. Conclusion

Free-Form Visualization

Below is the average payout achieved by the agent over 1000 trials of playing 1000 rounds of the game. As can be seen, the average payout/1000 rounds mostly lies between -100 and -150 and this fluctuation is an indication of the role luck/chance plays in the game.




```
Average payout after 1000 rounds is -123.54
```

average payout after 1000 rounds for trained agent

Reflection

In this project, a learning agent successfully learned how to play blackjack and collect a payout much better than the average casino player. Q-learning was used by the agent to continuously update its Q-table during the learning process based on the action taken and the corresponding reward received. The agent first explores the environment rapidly by taking random decisions before relying on its Q-table to make appropriate decisions.

It was very interesting to see a fairly simple algorithm learn a satisfactory strategy to play blackjack. The code for the agent is general enough to be used as a starting point to solve other environments from Open AI's gym that have small state spaces.

It was a bit frustrating that the trained agent could not match the performance of the strategies described in [5] despite tweaking the parameters a fair bit.

Improvement

Although the state space is fairly small, using a neural network as a function approximator might result in better payouts at the cost of implementation complexity and processing power/time.

Newer techniques like Double Q-learning or Experience Replay could be tested to see if they improve performance. I recently came across these and should learn more about these to see if they fit this problem.

'Normal Play Strategy' from figure 11 here [5] produces a better payout of around **-100** per 1000 rounds in this environment so there is certainly room for improvement.

References

[1] [Wikipedia entry for Blackjack](https://en.wikipedia.org/wiki/Blackjack)
[2] [The Optimum Strategy in Blackjack](http://blackjack-square.com/site/files/Baldwin_OptimalStrategyBlackjack.35.pdf)
[3] [A Markov Chain Analysis Of Blackjack Strategy](http://inside.mines.edu/fs_home/mwakin/papers/mcbj.pdf)
[4] [Q learning formula](https://en.wikipedia.org/wiki/Q-learning#Algorithm)
[5] [The Evolution of Blackjack Strategies](https://pdfs.semanticscholar.org/e1dd/06616e2d18179da7a3643cb3faab95222c8b.pdf)