# Deep ZSY

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## Introduction

争上游 (ZhengShangYou, or“Competition Upstream”) is a Chinese card game that is part strategy, part luck. Each player is dealt about 18 cards that they must get rid of to win, and they get rid of cards by matching patterns. Game rules are in the appendix.

Like chess and go, there are patterns to be seen that, if accurately modeled, convey a large advantage in game play. The state space is enormous—possibly on the order of the factorial of the number of cards in play. As far as I could tell, this particular game has not been studied before for automation. Unlike chess and go, the initial states are random and a very small portion of them can even be unwinnable.

A year and a quarter ago, I was in a 3-person CS 229 team that tackled ZSY. We used a TD-learning algorithm with hand-picked features that played many games against a random and a greedy agent we designed. While it did beat those purely manually designed agents, it could only beat humans about 30% of the time. There was no neural network involved and the hand-picked features didn’t work that well.

In this project, I aimed to apply neural networks to a q-learning agent to ultimately be better at ZSY than humans. The inputs were simplified encodings for (s, a) pairs representing the game states and moves from simulated games and the output was an estimated Q*(s, a). I used three and four layer dense neural networks with ReLu and sigmoid activations and dropout regularization.

## Related Work

The linear algorithm we built approached data purely sequentially: updating the model weights after each game. Inspired by Mnih et al.’s approach, I instead simulated between 10,000 and 100,000 games between each training session with experience replay.

## Dataset

The first challenge is to represent the game in a way that captures its complexity without being unworkably memory intensive. During gameplay, it is useful to represent hands as counts of cards of each value because they can be simply added to or subtracted from to represent taking a move. However, this obscures the fact that having two of a kind is fundamentally not just twice having a single: having a pair allows for different kinds of patterns to be formed.

Thus, I’ve made a dual-representation. During gameplay, the hands, the moves, and the history of moves are all represented by counts. During learning, they are represented by a stack of one-hot encodings of how many there are of each card.


*A hand of cards*

```
>>> h
array([[2, 1, 2, 0, 0, 0, 2, 2, 2, 1, 2, 1, 1, 0]])
```

*(1,15) array representing the counts of each value of card*

```
>>> zsy.dc.handToExpanded(h)
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0],
       [0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0],
       [0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1]], dtype=int64)
```

*(5,15) array with each column being a one-hot encoding of whether there are 0, 1, 2, 3, or 4 of a card*

Each player starts with 18 cards and keeps playing until one of the players runs out. The representations above work for both a hand and a move. Thus, I can represent the entire game as a sequence of (5, 15) move-arrays and reconstruct every aspect of the game from there.

For Q-learning, I let (s, a) be represented by the current history, the cards in a player’s hand, and the move that player makes. To simplify the representation of the history, I've summed over the moves the opponent has made and the move the agent has made in order to make the input sequences all of the same length. Thus, the final representation of (s, a) is 4 of the (5, 15) arrays: the cards played by the agent, the cards played by the opponent, the cards in a agent's hand, and the move the agent takes.

The reward is 1 or 0 at the end if the player won or lost. Defining the intermediate values is tougher: Q* should be the expectation of taking the best move, but at the beginning neither how to calculate the expectation nor what the best move is, is known—to know, after all, would be to have already solved the problem.

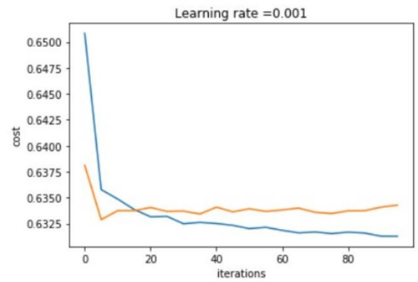
Applying a discount factor in this finite horizon problem doesn't strictly speaking make sense from a theoretical perspective, however during experimentation it proved to be crucial for the model's performance. An alternative method I thought of was to instead discount the costs so that the model was less penalized for a poor estimation of Q* when the actual value for Q* was less well known. In practice, however, this generally led to poorer performances and the idea was scrapped after a few iterations.

Ultimately, this means that I have x, y pairs where x is the 4 (5, 15) arrays representing (s, a) and y is the approximation of Q*(s, a) by discounted reward. The first round consisted of letting 2 random agents play 100,000 games against each other. Each game lasted an average of 19.2 back-and-forth moves for a total of 1.92M data points.

### The First model

I flattened and concatenated the 4 (5, 15) arrays for x into a (300, 1) array. I then fed this into a 3-layer fully connected network with 200, 40, and 1 units in the layers. 50% dropout was applied to each hidden layer. The first two used a ReLu activation, the last was sigmoid for the predicted Q*(s, a). The loss was the standard logistic loss function.

The data was split into 98/2 for train and dev. The graph shows the train and dev loss over 100 epochs in blue and orange, respectively. The 1.92M data points were trained with a mini-batch size of 1024. The dev loss throughout was calculated without dropout whereas the train loss was only calculated without dropout at the very end of training.




```
Parameters have been trained!
Train cost (No dropout): 0.62401
Test cost (No dropout): 0.634024
```

The training loss (blue) slowly but steadily decreased over the 100 epochs but the dev loss just flattened out after about 20 epochs. It is difficult to tell how much over-fitting there is because Bayes' error can't be known without the real Q*(s, a) values.

I then built an agent that played based on these trained parameters: at each turn, it sums over the histories and concatenates onto it every possible move it can make and the hand that results from it to create (s, a) pairs. It feeds these into model and chooses its move based on the best result.

The ultimate metric is how well it would perform against humans, but collecting large amounts of human data was not possible. To test the agent, I let it play 10,000 games against a random agent (that took legal moves uniformly at random) and a greedy agent (that took whatever move it could to get rid of its lowest value cards). I then created a combined loss metric that was the product of the percentage losses to each static agent.

Afterwards, the Deep Q agent played 100,000 games against itself, where with an exploration probability of 0.1 it would draw a move weighted by the estimate Q* value. After this agent was trained for 100 epochs, it was tested against a few humans, and the score below was how it faired against the best human player over 200 games.

The table atop the next page shows the results of the linear TD algorithm and the two iterations of Deep Q against the static agents and against humans.

| | Vs Greedy | Vs Random | Combined Loss | Vs Humans |
|---|---|---|---|---|
| TD (linear) | 81% | 92% | 152 | 30% |
| Deep Q | 71.9% | 96.6% | 95.7 | - |
| Deep Q, 2nd iteration | 75.7% | 97.2% | 67.3 | 43.5% |

### Hyperparameter Search/Next Models

Given the limited scope of the project, I primarily searched over 3 hyperparameters: the reward discount, the cost discount, and the learning rate. As such, using the 100,000 games of the first Deep Q agent, I trained several dozen models over these parameters. Given time constraints, after the first few I decided to curtain the remainder after 10 epochs before the testing phase. Below were some of the most promising models:

| Name | R_γ | C_γ | α | Vs Greedy | Vs Random | Combined loss |
|---|---|---|---|---|---|---|
| 10 | 1 | 1 | 1e-3 | 42.0% | 84.8% | 881.6 |
| 11 | 0.9 | 1 | 1e-3 | 41.0% | 76.7% | 1374.0 |
| 12 | 0.95 | 1 | 1e-3 | 56.9% | 92.5% | 323.3 |
| 13 | 0.95 | 1 | 1e-4 | 62.9% | 93.7% | 236.0 |
| 14 | 0.95 | 0.99 | 1e-4 | 63.3% | 94.7% | 193.2 |
| 15 | 0.95 | 0.95 | 1e-4 | 60.4% | 94.5% | 218.5 |
| 16 | 0.95 | 0.9 | 1e-4 | 61.0% | 94.1% | 231.0 |

While Model 14 with the small cost discount did perform the best, most of the models with cost discount performed very poorly for unknown reasons. As such, I thought it more prudent to continue iterating with Model 13, the best performing model without cost discount.

Model 13 was iterated as follows: 100k games were simulated, it trained over the simulated data for 30 epochs, it was tested for 10k games against random and greedy and another 100k games were simulated. Below is the performance over several of these cycles.

| Model 13 Iteration # | Vs Greedy | Vs Random | Combined loss |
|---|---|---|---|
| 1 | 67.2% | 94.4% | 183.7 |
| 2 | 46.8% | 89.4% | 563.9 |
| 3 | 65.0% | 95.0% | 173.8 |
| 4 | 64.8% | 95.1% | 169.6 |
| 5 | 64.8% | 94.7% | 186.1 |
| 6 | 62.3% | 94.2% | 218.2 |
| 7 | 62.4% | 94.1% | 223.3 |

As none of these models had a combined loss score better than the second iteration of the original model, I did not move forward with human testing.

### Conclusion and Discussion

Many of the algorithmic and hyperparameter choices in these models were made based on time and computational constraints. The reason that Model 13 was only trained for 30 epochs but simulated for 100k games was because I had access to two computing services: one with 4 vGPUs and one with 36 vCPUs. Simulations could be run in parallel very rapidly on the service with 36 vCPUs and so increasing the number of simulations was much less time intensive than increasing the training.

For Model 13, the train and dev costs continued to decrease with each iteration but after the fourth one the loss began to increase. This seems to imply that, although the estimations for Q* improved, the performance in game was worse. This could possibly mean that the values it was approximating were not good values to represent Q*. Ultimately, Model 13 did not do better than the original against the static agents and its combined loss score was, at its best, still worse than the linear algorithm.

I believe this was due to the lack of breadth and depth of the hyperparameter search. There were many more parameters to try such as the dropout percentage, more variations on the learning rate (I only tried 1e-3 and 1e-4), L2 regularization. Furthermore, several early models were 4-layer models, but those had issues with the losses exploding after 10-20 epochs possibly due to poor regularization; I did not have the chance to fully explore why these failed and instead proceeded with only 3 layer models.

Additionally, I did not implement an RNN over the history of moves, as I originally intended. Summing over the history looses the information of the specific patterns that the opponent had chosen and those patterns, I suspect, would have been very predictive of what cards the opponent had in its hand.

Finally, the human trials were done in a mobile app version of the game I developed for another class. Ideally, this app would have collected the human data so that the algorithms could train against actual humans, but I also did not have the time to implement this.

With only 200 games and a lot of variance between games, it is difficult to say for certain how well the algorithm actually performed. It did beat some of the human players, at best scoring 66% victory, but human level performance is not measured against the average but the best players.

If I had more time and resources, I would conduct a more thorough hyperparameter search. Then, I would keep multiple models through several iterations to simulate those models against each other instead of just against themselves, only filtering some percentage each time. As a second priority and depending on how much computational resource I had available, I would try to train an LSTM with the sequence of moves instead of the summation over the history.

Ultimately, the best model with deep learning did better than the best linear model. At the moment, the mobile app version is available to play against for Android and iOS if one downloads the Expo app available in either app store uses this link: [exp.host/@leonl0000/zsy](exp.host/@leonl0000/zsy). In the future, a tutorial will be added and perhaps human data can be collected. At the moment, the game rules are available in the appendix to this paper.

References:

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A., Veness, J., Bellemare, M., Graves, A., Riedmiller, M., Fidjeland, A., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S. and Hassabis, D. (2015). Human-level control through deep reinforcement learning. *Nature*, 518(7540), pp.529-533.

Appendix

*Rules for simplified ZSY:*

Two players are dealt 18 cards randomly from a deck of 54 cards (13 per value, 2 jokers). The goal is to get rid of all the cards in ones hand. A coin is flipped to determine who starts the first round.

That player that starts a round has these options to play:

- **Single**: 1 card
- **Double**: 2 cards of the same number
- **Triple**: 3 cards of the same number
- **Bomb**: 4 cards of the same number
- **Chain**: a series of consecutively-valued cards, for which each 'link' has at least two of that number. For example, 33444, JJQQKK, are valid patterns. 5556677778899 is, but 44566 is not because there's only one five and 7799 is not because it's not consecutive.

The next player must play cards that match the pattern exactly, but are higher. For example, if 777 was played, the next player could follow with 888, 999, QQQ, or so on. If 55666 was played, he could follow with 77888 or JJQQQ (but not JJJQQ). Alternatively, the player can play a "Bomb" over any pattern, and those can only be beaten by higher bombs. Or, the player could pass.

The order of card values is shifted slightly from typical, with 2 being the highest non-joker card. The order for ZSY from low to high is (suits don't matter):

3, 4, 5, 6, 7, 8, 9, 10, J, Q, K, A, 2, Black Joker, Red Joker

When every player has passed, the last player to play some cards wins the round, and gets to start the next round, setting the new pattern. As soon as a player runs out of cards, that player wins the game.