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## EWA Model with Recency Effect and Limited Memory

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Abstract: Game theory is an important field in economics; it studies how people make decisions amid conflict and cooperation. Various experiments have been carried to study the way people play those games, and economists study those data for various purposes. There has been a rise of need for using artificial agents to simulate the game, since we could save the cost of hiring human subjects for the experiments, and we could gain more control over the experiment settings.

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# EWA Model with Recency Effect and Limited Memory

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## 1. INTRODUCTION

Game theory is an important field in economics; it studies how people make decisions amid conflict and cooperation. Various experiments have been carried to study the way people play those games, and economists study those data for various purposes. There has been a rise of need for using artificial agents to simulate the game, since we could save the cost of hiring human subjects for the experiments, and we could gain more control over the experiment settings.

We are focusing on a particular field in game theory called Bayesian game, or game with incomplete information. In this kind of game the players have only part of the information, such as the payoff they receive when they make a move. In order to play well in this kind of game, players need to conjecture the structure of the game and make inferences about the actions and thoughts of the other players.

We gather data from the Market Entry Prediction Contest. They have carried a market entry game experiment in Harvard University; it is a 4-person repeated game with different parameter sets for different games. 120 people are divided into 30 4-person subgroups, and those subgroups will play 10 games; each game has 50 repeated trials or rounds. The players only have information about the obtained payoff, which is the payoff they receive, and the forgone payoff, which is the payoff they would have received if they had chosen the other strategy. They do not know the actions and payoffs of the other players, and they are unaware of the payoff matrix, or any structures of the game mechanisms.

Various models have been proposed to build the artificial agent for this game, such as Reinforcement Learning (RL), Fictitious Play (FL), Experience Weighted Attraction (EWA) [4] [5], and the Inertia, Weighting, and Sampling (I-SAW) model [6]. There has been a contest for new models that can make decent

predictions on the real data; contestants are given the estimation data set and are tested on the competition data set. Since the study is related different fields such as machine learning, economics, psychology, and neuroscience, The best model seems to take into consideration all of these fields, and combine the findings to simulate the process of playing the game. The objective of this research is to study various effects in the market entry game, and improve upon existing models on the prediction of the entry rate.

## 2. BOUNDED RATIONALITY, MEMORY, DEVIATION FROM THEORY

There are a lot of noises or variations in the environment when we conduct economics experiment in real life, and the result deviate from the predictions of theories. It has been found that differences in the experimental environment can play a huge role in the result [1]. We need to account for those various factors that are affecting the result of the experiments, make appropriate assumptions, and adjust our theories accordingly.

One finding of the market entry game is that there are more entries than predicted by Nash Equilibrium [2]. This excess entry suggests that human beings are not very rational in the market entry games. Studies on other market entry games also have similar findings [4]. Some modification of the models is required to take into consideration the bounded rationality and intelligence of human beings. We could discount the effect of learning, make the attraction lower for all in EWA, or add a random factor such as a discount factor on the equation to calculate the probability for each strategy.

We need to account for the heterogeneity of players. They have different preferences, rationality, intelligence, learning abilities, willingness to play well, incentives, and engagement level with the game. We also need to account for the small population of people just play randomly. If possible, we should also account for different behaviors in repeated games in game theory, such as reputation building, strategic teaching, and cooperation. We need to build models that can fit with QRE (Quantal Response Equilibrium), which allows human players to make mistakes during games.

In particular, we want to study the effect of bounded memory, which states that human beings could only remember a certain amount of information. Most of the proposed the models assume the players have perfect memories; in reality, the players would not be able to remember everything from previous rounds.

## 3. RECENCY EFFECT

It is an essentially a reinforcement learning problem, where the player is trying to learn about the world. The player is sometimes in exploration mode, and sometimes in exploitation mode, which means he sometimes tries to learn as much as he can, and sometimes he wants to use what he has learnt to get a better reward. Therefore the player is not stationary, he has different motives at different times. We want to examine how does the player change his behaviors throughout the game. Specifically, we are interested in the recency effect, and how it is changing during a game.

Recency effect states that the most recent round is most important for the player; all the other rounds are roughly equally important [7]. We could examine the effect of recency by adding it to each of the time period and study if there are differences among those time periods.

#### 4. IMPLEMENTAION

We implemented the simulation in Java. Various classes are created for various models. I made a class to integrate the recency and limited memory effects into the EWA model.

We use the self-tuning EWA model to make various improvements, since it has less free parameters to tune than raw EWA, it is a good combination of FL and FP, and unlike I-SAW, which takes into consideration many specific things of this market entry game, it is more generalized and have more room to improve. I-SAW might have the danger of over-fitting, since it has so many free parameters to tune.

We will use the official measuring criteria from the Market Entry Prediction Contest, which include three categories: entry rate, efficiency, and alternation. Entry rate is the proportion of time the players choose the option of entering in one round on average; efficiency is the average payoff in one round the players have gained; alternation is the proportion of time the players switch strategies in one round on average. Here we are mainly looking at the entry rate. Mean Squared Deviation (MSD) is used to measure the difference between the prediction of the simulations from the artificial agents and the actual data done by the human subjects.

We want to isolate a single effect, observe that effect in the context of a smaller period of time, and attempt to find how the effect changes over the course of a repeated game. In particular, we examine if there is a period in which the player is most sensitive to the most recent payoffs or when the recency and limited memory effect is strongest, and if there is a period in which it is more beneficial for the player to start from scratch by ignoring previous experiences.

We attempt to divide the game of 50 trials into 10 periods of 5 trials and examine the effect in each period. Some pattern is found and further division is desired, so we divide the game into 50 time blocks and the recency and limited memory effect on each.

#### 5. EXPERIMENT 1

We run 50 tests to study the effect of recency and limited memory. For each test we run 10-fold cross-validation on the 40 games; we run each game 2000 times and take the average of the results. For each of the test we study the effect of recency and limited memory on a particular trial, starting from trial 0 and ends with trial 49; at that trial the artificial agent forget about his experience from previous rounds and only look at the result of the most recent

obtained and foregone payoff. If the obtained payoff is higher than the foregone payoff, then keep the current strategy, otherwise switch to the other strategy. In other words, at that trial the artificial agent will play the game from scratch.

After conducting those experiments it is found that the recency and limited memory effect is strongest at the mid-range of the game. Possible explanation is that the player is in exploration mode at the beginning, so will be very sensitive to the differences in the obtained payoff and forgone payoff, they cannot afford to forget the previous experiences, and the recency effect is weak; near the end of the game the player might be reluctant to learn new information, thus reply heavily on the previous experiences, making the recency effect low.

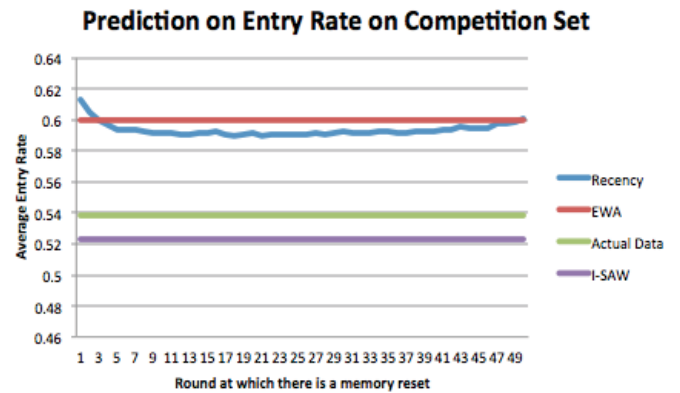
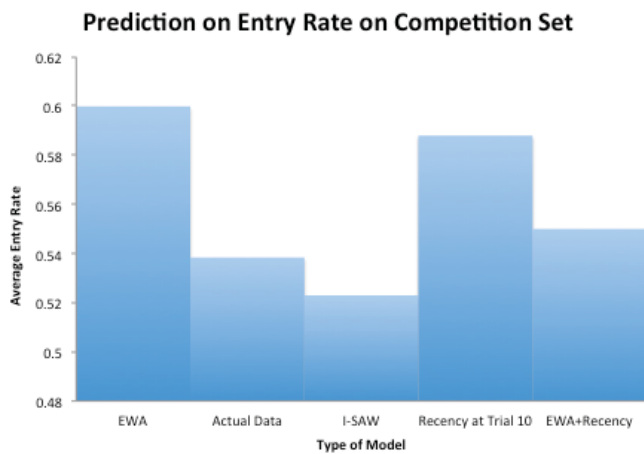


Figure 1: The prediction on the average entry rate on the competition set against the round at which there is a memory reset.

#### 6. EXPERIMENT II

We attempt to form a new model that is a integration of the recency and limited memory effect into the EWA model. We keep the logic response of the EWA model when calculating the probability for each strategy, and maintain its structure of updating the attraction. However, we will add recency and limited memory effect with some probability at some trials, based on the pattern found from the previous experiments. Various experiments are conducted, each with a different set of trials in which recency and limited memory effect take place, and each with different settings of other parameters, such as the probability of having this effect on that round. Various considerations such as the effect of loss aversion are also made to see they will make a difference on the performance. Again, for each test we run 10-fold cross-validation on the 40 games, and we run each game 2000 times.

It is found that a recency model with probability of 40% from trial 5 to 20, and from trial 25 to 40 have the best performance on the estimation set. Further experiment on the competition set also shows that it is doing well in predicting the entry rate, as shown on Figure 2. Although it is not doing well on the prediction of efficiency and alternation, it outperforms the current best model (I-SAW) on the prediction of entry rate. In other words, when we only want to focus on the entry rate, this hybrid model does the best job in predicting that. It also is fast to compute, with only two parameters to tune.



**Figure 2: The prediction on the average entry rate on the competition set of different models. The hybrid model is labeled as “EWA+Recency” on the graph.**

## 7. CONCLUSION

There are various factors affecting the Market Entry game that are not considered by the current models. The effects of recency, bounded rationality and limited memory are tested and verified through various experiments done using artificial agents built in Java. It is found that better prediction of the market entry rate could be achieved using an artificial agent that runs on a modified version of the EWA model that takes into account the effect of recency and limited memory. For future work, additional effects could be considered and modification of the current models could be made. We could also look how the effect of recency and limited memory could be applied to other games.

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## 8. REFERENCES

- [1] Salmon, T.C. An evaluation of econometric models of adaptive learning. *Econometrica* 2001, 69, 1597–1628.
- [2] Ido Erev, Eyal Ert, and Alvin E. Roth. “A Choice Prediction Competition for Market Entry Games: An Introduction”, *Games* 2010, 1, 117-136;
- [3] Urs Fischbacher and Christian Thöni, “Excess Entry in an Experimental Winner-Take-All Market”, *Journal of Economic Behavior & Organization* 67 (2008) 150–163
- [4] Colin Camerer, and Teck-Hua Ho, “Experience-Weighted Attraction Learning in Normal Form Games”, *Econometrica*, Vol. 67, No.4 (July,1999), 827-874.
- [5] Colin Camerer, and Teck-Hua Ho, “Self-tuning experience weighted attraction learning in games”, *Journal of Economic Theory* 133 (2007) 177 – 198.
- [6] W. Chen, S. Liu, C. Chen, and Y. Lee, Bounded Memory, Inertia, Sampling and Weighting Model for Market Entry Games. In *Proceedings of Games*. 2011, 187-199.
- [7] Iris Nevo and Ido Erev, “Onsurprise, change, and the effect of recent outcomes”, *Frontier in Psychology*, 2012.