Research proposal : Prediction of Individual Choice Behavior

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1 Introduction

Prediction of people's behavior is a fundamental task in many domains. For example, when offering public promotions we would like to be able to predict the public response to that promotion. Yet, even if we have a good predictive model for the response of "an average person", our performance can improve if we aim for prediction of individual choice behavior. Examples include predictions of online individual users behaviors to reduce ad costs and increase campaigns performance on social media by having a better understanding of each user, or prediction of individual buyer preferences on e-commerce websites to reach the optimal price point and better target the buyers.

Our research intends to give a better understanding of individual choice behavior beyond the models of the average choice that already exist. Our motivation for such explorations is that currently, the best model for this problem is the average choice. Our main interest in our research will be to improve it.

A recent prediction tournament (CPC18) challenged researchers to predict the individual choice behavior of agents in simple abstract economic games. To develop their predictive models, competitors could rely on a data set of 210 generated games divided in 7 sets. In total, 686 players received a single set of 30 games and had to play 25 times the same game. Each five trials define a block. There are a total of 5 blocks for each game. Competitors had to predict the average choice for every block of 5 random games from players of set 6 and 7 (0; 0.2; 0.4; 0.6; 0.8 or 1). In addition, the organizers published the results of a simple benchmark model: predicting that each individual behaves the same as the average agent in the training set.

Surprisingly, no submissions to the competition outperformed the simple benchmark. This result implied that no submission was able to extract knowledge about individual behavior that goes beyond what is known about the population. Here, we aim to provide improved predictions on this surprising benchmark winner.

Our conjecture is that the failure of the submissions to the competition to outperform the winner results from failures to take into account the environmental heterogeneity. Specifically, we assume that agents have hidden preferences in certain environmental settings, but not in others. Therefore, we can identify sub-classes of the data in which agents play in more predictable manner, and use standard machine learning algorithms to predict behavior of the agents in these sub-classes. In other settings, in which agents play more erratically, our learner predicts the average behavior of the agents in the training set.

2 Related Work

Research have already been made to predict human behavior in strategic choice settings. we can distinguish between three kinds of models that have already been tested on different, but similar, tasks.

A behavioral model like BEAST, Best Estimate and Sampling Tools, developed by Erev. et Al.[1], gives good results when predicting the progression overtime of the mean aggregate choice rate for one option in similar games. It is the baseline model of our problem.

A mixture of behavioral and data-driven approaches, the Psychological Forest, [2] developed by Ponlsky, Erev, Hazan and Tennenholzt, combines psychological theories and random forest algorithm to predict human behaviors. In this model three kind of features were taken in consideration. All the parameters of the games; the naive features, that translate basic property of a choice problems, such as the difference between the expected values, or the difference between the standard deviation of every outcome options, minimal outcomes and maximal outcomes; and psychological features. One of the parameters that have been explored in this last set of features is how subjects evaluated the expected value of a gamble when a game is ambiguous. Other notions, like immediate regret, best reply of previous trials, sign heuristic or minimax heuristic were considered in this research. On the average choice problem, the Psychological Forest outperforms BEAST by almost 30%.

A research made by Hartford et al.'s [3] shows that deep learning architecture can give a better results than any behavioral models to predict average human behavior in strate gic settings.

Theses works all tried to predict the mean aggregate choice : the choice of the "average" decision maker. Yet, they did not try to predict the behavior of individuals, and that will be our main interest in our research.

3 The Data

The Data was collected from two different experiments CPC15 (set 1 to 5) and CPC18 (set 6 and 7).

Each of the 210 games in our problem can be defined by 12 variables. For each option, A or B, we have the expected value of high lottery and their corresponding probability to get payoff drawn from lottery; the expected value of low lottery; the shape of the lottery; the number of lottery outcomes; whether Option B is ambiguous (i.e. its probabilities are not described to subjects);

whether payoffs generated by the two possible options are correlated and the sign of the correlation (-1/0/1),and whether (full) feedback was provided for the subject regarding payoffs in the current trial.

The games were generated using the same algorithm. Yet, in the first 5 sets, only one of the two options can have more than two possible outcomes whereas in the set 6 and 7, both can have up to ten possible outcomes. The second difference, is that in set 6 and 7, we have the response time of every player.

Each player play 25 times the same game, and for each trial we are given the following information: the response variable, whether or not the subject selected Option B in the current trial; the reaction time until choice of option; the payoff the subject got from her/his choice in the current trial; the payoff the subject would have gotten had she/he selected the other option in the current trial; the on-screen side of the chosen button ("L"/"R"); and the payoff that we get for A or B at this trial.

Finally for each player we are given, his age, location and gender.

Each of the 686 players had to play 30 games of one single set in different order. The competition set is composed of only 5 random games played by 30 players of set 6 and 7, and we need to predict the choice of each subject for every block of each of these 5 games.

4 The proposed research

The choice prediction competition that took place in 2018 showed that the baseline prediction was the best prediction model. The naive baseline predicts that each individual target decision maker in each block of its individual target problems would behave the same as the average decision maker behaves in the same block of that problem. Our challenge is to compute a model that will give a better MSE than the baseline.

In order to reach our goals, we first made feature engineering on our data.

On each game, we first added more basic details : the expected values of every options, the maximal expected value, the maximal expected value +/- 0.5, the max-min outcome of the game (the maximal outcome of the minimal outcome). We also added the true number of lottery outcome for each game and created 13 categories representing grouping games by : number of outcomes for A, number of outcomes for B, and the maximal expected value (A, B or AB when they are "almost" equal). For example group '1-M-B' represent all the games where A has only one possible outcome, B have more than 2 possible outcomes, and B has a greater expected value than A. The idea behind those groups is to evaluate if subjects have a preference playing A or B in particular settings, and if they all play the same way: for example when one of the options have multiple outcomes whereas the other have a less complicated distribution, and their expected value is almost the same, group 1-M-AB, or 2-M-AB.

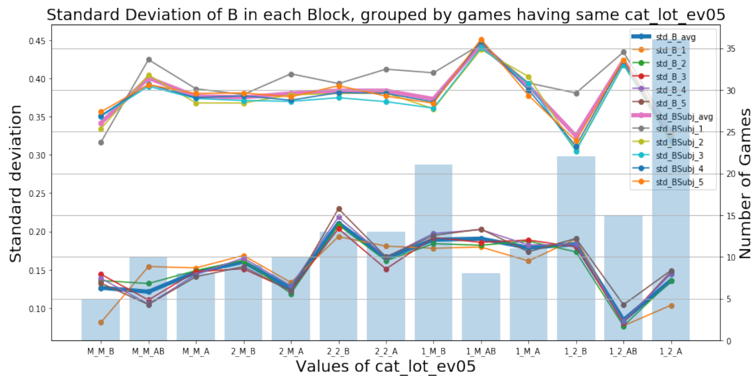

Figure 1: Standard Deviation of B in each block, grouped by games having same categories, for non ambiguous games

In the following graph, we can see the standard deviation of the baseline prediction and of the true value of B to predict, grouped by the categories describe above in case of non ambiguous games. Such graphs on the features we created helped us to understand in the first hand the difference between what the baseline sees and how we should predict for every subcategory. Here, we can see that our categories, although they give a low value of standard deviation for the baseline, still gives a large standard deviation for the value to predict. Moreover, the standard deviation average for the first block is always higher than for the other blocks : indeed, since subjects don't have feedback for the first block, people play more differently, than for the other blocks in most of the subcategories. Besides, for subcategories where A and B have almost the same expected value (groups 1-2-AB, 1-M-AB, M-M-AB), the standard deviation of the average true value is higher than for the other categories : subject play more differently when expected value of both outcome is almost the same. Another point that really interested us in such graphs, is that the baseline does not sees the disparity of what we are trying to predict for each categories. Thus, we are expecting to see an improvement of the baseline by adding such categories as features of our model.

In addition, we added some feature that can be computed only on the train set and assigned to the test set, such as the baseline prediction. Similarly, we added the moving average of the response of each player for each 5 consecutive trials of each game; and the average for each Subject and for each block. In deed, the baseline, which represent the average of each block per game is the most significant feature of our models, thus we look for more significant average that could have an impact on our predictions.

We also explore the best replies. For each game, and each trial above 6, (when we have feedback), we computed the best reply : if the best payoff in the previous trial was A, then the best reply for this trial should be A. The idea is to understand how people react to feedback and if it gives us more information on their behavior. Then for each player, we computed the probability over all the games and all the trial he did in the train set to play next the best reply when he has feedback. We assigned this value for each player in the test set. We can also compute this probability for every block separately, since most of the time the players play differently along the trials. We also computed the probability of a game to give the higher payoff to the best reply of the previous trial, and assign it to the games of the test set. Finally we added the multiplication of these two probabilities. Thus, with this composed probability we are expecting to better distinguish players playing games when best reply has an impact on both the player and the game.

Another type of feature that we added is consistent game block and subject. We realized that in some game and for specific block, more than 50% of the subject choose the same outcome (or A in all the block or B in all the block). In that case, we assume that this game, and this specific block is consistent. Moreover, we also looked for consistent player : player that have play more than 50% of the time like the majority in the consistent games. Having the set of consistent game-block and consistent players, we automatically assigned the baseline prediction to this player in the game-block of the test set. We also consider assigning the majority choice of those game-block to those players. By taking out those mostly predictable people playing the consistent games, we expect to build a better model on the remaining set.

On the top of all those kind of features, we decided to create groups of game-block. We started by creating 10 clusters according to the distance of each game-block from their average outcome across the players. Moreover, we computed different models for every cluster. We experimented the same idea with groups of lottery category and maximum expected value, and groups of people.

After all this first investigation, we realized that some cluster of people, game-block and type of games were more predictable than others, and thus we have some heterogeneity in our data set. Based on all those possible groups of people or game-block, we need to clearly differentiate some subjects and some game-blocks from others.

If for now our models does not out perform the baseline prediction by far, we are now willing to define and categorize all the kind of heterogeneity that we saw in our data set, use machine learning to make predictions for every predictable sub-classes, and assign the baseline for non predictable sub-classes.

References

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