On Modelling Typical General Human Behavior in Games

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Abstract

The question addressed in this work is 'What do people exactly typically do, if they interact strategically in games they have not much experience with?'. It is certain that human behavior in strategic interactions and games deviates from predictions of game theory. But, it is also certain that this behavior must have some kind of explanation. Eventually, people do not behave in a fully unpredictable way. This work considers general strategic interactions with untrained subjects. It does not consider human performance in well-known games like chess or poker. A very basic scenario is used to investigate human behavior. This scenario is a repeated zero sum game with imperfect information. An experiment with subjects is conducted and the data is analyzed using a set of different machine learning algorithms. As the result, a way of using machine learning is given. Finally, designing a formalism for representing human behavior is discussed.
Keywords: Game Theory, Data Mining, Artificial Intelligence, Domain-Specific Languages

Introduction

Typical human behavior in games is not optimal and deviates from game theoretic predictions (F.Camerer, 2003). Conceivable reasons are the bounded computational resources and the (seeming) absence of rationality. One can say without any doubt that if a human player is trained in a concrete game, he performs close to optimal. But, a chess master does not also play poker perfectly and vice versa. On the other side, a game theorist can find a way to compute an equilibrium for a game, but it does not make a successfull player out of him. For most of games, we are not trained. That is why it is more important to investigate our behavior in general game playing than game playing in concrete game.

This work is about the common human deviations from predicted equilibria in games, for which they are not trained. Modeling typical human behavior in general games needs a represention formalism which is not specific to a concrete game. An example-driven development of such a formalism is the challenge addressed in this paper. The example introduced in this work are repeated two-player zero-sum games with no pure strategy equilibria (Tagiew, 2009). Each player has a couple of actions called strategies. The solution of such games is to use mixed strategy equilibrium (MSE). An MSE is defined through a distribution over strategies, according to which the strategies are to be chosen.

The related works (Gal & Pfeffer, 2007) and (Marchiori & Warglien, 2008) use following approach. First, they construct a model, which is based on theoretical considerations. Second, they adjust the parameters of this model to the experimental data. This makes the human behavior explainable using the concepts from the model. On repeated zero sum games with more than two strategies, the correctness does not exceed 45% for all evaluated models.

Results

The seven evalutated games are related to paper-scissors-stone and have at least one MSE. The games denoted through IDs 31 till 61 have the following MSE solutions - 31$\Rightarrow \{(\frac{1}{3},\frac{1}{3},\frac{1}{3})\}$, 41$\Rightarrow \{(0,\frac{1}{2},0,\frac{1}{2}),(\frac{1}{2},0,\frac{1}{2},0)\}$, 51$\Rightarrow \{(\frac{1}{9},\frac{1}{9},\frac{1}{9},\frac{1}{3},\frac{1}{3})\}$, 52$\Rightarrow \{(\frac{1}{7},\frac{1}{7},\frac{1}{7},\frac{2}{7},\frac{2}{7})\}$, 53$\Rightarrow \{(\frac{1}{7},\frac{1}{7},\frac{1}{7},\frac{2}{7},\frac{2}{7})\}$, 54$\Rightarrow \{(0,\frac{1}{2},0,\frac{1}{2},0),(\frac{1}{4},\frac{1}{4},\frac{1}{4},\frac{1}{4},0)\}$ and 61$\Rightarrow \{(0,\frac{1}{2},0,\frac{1}{2},0),(\frac{1}{4},\frac{1}{4},\frac{1}{4},\frac{1}{4},0)\}$.

This work follows the so called *black box* approach. The black box in this case is the human player. The input are the game rules and previous decisions of players. The output is the current decision. Finding a hypothesis which matches the behavior of the black box is a typical problem called supervised learning (Mitchell, 1997). There is already a big amount of algorithms for supervised learning. Each algorithm has its own hypothesis space. For a Bayesian learner i.e., the hypothesis space is the set of all possible Bayesian networks. There are many different types of hypothesis spaces - rules, decision trees, Bayesian models, functions and so on. A concrete hypothesis is a relationship between input and output described by using the formal means of the corresponding hypothesis space.

Which hypothesis space is most appropriate to contain valid hypotheses about human behavior? That is a machine learning version of the question about a formalism for human behavior. The most appropriate hypothesis space contains the most correct hypothesis for every concrete example of human behavior. A correct hypothesis does not only perform well on the given data (training set), but it performs also well on new data (test set). Further, it can be assumed that the algorithms which choose a hypothesis perform alike well for all hypothesis spaces. This assumption is a useful simplification of the problem for a preliminary demonstration. Using it, one can consider the algorithm with the best performance on the given data as the algorithm with the most appropriate hypothesis space. The standard method for measurement of performance of a machine learning algorithm or also a classifier is cross validation.

The data of the experiment is transformed to sets of tuples for every game. Every tuple has the length $3+3+1=7$ (3 last pairs of turns and current turn). The size of a set is 540 tuples for games 31 till 53 and 340 for game 61. Implementations of classifiers provided by WEKA (Witten & Frank, 2005) are used for the cross validation on the sets of tuples. The task is to find a relationship between the last three players's decisions (6 items) and the current decision. There are 45 classifiers available, which can handle multi-valued nominal classes. Strategies in games are nominal, because there is no order between them. A cross validation of all 45

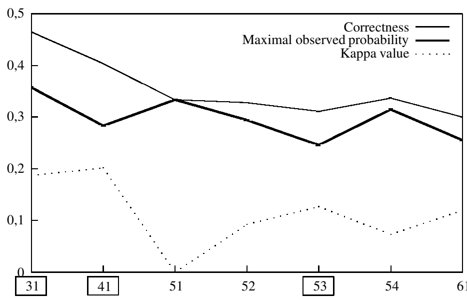

Figure 1: Average correctness in cross validation.

classifiers on all 7 sets of tuples is performed. The number of subsets for crossvalidation is 10.

There is no classifier which performs best on all games. Further even the highest average correctness is very low. Fig.1 shows the results. The gap between the highest observed probability of a strategy and the highest average correctness is different depending on the game. The Kappa value is a measure for the deviation of a classifier from random. In game 51, all classifiers completely fail to find a hypothesis in subsets better than 'always certain strategy'. The best classifiers for games with a significant gap (game ID in a box) between average correctness in cross validation and maximal probability of a gesture predictions are sequential minimal optimization (SMO) (Platt, 1998) for 31, multinomial logistic regression (L) (Cessie & Houwelingen, 1992) for 41 and Bayesian networks for 53.

Which classifier is the most robust? One can choose two criteria - highest minimum performance or highest average performance. In game playing conditions, if the correctness of prediction is 5 percentage points higher, one gets a 5% higher payoff. To find the classifier with the most robust usability in game playing conditions, the difference between average correctness and probability of equal distribution ($\frac{1}{|\text{Strategies}|}$) is calculated for each classifier and game. SMO has the highest minimum difference and a simple variant of L (SL) has the highest average difference. On the other side, L has the the highest average Kappa value and voting feature intervals classification (VFI) has the highest minimum Kappa value. Fig.2 shows the average correctness of these classifiers on the datasets. Three of these four classifiers have functions as hypothesis space. The problem of functions is that most of them can not be verbalised. Consequently, the first question from the abstract can be answered using natural language. On the other side, the success of function based classifiers means that we can not explain our behavior in our natural language. However, the correctness achieved for game 31 is about 46% and it is slightly higher than in the related work. It is doubtful, wether one can define an algorithm which predicts exactly general human strategic behavoir at all.

The single rule classifier (OneR), which is also included in the histogram on fig.2, produces a hypothesis which contains only one single rule. Using this classifier, one can

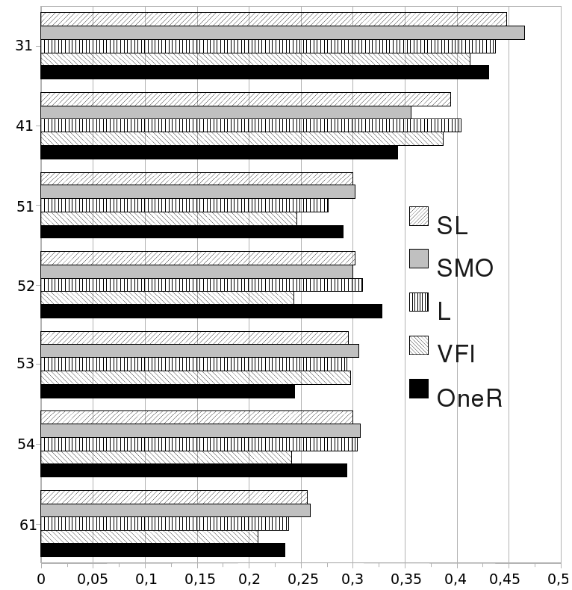

Figure 2: Cross validation

find out that 43.15% of the data in game 31 matches the rule 'choose paper after choosing rock, scissors after rock and rock after paper'. This rule is a very simple answer to the first question in the abstract in this paper. Such rules of thumb are not exact enough for explaining general human behavior. The difficulty of finding a relationship between input and output is the fact that the same input can cause different outputs. Even using the instance based approach K* which is validated on training data, one achieves only 80.37% correctness in game 31. Strategography and strategophony are possible future directions in understanding general human strategic behavior - if we can not verbalise our strategic behavior, can we represent it as images or music?

References

Cessie, S., & Houwelingen, J. C. (1992). Ridge estimators in logistic regression. *Applied Statistics*, *41*.

F.Camerer, C. (2003). *Behavioral game theory*. New Jersey: Princeton University Press.

Gal, Y., & Pfeffer, A. (2007). Modeling reciprocal behavior in human bilateral negotiation. In *Aaai.* AAAI Press.

Marchiori, D., & Warglien, M. (2008). Predicting human interactive learning by regret-driven neural networks. *Science*, *319*.

Mitchell, T. M. (1997). *Machine learning*. Mcgraw-Hill Higher Education.

Platt, J. (1998). Machines using sequential minimal optimization. In *Advances in kernel methods.* MIT Press.

Tagiew, R. (2009). Towards a framework for management of strategic interaction. In *Icaart.* INSTICC.

Witten, I. H., & Frank, E. (2005). *Data mining*. Morgan Kaufmann.