Partially Observable Stochastic Game-based Multi-Agent Prediction Markets

(Extended Abstract)

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ABSTRACT

We present a novel representation of the prediction market using a partially observable stochastic game with information (POSGI), that can be used by each trading agent to precisely calculate the state of the market. We then propose that a correlated equilibrium (CE) strategy can be used by the agents to dynamically calculate the prices at which they should trade securities in the prediction market. Simulation results comparing the CE strategy within our POSGI model with five other strategies commonly used in similar markets show that the CE strategy results in improved price predictions and higher utilities to the agents as compared to other strategies.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Miscellaneous

General Terms

Economics

Keywords

Prediction market, stochastic game, correlated equilibrium

1. INTRODUCTION

A prediction market is a market-based distributed aggregation mechanism that uses monetary bets from its participants to elicit their beliefs on the outcome of a future event. The main idea behind the prediction market paradigm is that the collective, aggregated opinions of humans on a future event represents the probability of occurrence of the event more accurately than corresponding surveys and opinion polls. Several researchers have modeled the behavior of prediction market participants using automated trading agents that interact within a game theoretic framework [1, 2] Despite their overwhelming success, many aspects of prediction markets such as a formal representation of the market model, the strategic behavior of the market's participants and the impact of information from external sources on their decision making have not been analyzed extensively for a better understanding. We attempt to address this deficit in this paper by developing a game theoretic representation of the traders' interaction and determining their strategic behavior using the equilibrium outcome of the game.

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2. PARTIALLY OBSERVABLE STOCHASTIC GAMES FOR AGENT INTERACTION

Our prediction market consists of N traders, with each trader being represented by a software *trading agent* that performs actions on behalf of the human trader. The market also has a set of future events whose outcome has not yet been determined. The outcome of each event is considered as a binary variable with the outcome being 1(0) if the event happens(doesn't happen). Each outcome has a security associated with it. We express the 'state' of the market as the quantity of the purchased units of the security in the market. Agents interact with each other in stages (trading periods), and in each stage the state of the market is determined stochastically based on the actions of the agents and the previous state. This scenario directly corresponds to the setting of a partially observable stochastic game [3]. Previous research has shown that information related parameters in a prediction market have a considerable effect on the belief (price) estimation by trading agents. Based on these findings, we posit that a component to model the impact of information related to an event should be added to the POSG framework. With this feature in mind, we propose an interaction model called a partially observable stochastic game with information (POSGI) for capturing the strategic decision making by trading agents. A POSGI is defined as: $\Gamma = (N, S, (A_i)_{i\in N}, (R_i)_{i\in N}, T, (O_i)_{i\in N}, \Omega, (\mathcal{I}_i)_{i\in N})$, where N is a finite set of agents, S is a finite, non-empty set of states - each state corresponding to certain quantity of the security being held (purchased) by the trading agents. A_i is a finite non-empty action space of agent i s.t. $\overline{a_k} = (a_{1,k}, ..., a_{|N|,k})$ is the joint action of the agents and $a_{i,k}$ is the action that agent i takes in state k. In terms of the prediction market, a trading agent's action corresponds to a certain quantity of security it buys or sells, while the joint action corresponds to changing the purchased quantity for a security and taking the market to a new state. $R_{i,k}$ is the reward or payoff for agent i in state k which is calculated using the logarithmic market scoring rule (LMSR). $T : T(s, \overline{a}, s') = P(s'|s, \overline{a})$ is the transition probability of moving from state s to state s' after joint action $\overline{a}$ has been performed by the agents. O_i is a finite non-empty set of observations for agent i that consists of the market price and the information signal, and $o_{i,k} \in O_i$ is the observation agent i receives in state k. $\Omega : \Omega(s_k, I_{i,k}, o_{i,k}) = P(o_{i,k}|s_k, I_{i,k})$ is the observation probability for agent i of receiving observation $o_{i,k}$ in state s_k when the information signal is $I_{i,k}$. Finally, $\mathcal{I}_i$ is the information set received by agent i for an event $\mathcal{I}_i = \bigcup_k I_{i,k}$ where $I_{i,k} \in \{-1, 0, +1\}$ is the information received by agent i in state k. Based on the POSGI

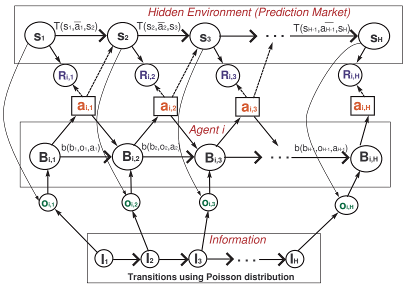
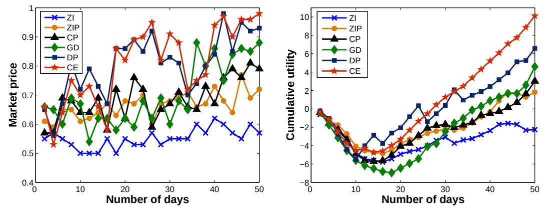


Figure 1: An agent interactions with the hidden environment (prediction market) and an external information source.

formulation of the prediction market, the interaction of an agent with the environment (prediction market) and the information source can be represented by the transition diagram shown in Figure 1[1]. The environment (prediction market) goes through a set of states $\tilde{S} = \{s_1, ..., s_H\} : \tilde{S} \in S$, where H is the duration of the event in the prediction market and s_h represents the state of the market during trading period h. This state of the market is not visible to any agent. Instead, each agent i has its own internal belief state $B_{i,h}$ corresponding to the actual state s_h. $B_{i,h}$ gives a probability distribution over the set of states S, where $B_{i,h} = (b_{1,h}, ..., b_{|S|,h})$. The agent i receives an observation $o_{i,S_h} = (\pi_{s_h}, \mathcal{I}_{i,s_h})$, that includes the market price π_{s_h} corresponding to the state s_h as informed by the market maker, and the information signal $\mathcal{I}_{i,s_h}$. The agent i then updates its beliefs, selects an action, and receives a reward R_{i,s_h}. To determine the outcome of the POSGI, we have used a correlated equilibrium (CE) solution, which is calculated by first representing CE through a linear program and then using the dual of this formulation to find CE in polynomial time.

3. EXPERIMENTAL RESULTS

We have conducted several simulations using our POSGI prediction market with 100 agents. The default values for the statistical distributions for market related parameters were taken from data obtained from the Iowa Electronic Marketplace(IEM) movie market for the event *Monsters Inc.* movie box office, which pays \$1 if Monsters, Inc. official box office receipts for the 11/2/2001 − 11/29/2001 period are greater than \$180 million, and \$0 otherwise. We report the market price for the security corresponding to the outcome of the event being 1 (event occurs). We use the following well-known strategies for comparison [2] [4] . 1) ZI (Zero Intelligence) - each agent submits randomly calculated orders; 2) ZIP (Zero Intelligence Plus) - each agent aims for a particular level of profit by adopting its profit margin based on past prices; 3) CP (by Preist and Tol) - each agent adjusts its orders based on past prices and tries to submit more competitive orders; 4) GD (by Gjerstad and Dickhaut) - each agent maintains a history of past transactions and chooses the order that maximizes its expected utility; 5) DP (Dynamic Programming solution for POSG game) - each agent uses dynamic programming solution to find the best order that maximizes its expected utility given past prices, past utility, past belief and the information signal [3]; 6) CE (Correlated Equilibrium solution) - each agent follows the correlated equilibrium calculated within POSGI setting. Figure 2(a) shows the prices of the orders placed by



a b

Figure 2: Market Prices(a) and Utilities(b) of the risk neutral agents under different trading strategies.

risk neutral agents and Figure 2(b) shows the corresponding utility received by these agents for different strategies during the duration of the event. Our results indicate that the agents using the CE strategy are able to obtain 38% more utility and 9% higher price than the agents following the next best performing strategy (DP). In summary, the POSGI model and the CE strategy result in better price tracking and higher utilities because they provide each agent with a strategic behavior while taking into account the observations of the prediction market and the new information of the events.

4. CONCLUSION

In this paper, we have described an agent-based POSGI prediction market with an LMSR market maker and empirically compared different agent behavior strategies in the prediction market. In the future we are interested in analyzing n-player scenario for the POSGI formulation given in Section 3. We also plan to investigate the dynamics evolving from multiple prediction markets that interact with each other. Finally, we are interested in exploring truthful revelation mechanisms that can be used to limit untruthful bidding in prediction markets.

5. REFERENCES

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9[1]We have only shown one agent i to keep the diagram legible, but the same representation is valid for every agent in the prediction market. The dotted lines represent that the reward and environment state is determined by the joint action of all agents.

9[2]An 'order' in each of the compared strategies corresponds to the quantity that an agent wishes to buy or sell