# A Multi-Agent System for Predicting Future Event Outcomes

# (Extended Abstract)

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## Categories and Subject Descriptors

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## 1. INTRODUCTION

Forecasting the outcome of events that will happen in the future is a frequently indulged and important task for humans. Despite the ubiquity of the forecasts, predicting the outcome of future events is a challenging task for humans or even computers - it requires extremely complex calculations involving a reasonable amount of domain knowledge, significant amounts of information processing and accurate reasoning. Recently, a market-based paradigm called *prediction markets* has shown ample success to solve this problem by using the aggregated 'wisdom of the crowds' to predict the outcome of future events. This is evidenced from the successful predictions of actual events done by the Iowa Electronic Marketplace(IEM), Tradesports, Hollywood Stock Exchange, the Gates-Hillman market, etc., and by companies such as Hewlett Packard, Google and Yahoo's Yootles.

A prediction market consists of human traders and future events whose outcome has not yet been determined. Traders bet their money on the possible future outcome of the events. A security is a financial instrument like a financial stock that is associated with an event. Each event can have one or more securities associated with it. Traders can buy or sell one or more of the securities for each event at a time. The decision of a trader to buy or sell a particular security depends on the trader's current belief about the outcome of the event. This belief is expressed as a price corresponding to the security. A prediction market also includes a central entity (e.g., the company running the prediction market) that aggregates the prices (or beliefs) from the market's traders into a single price, called the *market price*. This market price of a security represents the price at which the security can be bought or sold in the market. It also represents the aggregated beliefs or opinions of traders about what the most likely outcome of the event associated with the security. The aggregation mechanism used by the central entity of a prediction market has been studied actively in the past, and researchers have proposed aggregation rules (e.g. LMSR [3]) implemented through a *market maker* to address problems of liquidity, trading volume, etc. in a prediction market.

Prediction markets were initially introduced as social research tools for aggregating the opinions of a large number of people on the future outcome of imminent events. The following success of prediction markets as an effective aggregator of public opinion has led to their adoption in various domains ranging from academic research to commercial betting markets for popular events such as sporting events and Hollywood movies and predicting the performance or sales of products by software companies. 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.

## 2. MULTI-AGENT PREDICTION MARKET

My research focuses on understanding and analyzing prediction markets using multi-agent system and game theory-based tools. I have developed a multi-agent based prediction market that is composed of three main agent-based entities: an information agent external to the market which is responsible for information flow to the market's traders, trading agents that use different algorithms to calculate prices and update beliefs related to the market's securities, and a market maker agent that uses a scoring rule to perform information aggregation and calculate the market price for the different securities in the market. The major research questions that I am attempting to address in my dissertation research using the multi-agent prediction market are:
1) How do changes in different aspects of information affect the market prices in prediction markets?
2) How do different trading agent behaviors affect the market price in prediction markets?
3) What trading strategies give the highest utility to the trading agents?
4) How can prediction markets incentivize trading agents to participate in order to achieve a higher prediction accuracy?
5) How does a prediction market evolve and what are its dynamics under different market and trader conditions?
6) How can we make a prediction market robust to untruth-

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ful revelations from trading agents or noise in the information flowing into the market?

In the following sections, I have provided a more detailed description of my research on each of these topics.

## 2.1 Effect of Information Related Parameters on Trading Agent Behavior

The effect of information on prediction markets is a crucial factor that affects the behavior of the trading agents in the market. Information about an event that the trading agents receive affects their belief values about the outcome of an event, influences the prices corresponding to the event and finally determines the outcome of the event. Therefore, it makes sense to analyze the behavior of the trading agents in response to different information-related parameters in a prediction market. I have developed a multi-agent based system that incorporates different information-related aspects including the arrival rate of the information, the reliability of the information, the penetration or accessibility of the information among the different trades and the perception or impact of the information by the trading agents. The multi-agent implementation of a prediction market allows us to easily analyze and verify the trading agents' behavior while varying different market and agent related internal parameters of the prediction market, as well as external parameters related to the information about events arriving at the market. The developed multi-agent prediction market uses modeling parameters obtained from various sources such as existing analytical models of financial markets, empirical data from real prediction markets, and agent utility and belief theory. I have also performed extensive simulations of our agent-based prediction market for analyzing the effect of information related parameters on the trading agents' behaviors expressed through their trading prices. I have also compared our prediction market's behavior with an existing prediction market model, and, our agents' strategies with the zero-intelligence(ZI) agent strategy that has been formerly used for strategic pricing in prediction markets. The results show that our agent-based prediction market operates correctly and that our agents price predictions result in higher utilities than ZI agents[5].

## 2.2 Trading Agent Behavior

Researchers have proposed theoretical models capturing individual aspects of prediction markets such as utility theory-based models for participants' behavior, or aggregation strategies for combining the information from the market's participants [1, 2, 6]. However, a monolithic model that simultaneously captures the information flow in the market, the behavior of the prediction market's participants on the market's predicted outcome has not yet been fully investigated. In this part of my thesis I attempt to address this deficit by developing a game theoretic representation of the trading agents' interaction and determining their strategic behavior using the equilibrium outcome of the game. I have developed a new agent-based game theoretic model called Partially Observable Stochastic Game with Information (POSGI) which can be used by each trading agent to reason about its actions. Within this POSGI model, the correlated equilibrium strategy is calculated for each agent using the aggregated price from the market maker as a recommendation signal. I have proved the existence of the correlated equilibrium in the POSGI prediction market with risk neutral agents and have provided an algorithm for calculating the correlated equilibrium within POSGI prediction market. I have also considered risk preferences of the agents and I have shown that a Pareto optimal correlated equilibrium solution can incentivize truthful revelation from risk averse agents. Finally, I have empirically compared our POSGI/correlated equilibrium trading strategy with five different pricing strategies used in similar markets with pricing data obtained from real prediction prediction market events. The empirical results show that the agents using the correlated equilibrium strategy profile are able to predict prices that are closer to the actual prices that occurred in real markets and these trading agents also obtain $35 - 127\%$ higher profits[4].

## 2.3 Prediction Market Dynamics

Despite a growing research on prediction markets, their implementation in practice is still difficult. It is important to know under what conditions (e.g the number of trading agents, noise) the prediction market becomes most efficient. To address this question we modeled a prediction market as a dynamical system represented as a Boolean Network (BN). The advantage of BN modeling is that it can retain the essential aspects related to the dynamics of a prediction market while at the same time, being easy to understand and manipulate.

Using a BN approach and a mean-field approach from statistical physics I have generated a mathematical model for a prediction market in which one node represents the market maker that at each time step aggregates the information from the other nodes in the system which represent the trading agents. The states of the trading agents and the market maker are updated according to specific Boolean rules that model the actual rules in a prediction market. I have first verified that the operation of the prediction market remains the same under BN representation of the prediction market. Then using the tools from dynamical systems and chaos theory, I analyzed an evolution of the aggregated information under various scenarios. In particular, I identify parameter values that lead the system to a specific behavior (stability or chaos), and estimate the amount of time needed to reach that behavior. The sensitivity to disturbances of a BN has been analyzed in the literature for various types of BNs [7]. Using these BN techniques we are currently analyzing the robustness of the prediction market to various types of disturbances and estimating the influence of trading agent strategic behavior or other external influences on the overall network dynamics.

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