



# A DECENTRALISED PEER-PREDICTION MARKET

CS907 DISSERTATION PROJECT - DISSERTATION

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# 1 Introduction

Prediction markets are exchange-traded markets<sup>1</sup> which allow users to trade on the outcomes of future events as opposed to traditional financial instruments. Users participate by placing bets and buying or selling shares in the markets these bets give rise to. Since users stake their own money, market prices should indicate the true beliefs of the userbase and the perceived likelihood the events have of occurring. Different users will have different beliefs and knowledge informing their decisions, and prediction markets provide a means of aggregating information on events of interest using “the wisdom of the crowd”. Shares in these markets are usually traded between \$0 and \$1, and for binary events a market will typically pay out \$1 for every share held for a positive outcome, and \$0 otherwise.

Traditional prediction markets are centralised in the sense that the system provides the bets for the users to trade in, and traders simply choose the price point and size of stake at which to participate. Since the system knows all possible bets beforehand it is simple to allow it to determine the outcomes of the markets and pay out the winnings to stakeholders accordingly. There are two issues with this centralised approach: firstly, it restricts the types of bets that can be made, since they must be explicitly offered by the market maker; secondly, it operates on trust – there is nothing to stop the central market maker from manipulating the system for their own gain. We aim for a system that avoids both of these issues.

In this project we implement a *decentralised* prediction market in which it is up to the userbase itself to define the markets and determine the outcomes of these events – these outcomes are decided upon by consensus among a group of users, known as arbiters. This removes the need for a trusted centre, however with no central moderator bets may become ambiguous or their outcomes subjective, and arbiters may still attempt to manipulate the outcome of the market for their own gain by submitting false reports. It is also important that users continue to act according to their true beliefs so we may learn about the true public sentiment on the events. We base our design on the incentive compatible outcome determination mechanism proposed by Freeman, Lahaie, and Pennock [7], which allows us to crowdsource market outcomes while incentivising users to act truthfully in all stages of the prediction market.

The rest of this dissertation is structured as follows: in Section 2 we give an overview of the current literature on algorithmic mechanism design and prediction markets, and discuss recent implementations of decentralised markets. In Section ?? we outline the motivations for undertaking the project and why we believe it to be worthwhile, and detail the successes that have been achieved so far. Section ?? covers the high-level design of the market and introduces the theoretical model upon which our implementation is based, as well as issues related to project management and ethical considerations. In Section ?? we then discuss our implementation of the prediction market, including the tools we have used to do so. Finally in Section ?? we reflect on the project’s successes and failures and suggest areas for further development.

## 2 Background

### 2.1 Setup

Consider the following problem within algorithmic mechanism design known as the *information aggregation problem* [11, Ch. 26]. An individual known as the “aggregator” wishes to obtain a prediction about an uncertain variable which will be realised at some point in the future. There are a number of individuals known as the “informants” who each hold sets of information about the variable’s outcome. The goal is to design a mechanism that extracts the relevant information from the informants and uses it to provide a prediction of the variable’s realisation. In an ideal setting the mechanism should produce the same prediction as an omniscient forecast that has access to all information available to all informants. This may not be viable in practice, since each agent’s information is private information, and so the mechanism must incentivise them to act in the desired truth-telling manner.

A prediction market is one mechanism that can provide such a forecast. In this setting the aggregator creates a financial security whose payoff is tied to the outcome of the variable. In the simpler case of binary events, such a security may pay out \$1 for each share held if the variable has a “true” or “yes” outcome, and \$0 otherwise, however markets can be created for other types including discrete (“will the result of the match be a home win, away win, or a draw?”), continuous (“what will be the highest measured temperature in Coventry in September?”), or any combination of these types. Informants

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<sup>1</sup>Markets in which all transactions are routed through a central source.

are then able to participate in the market induced by the security by trading shares according to their beliefs: those who believe, for example, that global warming is real might buy shares at a given price in the market, “the global average temperature in 2020 will be higher than that in 2019”, while deniers may be inclined to sell shares. The share price will be adjusted accordingly, and the aggregator can view the current price as the informant’s combined belief of the outcome of the event.

In this model there is a set  $\Omega$  of possible states of the world and at any moment the world is in exactly one state  $\omega \in \Omega$ , though the informants do not know which. Each informant  $i$  may however possess partial information regarding this true state, and this is represented by a partition  $\pi_i$  of  $\Omega$ . The agent knows in which subset of this partition the true world state lies, but does not know the exact member of which is true. Given  $n$  agents, their combined information  $\hat{\pi}$  is the coarsest common refinement of the partitions  $\pi_1, \dots, \pi_n$ .<sup>2</sup>

We also assume a common prior probability distribution  $P \in \Delta^\Omega$  which describes the probabilities that all agents assign to the different world states before receiving any information. Once each agent receives their partial information, they form their posterior beliefs by restricting the common prior to the subset of their partition in which they know the true state to lie. For our purposes, a *forecast* is an estimate of the expected value of the function  $f : \Omega \rightarrow \{0, 1\}$ , known as an *event*, which equals one for exactly one subset of  $\Omega$  and 0 otherwise.

As mentioned, there is an ideal “omniscient” forecast that uses the distribution  $P$  restricted to the subset of  $\hat{\pi}$  in which the true world state lies but which is impractical given the private nature of each agent’s information. The goal is therefore a mechanism to incentivise agents to reveal their private information such that in equilibrium we achieve a forecast as close as possible to the omniscient one. Prediction markets offer the agents the chance of financial gain for revealing information regarding the expected value of  $f(\omega)$ , and the share price of the security can be interpreted as the collective forecast of the agents. In Section ?? we shall outline the different approaches one can take to designing the prediction market mechanism itself and the one among them, a Market Scoring Rule, that we implement. Importantly, Market Scoring Rules are one of the ways to increase liquidity in the market as the system itself assumes the opposite side to any trade, meaning users may participate even when no other user wishes to buy or sell for what they are asking or bidding. This means a trade is always able to be executed, although without care the system could make consistent losses.

## 2.2 Literature Review

The Iowa Electronic Markets (IEM) are real-money prediction markets developed by the University of Iowa [3] that have been running since 1988. They allow users to buy and sell contracts based on the outcome of U.S. political elections and economic indicators, and are currently offering markets for the winning party of the 2020 U.S. presidential election, the vote share between the Democratic and Republican parties in the 2020 U.S. presidential election, and the compositions of the houses of Congress, House of Representatives, and U.S. Senate after the outcome of the 2020 U.S. congressional elections. The number of markets offered is small and the topics are kept relevant to current events, meaning there is likely to be high liquidity for any security a user wishes to trade in. This has allowed the markets to predict the results of political elections with more accuracy and less error than traditional polls: for the presidential elections between 1988 and 2000, three-quarters of the time the IEM’s market price on the day each poll was released was more accurate for predicting vote share than the poll itself [13, pg. 19]. These markets inspired similar markets in the forms of the Hollywood Stock Exchange, NewsFutures, and the Foresight Exchange report, which achieved similar successes despite not using real money.

An issue with these markets is that they are restrictive in the bets they offer. Although this can be beneficial in that they provide a focused and liquid market in which to trade, it leaves them potentially less interesting to interact with. A combinatorial prediction market is a solution to this and drastically increases the number of events that can be bet on and outcomes predicted by offering securities on interrelated propositions that can be combined in various ways. One example of such a market is that of *Predictalot* [4], a combinatorial prediction market developed by Yahoo! that allowed users to trade securities in the 2010 NCAA Men’s Division I Basketball Tournament. The tournament sees the top 64 teams play 63 games in a knockout competition, yielding a total outcome space of size  $2^{63}$ . *Predictalot* then kept track of the odds, computing them by scanning through all of the predictions made by users. This prediction market was the original inspiration for this project in investigating prediction markets. Using a Market Scoring Rule for such a market would involve computing a summation over

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<sup>2</sup>A partition  $\alpha$  of a set  $X$  is a refinement of a partition  $\rho$  of  $X$  if every element of  $\alpha$  is a subset of some element of  $\rho$ . In this case  $\alpha$  is *finer* than  $\rho$  and  $\rho$  is *coarser* than  $\alpha$ .

the entire outcome space  $\Omega$ , an intractable, #P-hard problem akin to counting the number of variable assignments that satisfy a CNF formula, or the number of subsets in a list of integers that sum to zero. Instead, they employ an implementation of importance sampling, a technique for estimating properties of a particular probability distribution using only samples generated from a different distribution. This “naive” approach is then improved upon by the work of Dudik, Lahaie, and Pennock [6], who use convex optimisation and constraint generation to develop a market maker which is tractable. This approach lies somewhere between treating all securities as independent and a fully combinatorial, “ideal” market maker, propagating information among related securities for more complete information aggregation. The ways in which their odds are calculated are also natural: for example, a large bet on a team to win the entire tournament automatically increases the odds that the same team will progress past the first round, since they would not be able to win the competition without doing so. This work is then improved upon by Kroer, Dudik, Lahaie, and Balakrishnan [9], in which they use integer programming to achieve arbitrage-free trades, or always profitable risk-free trades. On top of achieving bounded loss, a crucial element behind a market mechanism operating in the real world and avoiding bankruptcy, avoiding arbitrage is desirable as it leads to more accurate forecasts: since users cannot make risk-free profits, they are forced to bet according to their true beliefs.

All examples so far have involved a centralised market mechanism. These types of systems involve a central authority providing the bets upon which users may bet and then verifying their outcome. *Decentralised* markets allow the users themselves to define their own bets and trade shares in them. These types of systems involve a central authority providing the bets upon which users may bet and then verifying their outcome. These types of markets allow the users themselves to define their own markets by providing custom bets and then trading shares in them. Several examples of decentralised markets exist and they are often implemented with cryptocurrencies. Peterson et al. [12] study the setting and use it to implement the oracle at the heart of *Augur* [1], a decentralised prediction market built upon the Ethereum blockchain that launched in 2018. It allows users to offer predictions on any topic, and markets may be either categorical, which are similar to binary markets in which the winner takes all, or scalar, which offer users a spectrum of outcomes in which to invest. For example, users may bet that the global average temperature for 2020 will lie in a certain range. As in many decentralised markets, outcomes of events are then resolved by the users, and in the case of *Augur* users are incentivised to report truthfully by way of paying reporting fees. This amounts to users depositing tokens to back their report, and token holders are then entitled to the trading fees generated.

As can often be the case with real-money markets, however, the platform had quickly devolved into an assassination market [5] – originally this referred to the case where users created markets on the deaths of certain people, which then incentivised their assassination. A user could stand to profit by placing a bet on the exact time of their death, and ensure this bet was profitable by assassinating the subject. More generally this refers to the users of a prediction market having the ability to influence a market’s outcome and acting on this opportunity. Another issue with *Augur* is the option to report a market’s outcome as “invalid”: this is for the case where the user-made bet is too ambiguous to decide, such as, “Bayern Munich will play well against Paris Saint Germain”.

Other decentralised markets based on cryptocurrencies exist, including *Omen* [?] and *Hivemind* [2]. The former is similar to *Augur* in that it allows users to create markets for any bet they like and whose outcomes are not decided by the system itself. Whereas *Augur* uses a reputation system in the form of requiring users to back their report of a market’s outcome with \$REP tokens, *Omen* asks the market creator to supply an “oracle” through which the outcome can be determined. They note that this oracle can even be *Augur*. Although this may solve the “invalid” outcome option for ambiguous bets, it may introduce bias into the process of outcome determination. For example, suppose a user creates a market for “The Democratic nominee will tell a lie during tonight’s debate” and lists the oracle as the conservative news channel, Fox News. Users would then trade on how they think the oracle will report the outcome, and not what they believe the outcome will be themselves. An important aspect of decentralised markets must therefore be that the outcome is determined by the community, not a single source.

In contrast to *Augur*, which implements a traditional orderbook using Ethereum, *Omen* uses an automated market maker to provide liquidity to its securities. Two approaches to this include using a Market Scoring Rule to update the odds on a given event, and implementing a parimutuel market where users compete for a share of the total money wagered while the share price varies dynamically according to some cost function. Hanson [8] shows that we can use any strictly proper scoring rule to implement an automated market maker: with such scoring rules, agents maximise their expected utility by truthfully revealing their predictions. In particular, in this project we implement the peer prediction

market introduced by Freeman, Lahaie, and Pennock [7], which specifies a market that uses a Market Scoring Rule to trade bets and crowdsources outcome determination, similarly to *Augur*, by asking users for reports. All they require is that the rule is strictly proper, giving plenty of choice to study the effects different rules have on user behaviour. While the choice of scoring rule is less important than the mechanism by which market outcomes are determined, a recent work by Liu, Wang, and Chen [10] introduces scoring rules for the setting where the aggregator has access only to user reports, which they call Surrogate Scoring Rules (SSRs). This appears to be an interesting avenue to further explore and adapt to a prediction market. One assumption they make, however, seems incompatible with the decentralised setting in that they require all events to be independent. Given that users can create a market for *any* bet, this condition is impossible to ensure. Since SSRs can be strictly proper under certain conditions, they may be applicable as the Market Scoring Rule in [7].

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