Decision markets in theory, experiment, and practice

Abstract

The increasing reach and capabilities of digital information technologies provide communities with novel opportunities to design decision-making processes. In particular, a larger number of processes can be opened up for collective decision-making; and for any given decision, a larger number of participants can have their say. Ideally, this translates into increased legitimacy in decision-making because diversity in individual preferences can be better accounted for. Moreover, decisions will be better informed because collective information, if aggregated correctly, outperforms that of any single individual. However, these positive sides of collective decision-making come with caveats. Findings from theoretical economics suggest that it is difficult to incentivize participants to truthfully act in line with their information or preferences; and many established decision-making mechanisms such as voting are prone to misinformation and strategic play. To take advantage of modern information technologies, more sophisticated mechanisms need to be investigated.

In the proposed project, I will study one such mechanism: decision markets. Decision markets are based on prediction markets, which are popular mechanisms to harness distributed information. Prediction markets allow participants to trade contracts with payoffs tied to the outcome of future events. The emerging price can then be interpreted as (often highly accurate) forecasts about the future. Such accurate forecasts can be of tremendous value for decision-making. Many decision-making problems, however, require more than just a peek into the future – they require conditional forecasts. To decide, for instance, between alternative infrastructure investments, a community needs to understand the socio-economic costs and benefits of each of the alternatives. Finding mechanisms that properly incentivize participants to provide their information for such conditional forecasts is non-trivial. Only recently, decision markets have been put forward as solution. Decision markets combine scoring rules, which translate individual forecasts into payoffs, with decision rules which translate aggregated forecasts into decisions. This novel combination turns decision markets into voting mechanisms that tie a vote on an action to an incentivized forecast of its consequences. Decision markets thereby can provide mechanistic properties that are desirable for voting. In the proposed project we will investigate the fundamental properties of these powerful new mechanisms in theory, experiment and practice.

Background

Prediction markets[1-10] are popular tools for aggregating distributed information into often highly accurate forecasts. Participants in prediction markets trade contracts with payoffs tied to the outcome of future events. The pricing of these contracts reflects aggregated information about the probabilities associated with the possible outcomes. A frequently used contract type are Arrow-Debreu securities that pay $1 when a particular outcome is realised, and otherwise pay $0. If such a security is traded at $0.30, this can be interpreted as forecast for that outcome to occur at 30% chance. Other contract types can be used to elicit other aspects of the probability distribution across possible outcomes of future events[3,4]. Prediction markets are well-studies in theory and practise. An experimental market at Hewlett Packard, for instance, yielded better predictions of future sales than its own sales department[2]; and forecasts from public platforms such as the Iowa Electronic Markets[5] are now frequently cited in the media, where they are given as much credibility as experts' predictions. In our own past research projects we have used prediction markets to successfully forecast the outcome of scientific experiments in the fields of experimental psychology and economics[9,10].

In many practical prediction markets applications, participants trade directly with each other, and one participant's gain is the other participant's loss. Prediction markets can, however, also be designed to offer net benefits to the participants. Such **incentivised prediction markets** can be used by an agent who is willing to compensate the market participants for the information obtained from the market[6,8]. Incentivised prediction markets rely on market maker algorithms to trade with the participants, and on market scoring rules to update prices based on past transactions. These market scoring rules are closely related to scoring rules such as the Brier (or quadratic) scoring rule and the logarithmic scoring rule[11,12], which measure the accuracy of forecasts and allow rewarding a single expert based on forecast and actual outcome. The market maker in an incentivised prediction market subsidises the entire market rather than single experts; but its maximal loss is finite and its expected loss depends on how much the participants 'improve' on the information entailed by the initial market maker pricing. In past projects, we have examined incentivised prediction markets in theory[8], laboratory experiments[13] and practical applications[9,10,14], and in general found them to quickly converge towards accurate forecasts.

Accurate forecasts, as obtained from prediction markets, can be of tremendous value. Many decision-making problems, however, require **conditional forecasts**[15]. To decide between different alternatives, one needs to understand how each of the alternatives will affect the future; thus one needs to predict, and choose between, "alternative futures". Finding mechanisms that properly incentivise participants to provide their information for such conditional forecasts is non-trivial. Only recently has theory emerged on how this can be achieved in so-called decision markets[15-16].

Decision markets work in a stepwise process to select one among a number of mutually exclusive actions. First, forecasts about the expected future consequences of each action are elicited in a step analogous to incentivised prediction markets. Second, a decision rule, with properties described further below, is used to select an action based on the forecasted consequences. Once an action has been selected, and its consequences are revealed, payoffs are provided for the forecasts as elicited in the first step. Importantly, the decision rule is stochastic, with each action being picked with a strictly positive probability[15]; and payoffs are only given for forecasts regarding the consequences of the selected action, but are scaled up by the inverse of the probability for this action in the decision rule. This procedure ensures that the participants' expected payoffs in decision markets remain analogous to those made in properly incentivised prediction markets[15], and that game-theoretical results on strategic interactions between participants in prediction markets[8] carry over. Other than the constraint on the probabilities, there is considerable freedom regarding the specific choice of decision rules. Actions can be selected based on their forecasted consequences along multiple criteria, as well as exogenous information; and as long as the participants are aware that there is a non-zero chance for each action to be selected, the decision rule does not even need to be revealed. This flexibility allows tailoring decision rules to specific decision-making scenarios.

Research Questions and Methodology

Properly incentivized decision markets have only recently been described in theory[15]. Aims of the proposed project are to a) investigate fundamental theoretical properties of decision markets; b) provide a proof-of-concept regarding their functioning in human-subject experiments; and c) test them in practical applications.

The **theory** component of the proposed project addresses a foundational question: **Can decision markets be used for decision-making by a self-governing collective without a central decision maker?** So far, in theoretical investigations of decision markets it is assumed that there is a decision-maker with an interest in (and a budget for) selecting the best among a set of possible actions. Participants reveal their private information solely because of the incentives offered by the decision-maker. Depending on the decision rule, they might influence the decision through their forecasts, but they are assumed to have no vested interest in the decision itself. When used by a self-governing group without a central decision maker, these assumptions need to be given up; the role of a decision market would resemble that of a voting mechanism. Because scoring rules are combined with decision rules, this mechanism ties a vote on an action to an incentivized forecast of its consequences; or put differently, a participant's forecast and vote represent different aspects of the same market transaction. This link between voting and forecasting in decision markets opens up fascinating opportunities for tailoring the design of voting mechanisms. On the other hand, findings from social choice theory[17] and implementation theory[18], such as the Gibbard–Satterthwaite theorem[19,20] and Gibbard's theorem[21] are known to put severe constraints on mechanisms to be incentive-compatible, i.e., incentivise participants to act truthfully in line with their information, or preferences. A first step in investigating the use of decision markets by self-governing groups is therefore to exactly pinpoint what theoretical constraints apply to this mechanism.

Human-subjects laboratory experiments provide an excellent methodology to empirically investigate decision markets. Existing human-subjects studies on decision markets have not yet provided a convincing proof-of-principle, but rather point to potential problems with information aggregation. A study by Gimpel and Teschner (2014)[22] showed that deterministic decision rules work better that probabilistic ones, which is in contrast to what theory suggests. In a preliminary study[23] conducted in collaboration with Yiling Chen and Anna Dreber, we observed that decision markets tend to perform worse than prediction markets with analogous incentive and information structure. Moreover, our experience with prediction markets indicates that there are practical limitations when eliciting forecasts for continuous rather than categorical outcomes[14]. Simplicity in the design seems to be important for the functioning of prediction and decision markets, especially when working within the typical time constraints of lab-based human-subjects experiments, and with typical human-subjects pools where participants have little experience in securities trading. To provide a proof-of-principle it is therefore essential to start with very simple scenarios. For our experiments we will adjust the experimental design of a seminal prediction market study by Plott and Sunder[1] to a conditional forecasting scenario with mutually exclusive actions. Experiments can be conducted at the DECIDE lab at the University of Auckland, and will involve about 300 human subjects.

Ultimate goal of the theoretical and experiment work is to pave the way for **practical decision market applications.** We will study such applications in the domain of scientific research. In previous studies we demonstrated that results of experiments in economics and psychology can be forecasted by prediction markets[9,10]. Next step is to harness such information for decision-making in science[24], and use decision market applications to "crowd-source" decisions on experimental designs. As in our previous prediction markets studies[9,10], we will recruit participants for this project from the relevant research communities.

Broader implications

Our work on the use on prediction and decision markets in science is to a substantial degree motivated by the "replication crisis" in science[25,26]. Interestingly, this crisis is occurring concurrently with a debate about a lack of truthfulness in other domains, such as political decision-making. We therefore believe that our research is of broad relevance and topicality as it offers the potential to improve evidence-based and forecast-based decision-making where desirable. While our past research focussed on crowd-sourcing for forecasting, the mechanisms we now aim to develop provide something more powerful: by harnessing the wisdom of the crowds for decisions, we will help collectives shaping their future. A promising aspect for future applications is that formalized decision-making through decision markets is very well-suited for implementation on blockchain technology[27], with one key ingredient, namely market scoring rules, already being under development[28].

Timeline

The research outlined in this proposal is designed for a 3 year period. Depending on budget constraints, I intend to be based at CRI for either a one year or three years. A series of short-term visits (e.g. 3-4 month per year for 3 years) is also an option. Suitable starting dates are the second half of 2018, or beginning 2019.

Match between researcher and project

I have a highly interdisciplinary research profile, and have been one of the driving forces in developing and implementing prediction market applications in the domain of science. Moreover, I have extensive experience with mathematical and computational approaches in particular in evolutionary game theory, and with human-subjects laboratory experiments in decision-making and forecasting. For the proposed research I will collaborate with Yiling Chen (Harvard, computational economics), Anna Dreber (Stockholm School of Economics, long-term collaborator on forecasting in science), Ananish Chaudhury (University of Auckland and head of the DECIDE lab), and Arkadii Slinko (University of Auckland, mathematics / theoretical economics).

Budget outline

Budget requirements will strongly depend on the outcome of related proposals. A related proposal to the Marsden fund in NZ is currently under evaluation, and would cover three PhD scholarships, and a fraction of the salary costs of the involved PIs. The funding decision will be made in early November, 2017. Moreover, I intend to submit a proposal to the New Zealand's MBIE for Catalyst: Seeding funding which provides up to NZD 80,000 for establishing novel research projects with international collaborators.

Funding will be required for the participants in the experiments and in the practical applications, software costs and software development costs. I expect this to be in order of EUR 10,000 per year. For a longer stay, I will very likely be required to cover a fraction of my salary costs. Moreover, a family allowance will be required for travel costs and to cover schooling for my kids.

Requirements in terms of personnel will depend on aforementioned proposals. Most valuable for the proposed research will be a postdoctoral position in computer science.

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