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Prediction Markets

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I. The First Bull (Ox) Market

INTRODUCTION

Prediction markets are a powerful means of harnessing network intelligence to predict future events. In the mid 2000s, there was a period of excitement around their potential that faded when confronted with poor accuracy and reliability. New developments in human-machine systems inspire us to revisit the topic.

ORIGINS OF PREDICTION MARKETS

In 1906, Francis Galton, half-cousin of Charles Darwin, and a polymath who created the statistical concept of correlation, observed a weight-judging competition in Plymouth, England. Eight hundred competitors bought stamped and numbered cards for 6 pence to inscribe their estimate of the weight of a chosen ox[1]. Galton observed that the average competitor, who is not likely to be an expert in oxen, was as well-equipped to make a fair estimate of the ox as the average voter is capable of judging the merits of most political issues on which he or she votes[2]. To his surprise, the vox populi, or voice of the people, was astonishingly accurate – the median was within 0.8% of the true weight[3], and the average within 0.08%[4]. Galton concluded that the result is more favorable to the credibility of a democratic judgment than he might have expected[5], and this story became immortalized as an early example of what we now call the "wisdom of the crowds".

Galton's Ox offers a glimpse of the concept that the aggregation of the opinions of many people can be surprisingly good predictors of outcomes, even where most of the individuals are not who we traditionally consider experts. This "wisdom of the crowds" shall emerge as a dominant theme as we explore the development of prediction markets.

DEFINITION OF PREDICTION MARKETS

Prediction markets are markets that involve making forecasts about states of the future, using predictive analytics. Here, we employ a broad definition. The term prediction market is sometimes used to refer to only markets forecasting outcomes of events, and in this paper we include forecasting of prices of different assets, such as futures markets and hedge funds that specialize in identifying patterns and predicting price movements.

Political prediction markets date back to the sixteenth century, when betting on the next pope was considered common practice and banned by Pop Gregory XIV in 1591[6]. Gambling odds were printed daily in newspapers such as the New York Times in the early twentieth century. They only declined in popularity due to the advent of scientific pooling[7] before interest was again re-kindled in this area.

Present-day examples include Iowa Electronic Markets, which has allowed students from participating institutions to invest and trade in a variety of contracts since 1998. Students make predictions on future events by buying shares in their outcomes, with the price an indication of the probability that the event will occur. While trading relating to outcomes of political processes are most well-known, students can also trade in a corporation's stock price, quarterly earnings, or movie's box office receipts[8]. PredictIt operates similarly to allow users, who need not be students, to buy shares in outcomes of future political events such as whether the Brexit, OPEC quota reduction, or North Korea hydrogen bomb test will happen[9].

Futures markets, which involve prices of real underlying assets, rather than probabilities of events, originated in the 1730s in Japan. Samurai were paid in rice, and the purchasing power of their income was strained when good rice harvests brought down the price of rice, leading to the first creation of rice bills. The first futures exchange, the Chicago Board of Trade, emerged a century later in 1848[10]. Futures markets of real underlying assets or their prices may also contain information about probabilities of future events. In 1984, economists studied the relationship between orange futures and the weather. Orange trees cannot withstand freezing temperatures for over a few hours, and the paper found that the prices of orange futures at the close of market at 2.45pm, predicted errors in the weather forecasts of the minimum temperature later that evening. This serves as an illustration of how the crowd, in this case the aggregation of orange buyers and suppliers, may end up revealing information about the weather that even the weather experts miss[11].

MECHANISMS OF ACTION

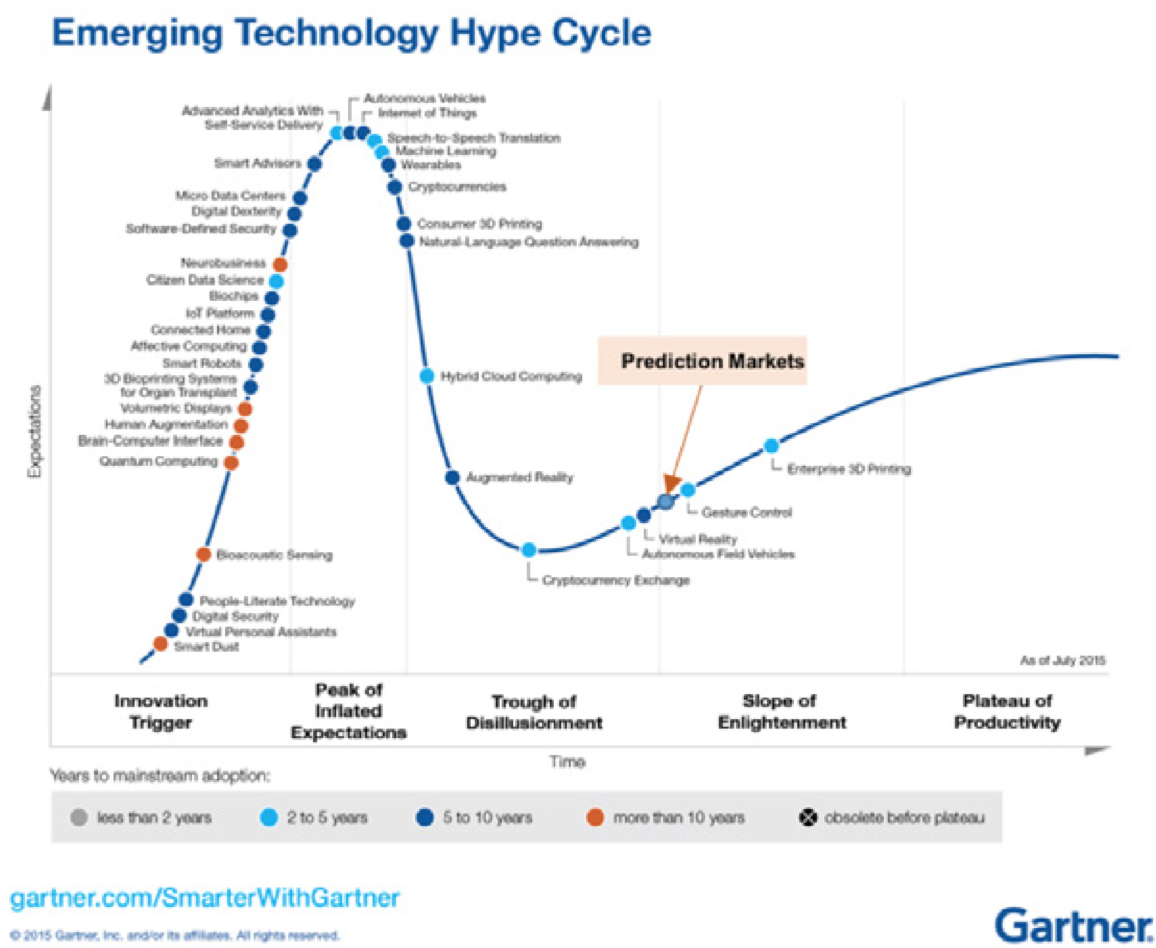
This leads us to the questions: Why do prediction markets work? Is this merely a coincidence or are there underlying reasons? The market mechanism naturally aggregates information of prices, as a transaction happens only when there is a willing buyer and seller at that price. There is a monetary incentive to reveal the truth because of potential gains[12]. In addition, there are long-term incentives for specialization in discovering new information and to trade on it[13]. The markets themselves can do a better job of predicting prices when the prediction errors of each individual are distributed symmetrically around the true value, and with finite variance, so law of large numbers applies. This is known in probability theory as an application of the central limit theorem.

AI AND PREDICTION MARKETS

Recent advances in artificial intelligence means that, beyond the crowd, advanced artificial intelligence techniques are also used to predict outcomes. This does not imply that artificial intelligence would leave wisdom of the crowds obsolete in the near future though. In 2016, we saw a breakthrough in artificial intelligence when Google's artificial intelligence AlphaGo defeated world champion, Lee Sedol, at the game "Go". "Go" is a 2,500 year-old game that is said to be exponentially more complex than chess and requires an added degree of intuition[14]. But we are reminded of the 'centaurs' – human-computer hybrid teams – that rose after the defeat of chess world champion Garry Kasparov by IBM's Deep Blue in 1997. Comparative chess amateurs Steven Cramton and Zackary Stephen, whose world rankings hovered around 1,400 to 1,700, won the freestyle chess tournament in 2005, beating Hydra, the most powerful chess computer at that time, using regular Dell and Hewlett-Packard computers and software that can be purchased for sixty dollars[15]. This reveals the power of human-computer collaboration, where a computer's ability to process large amounts of data reliably combines with human intuition and empathy to outdo what either man or machine could have achieved on their own.

II. Peak of hype, crash, fizzle and rebirth

Prediction markets are only just emerging from the trough of disillusionment in the Gartner Hype Cycle, as illustrated by our adaptation of their 2015 report:



The Gartner Hype cycle breaks down the life cycle of a technology into five phrases. First is a technology breakthrough, which triggers media interest and publicity. Early publicity, fueled by a small number of success stories, generates excitement, leading to the peak of inflated expectations in the second stage. As failures of these exaggerated expectations occur, the technology enters the trough of disillusionment in the third stage, with investments continuing only if surviving providers improve products to the satisfaction of the early adopters[16].

This is followed by the fourth stage of the slope of enlightenment, where the technology matures. During this phase, more benefits and use cases are found, and second-and third-generation products emerge. The fifth and last stage is the plateau of productivity, where mainstream adoption takes off[17].

PROLIFERATION OF PREDICTIONS

Prediction markets have existed for centuries and, while there was no single technology breakthrough that could be responsible for its increase in popularity, the rise of a more networked society (greater connectivity among predictors) and better software and hardware systems to manage this connectivity was undoubtedly a contributing factor.

In the early- to mid- 2000s, uses of prediction markets begun to proliferate, leading to the second stage peak of inflated expectations. After they accurately forecasted events from sales of computer printers to election results and the Federal Reserve's interest rate decisions, prediction markets were even used to forecast the spread of infectious diseases[18]. In 2001, the Defense Advanced Research Project Agency (DARPA) also started experimenting with prediction markets to forecast terrorism; only to have the program cancelled in 2003 under congressional criticism[19].

DAWNING DISILLUSIONMENT

Criticism of prediction markets came to a head around 2008. This could be seen as the ushering in of the third stage of the trough of disillusionment. When Obama did not win the California primary after Intrade, a prediction market founded in 1999, criticism emerged. Prediction markets were said to be too small, the stakes too low, and too slow to react to events[20]. Intrade also gave an 80% chance that the Supreme Court would overturn Obama's health care law, which did not materialize. Even then, however, it was recognized that Intrade's record is better than that of any single poll or pundit [21]. After all, if prediction markets gave an 80%-certain prediction, then it should be wrong one out of every five times. True to Gartner's Hype cycle, prediction markets could not meet some of the then-inflated expectations.

The trough of disillusionment was intensified by the collapse of Intrade. This is significant because at that time, Intrade was the only real-money prediction market focused on forecasting the likelihood of events. The Dodd-Frank financial reform signed by President Obama in 2010 bans futures related to terrorism, assassination, gaming, and anything “contrary to the public interest”, advising in 2012 that elections are covered. A Commodities Futures Trading Commission (CFTC) spokesperson declined to comment on Intrade. Then in 2012 the ‘Romney Whale’ appeared. The ‘Romney Whale’ added $3.8 million to an already enormous bet on Romney even as polls swung towards Obama, causing Intrade to put Obama’s price at 70 when an Obama victory was almost assured and quoted as 90% in the New York Times[22]. This raised suspicions that the price was being manipulated for political reasons. Separately, the CFTC sued Intrade citing its decision to return to offering markets on financial predictions like the future unemployment rate. Intrade suspended operations in March 2013 and financial discrepancies including $4.2 million missing in accounts from Intrade and a related company surfaced[23].

INNOVATION-FUELED REBIRTH

Since then, however, it has begun to appear that we are moving into the fourth Hype cycle stage of maturation of technologies, such as quadratic voting. Under quadratic voting, individuals buy votes in favor of their preferred alternative from a clearing house, paying the square of the number of votes purchased. Economists have recently shown that this mechanism ensures efficient outcomes in large populations[24]. Other innovations include incorporating information about the prior quality of predictions from a specific individual, gathering social information through iterated predictions, and removing outliers.

Vetr is an example of an investor platform that makes use of social information by providing crowdsourced stock ratings for stocks and exchange-traded funds. On Vetr, users can search for specific stocks, review ratings from other investors who have shared insights on stocks they are interested in, add stocks to their watch-list, and trade stocks on that information. "The system we have designed is not about timing the market, rather it's about helping investors make better investment decisions," explained Vetr CEO Mike Vien. Vetr users make specific predictions about the future price of a particular stock. Users who do especially well at beating the market are rewarded through social recognition and their reputations are promoted on the site as a "Top Rater". Vetr's algorithms then calculate a crowd target price and an aggregate rating from the users' target price predictions for the stock as well as users' past performance history. Traditionally, top raters have come from a variety of backgrounds, but Vetr's "theory is that when you have a broad distribution of people, coupled with diversity and independence, the predictions are better than industry experts", Vien says. "Our research demonstrates that Vetr's aggregated predictions are more informative about future stock prices than any individual Wall Street analyst or the target price consensus of industry professionals only[25]."

Today, it is perhaps best to view prediction markets as an application of predictive analytics to markets. Predictive analytics can have far wider applications than markets. Customer analytics, for example, is an extremely lucrative field of application. For instance, Framed Data started as a platform for data scientists to run and test markets before evolving to use machine learning technology to predict user churn and other customer metrics[26].

III. From Crisis, Opportunity

A conversation with MIT Sloan Professor Andrew Lo explored the relationship between the global financial crisis of 2008 and recent evolutions of prediction markets[27]. The global financial crisis caused many people to lose confidence in the financial markets and some of the newer financial innovations. In many people's eyes prediction markets failed to live up to their promise. That confidence further decayed as centralized prediction markets, created to allow user predictions to be packed and traded as securities, were deemed gambling by US regulatory bodies, resulting in a number being shut down. Eight years after the financial crisis, the subsequent developments in prediction markets now offer a new promise that is reflective of some of the lessons learned from the crash.

Any deep innovation requires time and commitment to overcome skepticism. Prediction models face a number of skeptics who view them as weird and difficult to implement. As with many hyped trends, the future promise of the technology was not in line with the current abilities. The crisis and subsequent research has also offered a deeper understanding of the implicit assumptions and limitations of these models.

THE NEW MACHINE SYSTEMS

So what's different now? First, technology developments can now more readily deliver the promise of prediction markets. Second, we have a better understanding about the human element underpinning these models.

Looking at the technology, we see developments in data availability, and that quantitative hedge funds have moved towards a purer model of machine learning. Not only have prediction methods reached speeds that enable high-speed action while analyzing ever larger amounts of data, a huge step forward has been made in how the algorithms learn. There are many different learning models used today, for example, neural networks that draw design inspiration from neurons in the human brain used independently or in concert. The results of these developments are that more data types, specifically raw live-feed data from real-world systems, can be analyzed without having to be preprocessed by hand, and consequently real-time analysis methods allow trading strategies to adapt to live market data.

Hedge funds were some of the first financial adopters of predictions markets and are still experimenting with new ways to push the technology forward. One way is by uniting Artificial Intelligence (AI) with prediction markets.

In January of 2016, Aidyia officially launched its AI hedge fund, in which all trades are executed entirely by machine. Their system identifies and executes its own trading strategies entirely autonomously using multiple forms of AI, from one inspired by genetic evolution to another using probabilistic logic. Analyzing everything from prices to macroeconomic data and corporate accounting documents, the Aidyia AI makes its own market predictions and then uses a probabilistic assessment to make its decisions[27]. Another example is Sentient, a distributed artificial intelligence platform that has first been used for trading, which is now being extended to other areas such as e-commerce and healthcare. Sentient is based on two pillars - evolutionary intelligence and deep learning. Sentient Investment Management develops and applies proprietary quantitative trading and investment strategies, and Sentient Aware helps customers find products they want by using visual search[28].

Numerai is an example of a start-up that is combining crowdsourcing and AI. Numerai is a hedge fund which harnesses and aggregates promising machine learning models from the masses, in the form of a global artificial intelligence tournament to predict the stock market. Using advanced encryption techniques, Numerai is able to give access to very private data to amateur and veteran data scientists all over the world while still ensuring that those data are not spread further. Users operate very much like consultants, contributing their human capital, without putting up any financial capital of their own. Payment is made through blockchain currencies and all interfacing happens through a distributed network and in an anonymous manner[29].

One direction to take these technological advancements is to try remove the human element from the decision making process. In specific scenarios, this will be a potentially lucrative approach, but does not incorporate some of the other learnings from the crash.

THE CHALLENGES LIMITING PREDICTION MARKETS

Any type of predictive analytics makes you a prisoner of the past. When creating and testing models you are always back testing against historical data. More and more evidence shows that markets are not only dynamic but adapting at a pace much faster than previously seen. A few years ago, high frequency trading was measured in minutes, where now it's measured in fractions of a second. The financial crisis showed us data never before seen in the public US markets and it wreaked havoc on predictions. Machine learning can do correlation very well but the gap between correlation, a pattern, and causation, a driving cause, is a long distance. The only way to fill that gap is through the narrative and context given to those patterns. An example of this approach is Endor.com, cofounded by Prof. Pentland, which couples quantitative models of human behavior with more standard machine learning techniques. As a consequence, they are able to derive accurate predictions from much shorter time-series data than other systems, allowing quicker reactions in volatile situations. This is particularly useful for churn, fraud, and similar prediction tasks where losses can happen quite quickly.

The second big change for prediction markets is in understanding, enabling and incentivizing the human behaviors of prediction markets. First, even in the relatively short span of eight years we have collectively become more tech savvy and connected. Tapping into the wisdom of crowds can be an almost frictionless process when individuals are motivated to contribute.

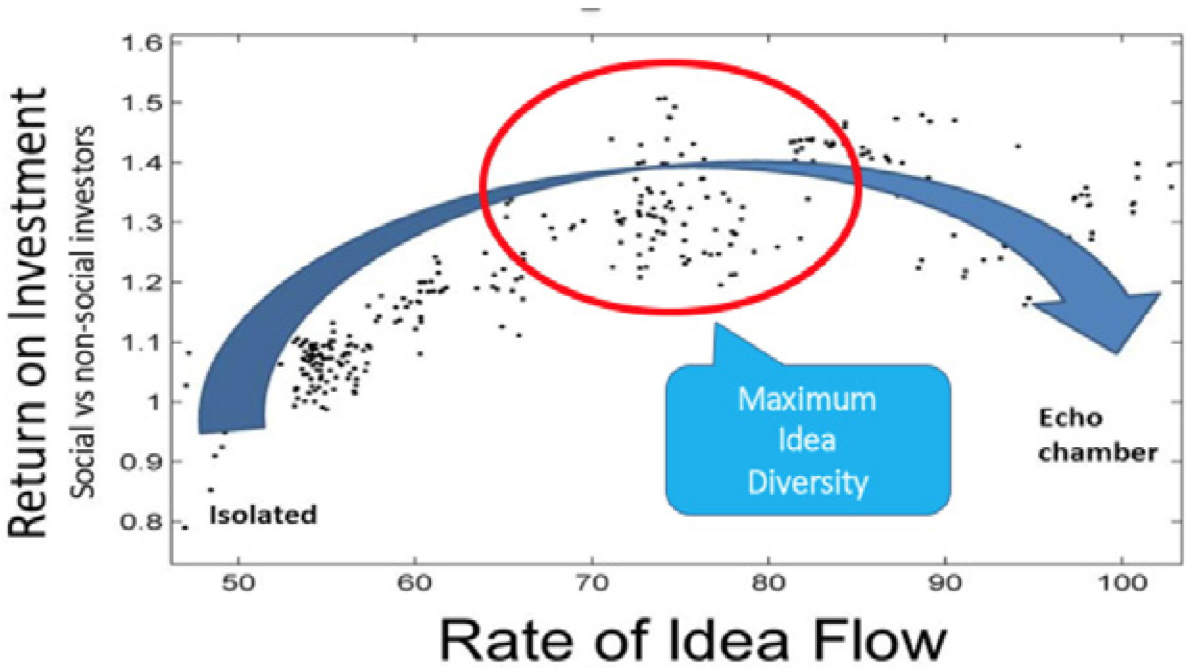
The ability to add more people would seem to add more wisdom to the crowd, and thus offering more predictive power. However, this is not always true: independent observations are critical to the idea of wisdom of crowds, primarily because they offer a diversity of information. Consequently small but highly independent “crowds” can still have predictive power, while large but highly connected crowds may not have significant predictive power. Natural human behavioral biases arise when an individual is aware of other people’s opinions. The running adage about the world getting smaller is true, particularly when you are talking about one asset type in one market in one industry, which calls into question the independence of the crowds’ observations.

BEYOND THE ECHO CHAMBER

Machines are not capable of making an intuitive leap, and humans are subject to mental biases - but what about human/machine systems? While most players are making a big push to advance machine learning technology, our team at MIT has sought to get a better understanding of social learning, to more clearly understand how people make decisions and follow idea flow through a human network. Published in the study “Beyond the Echo Chamber”, by looking at financial decision making among traders using a transparent and social trading platform, the study observed not only the ideal balance of information diversity and network connectivity that will enhance decision making skills, but more importantly that decision making skills could be improved through social learning.

Those that excelled at decision making are social explorers, continuously seeking out new people and ideas—but not using some preconceived notion about the “best” people or ideas. Social explorers seek connections with a diversity of people and to gain exposure to a large variety of viewpoints. The results of the analysis revealed that the effects of social learning were significantly better payoffs than peers. The traders who had the right balance and diversity of ideas in their network yielded 30% higher returns on investments than the returns of either isolated traders or those in the herd.

The research proved that if the flow of ideas becomes either too sparse or too dense, relatively small adjustments in a person's social learning strategy can help correct the situation. By providing small incentives or nudges to individuals, isolated traders could be encouraged to engage more while traders who are too interconnected within the same group could explore outside their immediate social network. With the help of deep learning techniques, this social network could be tuned so that it remained in the healthy "wisdom of the crowds" balance.



Utilizing these corrections in a large-scale experiment, the MIT team increased the return on investments of all social traders by more than 6%. Managing idea flows using the "idea flow" prediction model resulted in meaningful enhancements to human behaviors, also proving that markets can be structured with adaptive incentives to create better "wisdom of crowds" results. In this case it helped turn middling traders—often losers in the financial system—into winners[30].

IV. Predicting the Future of Prediction Markets

Information asymmetry drives competitive edge in finance, so the most successful work is the least talked about. To better uncover some of the trends we talked with researchers both within universities and at companies working on the future generations of prediction markets. Focusing on better predictions as well as new avenues for growth are some of the key trends centered on new data and technologies and new application areas.

NEW DATA AND TECHNOLOGIES

In addition to continuing to evolve better machine learning models, the push for greater amounts of unique data is a big focus of innovators, coupled with the corresponding integration of this new data with machine learning, prediction markets, and other modeling technology. Data has become an increasingly important competitive advantage, and there is an ever greater push for faster and novel data.

Thomson Reuters, for instance, is responding to this sort of client demand by experimenting with new business models and data collection methods, partially through its newly created Thomson Reuters Lab. One method of developing such new business models and new data is to look for companies with a unique perspective on a market, such as a company with large operations in a niche market. Reuters can work with such a company to anonymize and monetize their data for Reuters's audience. For prediction markets, having diversified information that is not otherwise readily accessible opens up unique and profitable opportunities.

Speaking with Henry Chong from Thomson Reuters Labs, he predicts the business of information is poised to change as new prediction technologies enter the market. Human data or data tied to physical content, collecting new forms and understanding it will play a greater role in the future.

We have seen AI and prediction markets converge, and the future could see further exploration with other emerging technologies such as blockchain and IoT. One such project, Augur, is exploring the union of two of these by creating a blockchain-based prediction market. Built upon the Truthcoin protocol, the goal is to prove prediction markets can be leveraged for social good by using a decentralized public ledger as a mechanism for fields such as healthcare and government to tap into the predictive power of global users. For example, if you wanted to research foods that can cause cancer, the sheer volume of information is overwhelming, as is the prospect of slogging through the amount of conflicting, misleading or pseudo-scientific work that exists. With a searchable prediction market using incentivized participants, you could find an opinion based on the wisdom of crowds rather than reviewing individual studies from lone experts[31,32].

NEW APPLICATION AREAS

Prediction markets are not just limited to finance or political polling. Used in other areas such as baseball – Rebellion Research for example uses learning networks to predict specific trade outcomes as well as market trends – the prediction market industry will continue to grow. But it's not just external, but rather internal company markets that are most promising. Forecasting for internal outcomes such as supply and demand imbalances is one example, which has proven previously successful. Not an entirely novel use, HP previously created an internal prediction market to forecast printer sales, which proved more accurate than their traditional marketing forecasting models. At Siemens, an internal market accurately predicted that a new software product would fail to be delivered on time, even though all the project planning tools projected that the deadlines would be met. In each case these were small "crowds" of 20 and 60 employees respectively[33]. This highlights the criticality of participants providing unique information to help draw a more complete future picture. Set up properly, companies can use prediction markets to leverage the knowledge of employees, knowledge that is often invisible to more senior management, in order to enable better decision making.

Further development and deployment of human/machine prediction systems will be another powerful future direction as well. This entails creating machine learning networks that will enable and enhance, rather than replace, human decision making. Part of this new human-machine approach will be using AI to embed proper structure and incentives into prediction markets by augmenting human abilities, building AI models that can automatically implement adaptive incentive structures to correct for negative human behaviors.

The authors welcome comment & feedback on this white paper:

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