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Extracting Collective Probabilistic Forecasts from Web Games

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ABSTRACT

Game sites on the World Wide Web draw people from around the world with specialized interests, skills, and knowledge. Data from the games often reflects the players' expertise and will to win. We extract probabilistic forecasts from data obtained from three online games: the Hollywood Stock Exchange (HSX), the Foresight Exchange (FX), and the Formula One Pick Six (F1P6) competition. We find that all three yield accurate forecasts of uncertain future events. In particular, prices of so-called "movie stocks" on HSX are good indicators of actual box office returns. Prices of HSX securities in Oscar, Emmy, and Grammy awards correlate well with observed frequencies of winning. FX prices are reliable indicators of future developments in science and technology. Collective predictions from players in the F1 competition serve as good forecasts of true race outcomes. In some cases, forecasts induced from game data are more reliable than expert opinions. We argue that web games naturally attract well-informed and well-motivated players, and thus offer a valuable and oft-overlooked source of high-quality data with significant predictive value.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications—*data mining*; H.3.5 [**Information Storage and Retrieval**]: Online Information Systems—*web-based services*; J.4 [**Computer Applications**]: Social and Behavioral Sciences—*economics*; K.8 [**Computing Milieux**]: Personal Computing—*games*

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Keywords

Collective probabilistic forecasts, World Wide Web games, data mining, knowledge discovery, artificial markets, Hollywood Stock Exchange, Foresight Exchange, Formula One Pick Six Competition

1. INTRODUCTION

Multiplayer games on the World Wide Web are growing in prevalence and popularity, fueled in part by low operating costs and global reach. Game players tend to be more knowledgeable and enthusiastic about their game's topic than the public at large. For example, the Hollywood Stock Exchange (HSX), a play-money market where traders bet on the future success of movies and stars, draws heavily from among film aficionados. In this paper, we investigate the use of such online games as topic-focused sources of data with relatively high signal-to-noise ratios, as compared to the web as a whole.

Section 2 discusses background and related work in exploiting collective knowledge to generate forecasts. Section 3 describes the three games under study. Sections 4 and 5 evaluate the collective competence of HSX players in predicting box office results and entertainment award outcomes, respectively. In both cases, we find that HSX forecasts are as accurate or more accurate than expert judgments. Section 6 shows that prices on the Foresight Exchange (FX) correlate strongly with observed outcome frequencies for events of broad scientific and societal interest. Section 7 examines the Formula One Pick Six (F1P6) competition, showing that a simple weighting of participants' predictions seems as reliable or more reliable than even the official race odds. Section 8 discusses the more general prospects of mining data and extracting knowledge from a variety of online games and related sources.

2. COLLECTIVE FORECASTS

For decades, and across many disciplines, scientists have investigated combining forecasts from multiple sources. Genest and Zidek [15] and French [13] survey the extensive literature on combining probability assessments from multiple experts. Clemen [3] reviews the equally large (and related) body of work on combining forecasts; most studies conclude that collective forecasts are indeed more accurate than individual ones. Some of today's best machine learning methods are so-called *ensemble* algorithms that combine classifications from multiple learners to yield more robust classifications [7]. Collaborative filtering algorithms or *recommender systems* leverage community information about many people's preferences in order to recommend items of interest (e.g., movies or books) to individuals [29].

Markets can also be thought of as combination devices. Prices reflect information distributed among many traders, each with direct monetary incentives to act on any pertinent information. Informative prices often translate directly into accurate forecasts of future events. For example, prices of financial options are good probability assessments of the future prices of the underlying assets [31]; prices in political stock markets, like the Iowa Electronic Market (IEM),[1] can furnish better estimates of likely election outcomes than traditional polls [11, 12]; odds in horse races, determined solely by how much is bet on which horses, match very closely with the horses' actual frequencies of winning [1, 30, 32, 33, 35]; and point-spread betting markets yield unbiased predictions of sporting event outcomes [14]. Several studies demonstrate that, in a laboratory setting, markets are often able to aggregate information optimally [10, 25, 26, 27].

In a game without monetary rewards, incentives to reveal information presumably derive from entertainment value, educational value, bragging rights, and/or other intangible sources. Our recent investigations [22, 23] conclude that even market games show signs of collective competence. For example, arbitrage opportunities on HSX (i.e., loopholes that allow traders to earn a sure profit without risk) tend to disappear over time, just as they do in real markets. Sections 4, 5, and 6 show that intangible rewards seem sufficient to drive forecast accuracy in market games. Section 7 presents evidence that, even without the "carrot" of monetary compensation, F1P6 players are motivated enough to generate very accurate collective predictions of Formula One racing outcomes.

3. THE GAMES

3.1 The Hollywood Stock Exchange

The Hollywood Stock Exchange (HSX)[2] is a popular online market game, with approximately 400,000 registered accounts. New accounts begin with H$ two million in "Hollywood dollars". Participants can buy and sell movie stocks, star bonds, movie options, and award options. The current top portfolio is worth just over H$1 billion. High ranking portfolios are actually sold at auction on Ebay[3] for real money on a regular basis. Based on these sales, the "exchange rate" seems to be approximately H$1 million to US$1, with the rate increasing for higher ranked portfolios. HSX is beginning to offer new investment opportunities backed with real money. For example, HSX investors could purchase shares in the movie *American Psycho* for H$1 million each; these shares paid off about US$1 for every US$5 million of the movie's box office proceeds. HSX cofounder Max Keiser hosts a weekly radio broadcast in Los Angeles, and appears regularly on NBC's *Access Hollywood* to discuss HSX information. HSX also sponsors a booth at the Sundance Film Festival, and holds an annual Oscar party in Hollywood. Media reports suggest that HSX prices are taken seriously by some Hollywood insiders.

Although the current price of any HSX movie stock is based on the collective whims of HSX traders, the value of the stock is ultimately grounded in the corresponding movie's performance at the box office. Specifically, after the movie has spent four weeks in release, the stock delists and cashes out: shareholders receive H$1 per share for every US$1 million that the movie has grossed up to that point in the US domestic market, as reported by ACNielsen EDI, Inc.[4] Traders buy (resp., short sell) stocks that they believe underestimate (overestimate) the movie's eventual performance. The current price, then, is a collective forecast of the movie's four-week box office returns.[5]

The prices of some stocks adjust after their first weekend in wide, national release. On Friday, trading in the stock is halted; on Sunday, the price adjusts to H$2.9 times the movie's weekend box office numbers (in US$ millions).[6] In this case, the stock's price prior to wide release is the HSX traders' forecast of 2.9 times the movie's opening weekend proceeds. The 2.9 factor is meant to project the movie's four week total based on its opening weekend results.

Occasionally, HSX offers "award options" associated with particular entertainment awards ceremonies—for example, the 72nd Annual Academy Awards, or *Oscars*, sponsored by the Academy of Motion Picture Arts and Sciences in 2000. Five options, corresponding to the five award nominees, are available within each award category (for example, Oscar award options were available for each of the eight major Oscar categories of best picture, best actor, best actress, best supporting actor, best supporting actress, best director, best original screenplay, and best adapted screenplay). Within each category, the winning option cashes out at H$25, and the other four cash out at H$0. Before awards are announced, an option's price can be interpreted as its estimated likelihood of winning. For example, when Kevin Spacey's price was twice that of Denzel Washington, the consensus of HSX opinions was that Spacey was roughly twice as likely to win as Washington. By normalizing prices within each category, likelihoods can be converted into probabilities.

3.2 The Foresight Exchange

Hanson [17, 18] proposes what he calls an *Idea Futures* market, where participants trade in securities that pay off contingent on future developments in science, technology, or other arenas of public interest. For example, a security might pay off US$1 if and only if a cure for cancer is discovered by a certain date. He argues that the reward structure of such a market encourages honest revelation of opinions among scientists, yielding more accurate forecasts for use by funding agencies, public policy leaders, the media, and

[1] `http://www.biz.uiowa.edu/iem/`. Other election markets have opened in Canada (`http://esm.ubc.ca/`) and Austria (`http://ebweb.tuwien.ac.at/apsm/`).

[2] `http://www.hsx.com/`

[3] `http://www.ebay.com/`

[4] `http://www.entdata.com/`

[5] Although cash holdings do accrue interest on HSX, all analyses in this paper ignore any time value of Hollywood dollars.

[6] Movies released on holiday weekends, and movies with substantial box office receipts prior to wide release, may adjust differently.

other interested parties. The concept is operational as a web game called the *Foresight Exchange* (FX).[7] There are currently on the order of 3000 registered participants and 200 active claims. Players start with an initial amount of "FX bucks" and receive an allowance every week, up to a certain maximum. Participants can buy and sell existing claims, or submit their own claims. Each claim is assigned a judge to arbitrate ambiguous wording, and to ultimately determine whether the claim is true or not on the judgment date. Claims range from technical (e.g., FX$1 if and only if an algorithm for three satisfiability is developed with a particular runtime complexity by the year 2020) to sociopolitical (e.g., FX$1 if and only if Japan possesses nuclear missiles by 2020) to irreverent (e.g, FX$1 if and only if Madonna names her first child Jesus). The developers of the site intend for the prices of these claims to be interpreted as assessments of the probabilities of the various events.

3.3 The Formula One Pick Six Competition

Formula One (F1) is one of the prime international race car competitions. Drivers compete in approximately 16 races during a season, accumulating points according to how well they place within each race. The sport draws a large and avid following, especially in Europe. Betting on the sport is also quite popular. A variety of bookmakers, both online and off, support bets on the outcomes of individual F1 races and on the results of an entire season. Media coverage of the sport is fairly extensive, including a variety of informative websites (e.g., `http://www.motorsport.com/`).

Formula One Pick Six (F1P6) is an email- and web-based competition for predicting F1 outcomes.[8] The game has been in existence for a number of years, and currently has several thousand registered participants. No monetary reward is associated with the F1P6 competition. The goal is to correctly forecast the top six drivers of each race. Participants receive a score based one how well their ranking of drivers matches the actual result. For each correct driver-place prediction, they receive 10 points. For each driver prediction that is one place off, they receive 6 points. For each driver prediction that is 2, 3, 4, or 5 places off, they receive 4, 3, 2, or 1 points, respectively. Drivers that finish in seventh place and below are disregarded. Wasserman [34] describes statistical analyses of the first three years (1994-1996) of the competition.

4. BOX OFFICE FORECASTS: HSX MOVIE STOCKS

In this section, we evaluate HSX movie box office forecasts according to several error metrics. We also investigate the benefit of augmenting game data with outside information to boost prediction quality.

Recall that, before a movie's opening weekend, its price on HSX is an estimate of 2.9 times its weekend proceeds. We collected the halt prices s_h (Friday morning's prices) and adjust prices s_a (2.9 times the actual return) from HSX for 50 movies opening during the period March 3, 2000 to September 1, 2000. Figure 1 plots the actual box office return $s_a/2.9$ versus the HSX estimate $s_h/2.9$ for each movie. We measure accuracy of the forecasts according to four metrics:

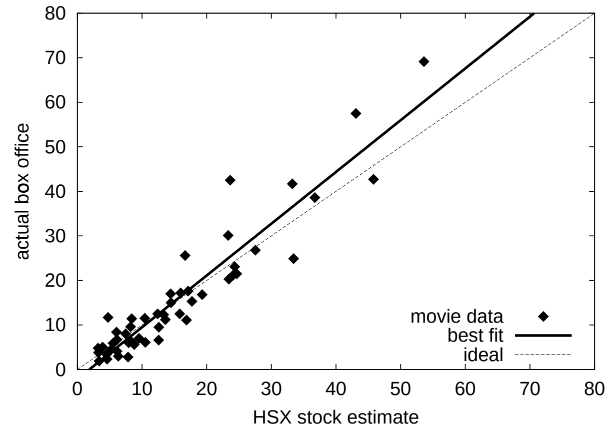

Figure 1: Accuracy of HSX movie stock forecasts to predict opening weekend box office returns. The dashed line corresponds to ideal accuracy; the solid line is the best linear fit.

(1) correlation between estimate and actual, (2) average absolute error, (3) average percent error, and (4) slope of the best-fit line to the data.[9] Table 1 reports these error measurements for baseline HSX data. Without any preprocessing (e.g., boosting, filtering, or learning), HSX forecasts are remarkably accurate. Game players—at least collectively—appear to be knowledgeable about the prospects of upcoming movies and are sufficiently well-motivated to reveal their information in the context of the game, even without much prospect for tangible compensation.

Next, we evaluate HSX predictions of four-week total box office proceeds. After a movie stock on HSX adjusts (or if it does not adjust), its price becomes a forecast of the movie's four-week box office total r_4. We gathered the delist prices r_4 and the prices three weeks before delist s_3 for 109 movies between March 3, 2000 to September 1, 2000. Figure 2 graphs r_4 versus s_3 for each movie. The correlation is 0.978, the best-fit line's slope is 1.04, and the average error is 4.01. The average percent error is undefined (infinite), since a few small movies apparently did not earn any measurable amount of money.

We also recorded the forecasts of opening weekend returns from movie expert Brandon Gray of Box Office Mojo.[10] Table 1 compares the accuracy of Box Office Mojo predictions to HSX predictions. The two forecasts are of comparable quality—Box Office Mojo performed 4% better than HSX in terms of average percent error. In fact, the two sources make similar errors. Figure 3 plots the correlation between HSX errors and Box Office Mojo errors. Both sources overestimate a larger fraction of movies; but when they do underestimate, they are off by a greater amount. This occurs because both tend to underestimate the best box office per-

[7] `http://www.ideafutures.com/`

[8] `http://www.motorsport.com/compete/p6/`

[9] We employ a standard least-squares regression to obtain the best-fit line. Since the variance of data increases with estimate magnitude, a weighted least-squares regression may be appropriate. Ideally, weights would be inversely proportional to variance [5], but we do not have enough data to accurately assess variance at each point.

[10] `http://boxofficemojo.com/`

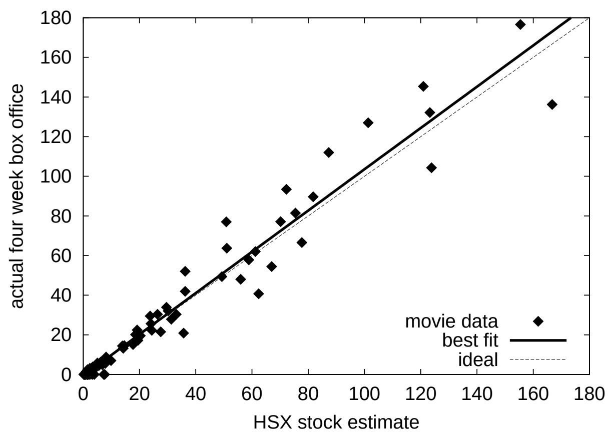

Figure 2: Accuracy of HSX movie stock forecasts to predict four week total box office returns. The dashed line corresponds to ideal accuracy; the solid line is the best linear fit.

Table 1: Accuracy of HSX, Box Office Mojo, and combined forecasts of opening weekend box office returns. Accuracy metrics are correlation, average error, average percent error, and slope of the least-squares best-fit line.

	corr	avg err	avg %err	fit
HSX	0.940	3.57	31.5	1.16
BOMojo	0.945	3.31	27.5	1.10
avg	0.950	3.16	27.0	1.15
avg-max	0.956	2.90	26.6	1.08

formers. The correlation in errors between HSX and Box Office Mojo is 0.818. The two estimates may result from overlapping sources of evidence—for example, it is possible that Brandon Gray observes HSX prices, and/or that some HSX traders read Box Office Mojo forecasts.

We investigate combining data from HSX and Box Office Mojo to sharpen predictions. The simplest method—averaging the two estimates—results in increased correlation, decreased average error, and decreased percent error, as reported in Table 1. Since both sources underestimate big box office winners, we tried a second combination procedure that returns the average of the two forecasts if that average is less than twenty-five, otherwise returning the maximum of the two forecasts. This "avg-max" combination gave the most accurate predictions according to all four metrics (see Table 1). Figure 4 graphs box office numbers versus this combined estimate. Without more data, we hesitate to employ more sophisticated learning and boosting techniques lest we begin to overfit; on the other hand, given access to training and test data over a larger time frame, such methods will likely become warranted.

Combining forecasts works best when individually accurate sources make uncorrelated errors [7]. Since HSX and Box Office Mojo exhibit dependent errors, the gain from merging data, while appreciable, is relatively small. Iden-

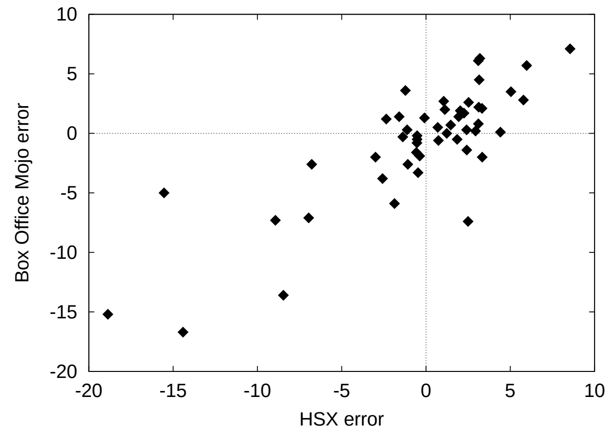

Figure 3: Correlation between HSX opening weekend forecast errors and Box Office Mojo forecast errors.

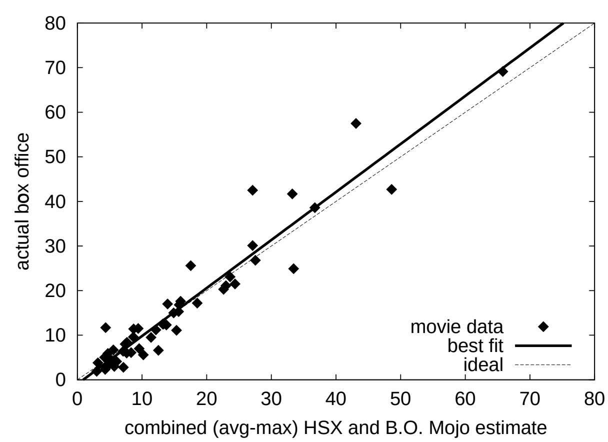

Figure 4: Accuracy of combined HSX and Box Office Mojo forecasts to predict opening weekend box office returns. The dashed line corresponds to ideal accuracy; the solid line is the best linear fit.

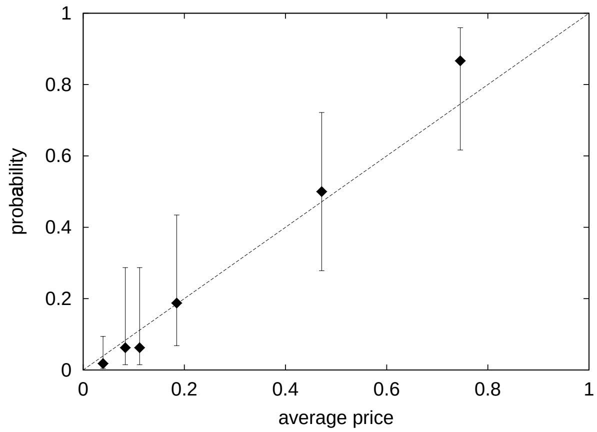

Figure 5: Accuracy of the HSX award options market. Points display observed frequency versus average normalized price for buckets of similarly-priced options. The dashed line where frequency equals price corresponds to ideal accuracy.

tifying alternative sources that yield independent forecasts will be a key component of any data combination strategy. Some candidate sources to explore include chat board postings, query logs, press coverage, movie reviews, and link structure on the web.

5. ENTERTAINMENT AWARD FORECASTS: HSX AWARD OPTIONS

In the 2000 HSX Oscar options market, as it turns out, each nominee with the highest final price in its category did indeed win an Oscar. The Wall Street Journal, amid controversy, published a poll of actual Academy voters days before the Oscar awards ceremony; their report correctly forecasted only seven out of eight winners.

Beyond predicting the most likely winner, we investigate how accurately HSX award option prices reflect all likelihoods of winning. For example, if prices are accurate, then among all options with a normalized price of H$0.1, about one in ten should end up winning. Our accuracy analysis is similar to that conducted for horse races [1, 30, 32, 33, 35] and other sports betting markets involving real money. We collected prices of award options associated with the 2000 Oscars, Grammies, and Emmies, for a total of 135 options. Grammy options (nine categories) and Emmy options (ten categories) functioned exactly as Oscar options, though winning Grammy options paid out H$42 instead of H$25.

Prices were recorded just before the markets closed, and before winners were announced. We sorted the options by price, and grouped them into six buckets. We placed the same number of options (16) in every bucket, under the constraint that every bucket include at least one winning option. We computed the average normalized price of options within each bucket, and the *observed frequency* within each bucket, or the number of winning options divided by the number of options. Figure 5 plots each bucket's observed frequency versus its average normalized price. If we model options as independent Bernoulli trials, then, in the limit as the number of options goes to infinity, completely accurate prices would imply that bucket points fall on the line $y = x$, where observed frequency equals price. Error bars display 95% confidence intervals under the independent Bernoulli trials assumption. Specifically, the lower error bound is the 0.025 quantile of a Beta distribution corresponding to the observed number of successes (wins) and trials in the bucket, and the upper error bound is the 0.975 quantile. The Beta distribution is the correct posterior distribution over frequency, assuming a uniform prior.[11] The length of an error bar decreases as the number of options in the bucket increases. The independence assumption is an idealization, since options within a single award category are actually mutually exclusive. The closeness of fit to the line $y = x$ can be considered a measure of the accuracy of HSX prices.

We compare HSX prices of Oscar options to reported likelihood assessments from five columnists at the Hollywood Stock Brokerage and Resource (HSBR),[12] a fansite of HSX. We use the logarithmic scoring rule to rate the market and the columnists. The logarithmic score is a *proper scoring rule* [36], and is an accepted method of evaluating probability assessors. When experts are rewarded according to a proper score, they can maximize their expected return by reporting their probabilities truthfully. Additionally, more accurate experts can expect to earn a higher average score than less competent experts. Scores are computed separately within each award category, then averaged. Index the five nominees in a category $i = 1, 2, \ldots, 5$. Let $w_i = 1$ if and only if the ith nominee wins, and $w_i = 0$ otherwise. let $p_1, p_2, \ldots, p_5$ be the market's or columnist's reported probabilities for the five nominees. Then the assessor's score for the current category is $\ln\left(\sum_{i=1}^{5} w_i p_i\right)$. Expert assessments were reported on February 18, 2000. Table 2 gives the average scores for the HSX market, the five columnists, and the consensus of the columnists. Higher scores are better, with 0 the maximum and negative infinity the minimum. Only one of the five experts scored appreciably better than the market on February 18. HSX's score increased almost continuously from the market's open on February 15 to the market's close on March 26. By February 19, the market's score had surpassed all of the scores for all five experts and for their consensus.

6. SCIENCE AND TECHNOLOGY FORECASTS: THE FORESIGHT EXCHANGE

Like HSX award options, FX prices constitute collective probability assessments of future events. To determine how accurate these assessment are, we collected historical price information for all retired (completed) claims as of September 8, 2000. Of these, we retained only the 172 that were binary (i.e., paid off if and only if some true-or-false event occurred). We recorded the price of each claim 30 days before it expired. A total of 161 claims were active for at least 30 days, and thus qualified for this data set. We sorted the claims by their 30-day-before-expiration price, grouped them into six buckets of size 17 (under the constraint that every bucket contain at least one winning claim), and com-

[11] Note that the expectation of the Beta distribution, $s+1/n+2$, does not coincide precisely with the observed frequency, s/n, where s is the number of successes and n the number of trials. However, as n grows, the two measures converge.

[12] `http://www.hsbr.net/`

Table 2: Accuracy of HSX Oscar forecasts and HSBR columnists' forecasts, evaluated according to average logarithmic score. Higher (less negative) scores are better.

forecast source	avg log score
Feb 18 HSX prices	-1.08
Feb 19 HSX prices	-0.854
Tom	-1.08
Jen	-1.25
John	-1.22
Fielding	-1.04
DPRoberts	-0.874
columnist consensus	-1.05

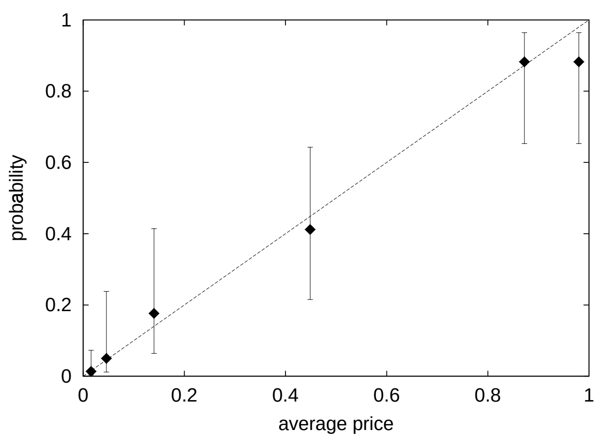

Figure 6: Accuracy of the Foresight Exchange market. Prices are 30 days before claim expiration. Points display observed frequency versus average price. The dashed line corresponds to ideal accuracy.

puted the average price and observed frequency for each bucket.

Figure 6 graphs the results. Prices correlate well with observed outcome frequencies. Error bars show 95% confidence intervals based on the assumption that claims are independent Bernoulli trials with a uniform prior over frequency.

7. FORMULA ONE FORECASTS: F1P6

The reward structure in the F1P6 competition is quite different than in HSX, FX, or the F1 betting market. Correctly predicting an improbable event yields no more points than correctly predicting a likely event. One might expect that competitors would consistently choose the six most probable winners. But this strategy may not always be optimal. By choosing only the best drivers, a participant is not likely to differentiate himself or herself from the pack (unless everyone reasons this way). For example, Kaplan and Garstka [19] show that, under some conditions, picking the top seeds in an NCAA basketball tournament pool does not always maximize the chances of winning. Moreover, when no money is involved, a player may not gain much sense of accomplishment when he or she simply picks the top six drivers, even if he or she does win. Thus, the nature of the competition may induce some strategic incentives to carefully pick a few upsets.

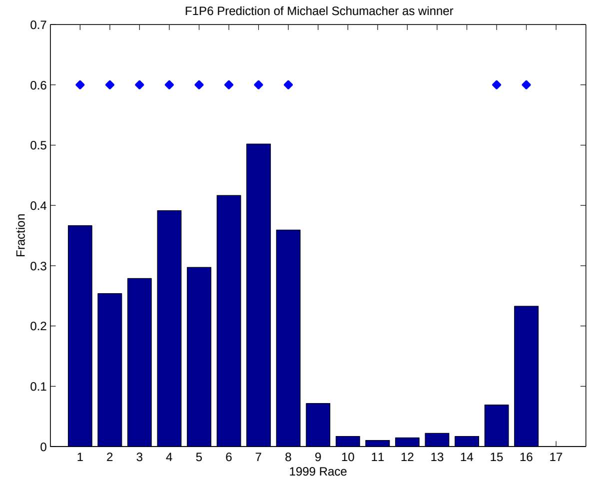

Figure 7: For each race in 1999, the fraction of F1P6 participants that predicted Michael Schumacher to win. Dots near the top of the chart indicate the races that he actually competed in.

Individuals in the competition are not always fully informed and rational. For example, when one of the best drivers—Michael Schumacher—was absent from some races due to injury, several of the F1P6 players continued to pick him to win. Figure 7 shows the races that Schumacher competed in during 1999, and the fraction of participants that predicted him to win. The observed behavior may be due to a lack of information, or because players skip races, in which case their previous predictions are carried over. However, carry-over occurs only once.

Although individuals clearly make faulty predictions, we examine whether collective information in the game is sufficient to yield accurate overall predictions. We obtained the predictions of all F1P6 participants from the competition web site for 32 of 41 races held from 1999 through June 10, 2001.[13] Unlike the other two games investigated, F1P6 does not contain a natural "price" statistic that summarizes the consensus of opinions of all participants. In an attempt to identify a good summary statistic, we tried four different ways of scoring the drivers according to the participants' predictions.

- linear scoring (6-5-4-3-2-1)
- F1-style scoring (10-6-4-3-2-1)[14]
- flat scoring (1-1-1-1-1-1)
- winner scoring (1-0-0-0-0-0)

[13]Data for the remaining 9 races was missing.

[14]We call this "F1 style" scoring because F1 drivers accumulate points toward their season championship according to the same scheme. Also, F1P6 players receive points in this manner.

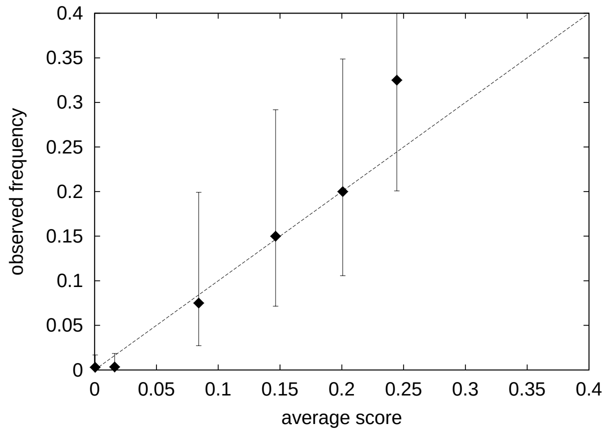

Figure 8: Accuracy of the F1P6 competition. Points display observed frequency versus linear score. The dashed line corresponds to ideal accuracy.

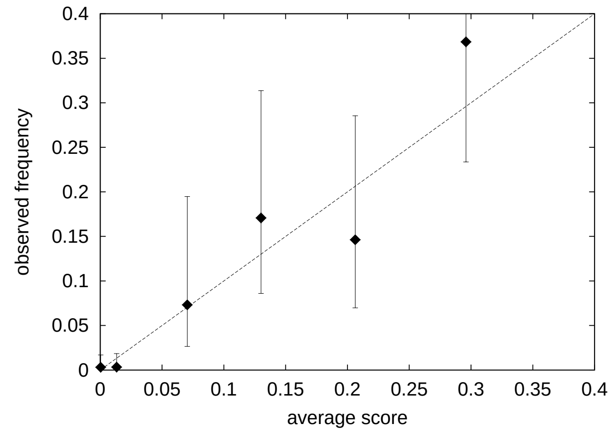

Figure 9: Observed frequency versus F1-style score.

For example, linear scoring assigns to a driver six points for every F1P6 participant that predicts that driver to finish in first place, five points for every participant that predicts the driver to finish in second, and so on. We normalized drivers' scores to obtain a pseudo-probability associated with each scoring rule.

We collected the actual race results from Atlas F1[15] and Gale Force F1.[16] We sorted driver-races by score, grouped them into buckets of constant size, and computed the average scores and observed frequencies in all buckets. To control against data snooping, we performed an initial analysis on the 1999 races only. On this data, linear scoring performed best, with F1-style scoring a close second; flat scoring and winner scoring performed poorly. The remainder of results in this section refer to all races from 1999 through June 10, 2001. Figure 8 plots the bucket points obtained from linear scoring. Error bars are 95% confidence intervals, under the independent Bernoulli trials assumption. The figure indicates that linear scores are good estimates of the actual frequencies of race outcomes. Figure 9 shows the accuracy of F1-style scoring; this method also appears to yield accurate psuedo-probabilities. Figures 10 and 11 display the same plots for flat scoring and winner scoring, respectively; neither of these scoring methods perform well. These results are consistent with our initial 1999-only analysis, providing a measure of confidence that results are robust.

In the case of F1 racing, we have access to a real-money market—namely the F1 betting market—that naturally lends itself to comparison with the F1P6 game results. We collected archive betting odds from Atlas F1 for 39 of 41 races held from 1999 through June 10, 2001.[17] The odds do not reflect a balanced market, since gamblers can only bet for a particular driver, not against. In order to ensure a profit, bookmakers purposefully set the odds such that the corresponding probabilities sum to greater than one. We found

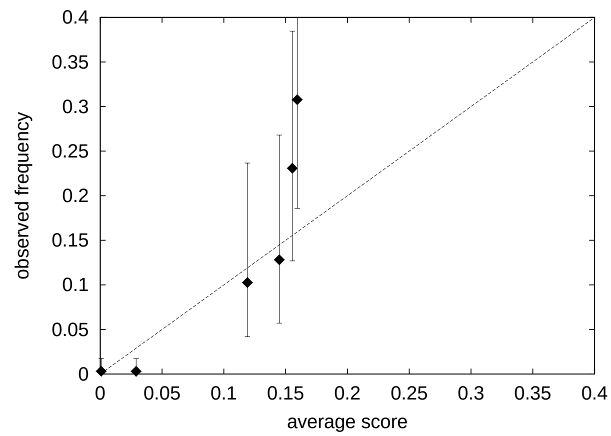

Figure 10: Observed frequency versus flat score.

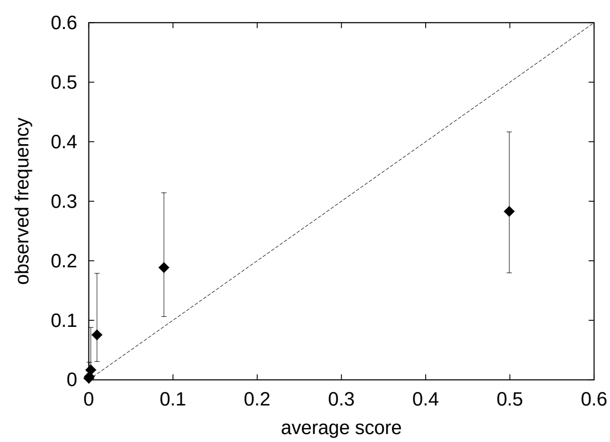

Figure 11: Observed frequency versus winner score.

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[15] `http://atlasf1.com/`

[16] `http://galeforcef1.com/`

[17] As of this writing, archive odds from the most recent two races were not publicly available from Atlas F1.

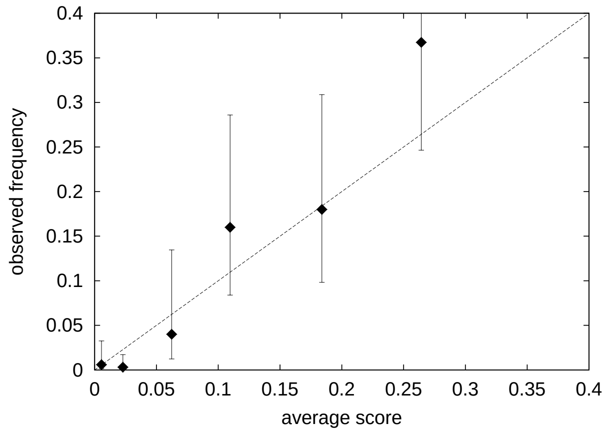

Figure 12: Accuracy of the bookmaker odds from Atlas F1. Points display observed frequency versus normalized odds.

Table 3: Accuracy of psuedo-probabilities from F1P6 and normalized odds from Atlas F1, evaluated according to average logarithmic score. Higher (less negative) scores are better.

forecast source	avg log score
F1P6 linear scoring	-1.84
F1P6 F1-style scoring	-1.82
F1P6 flat scoring	-2.03
F1P6 winner scoring	-2.32
Atlas F1 normalized odds	-1.86

the average excess probability to be 0.23. We normalized the odds, although it is possible that bookmakers overstate probabilities in some nonlinear way. There are some symmetric gambles available, where bettors choose which of two drivers will fare better. These bets had smaller excess probabilities (about 0.05), but there were not enough to determine probabilities across the entire field of drivers. Again, we sorted by probability (normalized odds), binned the data (in buckets of constant size), and computed average probability and observed frequency. Figure 12 graphs the results along with 95% confidence error bars.

Table 3 compares the average logarithmic score for the four types of F1P6 psuedo-probabilities and for the F1 betting odds, computed over the 30 races for which our data sets overlap. Perhaps surprisingly, F1-style scoring and linear scoring outperformed the official odds, if only slightly. Note, however, that the bookmaker odds may be purposefully biased in a nonlinear fashion.

It is interesting to note that the pattern of results for F1-style scoring (Figure 9) is very similar to that for the betting odds (Figure 12). Ideally, we would like a model of prediction strategies [19] and race outcomes that explains why F1-style scoring mimics the odds, why F1-style and linear scoring yield good predictions, and why the other two scoring methods fail. At this point, however, we have not formalized any explanations.

We tested only four scoring rules among a class of six dimensional weighted averaging rules, in part to avoid overfitting our limited data. With more training and test data, learning the vector of weights, or learning other functional mappings from F1P6 votes to psuedo-probabilities, begins to make sense. One might also explore combining F1P6 and betting odds data, or combining with data from other games, web sites, or other sources.

8. DATA MINING FROM ONLINE GAMES: IMPLICATIONS AND APPLICATIONS

A growing number of games and markets on the web provide vast amounts of data reflecting the interactions of millions of people around the world. Each source offers the opportunity to infer something about the players involved and the knowledge they possess. Data mining algorithms—typically fast algorithms for extracting knowledge from massive quantities of data [8, 28]—seem particularly well suited for the job. In this work, we employed simple extraction algorithms to obtain probabilistic forecasts of real-world events. Our results can be seen as statistical validation of the underlying quality of data from online games. The games themselves appear to serve as a mechanism for collecting, merging, and cleaning data from human experts, naturally handling some of the more difficult steps in a typical data mining application [4, 20]. Yet we expect room for improvement with the use of more sophisticated algorithms and data fusion techniques.

For example, with access to user-specific data, predictions could be improved by weighting users according to inferred measures of reliability or expertise, filtering out "noisy" users, and identifying and removing users attempting to manipulate the game. Game forecasts could also be boosted with information from outside sources. For example, baseline HSX box office predictions could benefit from additional data from expert forecasts, statistical sampling, critical reviews, actor popularity, advertising budgets, number of screens playing, discussion boards, newsgroups, search queries [2], distribution of inbound hyperlinks pointing to movie homepages, web community sizes [9], etc.

More detailed analysis of game dynamics can actually lead to algorithms for identifying and pinpointing the introduction of new knowledge into the public consciousness. For example, in August 1996, the rapid increase in the price of a bet on FX that extraterrestrial life will be discovered[18] can be traced to news at the time that fossils were potentially identified in a Martian meteorite [21]. Similarly, two sequential decreases in the price of a bet on the (real-money) Iowa Electronic Market that Rudy Giuliani will win the 2000 US Senate election in New York can be correlated with two announcements during his campaign: first that he had prostate cancer, and later that he was dropping out of the race.

In non-market games like F1P6, generating probabilistic forecasts requires more explicit data manipulation, since a natural price statistic is not available. In this paper, we tried weighted voting procedures as a first step, finding that a linear combination seems to work well, though more advanced machine learning and data mining techniques are certainly applicable. Additionally, with a model of how people play the game [19], one can infer the maximum likelihood opinion of each user, then combine results using known belief or

[18] `http://www.ideosphere.com/fx-bin/Claim?claim=XLif`

forecast aggregation methods [3, 15].

Inevitably, multiple sites will focus on interrelated topics, and extraction algorithms will benefit from combining data sources while accounting for correlations. More general online communities, for example chat boards or newsgroups, feature some of the same benefits as game sites—namely dedicated and knowledgeable participants often willing to divulge information—though leveraging this more free-form data will require more complex processing algorithms.

An obvious path for applications is to mine information from existing games. Alternatively, organizations may set up their own online games as a mechanism for gathering data on particular subjects of interest or concern, perhaps as an alternative to costly market research [16]. While Internet polls are notoriously skewed toward an unrepresentative (more educated, more wealthy, more conservative) demographic, it appears that web games actually benefit from the bias within their niche audiences. Perhaps the difference arises because, while polls typically ask questions of the form "what do you want?", these games pose questions of the form "what do you think will happen?" to an attentive and knowledgeable audience. However, if corporations begin to take game data seriously, players may feel wary about privacy issues and what information they are revealing for free and to whom. Moreover, once data is being used for consequential decisions, incentives to manipulate the game increase, and good mechanisms for filtering or controlling manipulation will be essential.

9. CONCLUSION

The World Wide Web fosters large-scale group activities of all sorts, from competing in games, to trading in markets, to competing in market trading games. We find that, beyond their entertainment and commercial value, these sites can be valuable resources for inferring predictions about real-world events. We show that HSX prices are informative signals for movie box office results and entertainment award outcomes—as accurate or more accurate than expert opinions. FX prices reliably forecast true outcome frequencies for scientific and societal questions. The combined judgments of F1P6 competitors are equally or better aligned with actual race outcomes than the official betting odds.

In both economics [24] and decision science [6, 36] it is known that appropriate monetary reward structures can induce people to reveal their inside information and expert knowledge. Our results provide evidence that well-designed games also provide sufficient incentives for people to divulge their information. In this context, the players' motivations derive from their competitive spirit and the value of entertainment, rather than directly from consumable (e.g., monetary) compensation. In all three games studied, participants appear to be (collectively) knowledgeable, and to take winning seriously enough to reveal that knowledge indirectly through their play. Such online games act as a sink for specialized information from experts. We believe that, in contrast to the low signal-to-noise ratio on web as a whole, many online games are good sources for targeted mining of pertinent and useful data.

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