Political Prediction Markets: Can we use them to predict election outcomes?

Sanith Wijesinghe, Joanne Rodrigues

Santa Fe Institue

Complex Summer School 2012

August 2012

Abstract

Political prediction markets such as INTRADE, in which people trade stocks based on their belief about the outcome of the election or political event, offer a unique opportunity to use market behavior to predict the outcome of political events. This paper provides a two-fold contribution to the literature. First, we analyze 457 political prediction markets contracts in terms of the accuracy of their predictions at various time intervals and high-level categorizations. Second, we attempt to forecast the outcome of political prediction markets using a standard feedforward/backpropagation neural network trained on the time history of contract prices. We find that we can out perform the market predictions by between 1% - 4% percent during times earlier than half-way to contract expiry. This suggests the market is not the most efficient aggregation of the likelihood of a future political event at these short times.

1 Introduction

Within the field of political forecasting, two election types are particularly difficult to predict: very competitive elections and elections without polling data [Campbell and Lewis-Beck, 2008]. Political prediction markets may offer ways to forecast these two election types. This paper will take a novel approach to forecasting by integrating an artificial neural net with political prediction market time series data to improve on the predictions of political events. Neural nets can capture complex non-linear processes and patterns that humans fail to identify. Political prediction markets offer an excellent training dataset to capture the aggregation of beliefs about the likelihood of a political outcome.

Traditional tools used to help guide election forecasters such as polls, expert panels, focus groups and structural or time series models fail to identify the dynamic nature of public sentiment subjected to numerous information shocks over time. [Berg *et al* 2008; Wolfers and Zitzewitz, 2004] In the present day, these shocks propagate rapidly through social networks and electronic media sources and can shift opinions widely within a few weeks or even days. Prediction markets can serve as an alternative forecasting tool that can better assess the evolving expectations of the public [Wolfers and Zitzewitz 2004, 2006]. Political prediction markets are shown to have less volatility than polls, to out predict polls for longer horizons, and have end prices that are often closer to final election outcomes than major polls. [Berg *et al*, 2003; Berg *et al*, 2008; Saxon, 2010 (Based on INTRADE markets)] Although there is some debate on this result [Erickson and Wlezien, 2008].

In 'winner-take-all' political prediction markets, individuals participating in these markets provide their opinion on a given outcome by actively trading their expectation using a market-based mechanism. A prediction market in this sense serves as an integrator of individual expectations subjected to numerous real-time information shocks. The price of a contract defined in this market provides a quantitative measure of the collective opinion of a diverse population. Moreover, prediction markets help harness the 'wisdom of crowds' whereby individuals across a diverse background can participate towards unraveling a quantitative measure that is otherwise ill-posed for determination through regular modeling approaches. When polling of an event does not exist, prediction markets may offer the best aggregation of collective opinion. When polling does exist, prediction markets may efficiently aggregate that information.

The road map for this paper is the following. First, we will explore the theory of political prediction markets and artificial neural nets. Second, we will delve into analyzing INTRADE political prediction markets. Finally, we will explore the results of a neural net compared to the prediction market itself.

Figure 1: Price-time history for "Barack Obama to be re-elected President in 2012" prediction market contract.

2 Theory

Prediction markets provide a framework that supports three necessary conditions for accurately inferring the expectation of individuals: 1) effective incentives to seek information, 2) mechanism for truthful information revelation and 3) an algorithm for aggregating diverse opinions[1]. Prediction markets offer one way to aggregate the expectation of future likelihoods of political events. Berg et al 2008 conclude, "we compare unadjusted market prices to unadjusted polls, demonstrating that market prices aggregate data better than simple surveys where the results are interpreted using sample theory."

Figure 1 is an example of the price-time history for a political prediction market contract. This contract trades on whether President Obama will be re-elected president in 2012. Political prediction markets respond quickly to information shocks and are able to interpret how they affect the likelihood of an event. The spike on May 2nd marks the news of the death of Osama Bin Laden. One shortcoming of these markets is if knowledge of the political event does not exist among traders, the prediction capabilities decline. Thus, political prediction markets are an aggregation of known information about an event subjected to real-time updates.

[1] Wolfers, J., Zitzewitz, E., Prediction Markets, Journal of Economic Perspectives Vol 18, No.2, Spring 2004 pg. 107-126

The efficient market hypothesis asserts that if the market is efficient the market price will out predict polls or any other information that can be used to improve on the market-generated forecasts [Wolfers and Zitzewitz, 2004]. If these political prediction markets are efficient, then we should not be able to out-predict them with a artificial neural net. If the neural net can out predict the market outcome, then it is doing so by exploiting underlying patterns in the data that traders are unaware of and this suggests at least for certain types of markets they are not efficient and arbitrage opportunities may exist.

The 'Expectation Hypothesis' and 'Efficient Market Hypothesis' are important components of the theoretical basis for forecasting. Futures and options markets aggregate information about the expected future value of stocks and commodities. According to Berg *et al*, (2008) the expectation hypothesis asserts 'if it is true that future prices are the best prediction of actual future spot prices, then future prices constitute forecasts.[2]

How do we access models of political forecasting? Lewis-Beck 1984 and Lewis-Beck 2005 offer us four criteria: 1) Accurary, 2)Parsimony, 3) Lead and 4) Reproducibility. Accuracy is the level of accurate prediction. Parsimony is the ability of the model to predicit given a few well-specified variables instead of many less well-specified ones. Lead is how early the model predicts the outcome. Reproducibility is the ability for the reseachers and other to efficiently replicate the results at a low cost. We will consider these criteria when evaluating our neural net using the political prediction market time series data. Our simple neural nets are more accurate then the market in the earlier time horizons. This result is reproducible at a relatively low cost.

3 Data and Methodology

This paper will use 457 political prediction market contracts traded on INTRADE[3] between 2004 and 2012. Not all these contracts pertain to elections, but are events all relating to

[2]There are has been a long running debate as to whether futures markets can forecast events because of secondary nature of information aggregation in these markets.

[3]INTRADE is an online trading website for a variety of prediction markets: political, financial, entertainment, weather and current events.

political organizations, processes and leaders. These contracts trade for monetary gain within the $\$0 - \$10$ range and are of 'winner-take-all' (binary) type, i.e. if an event occurs, the market pays traders \$10 per contract and \$0 otherwise as such all questions are based on a true/false proposition (for instance, 'Will President Obama be reelected in 2012?'). Note that the $[0, 1]$ binary proposition can be phrased in any way. For instance, a political prediction market question can be 'Will President Obama be re-elected in 2012?' or 'Will Pres. Obama not be re-elected in 2012?'. Even though these two markets will expire at opposite ends, the political outcome will be the same. The political market contracts in our sample are skewed such that 65 percent expire false while 35 percent expire true.

We use a traditional 3-layer feedforward artificial neural network to forecast the final outcome of the political prediction market contracts. Artificial neural networks are an artificial intelligence/machine learning technique that is used in a wide variety of contexts such as speech recognition, adaptive control, image analysis and time-series forecasting. The principles of artificial neural networks are drawn from the complex adaptive nature of biological neural networks. The simple case of one hidden node is the logistic model. Beck *et al* 2004 argue that

> Neural networks avoid 'underfitting' a key problem with logit analysis, which makes assumptions about fundamental substantive relationships that we know little about. In fields where prior knowledge is extensive, specific and highly informative, assumptions like these may be appropriate.

Artificial neural networks can capture patterns that the logistic and other traditional statistics models assume away. Recently artificial neural networks have been incorporated into political prediction.[Beck *et al*, 2004; Schneider *et al*, 2011]

We use 3 different schemes to train and test the neural network:

- **Spot**. Training and testing using the trader's spot price at a specific fraction xL of the contract length (where $0.1 \leq x \leq 0.9$).

- **Spot+STD**. Training and testing using the trader's spot price at a specific fraction xL of the contract length (where $0.1 \leq x \leq 0.9$) and the standard deviation in price upto that point.

- **Spot+Delta**. Training using the trader's spot price at a specific fraction xL of the contract length (where $0.1 \leq x \leq 0.9$) while testing based on this spot price modified by the change in price between xL and $(x - 0.1)L$.

A random selection of 229 contracts were used as a 'training set' while the remaining 228 contracts were used as the 'test set'. A single node was used in the input layer of the neural network when **Spot** and **Spot+Delta** were used for training, while two input nodes were used when **Spot+STD** were used. For all cases a total of 10 nodes were used in the hidden layer and 1 node for the output layer. A sigmoid activation function was used for both hidden and output layer nodes with no bias. The neural network prediction for the contract expiry was considered true if the output node value exceeded 0.5 and false otherwise. For each of the training methods a total 2000 iterations of backpropagation error correction was performed to converge the neural network node weights. We discuss the results from these tests next.

4 Results

4.1 Analyzing the Political Prediction Markets

In this section, we analyzed the political prediction market by two type measures: 1) market uncertainty and 2) subtype of political event. We assume two extreme types of markets. One type of market with high uncertainty were the majority of the contract price fluctuates between \$4 and \$6. The other type of market is the uncompetitive market where the price varies \$0 and \$4 or between \$6 and \$10. Here are some examples of these types of markets. Since our markets are biased down, we will break the distribution into these 6 frequency types: The majority of time is spent between: 1)\$0-\$1.50, 2)\$1.50-\$3.50, 3)\$3.50-\$4.50, 4)\$4.50-\$5.50, 5)\$5.50-\$7.50, and 6)\$7.50-\$10.

Figure 2 shows trader's prediction by degree of market competitiveness. The first graph is the market at 10% market length and the second graph is at full market length minus three

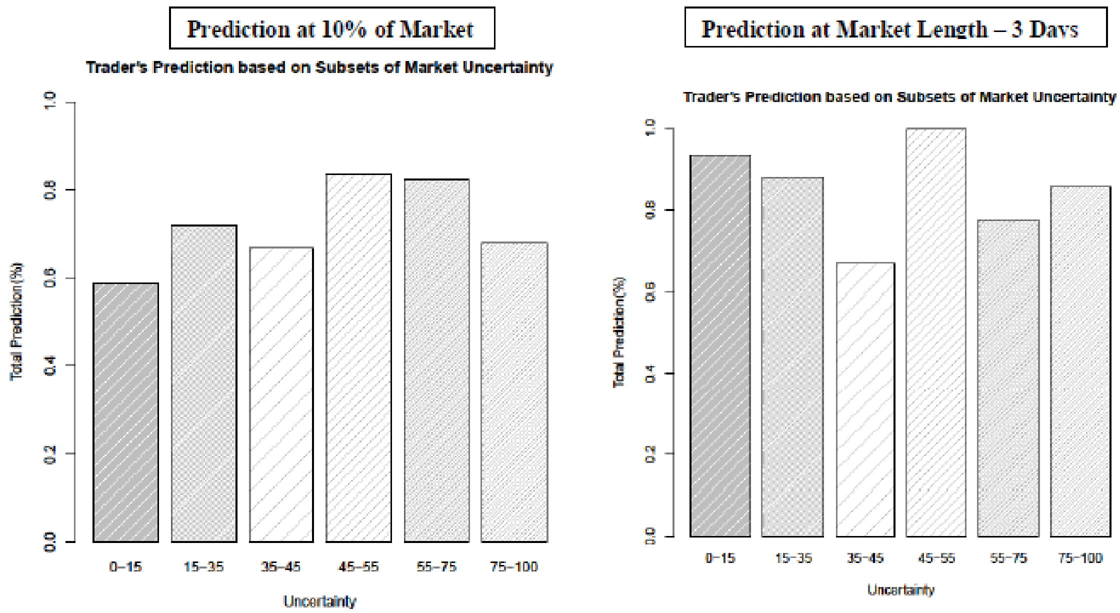

Figure 2: Variation in the prediction accuracy of traders by market price uncertainty. The left plot indicates the trader predictions made when the total trading time elapsed is only 10% of the total duration of the contract. The right plot shows the trader predictions 3 days prior to expiry. The price uncertainty categorization corresponds to the price interval in which the majority of the contract price fluctuates. *** The color gradient represents the number of markets in each category.

days. This graph shows that the most competitive subset of the market improves the least compared to the less competitive counterparts.

The second type of categorization of markets was by political type. There are four types that do not include the full set of markets. These include: 1) market's related to the US executive branch which includes primary elections, the presidential election, presidential appointments, and others, 2) markets related to Congress which includes House and Senate elections, 3) markets related to international politics such as Mexican elections 4) markets related to states include anything related to state politics such as gubinatorial elections. The categories are not evenly sized. Markets relating to the US Executive Branch and Congress are the largest categories.

Figure 3 shows trader's prediction by political category. The first graph is the market at 10% market length and the second graph is at full market length minus three days. The graph shows that the market is worse at predicting markets related to the House and Senate at the 10% length and substancially improves at predicting markets related to the House and Senate by full market length. Using a logistic regression, at 10% length the market is significantly worse at predicting markets related to Congress (25% below the baseline). While at full market length, the market is not worse at predicting this aggregate variable of all markets relating to the House and Senate.

Using a logistic regression, political prediction markets at full length are significantly worse below the 1% level at predicting the outcomes of US 2008 primaries (30% below the baseline), US Congressional Elections (50% below the baseline), US Presidential Debates (64% below the baseline) and the Massacussetts Special Election (65% below the baseline). There may be multiple reasons why the market is worse at predicting primaries, debates and special elections: 1) multiple candidates, 2) shorter time horizons, 3) in-party competition, 4) less polling far before the event, and 5) less well-known nationally about the state subpopulations and registered voters.[4] The prediction market and artifical neural net cannot predict outcomes when information about the event is unknown or not widespread.

The artifical neural net and market was significantly worse at predicting the MA special election. It is apparent from looking at the MA special election between Scott Brown and Martha Coakely why the neural net/prediction market struggled to predict this election. The market itself did not have very much information about the outcome until the final 20 percent of the market. The market stayed at 90% in favor of Coakley for 80% of the market, then took at sharp turn toward Brown at the very end. Polling for special elections is difficult due to the lack of information about turnout. The national media may have been portarying a very different reality than the one of the ground in Massacusetts. For these reasons, the political prediction market failed to predict this election outcome.

[4]This result has been shown in other papers on political predicion markets

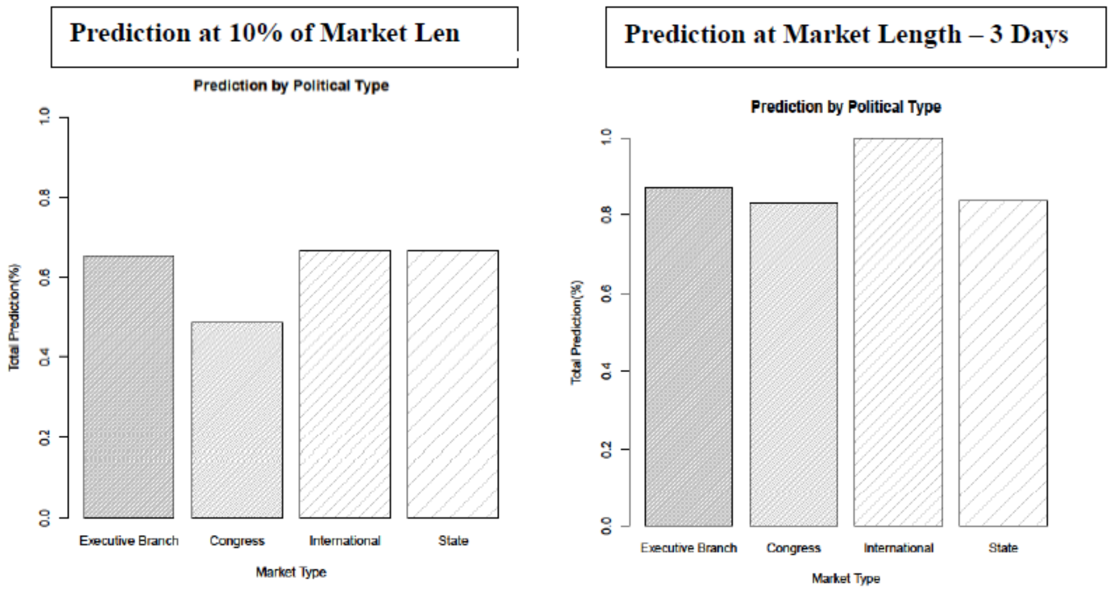

Figure 3: Variation in the prediction accuracy of traders by market contract type. The left plot indicates the trader predictions made when the total trading time elapsed is only 10% of the total duration of the contract. The right plot shows the trader predictions 3 days prior to expiry.

4.2 Neural Net Prediciton

Table 4.2 compares the percentage of correct contract expiry prices predicted by the neural network using different specifications for the input layer and with different specifications for training length. Also shown is the percentage of correct trader predictions for contract expiry (if the trader price for a contract is above \$5 at a given xL, we consider that it predicts a true outcome and false otherwise).

We see that the accuracy of all predictions generally increases as the time to expiry decreases (denoted by longer length of contract price-time history). This is as expected as more information pertaining to the outcome becomes available. The neural network based forecast percentages are seen to closely follow the trader predictions above $0.6L$ but are found to provide a 1%-4% improvement over the trader predictions at contract lengths $\leq 0.6L$.

From these results, it suggests that the efficient market hypothesis does not hold for the earlier time horizons in political prediction markets. In fact, simple neural net algorithms with

Training Method	Test data length								
	$0.9L$	$0.8L$	$0.7L$	$0.6L$	$0.5L$	$0.4L$	$0.3L$	$0.2L$	$0.1L$
Spot	86%	81%	77%	**75%**	73%	**71%**	**69%**	**68%**	68%
Spot+STD	86%	81%	78%	**75%**	73%	**70%**	**68%**	**69%**	68%
Spot+Delta	86%	79%	78%	**74%**	**75%**	**72%**	**69%**	67%	68%
Trader prediction	86%	82%	78%	73%	73%	69%	65%	67%	68%

Table 1: Variation in successfully forecasted prediction market contract outcomes as a function contract price-time history length L. Higher L indicates contracts closer to expiry. Results in bold indicate forecast percentages greater than that obtained by traders.

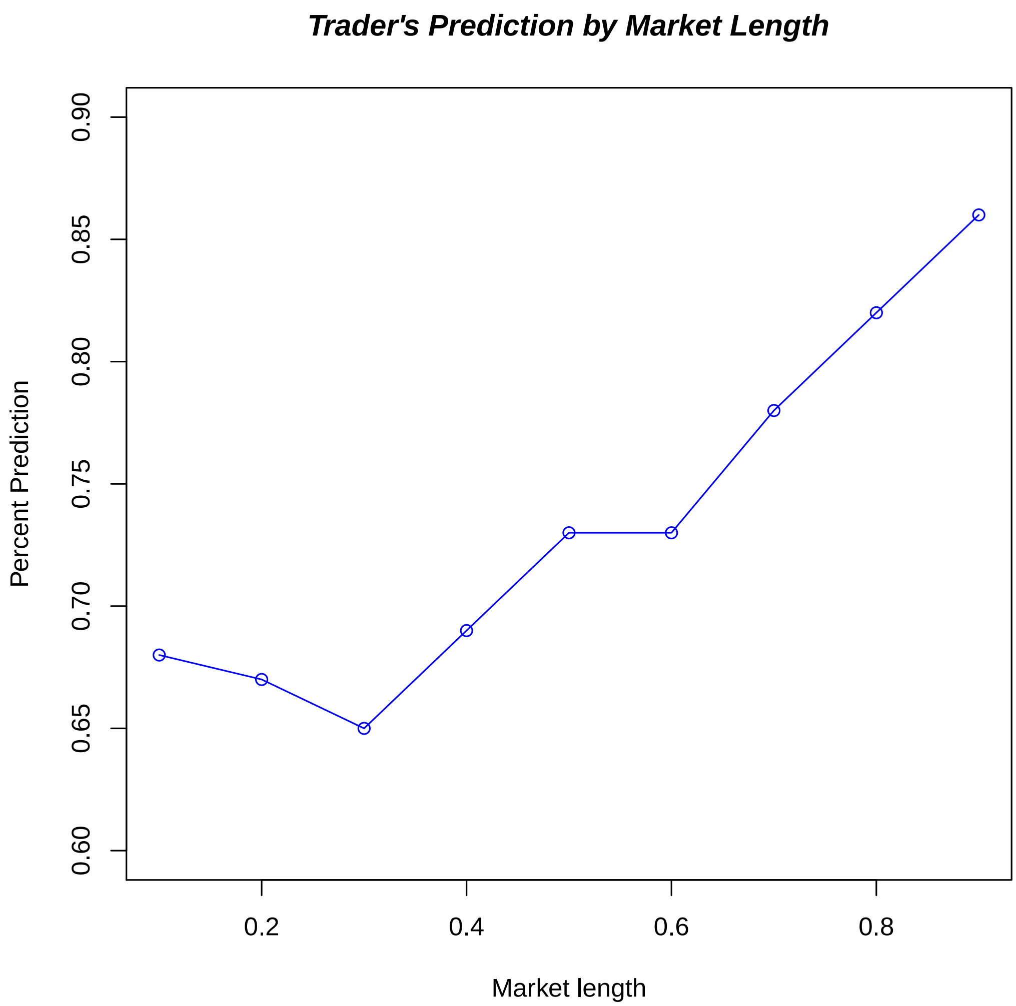

Figure 4: Variation in trader prediction as a function of length of trading time.

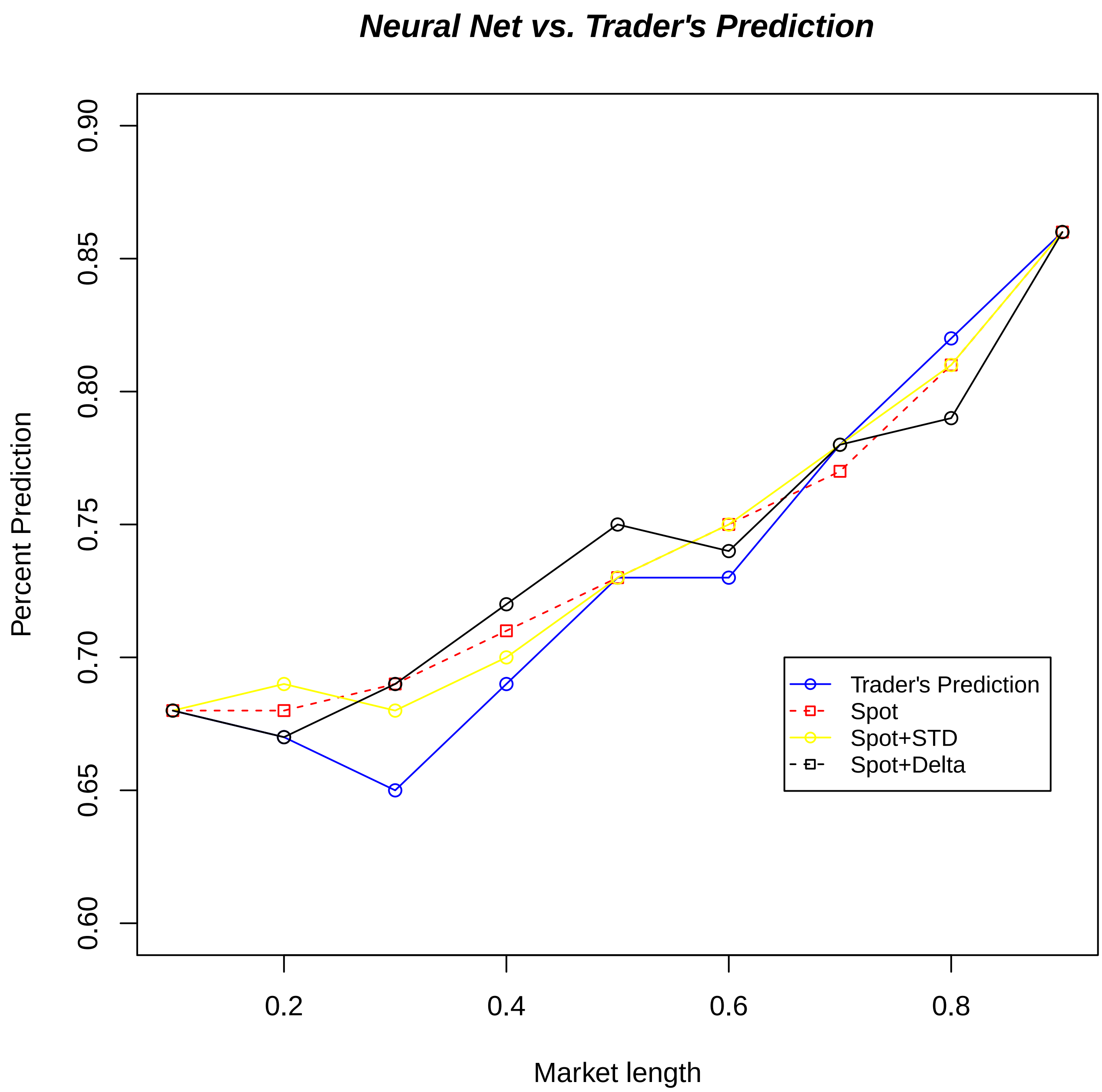

Figure 5: Comparison of accuracy of trader predictions and neural network predictions as a function of trading time.

only the spot price can outpredict the market by identifying patterns in all political prediction markets. A lack of information in earlier time horizons probably best explains the worse showing of the market. When the market length ranges from .7 to .8, the prediction market beats our neural net predictions. This suggests that the efficient market hypothesis may hold for later time horizons, but as the market moves toward expiry the neural net approximation and market prediction converge. It is important to note that more complex neural nets actually do worse than the **Spot** and **Spot+Delta**. Including number of traders, market volume, mean and other variables actually lowers the level of prediction.

5 Conclusion

Using artificial neural nets on political prediction markets is a new, highly effective way of forecasting political events. The political prediction markets are one of the best aggregation models of beliefs currently available and using a pattern recognition algorithm such as a neural network allows us to capture non-linear trends in the data that current methods are unable to capture. Our neural network forecasts are found to beat the actual market prediction by between 1% - 4% percent when less than 70% the time to contract expiry has elapsed. There may be better formulations or more complex neural net algorithms that may do far better than this model. This paper is only the first step in suggesting a novel method for election forecasting to integrate neural net algorithms with political prediction markets by using the spot price and delta method.

Certain types of events are easier to predict such as less competitive and markets related to the US Executive Branch. This may occur because of higher level of information available for these types of markets in earlier time horizons. Our model and the prediction market does worse in predicting markets related to Congress and very competitive markets. Overall, this approach may allow us to better forecast political events.

6 Acknowledgements

We would like to thank the Santa Fe Institute Complex Systems Summer School and the helpful feedback that we recieved from Vikram Vijayaraghavan, Matteo Chinazzi, Duenas-Esterling Marco-Antonio and Rengyee Lee.

This work was supported in part by MITRE Corporation under project code 1912M006-SF. This assistance is greatly appreciated.

References

[1] Beck, Nathaniel, King, Gary and Zeng, Langche. "'Theory and Evidence in International Conflict: A Response to de Marchi, Gelpi, and Grynaviski"'. American Political Science Review. 98 (2), 2004.

[2] Berg, Joyce,Nelson, Forrest and Rietz, Thomas. "Prediction Market Accuracy in the Long Run"'. International Journal of Forecasting. 24 (2) 283-298, 2008.

[3] Joyce Berg, Robert Forsythe, Forrest Nelson, and Thomas Rietz. Results from a Dozen Years of Election Futures Markets Research. 1:742751, 2008.

[4] Campbell, James and Lewis-Beck, Michael. "'US presidential election forecasting: An introduction"'. International Journal of Forecasting. 24 189-192, 2008.

[5] Erikson, Robert S., Christopher Wlezien. "Are Political Markets Really Superior to Polls as Election Predictors?" Public Opinion Quarterly 72(2) 190215, 2008.

[6] Lewis-Beck, Michael S. and Tom W. Rice. "Forecasting Presidential Elections: A Comparison of Naive Models," Political Behavior 6:39-51, 1984.

[7] Lewis-Beck, Michael S. Election Forecasting: Principles and Practice. British Journal of Politics and International Relations 7:14564, 2005.

[8] Saxon, Ian. "'Intrade Prediction Market Accuracy and Efficiency: An Analysis of the 2004 and 2008 Democratic Presidential Nomination Contests"' University of Nottingham. Dissertation, 2010.

[9] Schneider, Gerald, Gleditsch, Nils, and carey, Sabine. "'Exploring the Past, Anticipating the Future: A Symposium"' International Studies Review. 12 (1) 1-7, 2010.

[10] Wolfers, Justin and Eric Zitzewitz, Five Open Questions About Prediction Markets, in Robert Hahn and Paul Tetlock (eds) Information Markets: A New Way of Making Decisions in the Public and Private Sectors, (Washington DC: AEI-Brookings Press), 2006.

[11] Wolfers, Justin and Eric Zitzewitz, Prediction Markets, Journal of Economic Perspectives, 18(2) 107-126, 2004.

10