Multifaceted Predictive Algorithms in Commodities Markets

Blake Jennings
Vineet Ahluwalia
Hunter Ash

Momentum and Technical Indicators

We first attempted to predict prices of a sample of 40 Commodity ETFs over the past 10 years using only technical indicators. The model was unable to generalize successfully as shown below.

Training Accuracy	2 day	5 day	10 day	15 day	28 day
Train: 40%	0.609	0.647	0.685	0.715	0.768
Train: 60%	0.592	0.614	0.643	0.663	0.707
Train: 80%	0.573	0.594	0.616	0.634	0.665

Testing Accuracy	5 day	10 day	15 day
Train: 60%	0.527	0.493	0.516
Train 70%	0.495	0.504	0.501
Train: 80%	0.508	0.492	0.513
Train: 90%	0.518	0.519	0.545

Feature Spaces

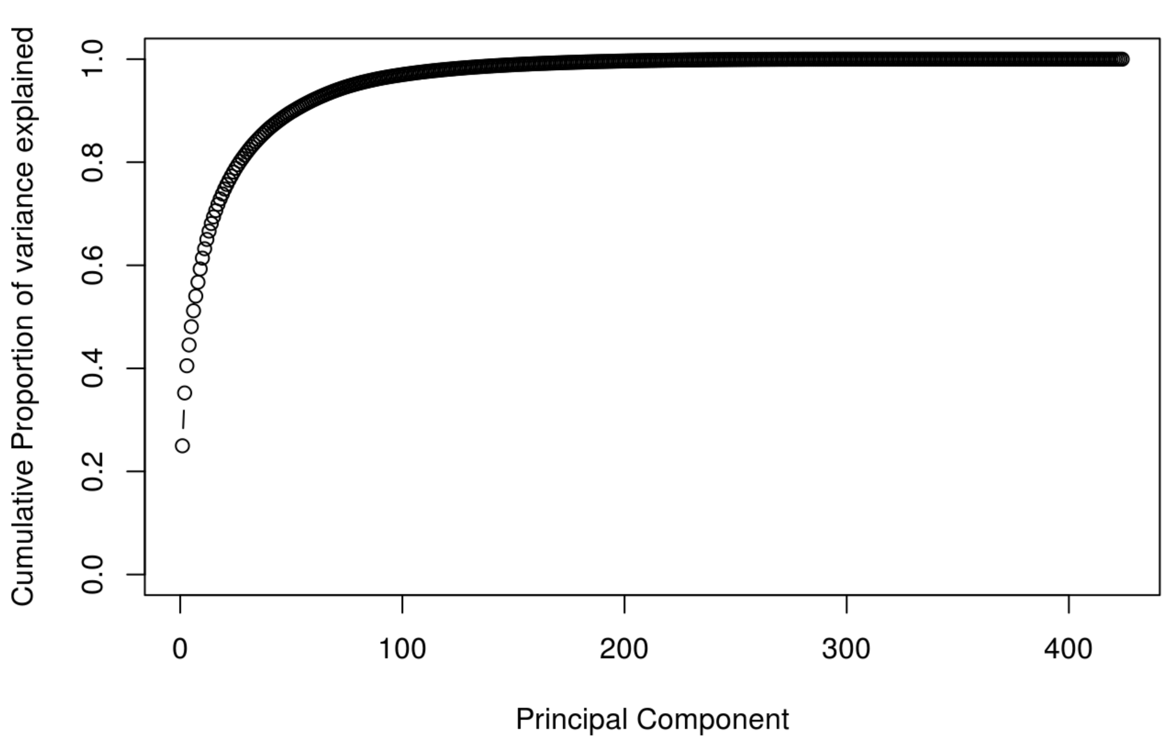
We explored 3 feature spaces in our project, all consisting of daily data.

The first consisted of the open, close, low, high, and a number of well-known momentum indicators such as RSI.

Next, we obtained a very large feature space consisting of multiple commodities prices and various technical indicators from a Bloomberg terminal. This data spans over 1990-2015.

Finally we pulled data for the KC1 index, together with economic indicators including the 5 and 10 year US Treasury bond rates, also from Bloomberg in order to gain insight into how macro-market features influence the commodities market.

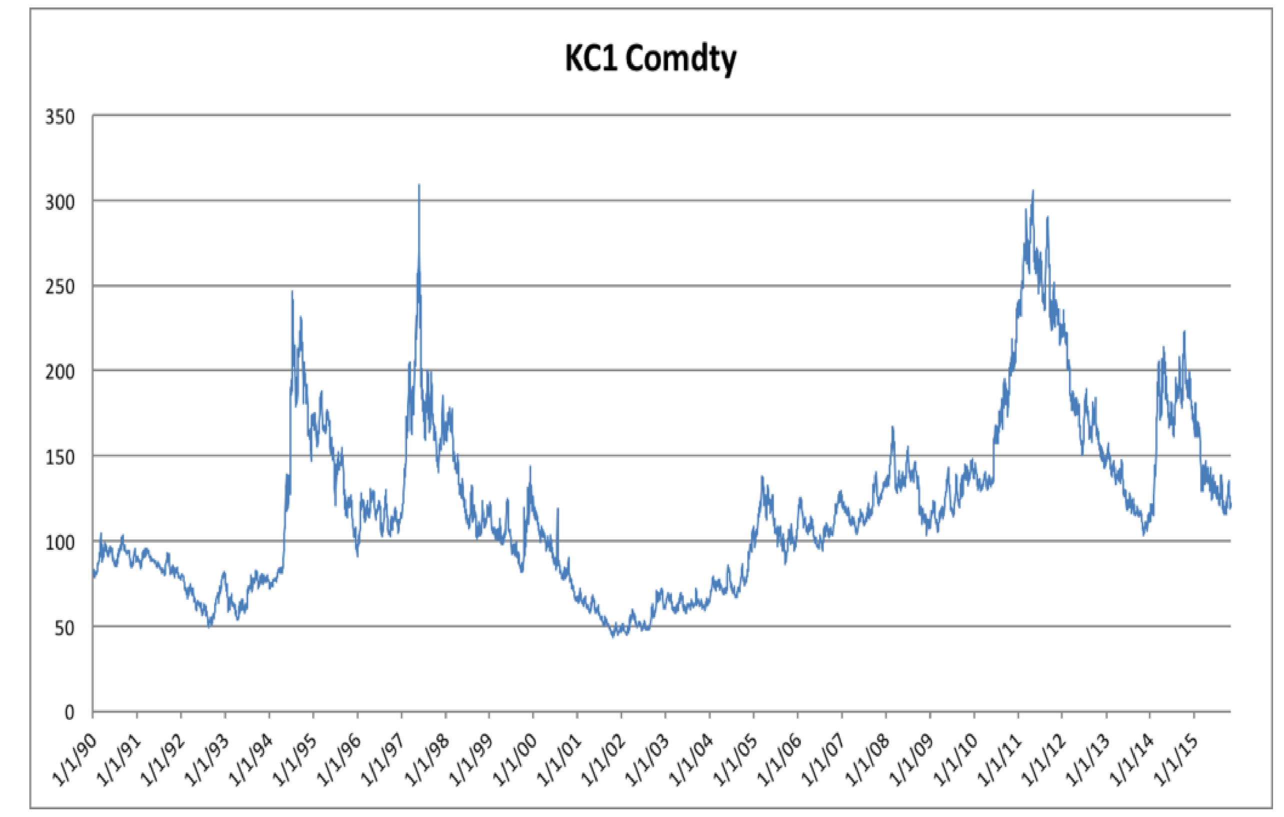
Exploratory Data Analysis



After performing principle component analysis, we find that the most heavily weighted features in the top components are macro indicators like US Treasury rates. We find similar results using recursive feature selection, making our findings more robust.

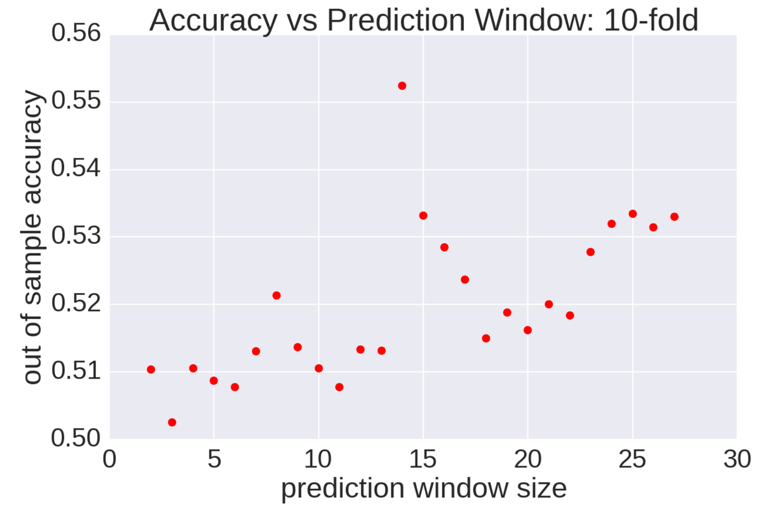
Introduction

Commodity price prediction is a notoriously difficult problem, and fluctuations have large economic consequences. Companies spend a significant amount of money and human resources trying to hedge against risk in this space. Our goal is to find and optimize an algorithm to predict whether the KC1 Coffee Futures Index will be net up or down a given number of days in the future.

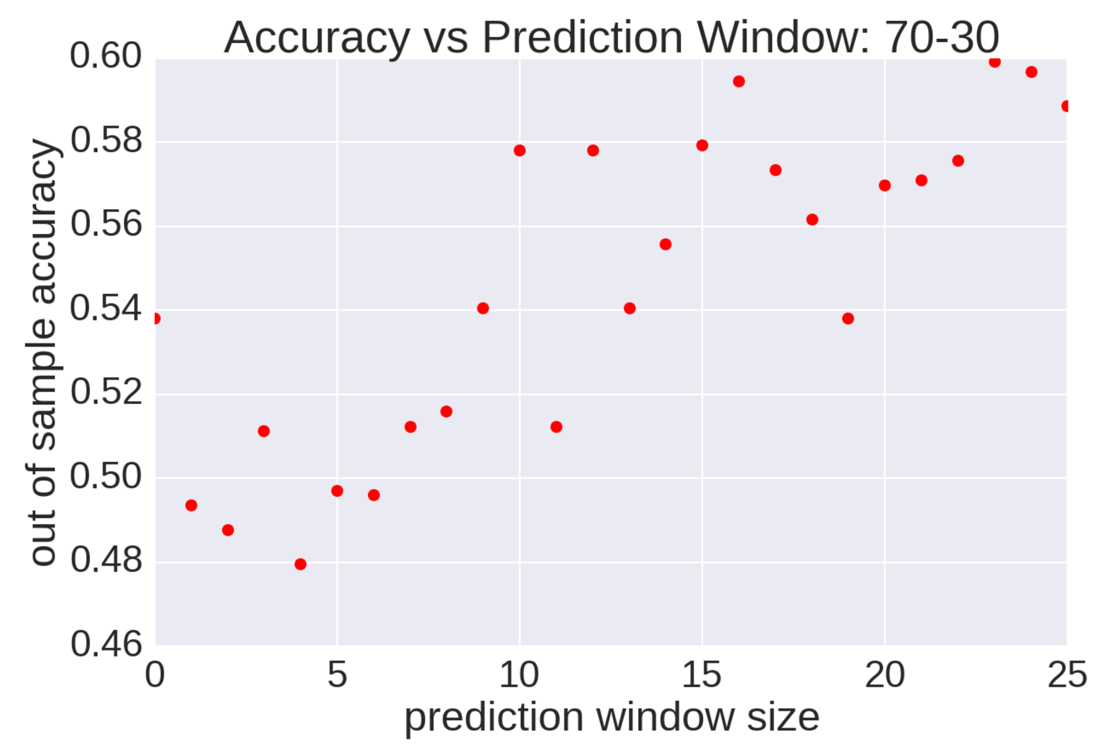


Results

Logistic Regression



We train N models, each predicting the net return n days into the future. The above plot shows 10-fold cross validation on our macro-market dataset.

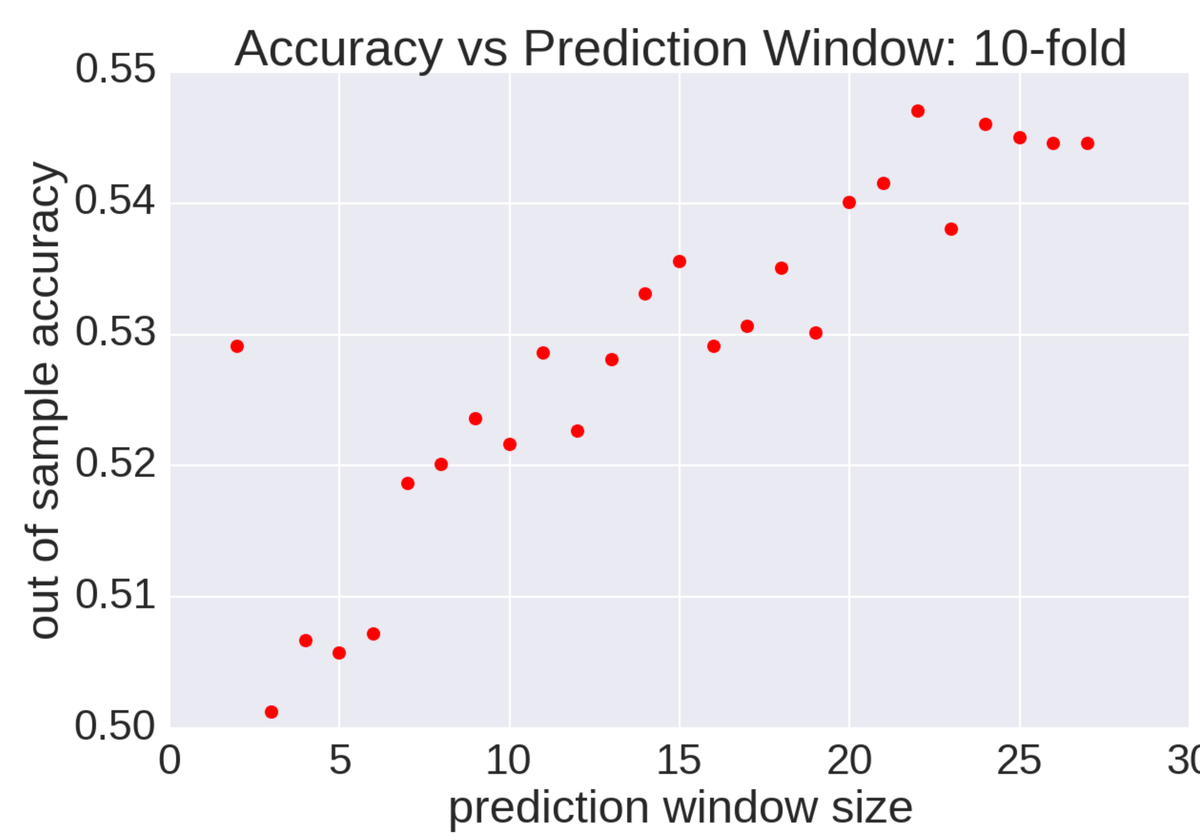


Precision: 55.02%
Recall: 72.25%

10-fold cross-validation reveals consistently above 50% accuracy, increasing with window size

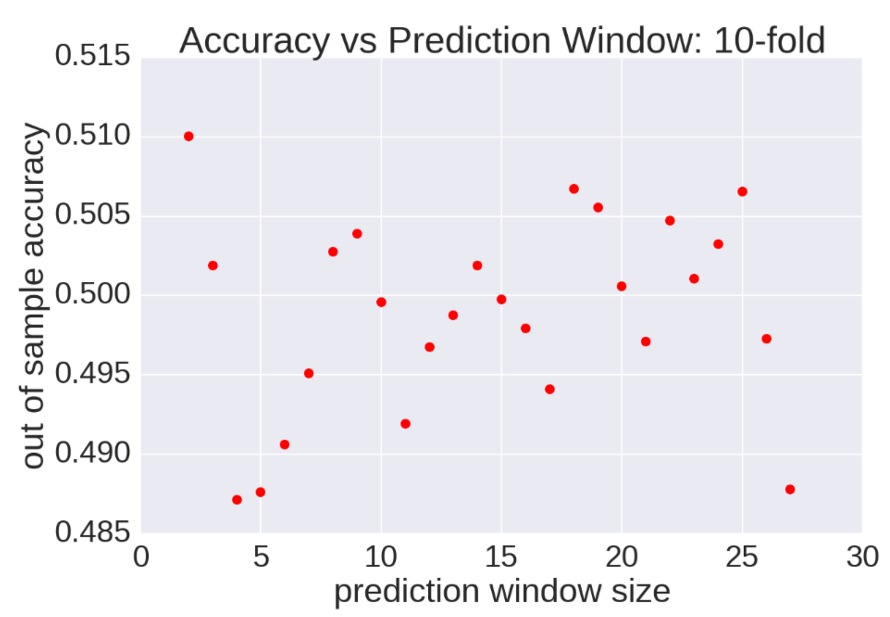
Support Vector Machine

Cross-validation on our SVM reveals a similar overall trend to logistic regression, but more tightly grouped.

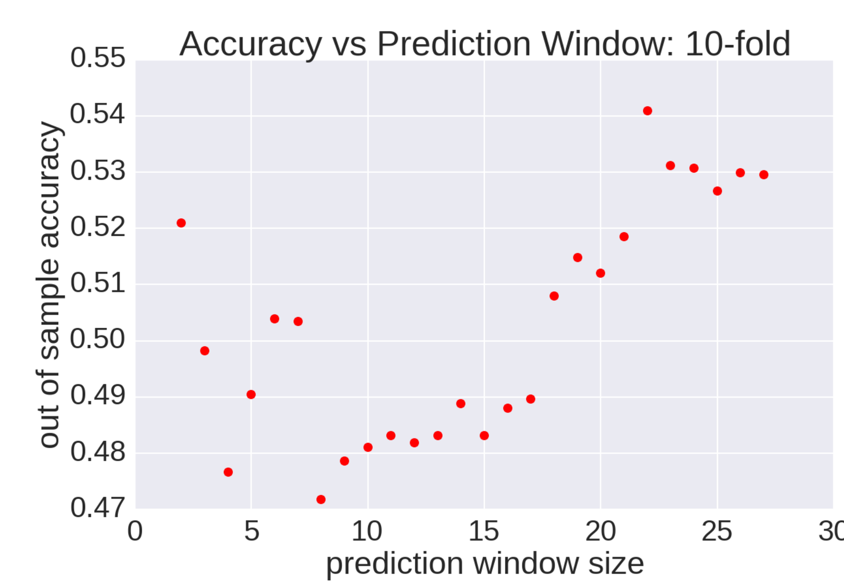


We outsourced our SVM 10-fold cross validation to Stanford's corn machines due to the large runtime. In particular, we observed slower performance when optimizing the SVM using a linear kernel versus the sigmoid kernel.

Naïve Bayes



On both the macro-market (left) and technical (right) data sets, Naïve Bayes was consistently our worst model.



Conclusion

Our exploratory analysis confirms that the most significant indicators for KC1 are macro-market features. We find that logistic regression and SVM generally outperform Naïve Bayes. Additionally, the predictions for more steps ahead tended to be more accurate. The feature set consisting of economic indicators had more explanatory power for KC1 than the technical indicators on commodities, even though it was much lower-dimensional.

Going forward, we are looking to establish a relationship between the variance and the reliability of different features. Additionally, we hope to employ ensemble methods to improve our out-of-sample testing accuracy.

References

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