Overview
Ether is a young cryptocurrency, and the predictability of Ether prices is not well-known. We assess the performance of several models which predict the directionality of Ether price changes. Our results show that a SVM using price features performs well on this task.

RNN with LSTM
- The model takes batches of short series of price data as input, and uses the last prediction frame as output.
- The model is trained using softmax cross-entropy loss.
- We experimented with batch size, learning rates, number of epochs, and activation functions.
- If the signal is encoded in the most recent data points, LSTM may not have a large advantage over other methods.
- We are still refining the model’s architecture and performance.

Results
- The best-performing SVM model achieves a classification accuracy of 96.1%, using a Radial Basis Function (RBF) kernel initialized with default parameters. While this performance is good, we expect performance to increase after hyperparameter tuning, which may involve tuning the kernel parameters and/or scaling the mean and variance of the training dataset.
- The Random Forest-based model also performs well, with a comparable accuracy of 94.2%. Random Forests perform well with data that has not been normalized and do not require involved hyperparameter tuning. The Random Forest can also learn different behavior for high prices vs. low prices, which could help its performance.
- The RNN with LSTM will benefit from additional tuning. We expect to modify the architecture and input additional features before the publication deadline.
- Logistic regression underperforms the SVM classifier, which suggests that the data is not linearly separable (relative to the price feature). Alternate feature selection may improve performance.
- The Naive Bayes classifier performs comparatively to the baseline, which classifies entirely based on the prior possibilities. The most logical explanation is that the training data is not normally distributed; alternatively the feature points may not be conditionally independent.

Summary Statistics
- Sample Size: 6383
- Minimum: 14.47
- 1st Quartile: 85.23
- Median: 255.93
- 3rd Quartile: 302.09
- Maximum: 397.31
- Mean: 210.42
- Standard Dev.: 115.44

Dataset & Feature Selection
Original dataset includes 19,473 Ether prices (sampled hourly). Prices before 2/26/17 are removed due to the drastic behavioral change after that date. The price feature is 6 price points, labeled with $\text{sign}(7^\text{th} \text{ price} - 6^\text{th} \text{ price})$. The dataset is split into train/test/dev datasets by following a 80%/10%/10% split.

Dataset: Hourly Ether prices since February 26, 2017, the founding date of the Ethereum Enterprise Alliance.

Model Performance

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Train Accuracy</th>
<th>Test Accuracy</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Support Vector Machine</td>
<td>91.7%</td>
<td>96.1%</td>
<td>0.96</td>
</tr>
<tr>
<td>Random Forest</td>
<td>96.7%</td>
<td>94.2%</td>
<td>0.94</td>
</tr>
<tr>
<td>RNN with LSTM</td>
<td>55.7% (preliminary)</td>
<td>58.2% (preliminary)</td>
<td>-</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>58.7%</td>
<td>56.7%</td>
<td>0.53</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>55.8%</td>
<td>55.8%</td>
<td>0.40</td>
</tr>
<tr>
<td>Momentum Baseline</td>
<td>55.5%</td>
<td>52.9%</td>
<td>0.56</td>
</tr>
<tr>
<td>Naive Baseline</td>
<td>55.8%</td>
<td>55.8%</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Conclusion
- The SVM-based model achieves a higher-than-expected accuracy with relatively little tuning, suggesting that the prediction task for Ether is less complicated than for comparable securities such as Bitcoin or common stock. This may change in the future as additional agents seek to invest more money in non-Bitcoin cryptocurrencies.
- The RNN-based model does not overfit on the training dataset, suggesting that it is limited by its configuration rather than by the model's expressive power. More work is needed.
- Logistic Regression and Naive bayes underperform. These algorithms are poor choices for this classification task, possibly due to their inherent assumptions that limit their applicability.

Future Work
- We will refine the RNN model in an effort to improve the performance.
- We may be able to train on other cryptocurrency price data to make our model more robust.
- Model expressivity can be increased by adding more market information, such as transaction cost, market capitalization, daily opening and closing prices, and other features.
- We may be able to compare accuracy of these classifiers for another dataset that contains daily data.

Part of a decision tree from Random Forest Classifier

Acknowledgments
We would like to thank our professors and TA's who helped with our project.
The data we used was obtained from etherscan.org.