Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

In the world of finance, particular on investment and stock trading, the disruption of cryptocurrencies[1] or crypto assets[2] related to the blockchain[3] technology, created a new ecosystem of possibilities for investors. Based on the quantity of public information related to cryptocurrencies available on the Web it's possible to perform different analysis related of valuation and future price predictions using the appropriate key data and supervised machine learning algorithms.

Ethereum[4] is a cryptocurrency that handles a technology called Ethereum Virtual Machine (EVM)[5]. This allows to process smart-contracts[6] which is custom code statements that enable multiple use cases like, creating autonomous organizations, making crowdfunding projects, or applications that can transfer value automatically if the rules defined in the contract are processed accordingly. In this way it's possible to understand this invention as a commodity like for instance a cloud-based provided for computing.

The idea of this project is to investigate if it's possible to predict Ethereum prices based on different machine learning algorithms and a sample dataset containing daily information about trades and network health.

Problem Statement

In this exploration, based on network and pricing information of Ethereum (ETH), the goal is to predict with some degree of confidence the 'close' price of this cryptocurrency. For that, the steps involved in the analysis and implementation includes:

- Analizing ethereum dataset prices and network
- Data cleaning / merge.
- Determine most important features in the dataset.
- Separate training and testing datasets.
- Determine an evaluation metric.
- Explore different supervised machine learning approaches to the problem.
- Test each model results using the evaluation metric defined.
- Giving a benchmark analysis.

With all this steps, it's possible to expect identify one or more approaches that may solve the problem of prices prediction, and determine if the performance of this models could be used on a real world application.

Metrics

In the case of a regression problem the selected metric is R^2 which provides a measure of how well future samples are likely tho be predicted for each model. The best scores are close to 1.0 and also can be negative if the model performs worse. In the case that the R^2 score is 0.0, this tells that the model doesn't take in account input features and always returns the same results.

R^2 it's more interesting in this context because using mean squared error doesn't give enough information if the model performs bad or worst than another.

II. Analysis

Data Exploration

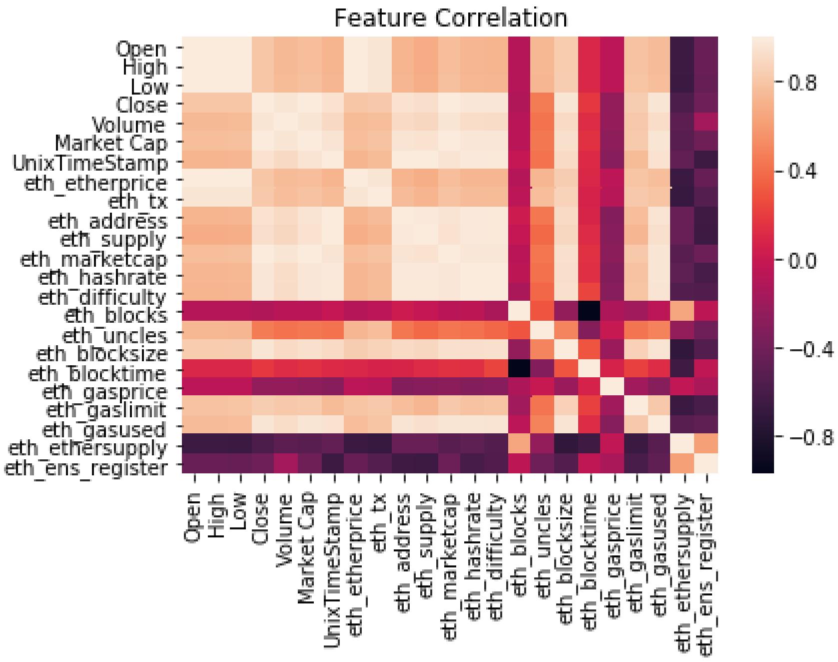
The dataset used is a composition of different sources that has historical information of different cryptocurrencies, but in this analysis only two sets are considered (ethereum_price and ethereum_dataset) [7]. The fields considered on each dataset are:

- Ethereum Dataset (ethereum_dataset.csv):
    - Date(UTC) : Date of transaction
    - UnixTimeStamp : unix timestamp
    - eth_etherprice : price of ethereum
    - eth_tx : number of transactions per day
    - eth_address : Cumulative address growth
    - eth_supply : Number of ethers in supply
    - eth_marketcap : Market cap in USD
    - eth_hashrate : hash rate in GH/s
    - eth_difficulty : Difficulty level in TH
    - eth_blocks : number of blocks per day
    - eth_uncles : number of uncles per day
    - eth_blocksize : average block size in bytes
    - eth_blocktime : average block time in seconds
    - eth_gasprice : Average gas price in Wei
    - eth_gaslimit : Gas limit per day
    - eth_gasused : total gas used per day
    - eth_ethersupply : new ether supply per day
    - eth_chaindatasize : chain data size in bytes
    - eth_ens_register : Ethereal Name Service (ENS) registrations per day
- Ethereum prices (ethereum_price.csv):
    - Date : date of observation
    - Open : Opening price on the given day
    - High : Highest price on the given day
    - Low : Lowest price on the given day
    - Close : Closing price on the given day (*)
    - Volume : Volume of transactions on the given day
    - Market Cap : Market capitalization in USD

Most of the information of each dataset contains dates and decimal features that go from negative values to thousands. To merge both datasets, each dataset has to be formatted using dates as key, also the last row in prices hasn't information about prices so needs to be excluded. There are also some 'Close' days that are missing from the dataset 'Prices'. Looking to each dataset statistics, appears to be consistent without many outliers on each feature.

Exploratory Visualization

The first task that needs to be done in order to identify the more relevant features is to visualize the correlation between each feature of the merged dataset.



In this graph it's possible to identify (in lighter colors) the correlation index. Using non correlated features doesn't really help when splitting data for each model. The high correlated features in comparison with the 'Close' are:

Field	Correlation index
eth_marketcap	0.999769
Market Cap	0.996268
eth_tx	0.966170
eth_address	0.958083
eth_gasused	0.951524
eth_hashrate	0.939107
eth_blocksize	0.930363
Volume	0.907974
eth_difficulty	0.827023

Algorithms and Techniques

In this exploration the idea behind forecasting a variable it's part of a regression problem. It's possible to use several algorithms and techniques. Nevertheless, in the context of this investigation, the set of algorithms to use focused on resolving the problem of predicting the ETH price are:

- Linear Regression: The most common and simple method when it's used to forecast a variable based on a different set of features. The set of input parameters used are ***de facto*** parameters
- K-Nearest Neighbors Reggressor: Often used for clustering problems, also have application on time series analysis and financial predictors. The only parameter changed is the number of neighbors to two.
- Random Forest Regressor: The set of parameters also are default parameters in this case.
- Ada Boost Regressor: In the case of this algorithm, the configuration parameters are different to the default values. Specifically the base estimator is set to a decision tree regressor with max depth of 10.
- Gradient Boosting Regressor: Has another input configuration:
  - Number of estimators: 1000
  - Max depth: 4
  - Minimun sample split: 2
  - Learning rate: 0.01
  - Loss: ls

In all this algorithms the way of work is the same, that is, pass training set of X and y to fit the algorithm and then make a prediction using a test set of X features.

Benchmark

To compare each of this techniques, the R^2 score it's computed based on a previous trained model, on the test set of features, and with this prediction, compare with the y values of the test case. So the results on each algorithm are:

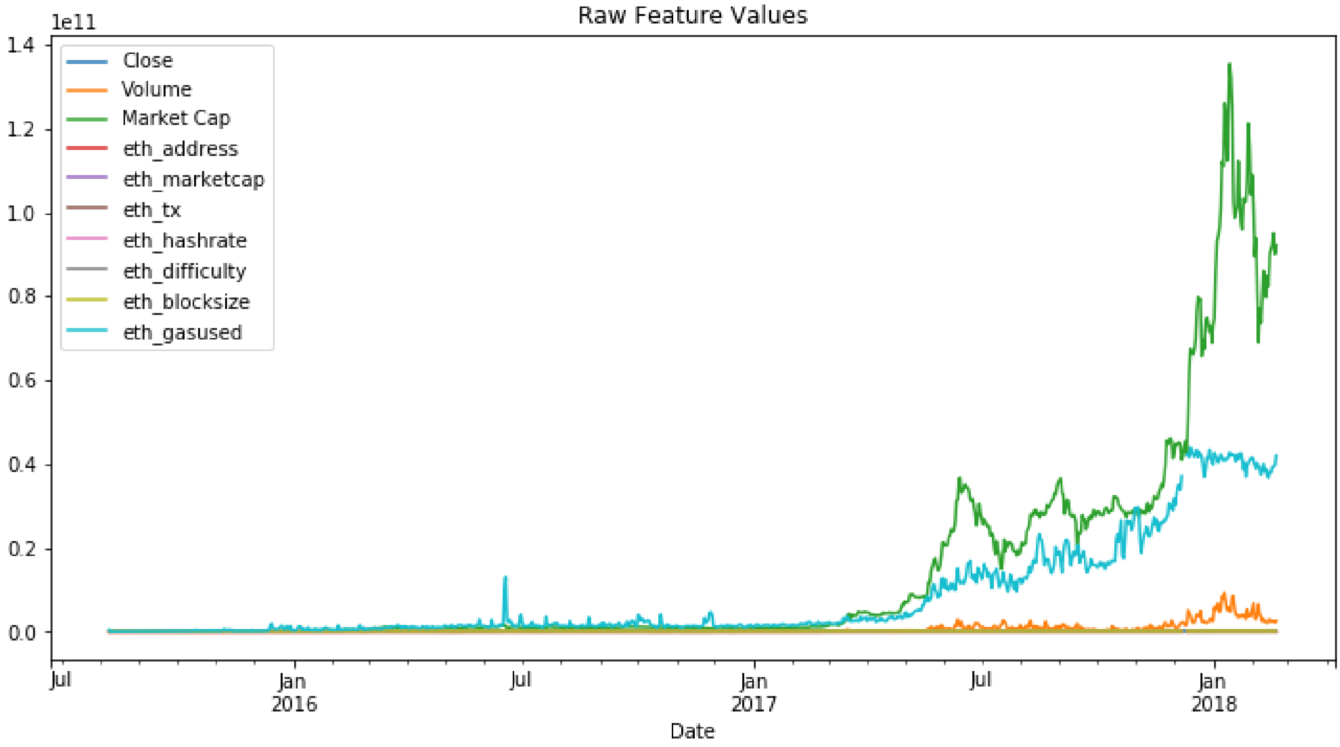
Model	R^2 Score
Linear Regression	0.7654767848001398
K-Nearest Neighbors Reggressor	-1.9013806360331635
Random Forest Regressor:	-1.169761995372531
Ada Boost Regressor	-1.112811356682978
Gradient Boosting Regressor	-1.3588933042301603

III. Methodology

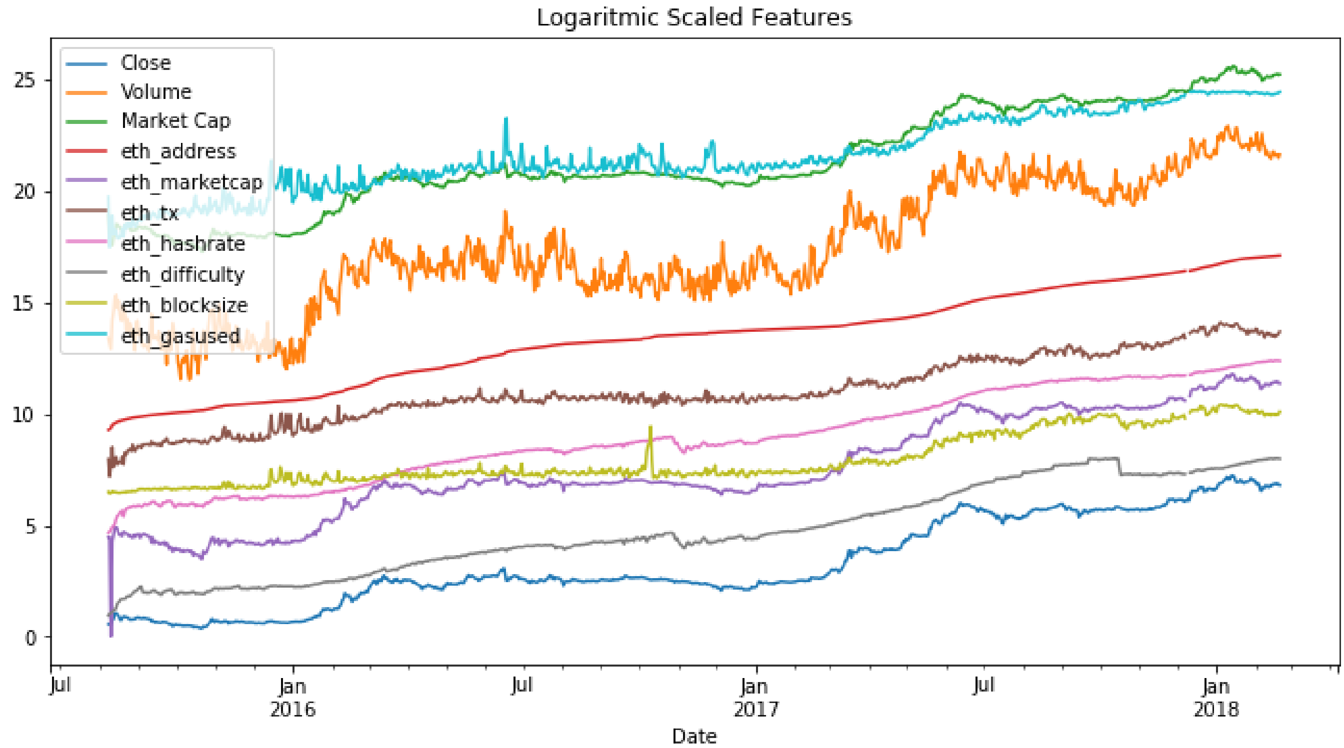
(approx. 3-5 pages)

Data Preprocessing

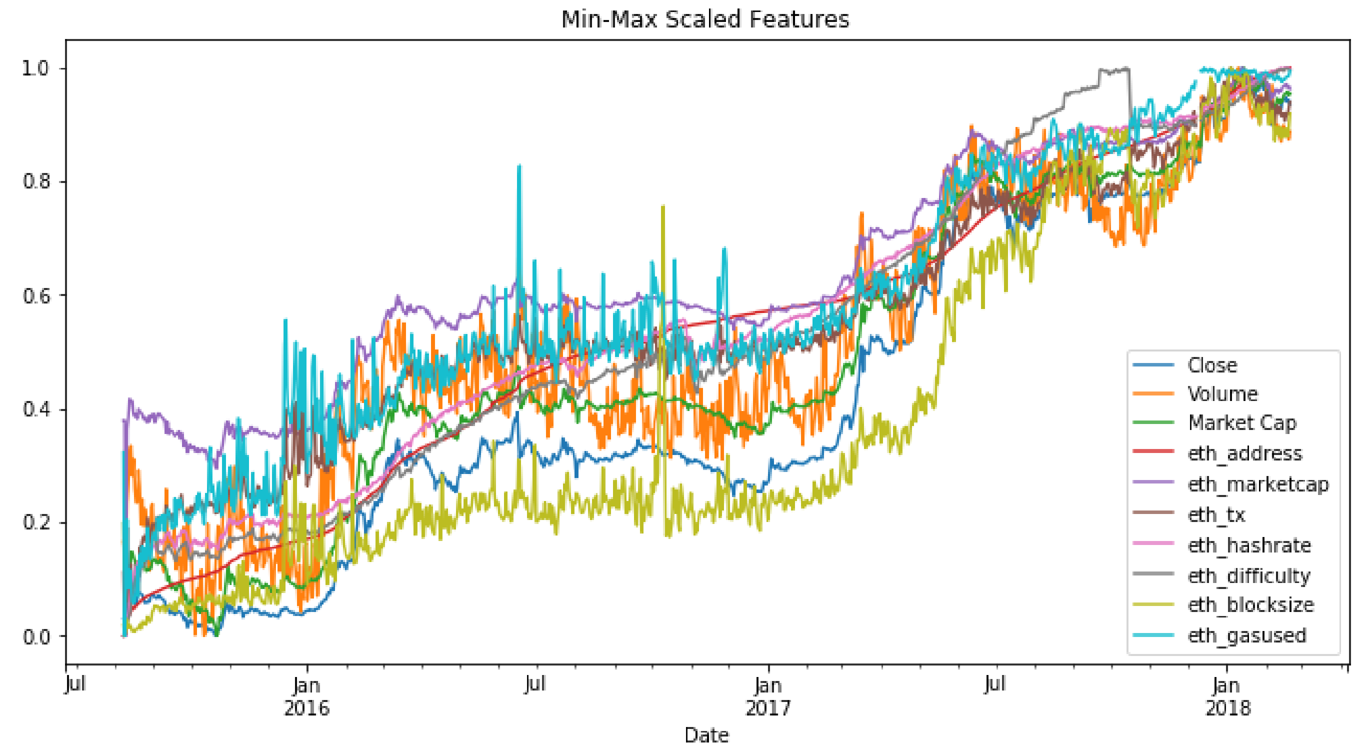
In the data exploration, given the nature of the data analyzed there, there was four steps in order to normalize data formats and some data of the close date that wasn't present.



- The two datasets needs to be merged by the key, in this case the date of the record, before analyzing. There was a date transformation to match the format of the 'price' dataset. The last record in the price dataset was discarded because hasn't information about the close price.
- The first step is to apply a logarithmic transformation to all numerical variables.

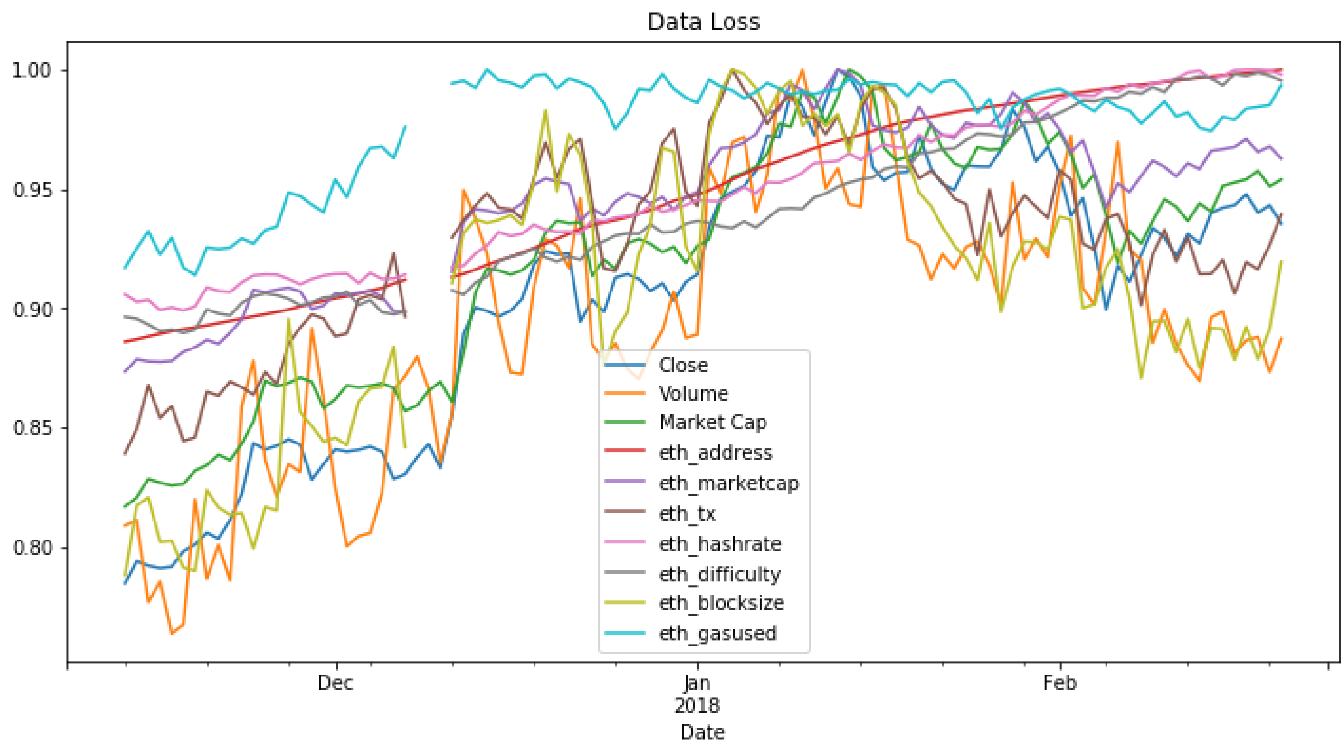


- Then using a scaler (Min-Max) all this numerical features was translated to values between 0 and 1.

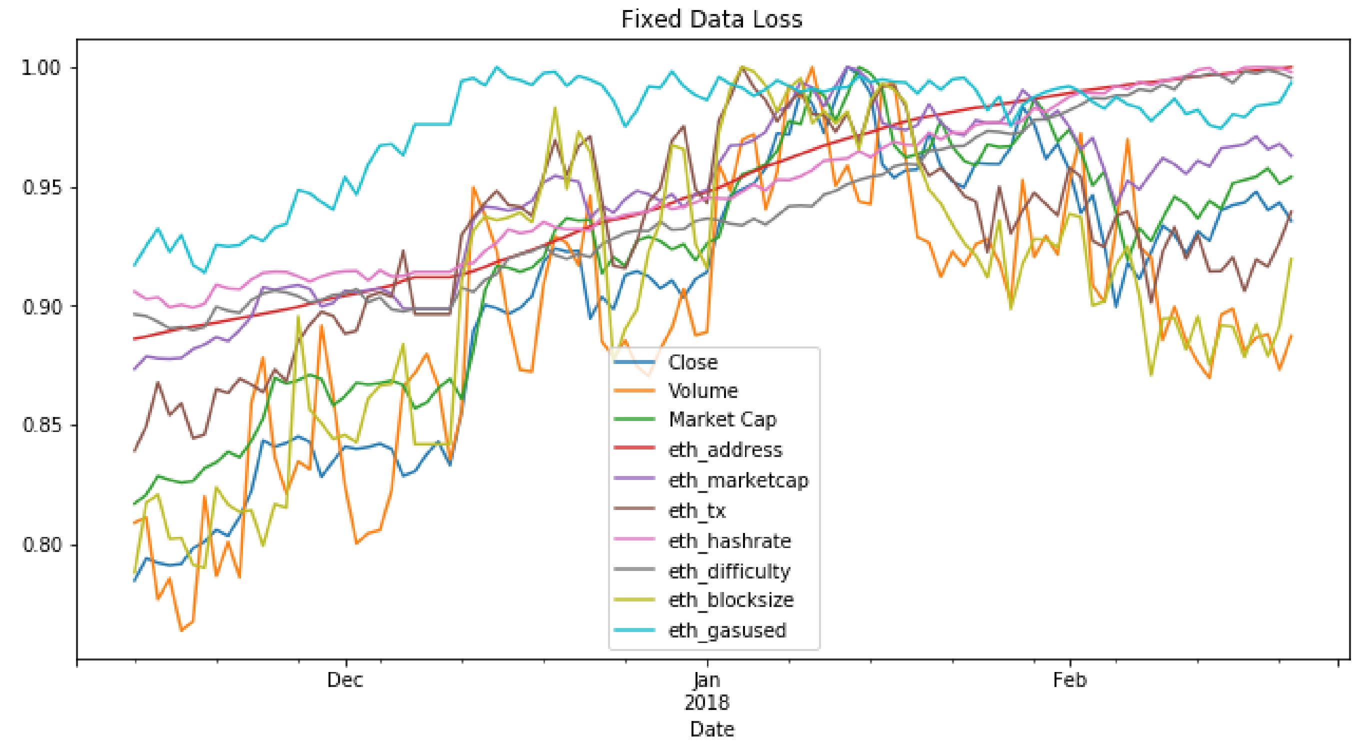


- Finally filling null values using a backfill method.

Before:



After:



Implementation

The implementation process has been done using a Jupyter notebook. All the process could be explained in two blocks:

- Splitting data for training and testing: In this step the data was separated by 70/30 for training and testing sets, but because it's a time serie, it's not recommended for the training set to be ***peeking the future***, because this can produce unrealistic optimistic predictions.
- For each algorithm choosen (Linear Regression, K-Nearest Neighbors Reggressor, Random Forest Regressor, Ada Boost Regressor, Gradient Boosting Regressor) the tasks implemented are:
  - Instantiate the model and set parameters (if the default values hasn't fit the needs).
  - Fit the model using X features and y variable of the training set.
  - Make a prediction of X features of the test set.
  - Get R^2 score results predicted with the actual $y^\wedge$ values of the test set.
  - Make a visualization of the predicted values vs actual $y^\wedge$ values.

Refinement

In general the algorithms doesn't perform the way it was expected, with the exception of Linear Regression that performs reasonable well. There was several actions performed in order to get better predictions from the models:

- Parameter tunning, in general, doesn't improve too much the results.
- Using PCA for dimesionality reduction. It helps to improve on Linear Regression but hasn't any improvement on the others algorithms.
- Reducing test samples to 50/50. In this case all algorithms perform notoriously better but K-Nearest Neighbors Reggressor, Random Forest Regressor, Ada Boost Regressor, Gradient Boosting Regressor get a good prediction until some point in the time line. In this point to the next days, the algorithms just give a fixed prediction values.

IV. Results

Model Evaluation and Validation

In the case of this evaluation and considering the unexpected poor results from the models,the only algorithm that could fit the problem is the Linear Regression. Again trying to adapt training and test sets using timeseries split gives some information about how models behave gives some clues about the overfitting problem in most cases.

For instance this are the results obtained running Linear Regression and K-Nearest Neighbors algoritms and different sizes of training and testing data. Also taking in consideration that the time series split technique use takes random splits of training and testing data but that are always one before the latest.

Training Set	**Testing Set**	**R^2 Linear Regression Score**	**R^2 K-Nearest Neighbors Score**
157	153	-0.713	-6.692
311	153	-2.6	-3.312
465	153	0.920	-0.029
619	153	0.767	-6.491
773	153	0.568	-0.986

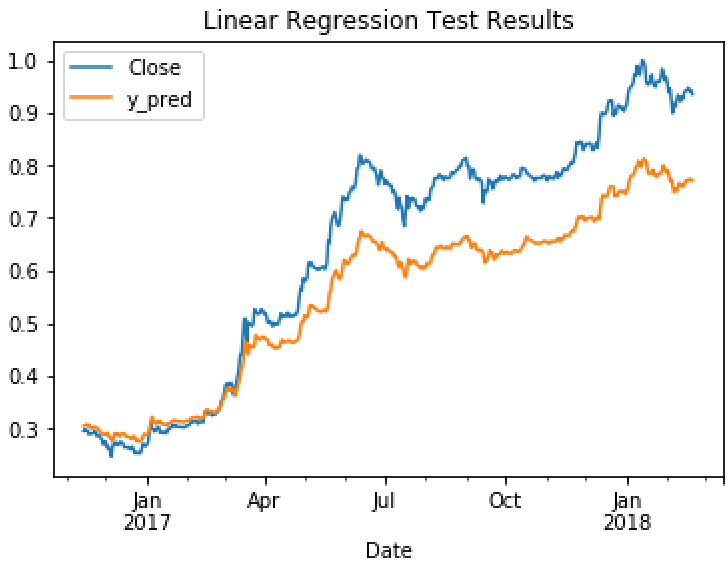
This means that changes on the data generate big differences in the prediction considering the scores. So a big training set doesn't mean that the result of the predictors improve. And results couldn't be trusted taking this in consideration.

Justification

On this exploration none of the results obtained has a considerable improvement from the begining of the exploration and benchmarks, so it's possible to conclude that the problem trying to resolve, that's the ETH price prediction isn't factible with the current strategy.

V. Conclusion

Free-Form Visualization


Linear Regression Test Results
Close
y_pred
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Jan
2017
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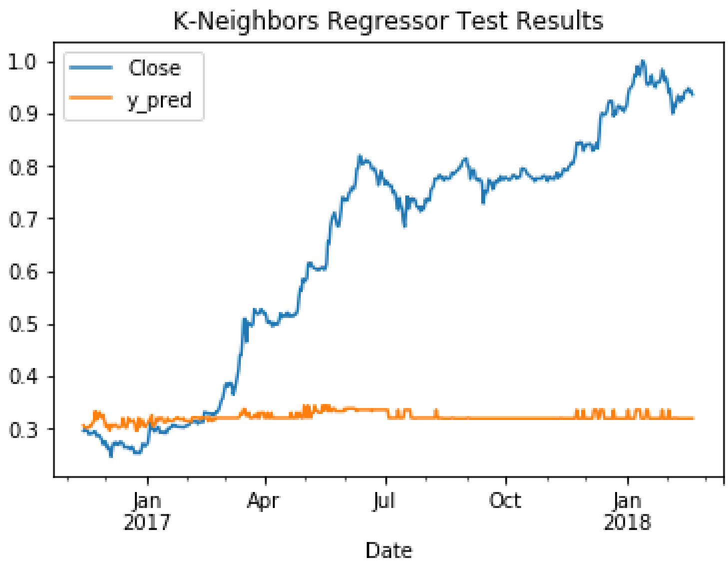
Date


K-Neighbors Regressor Test Results
Close
y_pred
1.0
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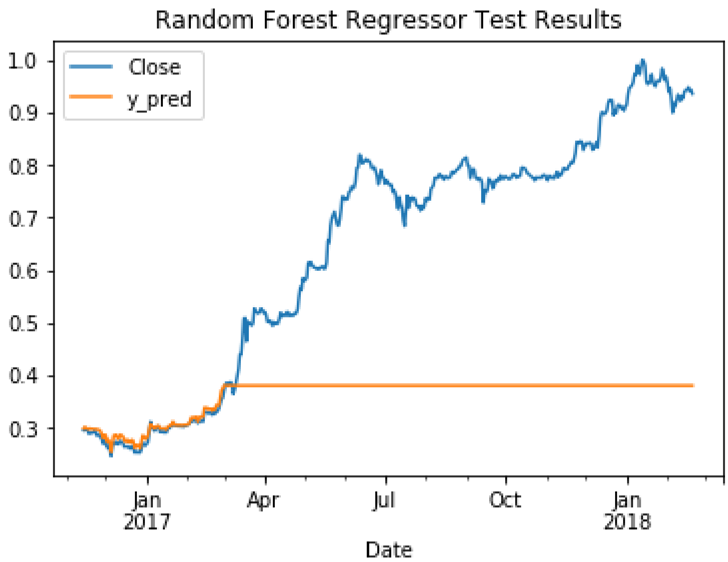
Random Forest Regressor Test Results
Close
y_pred
1.0
0.9
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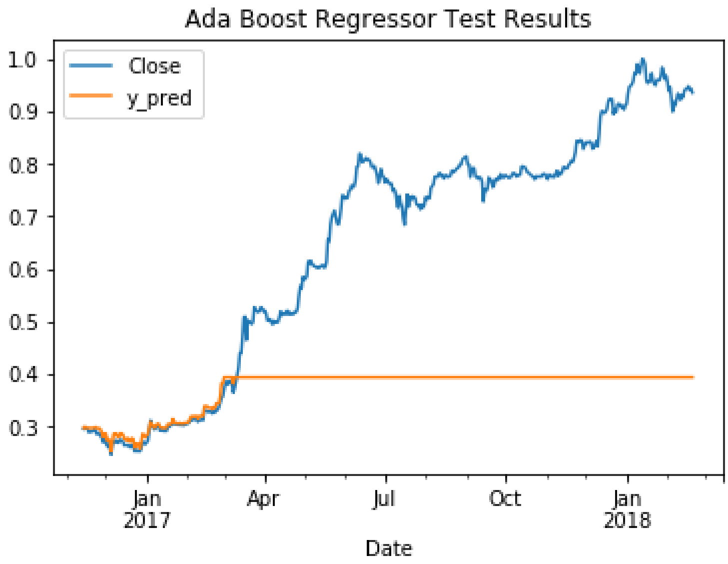
Ada Boost Regressor Test Results
Close
y_pred
1.0
0.9
0.8
0.7
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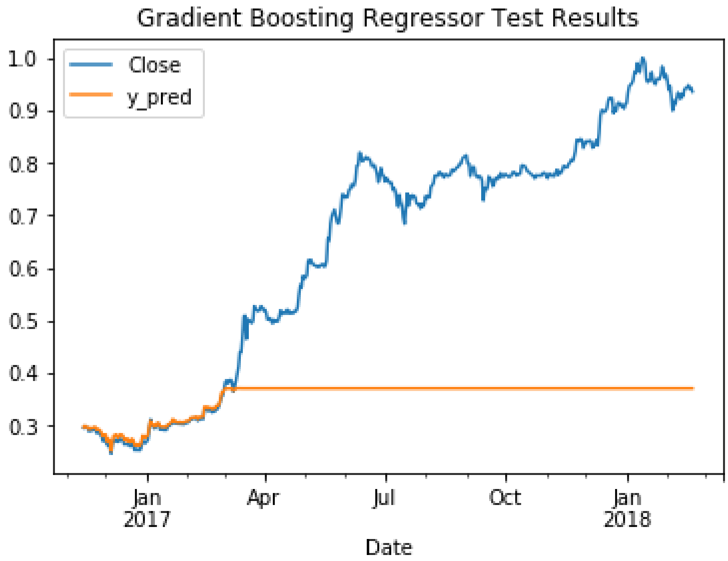
Gradient Boosting Regressor Test Results
Close
y_pred
1.0
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0.7
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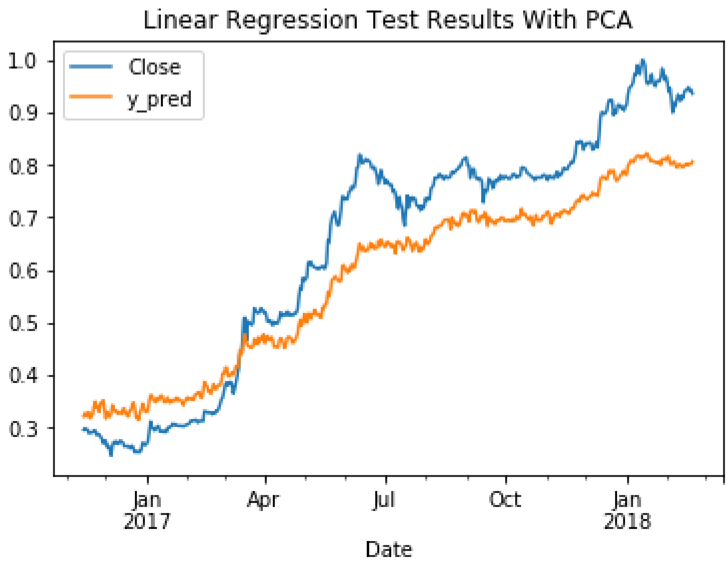
Linear Regression Test Results With PCA
Close
y_pred
1.0
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0.8
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Jan
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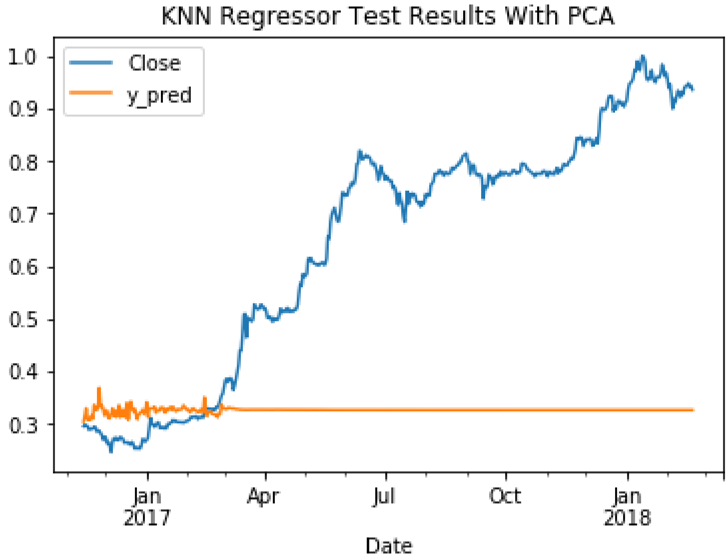

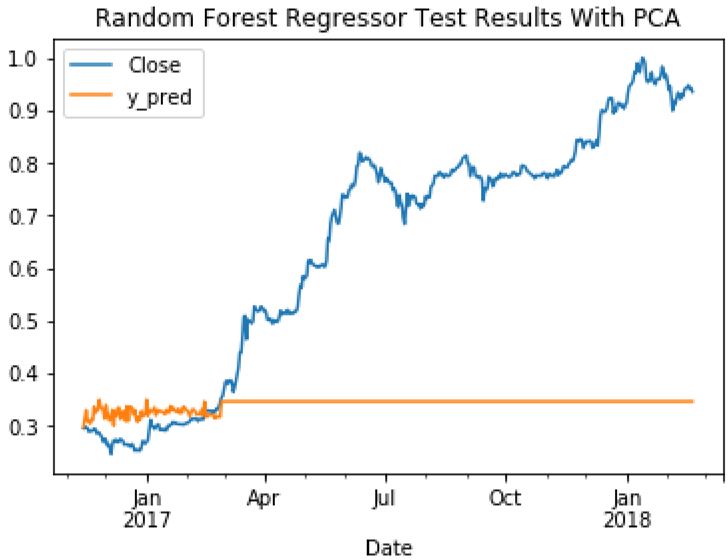

Reflection

In this exploration, the idea behind predicting the Ethereum price based on a daily dataset involves several steps as described in the problem statement section above.

One of the difficults found in this analysis was the time series nature of the datasets and how splitting the data in training and testing sets affects how models performs. Also the selected algorithms aside Linear Regression, doesn't seems to be quite appropiate for the given problem.

There isn't enough evidence to consider this exploration to suit a real world application for Ethereum price prediction. Nevertheless using Linear Regression could be used to analyse trends for buying and selling, and getting a rough estimator for portfolio management for Ethereum. In the case of using this approach for other cryptoassets it's needed to analyse and detect which features correlates with the close price before training and testing a model for this cryptocurrencies.

Improvement

Another exploration could include the use of Deep Learning or Reinforcement Learning and analyse the performance on prediction using such techniques. But in general predicting prices of stocks markets is a difficult task because there are many other variables that aren't so easy to management and capture. But including social media analysis and correlation with other assets like ***fiat*** currencies, price of metals and statistics of different markets could be another exploration to higher quality on prediction.

References

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6. Ídem nº4
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