Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

In this project we try to predict the closing value (adjusted for stock split and dividends) based on adjusted closing values in the past.

> **Disclaimer:** In this project we do not seek to make the best possible prediction, rather, it is an exploratory exercise in how machine learning can be used for predicting the future based on information about the past.

Predicting the closing value of stocks is interesting for several reasons:

1. The time series are sequential, so techniques in machine learning like randomization of the data and cross-validation can not be used in a straight forward manner.
2. Stocks are notoriously non -stationary. This means that both the measures changes with time, and the stochastic rule underlying their realization. The consequence is that traditional statistical techniques must be used with care when analysing the data. This also means that we need to take care when scaling the data, as several techniques uses the mean and standard deviation to scale the numbers.
3. Although we are predicting the stock market here, the *techniques* for forecasting can be applied to any forecasting problem, like forecasting weather, sales, populations etc. Note though, that the *findings* about the models and hyper parameters may not be directly transferable to a different forecasting problem.
4. The efficient-market hypothesis, or simply EMH, states that stocks are already properly priced and reflects all available information. Effectively, this means that "you can't beat the market". More specifically it states that you cannot make any profit from any trading strategies. Although there are several forms of this statement, even the weak form states that "Future prices cannot be predicted by analyzing prices from the past", and that "Technical

analysis techniques will not be able to consistently produce excess returns, though some forms of fundamental analysis may still provide excess returns." Stated differently, if we name our random variable ϕ, the EMH states that $p(\phi_{t+k}|\phi_t)=p(\phi_{t+k})\forall k$ and that $Cov(\phi_{t+k}|\phi_t)=0$, i.e. that all samples in the time series are independent (see also these slides for a nice introduction to the topic). A weaker statement would be that stock prices act like a random-walk. In that case, the next time step is dependent on the previous time step which gives the times series some degree of predictability.

The idea of using machine learning for trading is far from new, and both

have been studying the topic. There are several sources out there which have used similar approaches to predict the stock prices using machine learning. There are papers by academics and students; various blogs; kaggle notebooks; previous ML nanodegree graduates; even vlogs describing how to use support vector regression, lstm and sentiment analysis for stock prediction.

Daily stock data has until recently been readily and freely available. At the time of writing, the situation is somewhat changed, after Yahoo! Finance deprecated their APIs in late 2017, several of the distributors which provided daily stock data for free has deprecated their APIs. Latest Quandl stated

> As of April 11, 2018 this data feed is no longer actively supported by the Quandl community. We will continue to host this data feed on Quandl, but we do not recommend using it for investment or analysis.

Therefore, the data used in this project has been stored in the `data/` directory of the repository. More information about the origin of the downloaded data can be found under `proposal/capstone_proposal` under the section *Datasets and Inputs*.
In this project we have used the daily stock data containing information about opening price, highest traded price, lowest traded price, closing price, volume sold and adjusted closing value (ohlcva) for the 50 stocks with the highest weights in the S&P500 portfolio together with ^GSPC itself as of 6th of March 2018.

Problem Statement

In this project we would like to build estimators based on the k-nearest neighbors (kNN) and long short term memory (LSTM) algorithms and see if they can outperform the simple predictions made by latest day, random gaussian and linear regression algorithms in the task of predicting the adjusted closing price of the stocks. We will assume that what matters the most is the estimators ability to estimate the closing value 7, 14 and 28 days ahead, and that each prediction is of equal importance. The prediction will be done in an rolling matter for all models except the LSTM models. That is, we

1. Fit the data up until day x
2. Do the predictions of day y_1, y_2 and y_3, at day x
3. Add the true data of day $x+1$, refit the models and predict for day y_1+1, y_2+1 and y_3+1
4. Add the true data of day $x+2$, refit the models and predict for day y_1+2, y_2+2 and y_3+2, and so on

We will also assume that the training time of the models is crucial, which is why we are content with a normal prediction for the LSTM models. I.e., we

1. Fit the data on the training set
2. Make predictions of y_1, y_2 and y_3 on the test set.

Note: We will fit one model (with the same hyper parameters) for each stock we are predicting for. I.e. we will not use model fitted on stock A to make predictions on stock B.

We will use the ochlva data Standard and Poor's 500 (S&P500) portfolio as of 2018-03-06.

The number of ways to investigate and solve this problem is enormous, so in order to limit the scope we:

- Only look at four stocks: The `^GSPC`, `AAPL` (which had the highest weight in the S&P 500 portfolio), `CMCSA` (which was the 25th highest weighted stock in the S&P 500 portfolio) and `GILD` (which was the 50th highest weighted stock in the S&P 500 portfolio)
- Only use the data for one stock at the time
- Only use the data from the adjusted close

That being said, it would be very interesting to include more of the ochlv data and even the information about other stocks in the prediction after doing a proper feature analysis (like looking at correlations, doing a PCA analysis etc.).

The strategy to solve the problem can be outlined as follows (for a more detailed description, see section III. Methodolody):

1. Investigate the predictive capability of the "simple models" (`latest_day`, `random_gaussian` and `linear_regression`). The notebooks for investigation can be found in `notebooks/1.*.ipynb`.
2. Investigate the predictive capability of the "advanced models" (`knn` and `lstm`). The notebooks for investigation can be found in `notebooks/2.*.ipynb`.
3. Tune the features and hyper parameters for the "advanced models" one by one. Note that this could be done by performing a grid search. However, as we

are interested in the trends, and since we are using a non-standard metric (see the metrics section), we will search the parameters one by one, well aware of the fact that there may be combinations of the hyper parameters that potentially could give better predictions. The notebooks for investigation can be found in `notebooks/3.*.ipynb`.

For each analysis we will for each stock investigated:

1. Read the data
2. Clean the data
3. Extract the adjusted close feature
4. Create the targets from the adjusted close, by shifting them by *t* days towards the future (note that the *t* latest observation would be without a target value)
5. (Optional) Make more features from the adjusted close by shifting them *u* days towards the past (note that the *s* first observations would be without a target value)
6. (Optional) Scale the data
7. Split the data into a training set and a test set, or a training set, validation set and test set if we are tuning the hyper parameters
8. Perform a rolling or normal prediction.
9. (Optional) Rescale the data

Metrics

As stated in the problem statement we assume that the important factor when for example making a trading decision is the predicted value 7, 14 and 28 days ahead, and that each of these prediction is of equal importance. We must find a proper metric to address this problem. We could have said that a prediction is good if it on average mispredicts the closing value by less than 5 %. However, if we look at the stocks we try to predict, we see that the stocks varies far less than 5 % on the course of 28 days. Instead, we could have used the mean squared error (MSE) of the test set to give an indication of how good the prediction is. Using the positive square root of the MSE (RMSE) can be beneficial in order to make the order of the error easier comparable to the price by cancelling the effect of squaring. However, as the absolute value of the stocks are quite different (especially when comparing `^GSPC` with the other stocks), the RMSE is a bad metric when comparing across different stocks, Therefore, we will be using a form of normalized mean squared error (NMRSE) defined by

$$\frac{\sqrt{\frac{\sum_{i=0}^{n}(y'_i - y_i)^2}{n}}}{y_{max} - y_{min}}$$

to assess the error.

II. Analysis

Data Exploration

In section, we will present the findings from `notebooks/0-data_analysis.ipynb`.
As noted above, we will focus on the four stocks

- `^GSPC` - Standard and Poor 500 portfolio
- `AAPL` - Apple Inc.
- `CMCSA` - Comcast corporation
- `GILD` - Gilead Sciences, Inc.

The adjusted closing value of the stocks (which we will take up the main focus in this project) can be summarized in the following table:

Stock	Samples	Start date	End date	NaNs	Mean	Max
^GSPC	1260	2013-03-07	2018-03-07	0	2079.750175	2872.870117
AAPL	1254	2013-03-06	2018-02-28	0	106.716004	179.260000
CMCSA	1258	2013-03-06	2018-03-06	0	29.283641	42.990000
GILD	1259	2013-03-06	2018-03-06	0	79.645139	115.929959

Min	Std	Q1	Q2	Q3
1541.609985	286.663626	1884.517517	2065.594971	2206.597473
50.928800	32.229902	85.194266	106.182039	122.349196
18.031155	6.269263	24.920172	28.271251	33.938108
41.946136	16.337412	69.417169	77.871612	94.513256

From the table, we can observe that:

1. The number of samples are almost the same, indicating that some trade days are missing for some of the stocks
2. There are no NaNs or 0s present
3. ^GSPC has values roughly one order of magnitude larger than the rest of the stocks

Note that the mean and standard deviation are the sample mean and standard deviation. I.e. it does not represent the true mean and standard deviation, at least not if the process is non-stationary.

Also note that there are 1826 days between 2013-03-07 and 2018-03-07. The 1260 days reflects the fact that there are no trading during week-ends and bank holidays. Also, if we were looking at smaller stocks, they could have "missing" data simply from the fact that no one was trading those stocks on the given day.

Visual inspection (see Exploratory Visualization) shows no sign of outliers in terms of erroneous data in the adjusted close values; one example of such error could be a single day which has 10 times higher closing value due to a decimal error arising from manual typing of the data.

Further we can clearly observe that the full time series contain clear growing and decaying trend in the range we are observing. By performing a stationarity test (similar to the one performed here) we will investigate if the test set of `CMCSA`, which appears to have the least linear trend, is indeed non-stationary.
We will use the Augmented Dickey-Fuller test to test the probability that the time series contain a unit root and thereby is trend-stationary, i.e. if the trend is removed, then the resulting data is stationary. If the time series is trend-stationary it is at least not stationary. The hypotheses are:

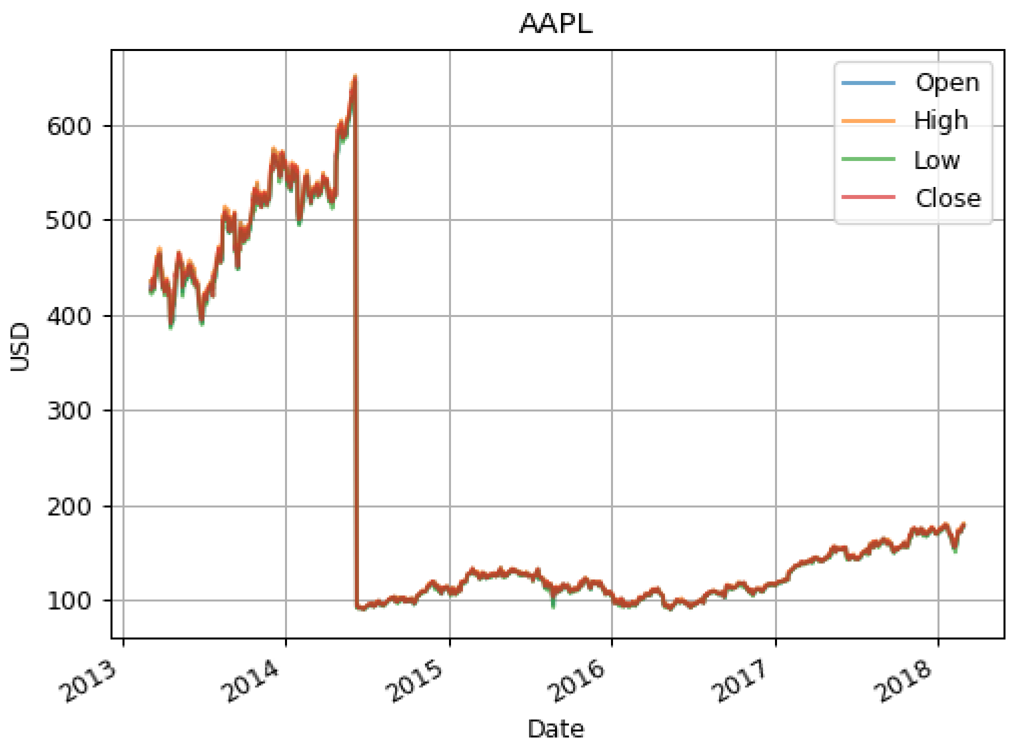
- Null hypothesis: The series are non-stationary (i.e. there exist an time dependent trend)
- Alternative hypothesis: The series is stationary (i.e. no trend exist)

We've set the rejection hypothesis threshold of the p-value to 55 , meaning that we reject the null hypothesis (the series are stationary) if the p-value is less than or equal to 0.05.

We found that since p > 0.05 there was no evidence to reject the null hypothesis. In other words, the time series is probably non-stationary.

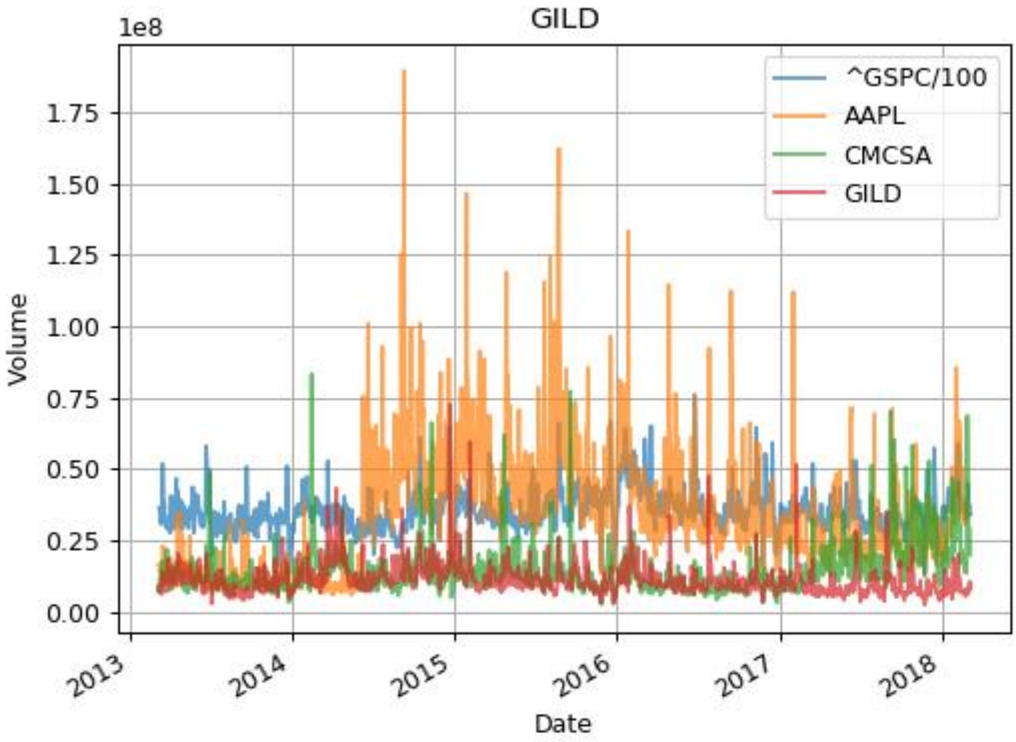
Exploratory Visualization

In section, we will present more findings from `notebooks/0-data_analysis.ipynb`.
In order to justify our choice of `Adj. Close` as the sole variable we will create the data set from we will perform some visual inspections on the features contained in the `.csv` files in the `data/` directory.
If we for example look at the ochl features of the `AAPL` stock (the rest can be found in `notebooks/0-data_analysis.ipynb`) shown below



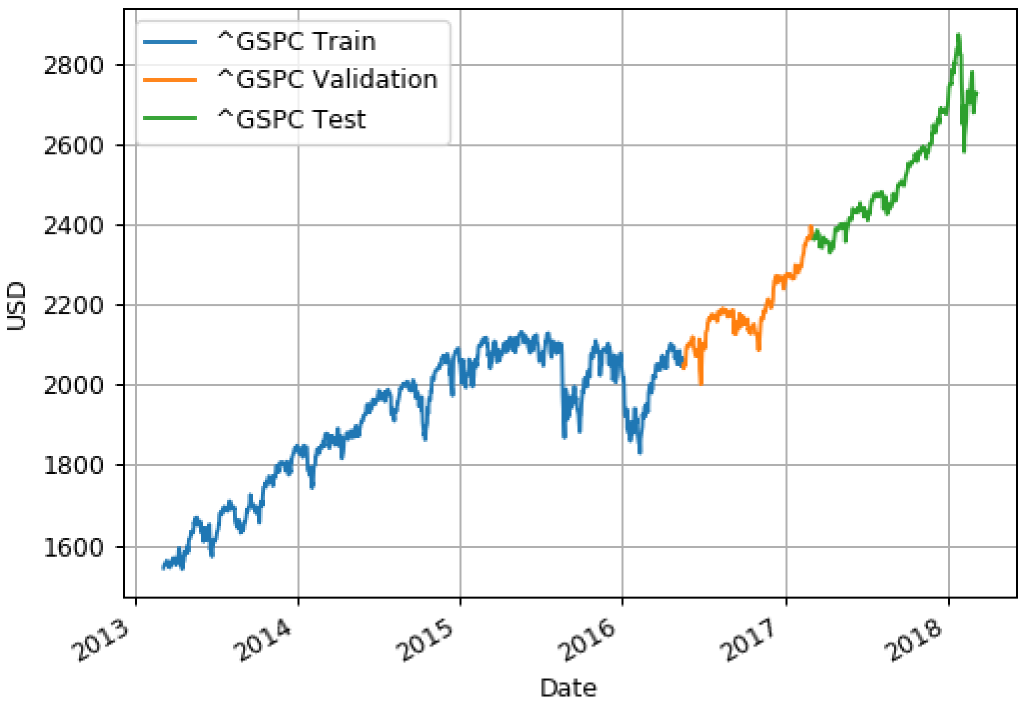
We observe that overall, the ochl values follow each other to a high degree. It is important to note that they are not exactly the same, and in fact, how the open, high and low aligns with the closing value can give important hints about the closing value the following day. The sudden drop is due to a stock split (which is accounted for in the adjusted close price).

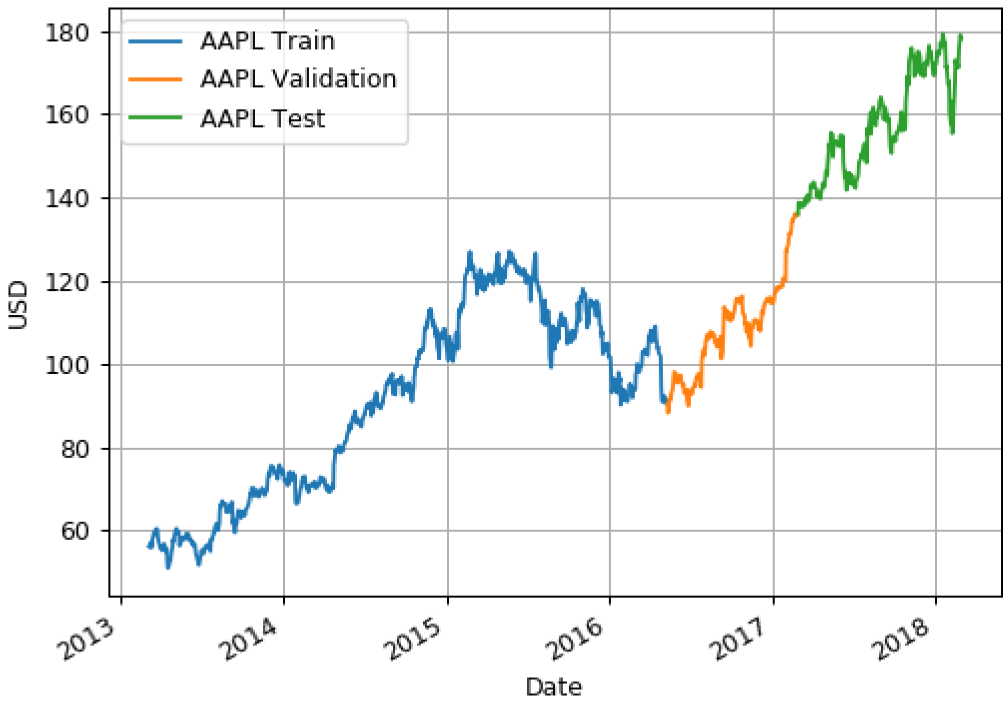
These features can be compared with the plot of the volume data given below

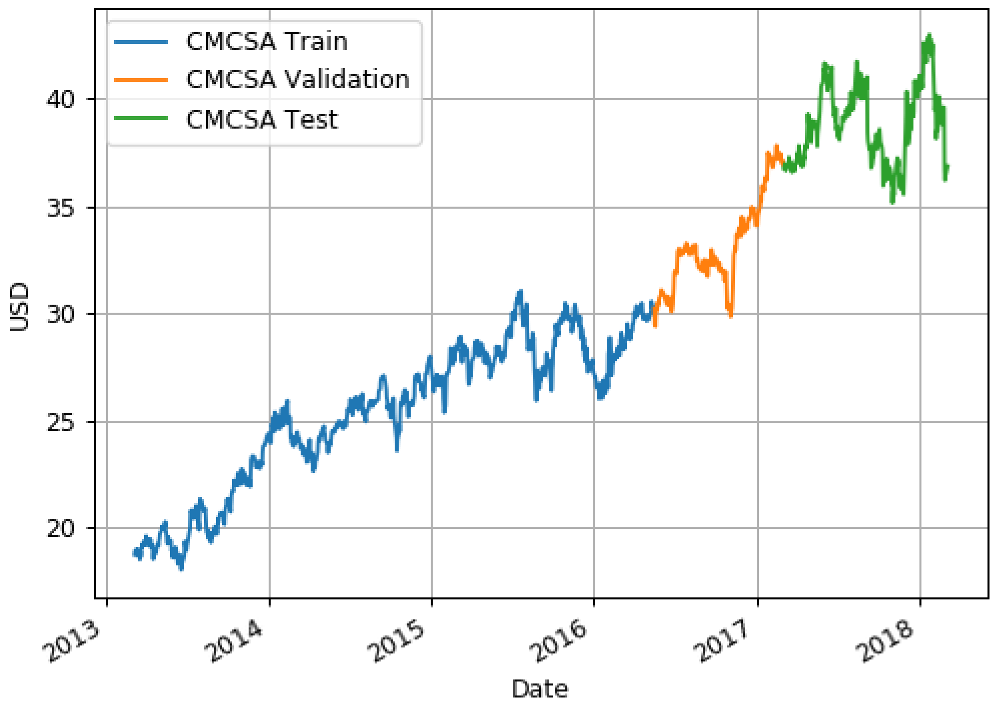


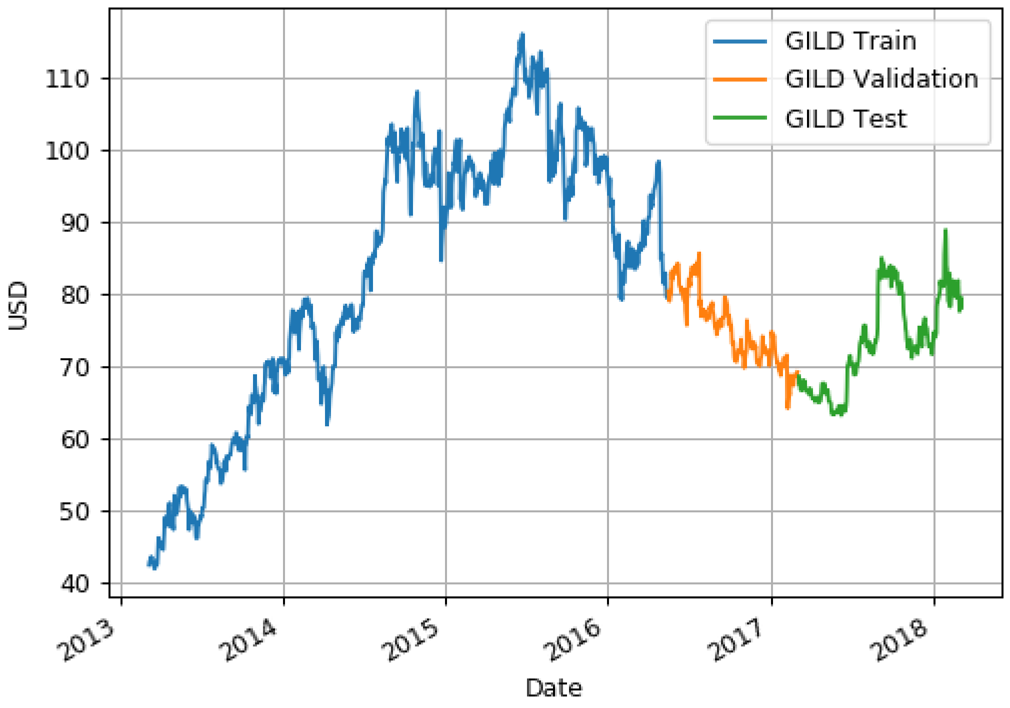
We observe that the volume does not follow the same trend as the ochl data, and has far less structure. Note that the ^GSPC volume has been divided by 100 to make it easier to visually compare the results.

As the ochl features are quite similar, and as the volume data contain less structure we choose (in order to limit the scope) to only look at the adjusted close values (shown below), as these contain strong structures and are likely to contain data needed for accurate prediction.


^GSPC Train
^GSPC Validation
^GSPC Test
2800
2600
2400
2200
2000
1800
1600
USD
2013
2014
2015
2016
2017
2018
Date


AAPL Train
AAPL Validation
AAPL Test
180
160
140
120
100
80
60
USD
2013
2014
2015
2016
2017
2018
Date





Algorithms and Techniques

In this project we will use some quite different techniques in order to try to estimate the closing value, and we will here present each one briefly.

In order to make the benchmarking tests we will use the following techniques:

- *Last day prediction (custom made)*: This estimator simply uses the current value to make the predictions. For example, assume that at day *d* the closing value is *y*, then the estimator would predict a closing value of *y* for the days *d*+7, *d*+14 and *d*+28. The estimator is very simple, and has the potential to yield great results (at least in the case where the closing value changes minimally). The fitting routine only looks at the last value of the data, and stores this or these values in a variable. In the prediction phase, the stored value(s) will be set to the predicted value. This estimator has no hyper parameters to tune.

- *Random gaussian (custom made)*: It's often stated random guessing, or even using monkeys for stock trading can outperform professional humans. Having no monkeys at hand, it easier to implement a random number generator to do the stock prediction. This predictor will store the mean and the standard deviation of the training data in the fitting step, and use a gaussian random number generator with using the means and standard deviations from the fitting step in order to make predictions. Note that as the processes are non-stationary, the mean and standard deviation will change as time evolves. Neither this estimator has any hyper parameters to tune.

- *Linear regression (from the `skLearn` package)*: This is considered to be the simplest of the linear regressors. It is using theordinary least squares during fitting. This will give the coefficients *a* and *b* in the linear equation *y*=*ax*+*b* which will be used when predicting *y* based on the input *x*. Although the class have some input parameters for the constructor, we would not usually define these as tunable hyper parameters for the model

For trying to predict the closing value we will use the following techniques:

- *k-nearest neighbor regression (from the `skLearn` package)*: Also this is a quite simple model, but often yields good results despite its simplicity. Even sophisticated software like QuantDesk are using kNN. The fitting phase just uploads the available data to a storage location (like the local memory or a database). When predicting, the algorithm will find the k nearest neighbors (according to a distance metric) and predict the new value based on the mean of these. The algorithm has at least some hyper parameters to play around with. We can choose whether the mean should be weighted by for example distance or not, what metric to use for the calculation of distance and last but not least, the number of neighbors to take into account.
- *A Long Short Time Memory Recurring Neural Network (from the `keras` package, modified for our needs)*: The Long Short Time Memory (LSTM) neural network is a type of recurring neural network (RNN), which means that output of one of

therecurrences in the neural network serves as the input for the next one, like explained here. A nice introduction to LSTM can be found in this blog. Although figuring out how the input to this machinery can be mind boggling at first, all we need to do is to reshape our data to a 3-dimensional array\ where the dimensions represents `[samples, time steps, features]`, where the `time step` dimension tells the LSTM how many times the recurrence should occur. The LSTM overcomes the vanishing gradient problem found in RNNs by having gates in each cell (equivalent to nodes in traditional neural network) which determines what should be kept in memory, and what should be forgotten, and is therefore very well suited for time series forecasting. The LSTM learns the weights of the gates and the cells in the fitting phase and uses these in the prediction phase. The hyper parameter tuning can be quite extensive, so we have in this project limited the hyper parameter tuning to epochs, batch size, drop out rates, number of cells in the first layer, number of cells in the second layer and the number of time steps.

Benchmark

The calculations of the benchmarks can be found in `notebooks/1.*.ipynb`. We use the results of the simple algorithms above to get a feeling with how well we can perform with the simplest tools in the toolbox. If one of the more advanced methods is only slightly better than these results, one should consider if it is worth the cost to use a more complex model.
By using the rolling prediction technique described in the Problem Statement and the metric described in Metrics, we end up with the following scores (the complete table with all the results can be found in the Justification section)

Stock	Last day	Random Gaussian	Linear regression
^GSPC	7.01	577.33	6.15
AAPL	1.50	96.01	1.34
CMCSA	0.51	18.11	0.48
GILD	0.94	15.55	0.76
Sum	9.95	706.99	8.72

III. Methodology

Note: All classes and functions has been extensively documented in the source code, and more details can be found in the documentation.

Data Preprocessing

Before the models can be used, the data needs to be preprocessed. Preprocessing is firstly done when reading the data by using the `OCHLVAData` class in `data_preparation/ochlva_data.py`. When cleaning the data, the class makes sure that only dates present in `^GSPC` is considered, and if any `NaNs` are detected, they will be filled by first running a forward fill (setting missing data to the date with previous value), then by running a backwards fill (setting remaining missing data in the past to the nearest value in relative future).
The targets are then being created from the time series by using the `target_generator` found in `utils/column_modifiers.py`. The targets are simply the time series under consideration shifted by the number of days we would like to predict for. This means that the last observation will contain `NaNs` as we do not know the future value, and these `NaNs` are removed before using the data in the models.
When predicting using the KNN algorithm we are also generating features with the `feature_generator` of `utils/column_modifiers.py` by shifting the time series under consideration backwards in time. This means that we will generate `NaNs` for the first observations in the time series, and also these `NaNs` are removed before using the data in the models.
For predictions with the LSTM models we need to create a 3-dimensional array. The dimensions represents `[samples, time steps, features]`. After reading the data from file and generating targets (and possibly features), the dimension of the data set is on the form `[samples, features]`. We therefore create a `time step` dimension in `prepare_input` in `estimators/lstm.py`, which tells the LSTM how many times the recurrence should occur.
As seen from `notebooks/2.2.1-lstm_prediction.ipynb`, the LSTM performs quite poorly for unscaled features as it is trying to predict numbers far outside of the range. If we were to predict only the closing price the next day we could have subtracted the value of the previous day to the current day, and thereby detrended the series. However, in this project we aim to predict the adjusted close value 7, 14 and 28 days ahead. Even if we had successfully predicted the new target, we would not be able to do the back transformation which would depend on the values 6 days ahead, 13 days ahead and 27 days ahead, which again would depend on the values 5 days ahead an so on. In other words, we would need a prediction all the way until the last prediction day if we wanted to back transform to the adjusted close. Instead, we will scale the features by using the `StockMinMax.transform` found in `utils/transformations.py`. The transformation reads

$x' = (x - x_{min}) / (x_{max} - x_{min})$

and the back transformation reads

$x = x'(x_{max} - x_{min}) + x_{min}$.

It is important when scaling the features that we do not leak information from the unseen test set into the training and validation set. In other words, the `max` and `min` in the above formulas refers to the maximum and minimum of the training set. This can be problematic in the case where the test set deviates significantly from the training set. However, although the test sets deviates some form the training set in our examples, it's still within the range where the LSTM models can make meaningful predictions.

Implementation

Although the code is well documented in the code, we will in this section provide some documentation of the "big picture" implementation.

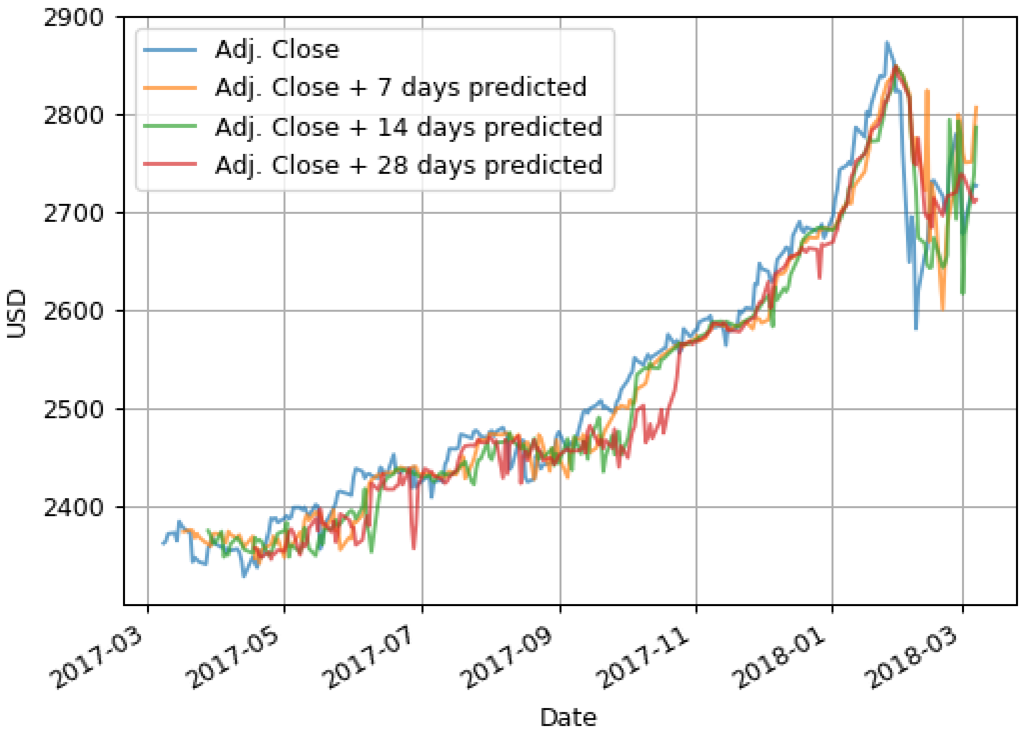
In order to read the data from the files, an `OCHLVAData` class has been provided in `data_preparation/ochlva_data.py`. This class handles everything related to the data sets. In other words, it contains copy of the raw data of the stocks, the cleaned data of the stocks (where `NaNs` and bad dates have been removed) and transformed data (for example where some features have been added or removed). By abstracting the handling of the data it is easier to loop over the stocks one by one for model fitting and prediction.
The estimators used in this project are found in the `estimators` directory if they are not already implemented in `sklearn`. The estimators inherits from the `sklearn` regressors so that they in principle can be used in a `sklearn` pipeline. Also, as the estimators shares the same member functions it is easier to reuse the code. In the case of the LSTM estimator, the architecture of the net has been put as input parameters in the constructor so that it can be used in the same way other `sklearn` objects treat hyper parameters.
In principle we could have looped over all regressors in a notebook, and shown the result, but the results from different regressors have been separated to different notebooks in order to get a better overview.

The notebooks for the unoptimized models found in `notebooks/2.*.ipynb` are quite similar those for obtaining the benchmarks in `notebooks/1.*.ipynb`. The process contains the following steps:

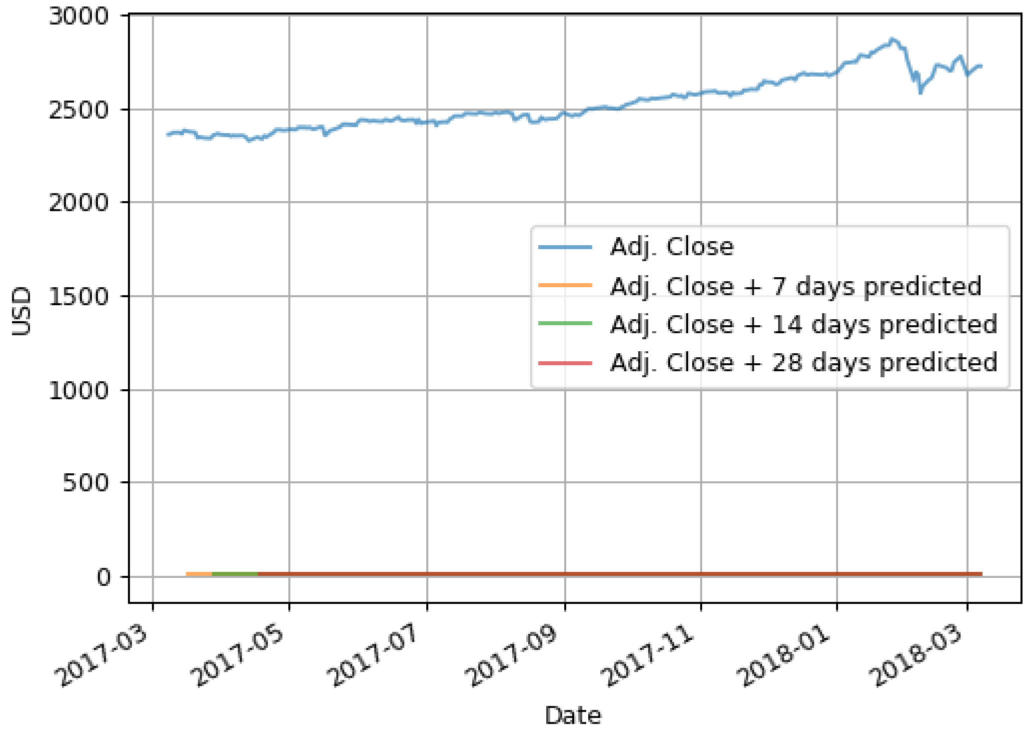
1. Read the different stock data from the files
2. Remove all features except `Adj. Close`
3. Generate the targets from the `Adj. Close`
4. Initialize the regressor

5. Loop through the stocks
    i. Split into a training and test set
    ii. Make either a rolling or a normal prediction (found in `estimators/predictions.py`)
    iii. Calculate the score from the predictions

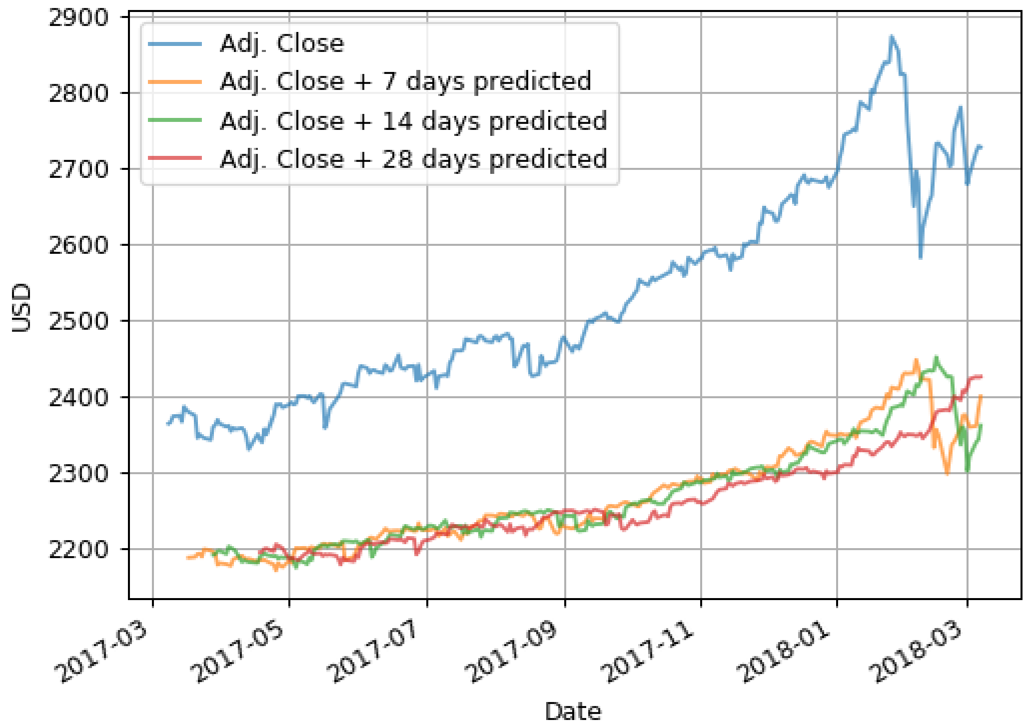
The result of the basic kNN prediction can be seen below for `^GSPC`



As mentioned, the unscaled LSTM predictions perform quite poorly as seen for `^GSPC` in the figure below



However, the predictions are not so bleak when we scale as seen below



A summary of the score of all the unoptimized predictions can be seen in the table below.

Stock	knn (unoptimized)	lstm (unoptimized, unscaled)	lstm (unoptimized, scaled)
^GSPC	2.38	11827.14	148.83
AAPL	0.99	503.91	7.59
CMCSA	0.33	23.31	0.59
GILD	0.88	42.67	0.75
Sum	4.58	12397.03	157.77

Note: As training LSTM models are quite computationally heavy, all the predictions with LSTM in this project has been performed with a "normal" prediction. One should therefore compare the scores between the different models with care.

Refinement

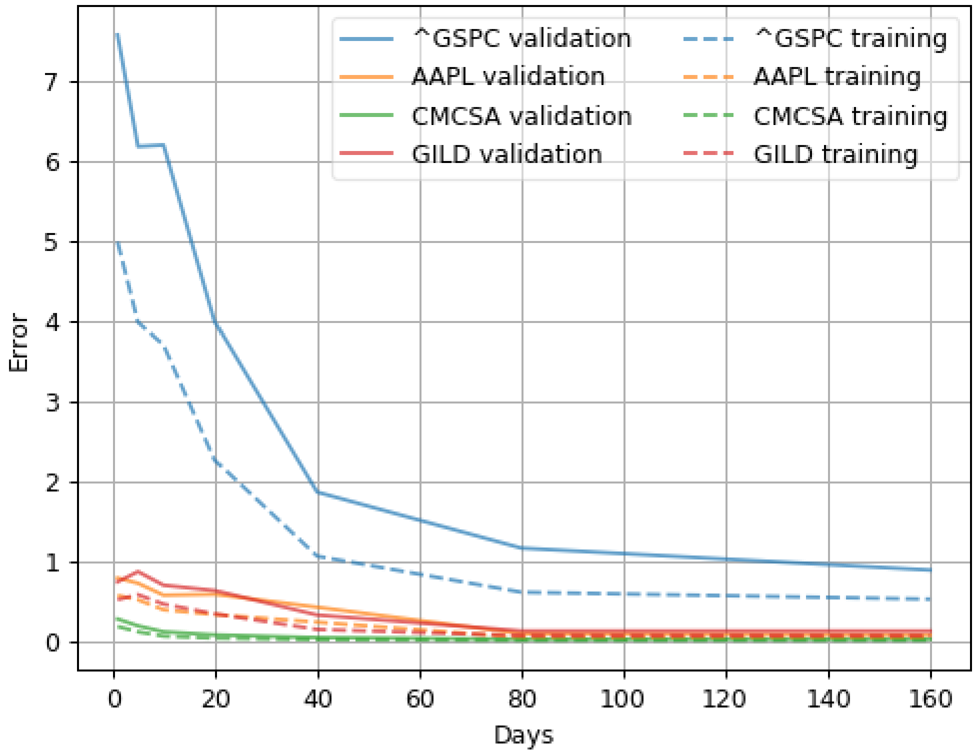
We will now investigate whether we can improve the models to yield better results than those obtained in Implementation. In order to that we will tune the hyper parameters of the two models. For the kNN estimator this means tuning:

1. The number of features
2. The number of nearest neighbors

For the LSTM estimator this means tuning:

1. The number of epochs
2. The batch size
3. The drop out rates
4. The number of cells (the equivalent to number of neurons in a conventional neural network)
5. The number of cells in a secondary layer
6. The time steps

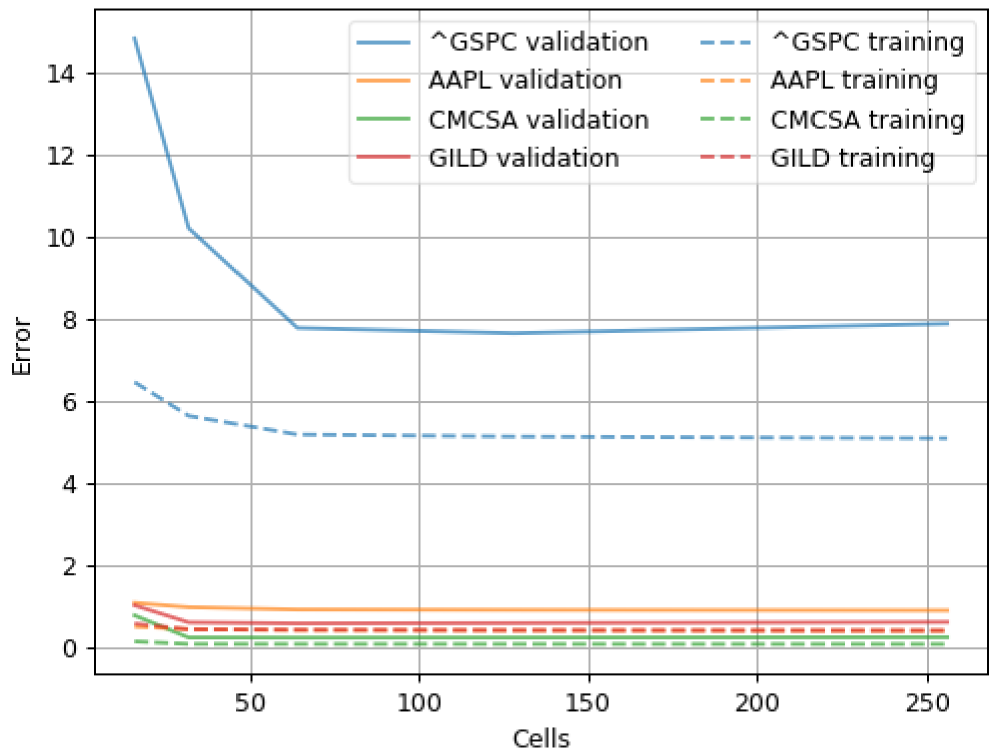
Note that we could have performed an entire grid search, by doing some modifications to the scoring function and they way the predictions are made, this could be done with the estimators in `sklearn` as all of the estimators behaves as `sklearn`regression objects. The full grid search however, can be computational heavy, and sometimes it suffices to know how the hyper parameters scales when changing one parameter at the time. The drawback of the latter approach is of course that there may exist optima arising from special combinations of the parameters which are different than the optima for the individual parameters. Nevertheless we will go for the last approach in this project.
When optimizing the parameters for the kNN estimator, we observe from `notebooks/3.1.1-knn_prediction_tuning_features.ipynb` that the more features the better the prediction. However, the gain is diminishing for very high number of neighbors (as seen from the figure below), and we must also consider that we are losing training data for each new feature day as we do not know the previous values for the very first observations. Therefore, we fix the number of features to `160`. This means that we have a feature for the 160 previous days prior to the current observation day.



Interestingly we see from `notebooks/3.1.2-knn_prediction_tuning_number_of_neighbors.ipynb` that the estimator performs best when only the nearest neighbor is considered. One possible explanation is that features from previous days get close to the query point in the hyperspace, and that the mean of these is therefore worse than considering the closest point alone.

For the LSTM it turns out that our initial set of parameters were almost optimal. The following was found during the investigation:

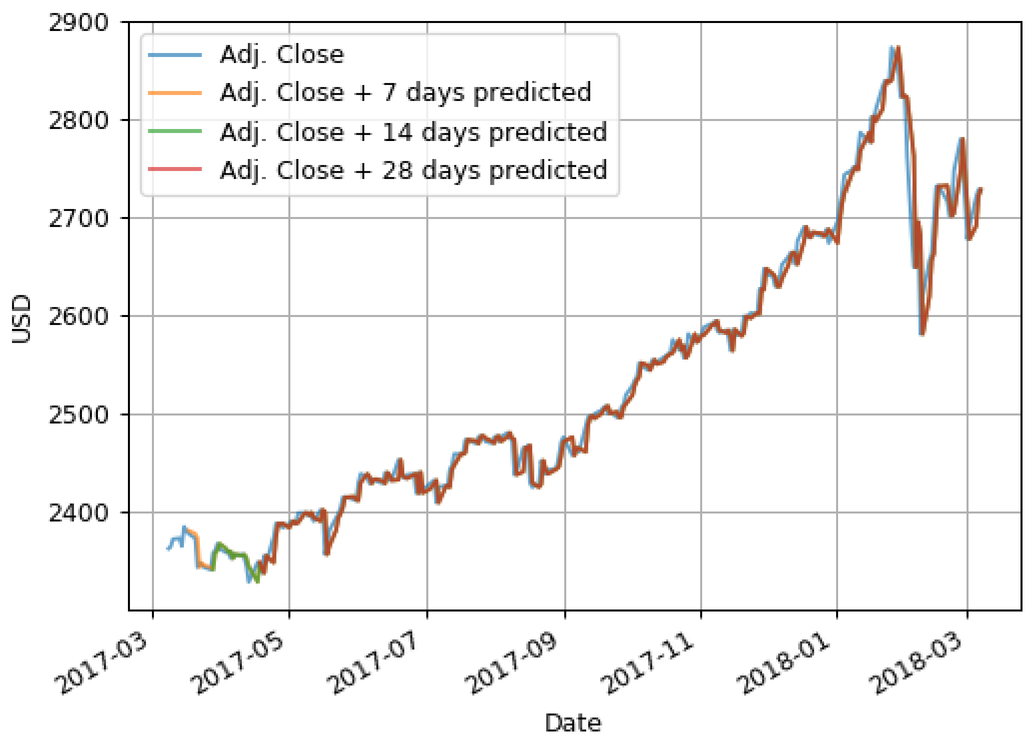
1. Increased number of epochs gives reduced error, but the decrease is diminishing for high number of epochs. This makes sense at the models gets to know the data better for increased number of epochs. A balance between training time and error is found at 160 epochs.
2. The error as a function of batch size seem to have a minima at a size of 128. Both lower and higher size yields poorer performance.
3. Increased drop out rates yield worse performance. This indicates that the sequential information is highly connected, and should not be considered separately.
4. The number of cells seem to have a minima at 128 cells. Less cells seems to underfit, and more cells seems to overfit, as indicated in the figure below. This means that 128 cells better matches the complexity of the problem compared to other values.
5. A secondary LSTM layer seem to overfit as well.
6. 1 time step seems to be optimal. In other words, no recurrence seems to be the best. Although this may be the case, it is likely that the LSTM is poorly constructed as recurrence is known for usually improving performance for sequential data.



A summary of the obtained scores can be found in the table below.

Stock	knn (optimized)	lstm (optimized)
^GSPC	0.54	6.70
AAPL	0.10	1.59
CMCSA	0.04	0.58
GILD	0.05	0.76
Sum	0.73	9.63

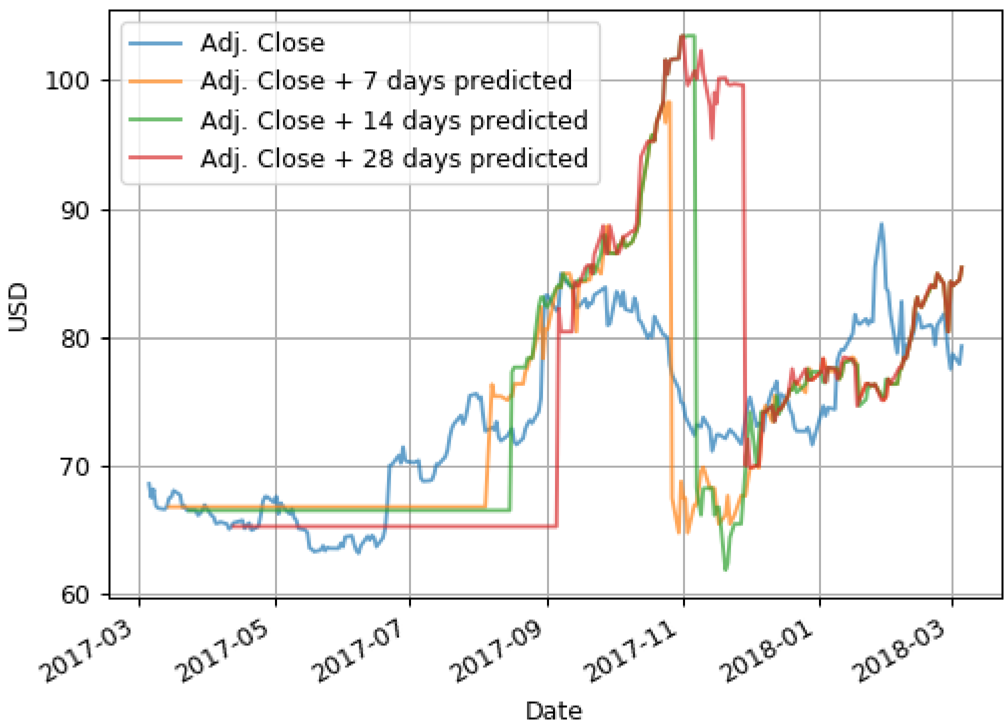
As we can observe, the optimized kNN performs really well as shown for the `^GPSC` in the figure below



As mentioned above, the comparison between the kNN and LSTM is unfair as we are making a rolling prediction (where we update the model after each prediction) for the kNN predictions, and do a normal prediction (no update) for the LSTM. If we were to do a normal prediction for the kNN as well, the scores would yield what is presented in the table below.

Stock	knn (normal prediction)
^GSPC	93.65
AAPL	55.64
CMCSA	0.97
GILD	2.42
Sum	152.68

A visualization of the `GILD` stock with the normal prediction with optimal parameters for kNN is shown below



IV. Results

Model Evaluation and Validation

As we saw in the Refinement section we saw that the nearest neighbor estimator performed quite well with the optimal set of parameters. Even though the prediction time of kNN can be long for large data sets, the rolling prediction (which includes refitting of the model every day) was faster than the normal prediction of the optimal LSTM estimator. Finally, the kNN is complex to understand and set up than the LSTM models. These three arguments makes the optimal kNN model the "winner" amongst the different models.

We note that even though the adjusted closing price for the `^GSPC` stock is one order of magnitude larger than the rest of the stocks, the optimal model performs well for all of them. We can also see that the overall patterns of the different stocks are different, so the architecture is robust to unseen data.
We can also observe that the predictions for the 7, 14 and 28 day prediction is the same, as the algorithm finds the same nearest neighbors for the predictions in the query space.

The robustness towards the input data can be observed in the plot showing the error as a function of days (that is features) in the Implementation section.

With a healthy skeptism, we can conclude that the model architecture is trustworthy.

Justification

Let us now make a summary of all the scores obtained in this project.

Stock	Last day	Random Gaussian	Linear regression	knn (unoptimized)	lstm (unoptimized, unscaled)	lstm (unoptimized, scaled)
^GSPC	7.01	577.33	6.15	2.38	11827.14	148.83
AAPL	1.50	96.01	1.34	0.99	503.91	7.59
CMCSA	0.51	18.11	0.48	0.33	23.31	0.59
GILD	0.94	15.55	0.76	0.88	42.67	0.75
Sum	9.95	706.99	8.72	4.58	12397.03	157.77

knn (optimized)	lstm (optimized)	knn (normal prediction)
0.54	6.70	93.65
0.10	1.59	55.64
0.04	0.58	0.97
0.05	0.76	2.42
0.73	9.63	152.68

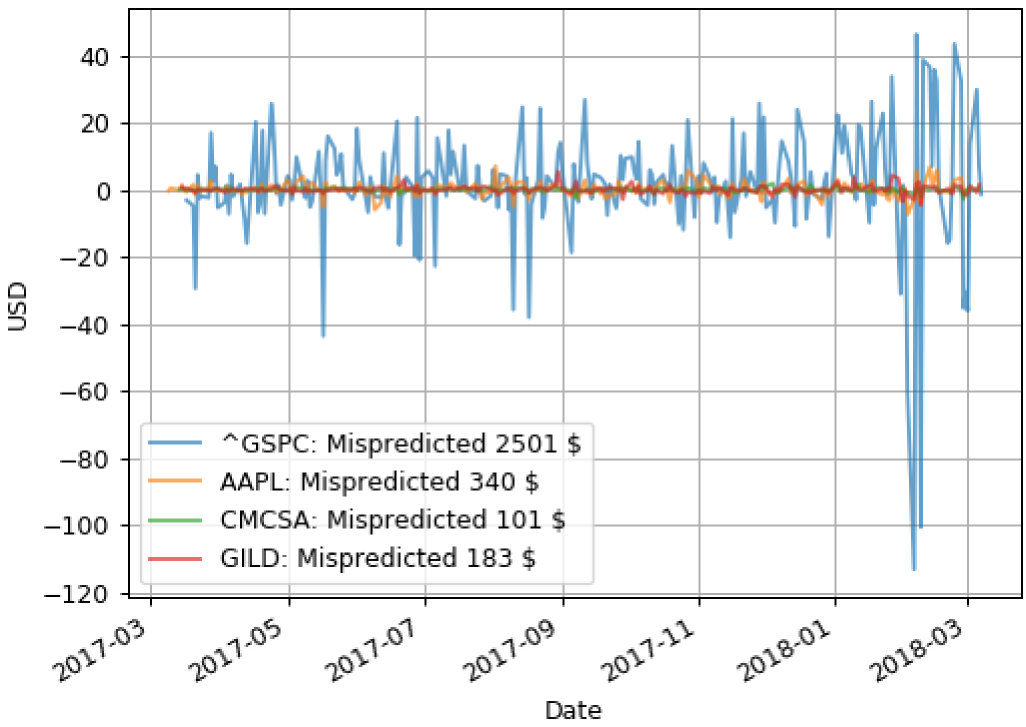
We can see that even though the benchmarks (the three first columns in the table above) are quite good, the optimal kNN model manages to beat all the scores by a factor of 10 (at least when comparing to the sum of the Linear regression estimator and).

The optimized LSTM model manages to beat the sum of the last day prediction and random gaussian prediction, but has a higher error than what was found in the linear regression benchmark. Again, it should be taken into account that the LSTM predictions are done in a non-updating manner, and it is expected that the model would yield a better result if we had the patience and computational power to perform a rolling prediction for the LSTM.

V. Conclusion

Free-Form Visualization

In order to see how well the optimal model performed, we will present a figure below which shows the absolute difference between the predicted value and the true value.



In the end it is dollar we are investing, so the total amount of dollars mispredicted can be crucial. We observe that over the course of approximately one year the optimal model mispredicted 2501 $ for the `^GSPC` stock, and mere 183 $ for the `CMCSA` stock. Luckily, the mispredictions are not more than 20 $ on a usual day for the `^GSPC` stock which are operating with the highest values. This tells us that even though the predictions are good, we should not believe blindly in the results as it might have dire consequences for investments.

Reflection

In this project we have looked at ways to predict the future adjusted closing price. We have implemented three models for benchmarking: The last day estimator, the random gaussian estimator and the linear regression estimator, and we have implemented to estimators which we try to beat the benchmark with, namely the kNN estimator and the LSTM estimator. We have further implemented algorithms to create targets and additional features, and an algorithm to update the model after each prediction (the rolling prediction), and constructed a scoring parameter which takes the 7, 14 and 28 days prediction into account. Although the LSTM models usually outperforms other models, we have seen that the simple kNN estimator had the best results (that is if we say that we only make normal predictions with the LSTM models as they are slow to train). We have also hinted to the fact that we should not trust the optimal model blindly if used to make investment decisions.

The final question is of course how much we trust in the final model. Are we willing to risk actual money on the model. This of course depends on how much risk we are willing to take. If the stock market was as simple as these stocks for all eternity it would make sense to have some faith in the model.

However, the stocks presented in this project represents only a tiny time window compared to stock market trading. No major depressions occurred during this period, and it is unknown how well the model would perform in a more volatile environment.

Also the stocks presented here are big, massively traded stocks all in the top range of the S&P 500. The story could have been quite different for let's say small stocks, or stocks just appearing on the market. As the optimal model is now, it needs at least 80 days of historic data until it gives somewhat trustworthy results.

Personally it has been quite satisfying learning about forecasting with machine learning, an in particular to learn about the exotic LSTM architecture. I think the most challenging has been to book-keep the different days properly. There has been a lot of "off-by-one" mistakes along the way.

Improvement

The scope of this project is quite limited considering the vast field of both financial analysis and forecasting in general. In other words, there is a lot of room for improvement. One could for example consider to

- Do a full grid scan in search for the optima
- Different estimators could have been investigated. One could even have considered to make use of reinforced learning
- One could have made a rolling prediction for the LSTM if one had enough data resources to see how good/bad it actually performed
- More stocks could have been investigated to get a better understanding of the performance
- One could have tried to use features containing the closing values at the previous day to see the effect of this on the LSTM model
- Features like high, low, volume etc. could have been included
- Categorical features such as sentiment analysis could have been added
- Other stocks could have been included as features as stocks are not statistical independent
- A proper feature analysis could have been done on the data

There are also room for improvements in the pipeline. The APIs could have been made more user friendly when querying for a prediction. For example could the input be predict stock `x`, and the training and prediction would work seamlessly in the background. If there was a good working API for obtaining the daily stock values, it would also bee nice to have an algorithm which automatically downloaded and updated the datasets each day.

VI. Additional resources (not mentioned in the text)

Tutorials from Machine learning mastery

https://machinelearningmastery.com/prepare-univariate-time-series-data-long-short-term-memory-networks/https://machinelearningmastery.com/time-series-forecasting-long-short-term-memory-network-python/

Machine learning for trading (Udacitiy course)

https://classroom.udacity.com/courses/ud501