Udacity Capstone Project

Hugo Perrier, March 2017

Table of Contents

1 Introduction

1.1 Stock Market Overview

The ownership of a company can belong to a single person but most of the time the ownership is divided between several shareholders. The values of these company shares depend of the total market valuation of the company, which may change over time depending on a variety of factors. Stocks or company shares can be bought and sold; there is therefore a market for company shares called the Stock Market. Stock trades are performed in stock exchanges such as:
- NASDAQ
- London Stock Exchange Group
- Tokyo Stock Exchange Group

Depending on the country they are based in, these stock exchanges have different opening days and times. Stock trades can only be executed during the opening hours of a stock exchange.
The most valuable companies in 2015 according to the FT500 ranking (link) are:
- Apple
- Exxon Mobil
- Berkshire Hathaway
- Google
- Microsoft

A good capacity to understand and predict movements in the stock market is crucial for investors to make profitable investments. To help investors choose which investment will be most profitable, they can use large amount of data on the history of the stock prices of companies. To process all these data, predictive models are created using machine learning. Machine learning models are "trained" to predict future stock prices based on a set of available features. This report explores how machine learning can be used to predict stock prices.

1.2 Objective of the project

The NASDAQ 100 index is a stock market index related to the capitalization value of the 100 largest non-financial companies. The objective of this project is to create a predictive tool that uses machine learning to predict the daily variation of the NASDAQ 100 index (NDX) using historical stock prices of different companies. An investor could use the predictive tool as follows:

- Predict if the NDX will go up or down
- If “Up” is predicted buy NDX stocks

- If “Down” is predicted sell NDX stocks

Section 2 of this report describes the data used to create a machine learning model for stock prices prediction, section 3 describes the numerical models involved in the creation of a prediction tool and section 4 shows results of the predictive model built.

1.3 Metrics

In this project, we propose to determine whether the NASDAQ 100 index will go up or down. This is a classification problem where the type of misclassification (predict “Up” when the stock value goes down or predict “Down” when the stock value goes up) does not matter. Indeed, if an investor buys a stock that subsequently loses value or if he sells a stock that subsequently gains value, he does not get the best possible return on his investment and there is not a situation that is obviously worse than the other. In this condition, using an accuracy score to measure how a predictive model is appropriate. Accuracy score is defined as the ratio of correctly labeled predictions over the total number of predictions and it is blind to the type of classification error.

$$Accuracy = \frac{n\,Correct\ Predictions}{n\,Predictions}$$

A set of predictions and corresponding true labels are presented below. The misclassifications are colored in red and the correct ones in green:

Date	01/01/2014	02/01/2014	03/01/2014	04/01/2014
Predictions	Up	Down	Up	Down
True Labels	Up	Up	Up	Down

In this example, one day was misclassified out of four, the accuracy score is thus ¾ = 75%.

1.4 Benchmark

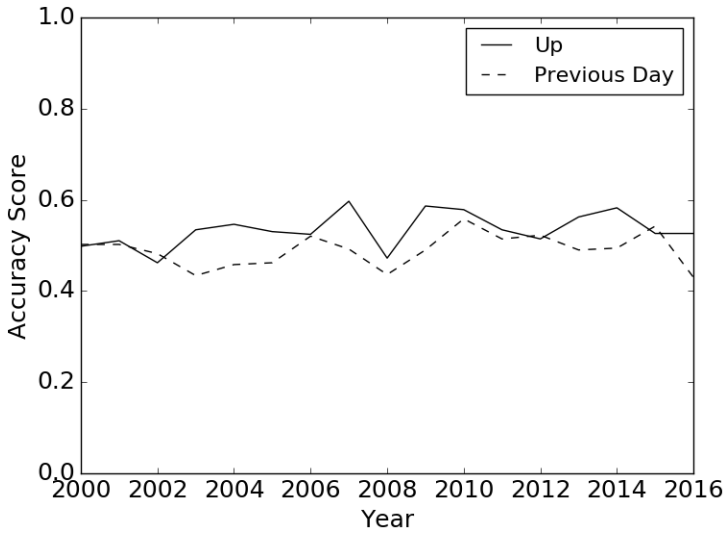
As mentioned in section 1.3, the accuracy metrics is used to score the results of the predictive model we develop. To help with the interpretation and analysis of prediction results, a benchmark case is defined. The accuracy obtained with the different models developed in this project can then be compared to the benchmark score.

The maximum accuracy that can be reached is 1.0 (or 100%) when every prediction is correct. Since the prediction outputs are binary

("Up" or "Down"), randomly predicting the output would yield an accuracy score of 0.5 on average. An accuracy of 0.5 is thus the lowest acceptable accuracy for a predictive model. Two more options are tested for the benchmark case:

- Predict the same variation as the previous day all the time
- Always predict "Up" (NDX index value increases)

In the graph below, we calculate the accuracy score obtained at the end of each year by predicting either the same variation as the previous day ("Previous day") or by predicting the NDX index to go up all the time ("Up").



Benchmark	Random (Theoretical)	Up	Previous day
Average	0.5	0.532	0.490

The "previous day" benchmark gets a score lower than 0.5, which could be explained by the oscillating behavior of the NDX index (see section "Data visualization"), this benchmark might give better results on smoothed data. On the other hand, the "Up" benchmark gets a surprisingly high score, this could be explained by the general trend of the NASDAQ 100 index which goes up much more often than it goes down.

For the rest of this project, the "Up benchmark" is used as a reference and we aim to get an accuracy score better than 0.532.

2 Data description

2.1 Historical stock prices data exploration

To create a machine learning model to make predictions, it is necessary to first "train" the model using past data. In the context of stock market pricing, the model is trained using historical data of the stock prices. For example we can use data from the past period 2003 to 2005 to train a model and then use that model to make predictions about the future stock values. The stock price data consist of the following information:

Open	High	Low	Close	Volume	ExDividend	SplitRatio

and adjusted values:

Adj.Open	Adj.Close	Adj.Low	Adj.High	Adj.Volume

For a given day, the "Open" and "Close" values are the values of a stock at the opening and closing of the stock exchange. The "High" and "Low" value are the maximum and minimum values that the stock has reached during that day. The "Volume" is the total amount of stock that was sold on that day. A company can decide to give dividend to shareholders ("Ex-Dividend" feature) or modify the number of shares that compose the company (adjusting the share value to keep the total capitalization value constant), this is described by the feature "Split Ratio". After this actions are taken, the values of Open, Close, High and Low are adjusted accordingly (Adj features).

All these features are of numerical type except “ExDividend” which is one if dividends are given away and zero otherwise.

A historical stock price dataset for a given company would typically look as follows:

Date	**Open**	**Close**	**…**	**Adj.Volume**
2000-01-01	10.0	11.4	…	1212121
2000-01-02	11.2	12.5	…	2001001
2000-01-03	12.2	12.4	…	1230010

The table below gathers statistics related to the stock prices of the company Apple over the period January 1st 2014 to December 31st 2015. This corresponds to a DataFrame with 504 rows (working days) and 13 columns (stock data).

Statistics	Open	High	Low	Close	Volume	ExDividend
Mean	207.7	209.4	205.9	207.7	4.4e+07	0.0185
Std	181.2	182.7	180.2	181.5	2.5e+07	0.2064
Max	649.9	651.26	644.5	647.35	1.9e+08	1.0
Min	90.2	90.7	89.7	90.28	5.7e+06	0.0
Statistics	**SplitRatio**	**Adj.Open**	**Adj.High**	**Adj.Low**	**Adj.Close**	**Adj.Volume**
Mean	1.01	101.8	101.8	100.9	102.7	5.7e+07
Std	0.27	17.8	17.71	17.55	17.9	2.6e+07
Max	7.0	129.3	128.0	126.9	129.4	2.66e+08
Min	1.0	66.4	67.0	66.1	67.2	1.3e+07

It should be noticed that these data will used as training data to create a predictive model but not in this form. Data preprocessing will be necessary to create the features used by the machine learning algorithm to create the predictive model (discussed later in this report).

2.2 Data Acquisition

Quandl API

The python Quandl API allows users to query historical stock prices from databases. With the free version only one data point per day can be accessed and there is a maximum amount of queries that can be performed in every 24h period. This is used to get the stock prices of the companies in the NASDAQ 100.

Pandas stock price data reader

Historical stock prices from yahoo finance can be queried directly using a pandas module. This is used to get the values of the NASDAQ 100 index.

List of NASDAQ 100 companies

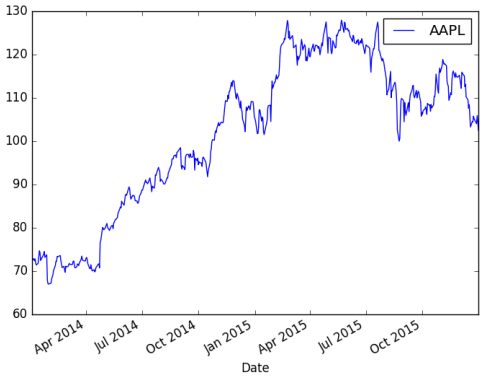
To obtain the current list of companies included in the NASDAQ 100 index, web scraping is performed on the NASDAQ website.

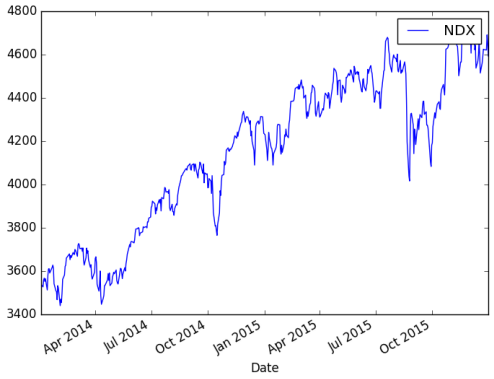
2.3 Data visualization

The graphs below show the evolution of the adjusted close price for the Apple stock (left) and the NASDAQ 100 index (right) for the period 2014-2015.

AAPL Adjusted Close price
(In US dollars)

NDX Adjusted Close
(Index value)





On the graphs, we observe that the general trend is common to AAPL and NDX (An increase over the period) however over short periods of time (few days) the prices are very variable and seem to oscillate.

In this project, we want to predict daily variations of NDX therefore the short term oscillations will have much more impact than the trend over several months. It seems reasonable to limit the features used to make predictions to the data from the previous days (rather than months).

2.4 Data Format

The data obtained from Quandl API queries are in a pandas DataFrame format. The size of a dataset corresponding one year of historical stock prices for a single company is about 26kb in size.

3 Data Preprocessing

3.1 Missing data

Historical stock prices for a company on a given day may not be available for the following reasons:

- The company didn't exist at that time (Google was created in 1998)
- The company existed but was not traded in the stock market (Facebook entered the stock market in 2012)
- The stock market where that company's stock is traded was closed on that day
- The historical stock prices of that company are freely accessible in Quandl API

However, to train a machine learning model, the datasets can not contain missing values. Two options are available to ensure the dataset does not contain missing values:

- Model the missing values
- Remove the datapoints containing missing values

Both options can impact the predictions therefore the way missing values are handled needs to be explained. In this project, all the companies whose data were not accessible through Quandl were not included in the model. If on a given day some companies have stock price data but others don't, the missing data are replaced with the data from the previous working day (This is called a forward fill method).

Below is a list of data that couldn't be accessed using Quandl:

- JD, NCLH : Non American companies data are not available in the Quandl WIKI free database
- KHC : Kraft Heinz Company didn't exist in 2013, Kraft and Heinz merged in 2015
- PYPL : Paypal was a wholly owned subsidiary of eBay until 2015
- WBA : Walgreens Boots didn't exist in 2013

Changing the period used for the training set may require changing the list of companies used. This could cause problems for example if the predictive model is used to predict NDX of year 2016 but was trained using data from the period 2011-2015. Indeed, Facebook data that could be relevant in 2016 would not be used as features because of the missing data in year 2011. There is thus a tradeoff between increasing the range of the training period to have more data and limiting this range to avoid missing data from recent companies.

3.2 Feature naming

When the data for different companies are queried from Quandl, they all have the same feature names; it is thus necessary to run a renaming operation when joining the datasets of the different companies. The company "ticker" symbol is simply added to the feature name: "Open" feature for "Apple" company (Ticker "AAPL") becomes "AAPL_Open".

3.3 Split of the data into train, cross validation and test datasets

To create a machine learning model we create a set of data called training set for which the true value of NDX are known. This set is used to find the model (with fixed hyperparameters) coefficients that minimize the error between predictions and true values of NDX.
Then a cross validation set similar to the training set is used to find the hyperparameters that make the predictions as general as possible. In other words, the model shouldn't just be able to predict NDX values from the dataset used for training but it should predict well NDX values for any other dataset.
Finally a test set is created to evaluate the performance of the model on data that were not used in the training process. The test dataset has to contain data posterior to the data in the training and cross validation sets as it is not possible to train a model using data from the future.

3.4 Creation of the final features

The objective of a predictive model is to predict future values of the NASDAQ 100 index, therefore company stock prices of day N should be used to predict NDX value of day N+1 or N+x. It is thus necessary to shift in time the NDX column compared to the feature columns.

Finally, we need to choose which data are used as features to predict NDX, we can't use all of the historical data of every company prior to day N+1 to predict NDX on day N+1. It is therefore necessary to decide how many historical data to use for prediction, which features we want to use and adapt the dataset accordingly. A mock-up dataset that could be used in a machine learning model using just the "Open" data from the previous 2 days of companies "X" and "Y" is shown below (the date is written down to help with explanation but it is not used as a feature):

Date	X Open Day N-2	X Open Day N-1	Y Open Day N-2	Y Open Day N-1	NDX Variation

					day N
01/01/98	100	105	10	11	“Up”
02/01/98	105	110	11	12	“Down”

In the rest of the report, the features used to train a particular model will be written as follows:
Features: Company List = [“A”, “B”], nHist = C, Stock data = [“D”, “E”]
Where:

- Company list is a list of the companies whose stock data were used to train the classifier
- nHist is the number of days prior to the prediction used to train the classifier (ex. if nHist = 2 we use the data from the last 2 days)
- Stock data is the type of stock data used as input features, it could be any of the data presented in the section “Historical stock prices data exploration” (ex. “Open”, “Close”, “Variation”, …).

The size of the corresponding feature matrix is written as:

Feature matrix size: Nday x Nfeatures

Where

- Nday is the number of days available in the training dataset (number of rows).
- N features in the number of features available for each working day

In this project, data from the 2014-2015 period are used for the training and cross validation datasets, which corresponds to about 500 working days. Since 80% of the data in this period are used for training and 20% for validation, Nday is around 400.

4 Numerical models

4.1 Software requirements

The software requirements to build the predictive models are:

- python: Main programing language
- numpy: Package for scientific computing in python
- pandas: Package for data structures with python
- matplotlib: Plotting with python
- sklearn: Package for machine learning in python
- urllib: Package for data fetching across the web
- re: Package for regular expression operations
- Quandl: API to access historical stock prices from Quandl databases using Python

4.2 Classification models

A classification model or classifier associates input features (historical stock prices of companies) to an output label (NASDAQ 100 index "NDX" goes “Up” or “Down”). To correctly classify inputs, a classifier needs to be trained. For that, an iterative process is used where the model is fed a set of input data from a “training dataset”, predictions are made, the predictions are compared with the true label of these data and the model coefficients are updated to improve the classification.

The models used in the present work are:

Logistic regression:

In logistic regression, a function between dependent variable (categorical variable: Variation of NDX) and independent variables (Features) is determined. The parameters of that function are adjusted in the training process so that the output of the function is one for exemple that belong to the “Up” class and zero for example belonging to the “down” class.It is a linear classifier so if the data is not linearly separable (i.e. we can’t find a plane in parameter space that separates the data into two classes), we will never be able to reach a 100% accuracy.

Linear support vector machine (SVM):

SVM draw a separation in parameter space (linear for a linear SVM) that separates the two classes (in case of a binary classification) and in the training process, the margin between the separation line and the closest data points is maximized.
Parameters: C

The C parameter is a penalization term in the cost function (function that the is minimized in the training process). It helps preventing overfitting.

Decision tree:

A decision tree classifies a data point by making a sequence of decisions related to the value of the features. For example, in the present example a sequence could look like:

- Did the Apple stock decrease yesterday? Yes/No
- Was the Google highest stock price bigger than X yesterday? Yes/No

In the training process, the decision tree learns which features are most relevant to the classification and what are the threshold values (i.e. it learns which questions to ask).
Parameter: Max depth
Max depth is the number of “questions” a tree will ask, limiting the depth prevents overfitting.

Random forest:

In a random forest, a set of decision trees is train using randomly chosen subdivisions of the data and the features. Making a vote out of the classification results of the different decision trees then makes the final classification.
Parameters: Number of decision trees in the forest
The more trees used in the forest, the more the model is likely to overfit the data

4.3 Computational resources

The computer used for these calculations is a Macbook Pro 13-inch, Late 2011) with 8 GB of 1333 MHz DDR3 RAM and a 2.4 GHz Intel Core i5 processor. The linear regression models (linear regression + SVR(kernel="linear")) could be trained in a fraction of a second on a laptop with a 2 years long dataset for the training set, 2 features per companies and a few companies. On the other hand the training times for the non-linear models quickly become prohibitively long as the number of features and datapoints increases.

5 Results and analysis

5.1 Prediction of the Next day NDX variation: Basics

This section describes the general sequence of actions performed to build a predictive model that predicts how the NDX index will vary the following day:

1. Data Acquisition
   - Since the data acquisition takes time, the data for all companies are acquired once and stored locally in csv files.
   - Get Quandl data
   - Get NDX data
   - Remove missing values (use forward fill)
   - Rename features
   - Calculate engineered features such as "Variation" = "Close" - "Open"
   - Make sure all sets of data have the same length (if necessary truncate the longer sets)
   - Merge NDX and Quandl datasets
   - Save dataset into a CSV file
2. Parameters settings
   - Choose desired the date range for the training, cv and test sets
   - Choose the companies that should be used as features
   - Choose the stock data used as features
   - Choose the number of historical data points used for predictions
   - Choose the classification model
3. Preprocess data
   - Create and initialize dataset class object for Train+CV and Test
   - Open CSV file and read data as pandas DataFrames
   - Check if the chosen companies are available in the datasets at the desired date (otherwise ignore the companies)
   - Create feature matrix
     - Drop undesired features
     - Shift data to create historical data features
     - Organize features as described in section 3.4
   - Randomly split the Train+CV dataset into two sets using a random seed to make the results reproducible
4. Train predictive model
   - Use the training dataset to train the classifier
5. Score

- Use accuracy metrics to get the classification score on the train, cv and test datasets

5.2 Choice of datasets

In a section 3.3, we said that the full set of data should be split into a training set, a cross-validation (CV) set and a test set. The test set has to contain data corresponding to a period of time posterior compared to the training and CV sets. In this project we use the year 2016 for the test set. The choice of the time period for the train and CV sets is then influenced by the following factors:

- Train and CV set periods have to be prior to 2016
- To train a model that generalizes well to any dataset, the training dataset has to contain enough data
- New companies join the NASDAQ over time therefore if the training set corresponds to an old data periods, recent companies cannot be included as features. (ex. Facebook entered the stock market in 2012 so if the training dataset starts before 2012, Facebook stock data cannot be used as features).
- In 2008 there was a financial crisis so data from that year may strongly differ from other time periods

Based on these constraints, it was decided to use data from the 2009-2015 time period for the train and CV datasets. The amount of data available for this period is still limited (250 workdays per year * 7 years = 1750 rows in the feature matrix) but the NASDAQ company list for that period is similar to the 2016 list which is the period we are interested in to make predictions. It also avoids including the data corresponding to the financial crisis of 2008.

Once the period for the train and CV sets have been chosen, there are two ways to split that data into training and CV sets:

- Randomly split data from the whole period into the two sets
- Choose two different time period for the train and CV sets

Here we compare results using these two strategies: Randomly split the 2009-2015 period or use 2009-2014 as training set and 2015 as CV set (The size of the cv set is about 250 data points in each situation). The features used for to train the model are summarized below:

List of companies	All available companies
Number of days of historical data	1
Stock Data	All available stock data
Classifier	Logistic Regression
Feature matrix size	1760x926

The following results are obtained:

Strategy	**Random split**	**Segregated split**

Score on training set	0.749	0.550
Score on CV set	0,762	0.524

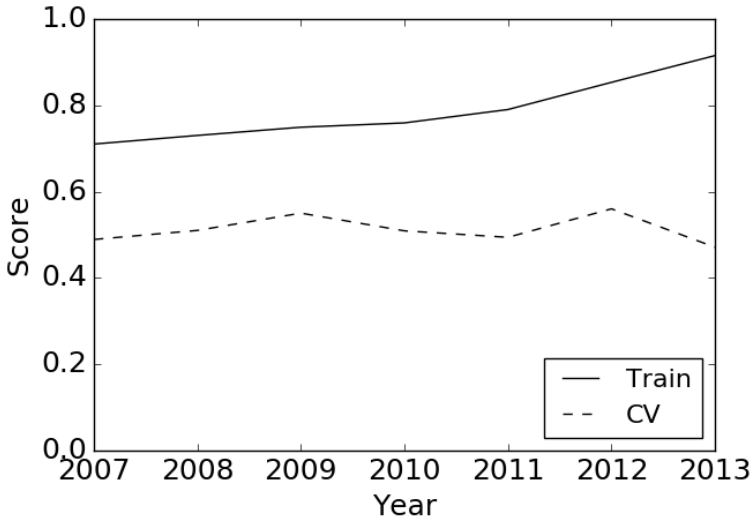
Using the random split strategy leads to better results on the CV set and less overfitting (difference between score on train set and CV set). With this strategy, the data in the training dataset are more diverse (they cover a longer period) so it seems realistic that it gives more generalizable results.

5.3 Length of training dataset

In the previous section, the 2009-2015 period was used for the train and CV datasets. In this section we look at the influence of the dataset length on the prediction accuracy. For that we change the start year if the training set.

List of companies	All available companies
Number of days of historical data	1
Stock Data	All available stock data
Classifier	Logistic Regression
Train + CV set starting date	[2007-2012]
Feature matrix size	[502-2264]x[883-981]

The results are shown in the graph below:



On the graph we see that if the training set includes data of the 2008 financial crisis (ex. Using range [2007-2015] or [2008-2015]), the cv score decreases below 0.5. We also observe very high train score if fewer data are present in the training set, this is probably due to

overfitting. The best cv score are obtained using range [2009-2015] and [2012-2015].

In the rest of the project, the period [2009-2015] will be used for the train and cv datasets.

5.4 Number of days of historical data

So far, we used only data from the previous day to make predictions about the next day NDX variation. In this section we try to use more days and check the influence on the cross validation accuracy score. It should be noticed that the number of features is doubled if we double the number of days of historical data used (nHist) so the total number of features can get very large. If the number of features is bigger than the number of rows in the feature matrix, strong overfitting and long calculation time can be expected therefore we limit nHist to 3 and we reduce the number of company used to 50 (This way the number of data points remains bigger than the number of features).

List of companies	All available companies
Number of days of historical data	[1-3]
Stock Data	All available stock data
Classifier	Logistic Regression
Feature matrix size	1760x[578-1734]

The results are given in the following table:

nHist	**1**	**2**	**3**
Score on training set	0.686	0.763	0.755
Score on CV set	0.530	0,465	0.530

The results obtained are very variable so it is not possible to draw conclusions on the influence of nHist on the cv_score. However we see that the difference between train score and cv score is smaller when one day is used, the overfitting is reduced.

In the rest of this project, nHist = 1 will be used.

5.5 Choice of stock data used for features

Several strategies to select the best combinations of stock data were tried:

- Making predictions with just one stock data and determining which gives the best results

- Making predictions with all stock data but one and determining which in which case the cv score was increased or decreased
- Using custom set of stock data, for example using just adjusted stock data, using anything but adjusted stock data, using only stock data related to market closing…

After training models using many combinations of stock data as features, it was not possible to isolate stock data that perform better than others and overall using all stock data gave the most consistent results. When the number of feature is not too high, we will keep using all available stock data.

5.6 Choice of classifier

In this section, the different classification models described in section 4.2 are tested with different values for the coefficients. Several sets of parameters and random seeds are tried to test the stability of the results. It was observed that the classifications are very variable and it is difficult to choose the best classifier but general observations can be made.

List of companies	All available companies
Number of days of historical data	[1]
Stock Data	All available stock data
Classifier	Many models
Feature matrix size	1760x1010

Score	**Training set**	**CV set**
Random Forest 100 Trees	0.989	0.470
Random Forest 10 Trees	0,762	0.524
Random Forest 5 Trees	0.535	0.478
Decision Tree Max depth 3	0.619	0.559
Linear SVM C=1	0.549	0.591
Linear SVM C=0.5	0.580	0.591
Linear SVM C=0.2	0.566	0.583
Linear SVM C=0.1	0.473	0.413
Logistic Regression	0.751	0.555

Overall, the random forest with 10 trees or more seem to overfit the data and the decision trees with max depth above 5 as well. The linear SVMs do not seem to suffer from overfitting issues but the results are very variable if we change the parameter slightly. The logistic regression model has a tendency to overfit when many features are used.

In the end, a linear SVM with coefficient C=0.2 is chosen.

5.7 Predictions on the test dataset

In the previous sections, the different parameters of the classification model were chosen using the cross validation dataset. In this section, the model built is used to make predictions on the test dataset (Corresponding to the year 2016).

List of companies	All available companies
Number of days of historical data	[1]
Stock Data	All available stock data
Classifier	Linear SVC C=0.2
Feature matrix size	1760x1010
Test set accuracy score	0.544

We obtain an accuracy score of 0.544 on the test data set. This score is higher than a result obtained by pure chance (0.5), it is higher than results obtained by predicting that the next day variation is the same as previous day variation (0.49) and it is higher than predicting the NDX index to go up all the time (0.532). The predictive model we built thus performs better than the benchmark cases introduced previously.

6 Conclusions

In this work a machine learning model was set up to predict the variation of the NASDAQ 100 index using historical stock prices of NASDAQ companies. A pipeline to acquire data, preprocess data, create training, cross validation and test data sets, fit the machine learning model and make predictions was set up.

It was shown that the period of time chosen for the training dataset is important, it should be close to the test period (2016) so that the NASDAQ company list is similar for these periods, it shouldn't long enough to have enough data to train the models and it should avoid containing data related to financial crisis. In the end the period (2009-2015) was the most adequate choice.

We showed that increasing the number of days preceding the prediction used as features for the classifier did not improve the classification accuracy but could favor overfitting. The effect of the type of classifier was also tested, it was observed that random forest and logistic regression models tend to overfit when linear Support Vector Machines could give good classification accuracy with limited overfit.

The type of stock data used as features was also tested (price at stock market opening, price at closing, etc), we couldn't isolate a stock data that is much better than the others. In the end using all the stock data available seemed to give the most stable results.

The variability of the results has been a big issue, two predictions with the same parameters but different random splitting of the data between train and cross validation sets could give very different accuracy scores. The same variability was observed when removing companies or changing stock data used as features. This issue is probably due to the small amount of data points available; indeed the (2009-2015) period only contains 1750 working days. Most machine learning applications are based on datasets that contain more than 10 000 data points.

To improve the predictive model further, it seems important to get access to more than one data point per day; however, most free financial databases do not offer that possibility.