Machine Learning Engineer Nanodegree

Capstone Project

Project Domain: Investment and Trading

Project Title: Market sentiment prediction for Commodity prices

Riccardo Rizzari
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I. Definition

Project Overview

As stated in the capstone proposal, Quantitative investing and the quest for an algorithm or a mathematical formula to beat the market have a long history. One of the earliest documented attempts is the 1967 famous book [Beat the market: a Scientific Stock Market System by E. O. Thorp and S. T. Kassouf. In recent years, the number of firms that use algorithms to trade financial markets has grown steadily.

On the other side though, there is strong skepticism about the possibility to beat or predict the market consistently. There are also very famous theoretical results in Financial Economics on this topic, like the **Efficient Market Hypothesis** (https://en.wikipedia.org/wiki/Efficient-market_hypothesis). According to the Efficient Market Hypothesis (EMH), current asset prices in financial markets already reflect all available information. Therefore it should not be possible to profit from the market in a consistent way.

Although the EMH's implication about the impossibility to beat the market has been criticized (for instance pointing out that the EMH does not explicitly say that you can't beat the market), the financial industry has widely applied the principle of the *impossibility of arbitrage* opportunities in the market. One example is the *Black-Scholes model* (https://en.wikipedia.org/wiki/Black%E2%80%93Scholes_model) for option pricing (particularly in the assumption that stock prices can be modelled as *martingales*).

As a Commodity Trader in the Investment Banking industry, it is of paramount importance to deploy quantitative techniques to try to understand the market trend in the near future. As a result of the specific market I trade, the analysis of the capstone project will focus on Commodity Futures markets.

Problem Statement

Problem Definition

As we have seen in the previous section, the problem that is to be solved is whether it is possible or not to consistently predict the market.

Specifically, a way of restricting the scope of the analysis is: **given the information we have today, can I predict whether the market is going up or down tomorrow?**

As anticipated above, I will restrict the analysis to liquid Commodity Futures. I will start by considering one of the most liquid and traded market: the *West Texas Intermediate Crude Oil* futures market (https://en.wikipedia.org/wiki/West_Texas_Intermediate) (or 'WTI').

A simple way to picture the problem is the following: an investor is looking for an investment strategy in the Oil market. One of the very first steps that might be useful is to have a methodology to assess whether the market is going to trade higher or lower from the moment a position in the market is entered.

A natural question is: What information is available for this methodology? The answer is: all present information is available.
Information can be of technical nature (such as technical analysis indicators) or fundamental nature (such as data regarding the world Oil production).

So, we can summarize the purpose of the capstone project as follows:

Given a series of past data of a given commodity futures market, can we find a way to predict whether the next observation will be represented by a higher or a lower trend? Or equivalently: given the information we have today, can we predict whether the market is going up or down tomorrow?

Datasets and Inputs

As inputs features, I will select a bunch of technical indicators together with some data regarding trading activity. The dataset will be a time series, with every row being a collection of technical and fundamental indicators for a specific date in the past.

In particular, I will start by considering data for the Oil market. These are the columns of the dataset:

- 'Dates': given that we are working with time series, we will store the dates in the first columns
- 'y': the labels. `1` if the market on the corresponding date was up, `0` if it was down.

Price indicators

- 'CHG_PCT_1D': the percentage change of the market on that specific trading date
- 'CHG_PCT_5D': the percentage change of the market on the last five trading days
- 'PX_OPEN': the opening price
- 'PX_HIGH': the highest price during the trading day
- 'PX_LOW': the lowest price
- 'PX_VOLUME': the total volume of contracts traded
- 'PX LAST': the closing price

Technical indicators

- 'MOV_AVG_5D': the five days moving average
- 'MOV_AVG_30D': the moving average calculated over the previous 30 days
- 'RSI_9D': the 9-day Relative Strength Index, which is defined according to the following formula:

$$RSI=100-[100/(1+Avg_{Up}/Avg_{Down})]$$RSI=100−[100/(1+AvgUp/AvgDown)]

Where Avg_{Up} is the average of all day-on-day changes when the security closed up for the day during the period. Avg_{Down} is the average of all down changes for the period.

- 'RSI_14D': the RSI for the last 14 trading days
- 'RSI_30D': the RSI for the last 30 trading days

Volatility Market activity indicators

- 'VOLUME_TOTAL_CALL': the total daily volume traded in call options
- 'VOLUME_TOTAL_PUT' the total daily volume traded in put options
- 'VOLATILITY_10D': the 10-day realized volatility
- 'VOLATILITY_30D': the 30-day realized volatility
- '30DAY_IMPVOL_105.0%MNY_DF': the 105% strike implied volatility for options expiring in 30-days time
- '30DAY_IMPVOL_100.0%MNY_DF': the 100% strike implied volatility for options expiring in 30-days time
- '30DAY_IMPVOL_95.0%MNY_DF': the 95% strike implied volatility for options expiring in 30-days time
- '30DAY_IMPVOL_110.0%MNY_DF': the 110% strike implied volatility for options expiring in 30-days time
- '30DAY_IMPVOL_90.0%MNY_DF': the 90% strike implied volatility for options expiring in 30-days time

Dataset size

I will have a separate dataset for each commodity futures market. Each dataset will be in CSV format. Each CSV file has a size of approx. 70 KB and it is formed of 499 entries. Each entry represents a single trading day. Rows of data which display any '#N/A' or error in the CSV file will be dropped after being loaded in Pandas.

Data source

I download the data and generate the CSV file for each market via an Excel spreadsheet (named *Bbg_Market_Data.xlsm*). This Excel spreadsheet has a size of 923 KB. It contains Bloomberg Excel formulas to download data via the Bloomberg Excel API. All the features are downloaded from Bloomberg. The labels instead are calculated in the spreadsheet (essentially, by looking at the column 'CHG_PCT*1D', the label will be 1 if the daily*% change was positive and `0` otherwise). Once the dataset is loaded in Pandas, I will shift the labels with the Pandas Shift function, so that, at every time step, the corresponding labels will be `1` if the **next** trading day showed a positive performance, `0` if the performance was negative.

Intended Solution

The problem of predicting the market trend on a given day, given the information available from the previous days, can be viewed as a binary classification problem. In fact, for each dataset `X` representing all available information at time `t0` (this dataset `X` will be a time series); there will be a label `y` which is `1` if the market on the next day goes up, `0` otherwise. We can therefore treat the market sentiment prediction problem with the tools from *supervised learning*. My purpose is to compare different supervised learning algorithms, and calculate the accuracy

score for each of the methods deployed. If the accuracy is greater than 50% (the coin flip), we have a good candidate for a market predictor. We will then check if this algorithm is robust enough to maintain an accuracy of 50% consistently, i.e. moving the time forward as the algorithm faces data that has never seen yet. We will have to check also if the success of the algorithm does not depend on the particular market chosen, say, the oil market, but is able to generalize well for also the corn market or the corn one.

The plan of the capstone is to start with a simple model, such as Gaussian Naive Bayes, and progressively increasing the complexity of the model. I will explore 4 models in total. In ascending complexity order, these models are:

- Gaussian Naive Bayes
- Random Forest
- Feed-Forward Multi-Layered Perceptron (MLP) Neural Network
- LSTM (Long-Short Term Memory) Neural Network

I will scale up model complexity from Naive Bayes to LSTM to see if there is a gain in performance when the model complexity is increased. Ideally, I would expect to see better performance when a more complex model is finely tuned. As outlined in the section below, performance will be evaluated under the accuracy score. This means that, say, if we get a 51% accuracy with Naive Bayes, I expect to be able to increase the accuracy towards, say, 55% with Random Forest and MLP and, hopefully, to get something in the 60% ballpark with LSTM.

For the first three models, I will check the performance with two different approaches: a) the Walk-Forward validation; and b) the Static Validation.

For LSTM instead I will only check the more realistic Walk-Forward validation.

Given that the Walk-Forward validation should be more accurate in principle, as we make new information immediately available for any model to re-fit to it in order to predict the next state (in contrast with the Static validation, where we fit the model only once on the training set and use such a fit to predict all labels in the test set), we can view any over-performance of the Static validation as a failure of the model to accurately take new information into account when moving along the time series.

Tasks Outline

In synthesis, the outline of the tasks of the project is the following:

1) We start with the Oil Market, loading the data in Pandas;

2) We explore the data checking a few basic statistics, the composition of the dataset (number of rows and columns) and if one or more features are skewed.

3) If any feature is skewed, we apply a log transformation to it (see the 'flatten_skew' function).

4) We adjust the data so that each label represents the futures step market trend; we drop the last (i.e. the more recent) data row of the dataset because we do not have a future label for it yet.

5) We define three benchmarks: a) the single trend follower; b) the coin flip; c) the Persistence Forecast model. The first two benchmarks do not actually depend on the data. In fact, the single trend follower simply assumes the market will follow only one trend in the next outcomes, e.g. always predicting the market to go higher; the coin-flip instead randomly choose one trend for each period (it literally flips a coin to predict whether the market will be higher or lower). Finally, the Persistence Forecast model checks what was the trend in the previous period and predicts the market will have the same trend for the next single time step.

6) We define a 'train and test' function that will be called by each model except LSTM, which will have its own dedicated function for training and testing, giving the specificity and the complexity of this model.

7) We run Naive Bayes, Random Forest and MLP in both Walk-Forward and Static validation mode and we check the accuracy score. We optimize Random Forest and extract feature importances for the sets of parameters yielding the best and the worst results in terms of accuracy to gauge additional information about the features selection.

8) We build and test the LSTM model in Walk-Forward Validation only.

9) We compare accuracies for all the models and we introduce the 'modified_accuracy' function to adjust the accuracy to the actually performance of the classifier on a particular prediction. For example, if a classifier predicts `0`, i.e. a down-trend, and the percentage change for that sample has been `+5%`, such a prediction will be much worse than if the market predicts `0` and the percentage move is only `+0.25%`.

10) We repeat all the steps above for all other markets we have data for (i.e. Corn, Gold, Wheat, Coffee and Soybeans) and analyze performances for each market.

Metrics

As anticipated above, the main metric of choice will be the *accuracy score*. Only towards the end of the analysis we will make use of a *modified_accuracy* to keep into account the amplitude of a prediction, but from a pure binary classification standpoint, the accuracy store is the simplest and best metric.

The reason why the accuracy score is the best metric for the binary classification problem of the capstone is that in such a trading environment we do not care about type1 or type2 errors. In fact, we do not care about False positives or False negatives because, ideally, there is no significant distinction between buying or selling a futures contract. If the model predicts `1` (i.e. 'uptrend') and we invest 'X' USD in a long position in futures contract (i.e. we buy) based on this signal, if the market performs `-1%` we lose `1%` of 'X' (our initial investment). This is exactly the same scenario as if the model predicts `0` (lower trend), we short 'X' USD of futures equivalent value and the market performs `+1%`, again, we lose `1%` of the invested amount. Because of this specularity, we only care about the accuracy score, and not on the 'direction' of the error.

II. Analysis

Data Exploration

The first market we investigate is the Crude Oil market. Daily data for trading days between 10Apr2017 and 10Apr2015 are stored in the `dataCL.csv` file.

I start by exploring some generic statistical properties of the dataset. We have 499 rows of data. We will use the latest 249 data rows as a test in both the Walk-Forward validation and the Static validation. (`249 = 499 // 2` in Python). Out of the 499 trading days, the market has trended higher on 233 days (i.e. `46.69%` of the times). If we restrict the scope to the test set instead, the market has gone up `50.20%` of the times. This is extremely close to what we would get with a coin flip and justifies the use of the coin-flip as one of the naive predictors.

Let's have a look at a few sample rows from the dataset (for visualization purposes I transpose the rows and the columns of the dataset in the table below):

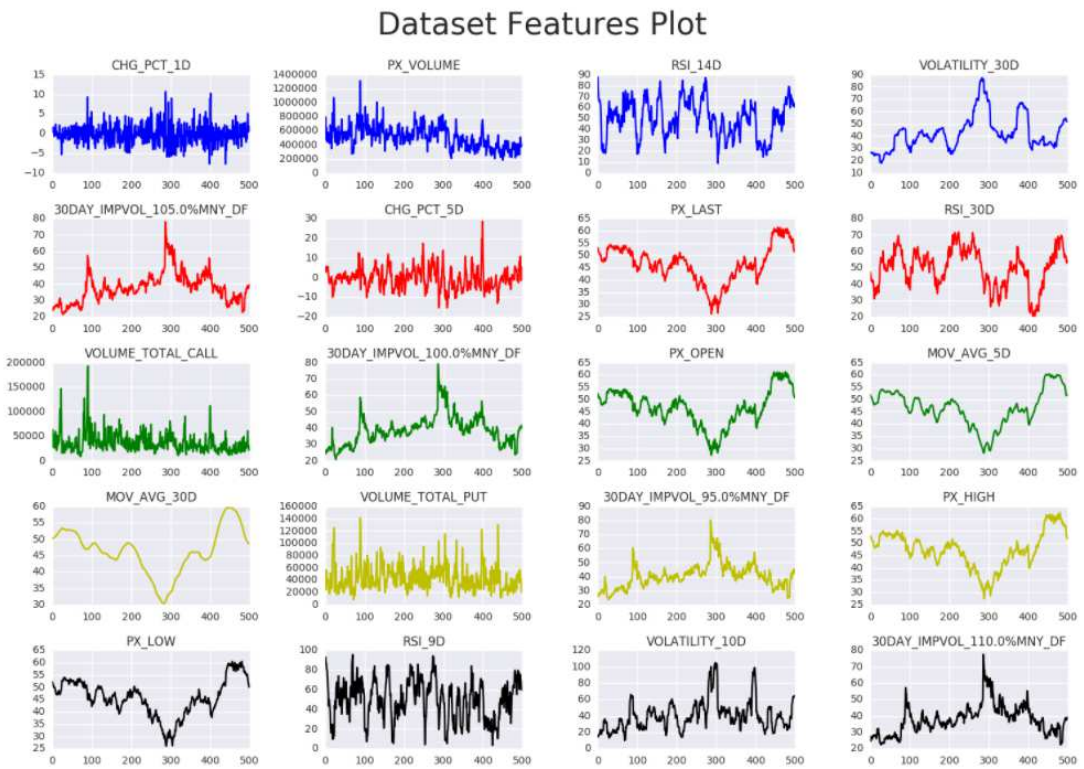
	498	497	496	495	494
Dates	10/04/2015	13/04/2015	14/04/2015	15/04/2015	16/04/2015
y	1	1	1	1	1
CHG_PCT_1D	1.78	0.47	2.21	5.14	0.73
CHG_PCT_5D	5.3	-0.3	-1.57	10.8	10.69
PX_OPEN	50.73	51.81	52.05	53.55	55.92
PX_HIGH	51.93	53.1	53.79	56.69	57.42
PX_LOW	50.08	51.47	51.83	53.39	55.07
PX_VOLUME	395135	375534	431026	508904	413134
PX_LAST	51.64	51.91	53.29	56.39	56.71
MOV_AVG_5D	51.794	51.748	51.61	52.804	53.988
MOV_AVG_30D	48.692	48.763	48.887	49.082	49.255
RSI_9D	59.67	61.21	69.34	70.56	75.77
RSI_14D	63.1	60.55	62.87	65.05	62.02
RSI_30D	54.47	52.87	54.78	57.18	56.45
VOLUME_TOTAL_CALL	21493	31179	26845	60948	43269
VOLUME_TOTAL_PUT	20081	32218	42999	40905	57342
VOLATILITY_10D	64.61	64.34	62.35	63.53	60.77
VOLATILITY_30D	51.93	51.93	52.21	54.49	54.2
30DAY_IMPVOL_105.0%MNY_DF	39.5	37.49	38.56	38.46	38.85
30DAY_IMPVOL_100.0%MNY_DF	41.82	39.7	39.99	40.17	40.76
30DAY_IMPVOL_95.0%MNY_DF	45.43	42.58	42.76	41.95	44.28
30DAY_IMPVOL_110.0%MNY_DF	39.15	37.46	37.7	37.7	38.78
30DAY_IMPVOL_90.0%MNY_DF	48.72	46.16	45.77	44.32	44.36

Let’s also have a look at some descriptive statistics of the features:

	count	mean	std	min	25%	50%	75%	max
CHG_PCT_1D	499.0	-0.043788	2.611989	-7.730	-1.5200	-0.180	1.4900	10.680
CHG_PCT_5D	499.0	-0.349900	5.551204	-15.360	-4.0500	-0.350	2.6650	28.660
PX_OPEN	499.0	46.592665	7.398920	27.300	42.6850	46.770	51.4500	61.230
PX_HIGH	499.0	47.417836	7.322596	27.480	43.3600	47.710	52.2700	62.580
PX_LOW	499.0	45.745631	7.453226	26.050	41.6750	45.830	50.7450	60.540
PX_VOLUME	499.0	511312.194389	156936.732909	181875.000	395996.5000	508680.000	608428.5000	1311000.000
PX_LAST	499.0	46.563086	7.424770	26.210	42.6250	46.750	51.5500	61.430
MOV_AVG_5D	499.0	46.559752	7.348101	28.146	42.5310	46.714	51.7190	60.364
MOV_AVG_30D	499.0	46.520279	6.987970	30.373	43.7545	46.669	51.2825	59.643
RSI_9D	499.0	49.752766	20.491916	3.460	35.4100	51.610	64.9250	95.760
RSI_14D	499.0	49.706032	16.648588	8.750	37.3850	50.730	62.3400	87.660
RSI_30D	499.0	49.796092	11.677819	20.010	41.9500	51.030	58.4550	71.760
VOLUME_TOTAL_CALL	499.0	37255.116232	20926.775386	8582.000	23953.5000	32537.000	45025.5000	193207.000
VOLUME_TOTAL_PUT	499.0	43279.879760	20359.469365	8412.000	28651.5000	39012.000	53388.5000	141428.000
VOLATILITY_10D	499.0	40.277956	18.225575	9.910	27.5650	37.100	47.9950	105.100
VOLATILITY_30D	499.0	42.305431	13.856598	17.890	33.0800	40.080	46.6950	87.410
30DAY_IMPVOL_105.0%MNY_DF	499.0	37.756293	9.096887	21.500	31.4650	37.390	42.2600	78.120
30DAY_IMPVOL_100.0%MNY_DF	499.0	38.673587	8.987197	20.680	32.8050	38.480	42.7400	79.160
30DAY_IMPVOL_95.0%MNY_DF	499.0	40.399800	8.767756	23.480	34.9850	40.090	44.2350	80.320
30DAY_IMPVOL_110.0%MNY_DF	499.0	37.708257	8.926572	22.390	31.9350	36.970	42.0800	77.560
30DAY_IMPVOL_90.0%MNY_DF	499.0	42.426733	8.768051	25.350	37.3000	42.250	46.4500	81.660

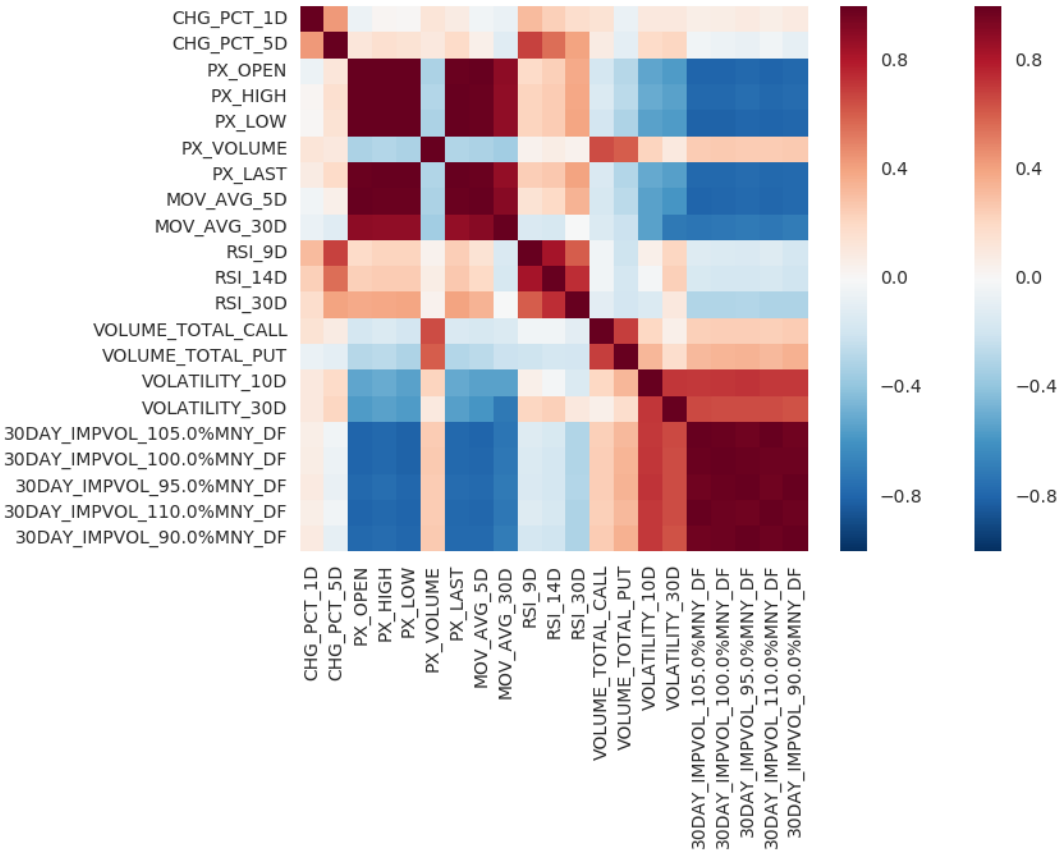
Explanatory Visualization

In this section, we visualize properties of the features. First, let's start with a plot containing subplots for each feature:



This plot is interesting because it can show significant trends in the features and, to a more intuitive and qualitative extent, it can also show any sign of correlation among the data. For example, we can see that periods of negative trend in the market (see for instance the "PX_LAST" graph) are associated with peaks in implied and realized volatility (we can see that from the "VOLATILITY 10D" and the "30DAY_IMPVOL_100.0%MNY_DF" graphs). This negative correlation between price and volatility (i.e. lower prices are usually associated with higher volatility) is rather typical in equity-like financial markets, or so-called *risky assets*. In fact, in Equity markets, volatility tends to rise when prices fall and vice versa. On the other hand, some assets like Gold are considered *safe heaven* by investors, therefore they usually tend to spike in price together with their volatility when there are sudden shocks in the market. These considerations can be helpful in a later stage of the project, where we might want to implement two classes of classifiers to distinguish between risky-assets and safe-heavens (for now I will not follow this path in this project).

Another interesting plot to look at (please see below) is the Correlation heatmap. This is a good synthetic way to grasp significant correlations among the features.
From the heatmap we can have a more precise picture of the correlation among the various features. In particular, as we could have expected, features concerning volatility are highly positively correlated with each other (the color shift is dark red), while the price and volatility features are rather negatively correlated (as the look we had at graphs above suggested). Checking the correlation among the features can be important because, ideally, we would like to dispose of as much (relevant) information as possible: if we noticed that most of the features were correlated with each other, then we would not have got any benefit than just using several less features in the classification problem. Using all the features will just slow down the convergence of the optimization in the algorithms like SVMs, Decision Trees/Random Forest and MLP.



Algorithms and Techniques

As anticipated above, I will explore 4 models in total:

- Gaussian Naive Bayes
- Random Forest
- Feed-Forward Multi-Layered Perceptron (MLP) Neural Network
- LSTM (Long-Short Term Memory) Neural Network

The main reason behind the choice of these algorithms is the following.
If the Efficient market hypothesis is correct, it should be impossible to achieve a forecast that beats the naive predictors listed above. In particular, any machine learning algorithm should perform just as poorly as a coin-flip. Therefore there should be no difference: whatever supervised learning algorithm we use, we should never get too far from a 50% accuracy score.
To test this fact, I start from a simple Gaussian Naive Bayes, where there is a strong assumption: all features are independent from each other. This is clearly an over-simplification, as we can see that, for example, the total volume in call options tend to be higher whenever the total volume of put options is higher as well (and vice versa obviously).
Then I moved to a Random Forest classifier. The reason for this choice is the ensemble feature of this classifier. It should therefore be less prone to overfitting.
Then we will move to Neural Networks, which in theory should be able to grasp structural non-linearity in the data. I will start with a simple feed-forward neural network. I will not tune the parameters in the project but I will provide an-already-fine-tuned version of the MLP in both the Feed-forward and static validation mode.

Finally, I move on the model that should be the best to handle time series: the LSTM (Long Short Term Memory) neural network.

Again, if the EMH holds, none of the models above should significantly outperform the others.

Now, let's move on to a short description of the basic working of each algorithm.

Gaussian Naïve Bayes – Short Description

This algorithm will create a decision surface using the relative frequencies of the distribution of each feature in the dataset. This algorithm will treat the features as independent of each other (hence the name "Naïve"). Then, after calculating relative frequencies, the algorithm will check every feature of each single test set data point to classify, and for each class of labels it will retrieve the probability associated to the feature corresponding to that class. Finally, It will multiply this probability with the probabilities associated to all other features and it will assign the data point in the test set to the class with the highest "cumulative probability". In formulae:

$$\hat{y} = \arg\max_y P(y) \prod_{i=1}^{n} P(x_i \mid y),$$

Where `P(y)` is the prior probability of a point belonging to class "y" (i.e. the relative frequency of each label), and `P(xi|y)` is the likelihood of the features given label "y" (assumed here to be Gaussian distributed).

Random Forest– Short Description

The Random Forest classifier is an extension of the Decision Tree classifier. It is an ensemble method, i.e. it builds an ensemble of decision trees. Each decision tree is built from a sample from the training set (drawn with replacement). As a result, each decision tree will find the best split on the sample it is trained on (not on the full training set). This ensemble feature generally helps reducing the variance of the classifier (at the expense of higher bias, in general).

Multi-Layer Perceptron – Short Description

The Multi-Layer Perceptron (`MLP`) is a Neural Network, i.e. an extension of the Logistic Classifier. MLP represents the building block of *Deep Learning*. Here is an intuitive explanation of how it works.
The training set is multiplied by a set of weights (and a bias vector is added to this matrix product). This output is passed to a so-called activation function (such as the `relu`, i.e. the `max(x,0)` function). The one just described is the basic unit (or layer) of the network, a.k.a. a Neuron. If we stack additional layers we make the network *deeper*. The final output is then usually passed through a final activation function such as the `softmax` function (not the `relu`), in order to obtain probabilities of each data to belong to a label. Finally, a loss function is computed (such as Binary Cross Entropy for binary classification tasks or Mean Squared Error for Regression tasks).
The weights and biases of each layer are trained via *Backpropagation* (which is an application of the Chain Rule for derivatives of "functions of functions") using an optimization procedure like Stochastic Gradient Descent (SGD).

The `LSTM` Model – Short Description

For an excellent introduction to `LSTM`, I suggest this webpage:
https://medium.com/@aidangomez/let-s-do-this-f9b699de31d9

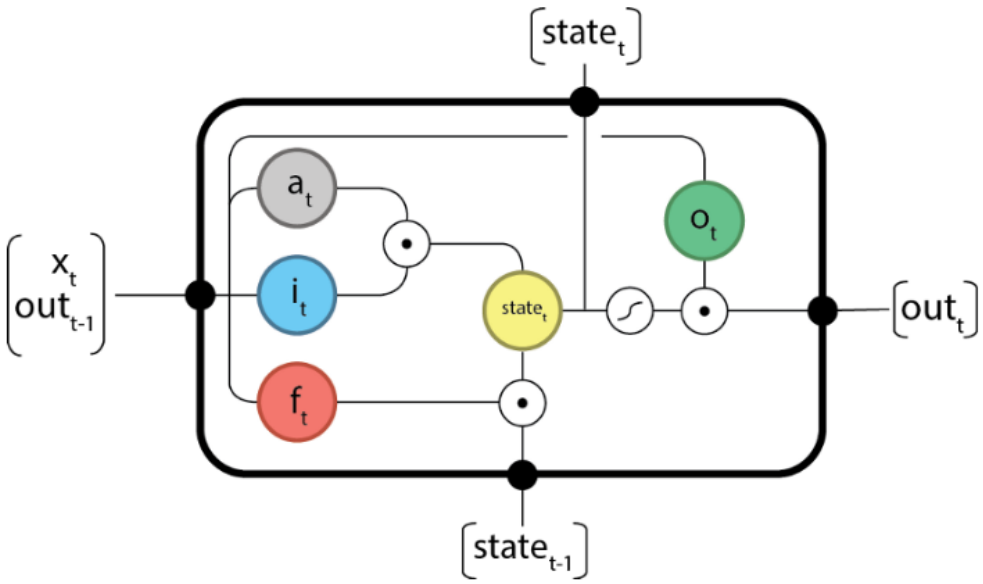
The LSTM model uses the following layers/gates:

$$\text{Input activation:}$$
$$a_t = \tanh(W_a \cdot x_t + U_a \cdot out_{t-1} + b_a)$$
$$\text{Input gate:}$$
$$i_t = \sigma(W_i \cdot x_t + U_i \cdot out_{t-1} + b_i)$$
$$\text{Forget gate:}$$
$$f_t = \sigma(W_f \cdot x_t + U_f \cdot out_{t-1} + b_f)$$
$$\text{Output gate:}$$
$$o_t = \sigma(W_o \cdot x_t + U_o \cdot out_{t-1} + b_o)$$

Which leads to:

$$\text{Internal state:}$$
$$state_t = a_t \odot i_t + f_t \odot state_{t-1}$$
$$\text{Output:}$$
$$out_t = \tanh(state_t) \odot o_t$$

This is a common way to represent the model:



Benchmark

As we already indicated above, we could consider three benchmark models for the market sentiment prediction problem:

1) the random walk/coin-flip, i.e. at every step when we try to predict the market trend, we flip a coin. At the end of the time series (*the walk*) we calculate the accuracy over the real trend we observed in the market, i.e. we calculates how many times the coin flip managed to guess the market trend correctly over the total number of steps in the time series.

2) the Naive predictor, i.e. a predictor which predicts that the market is always rising

However, 1) (the coin flip) seems to be a more plausible choice of benchmark. Under the Efficient Market Hypothesis, flipping a coin should make no difference compared to any algorithm which tries to analyze the past to predict the future. The Naive predictors could be distorted, because the market could in fact be trending higher or lower for many consecutive days, and we want our algorithm to capture this effect. On the contrary, we could have a market which trades roughly around the same levels for many days in a row. In this case, the Naive predictors would both perform poorly, while the random walk should still provide a solid benchmark to beat.

3) Another interesting benchmark is the *Persistence Forecast model*: this model checks what was the trend in the previous period and predicts the market will have the same trend for the next single time step.

III. Methodology

Data Preprocessing

The first step is to check the skew across the features of the dataset. Skewed features in fact could lead to bad convergence of the classifiers we use and one way to prevent that is to apply a log-transformation to the features. In doing so, we have to pay extra care if some of the features values are close to `0`. To that extent, in the 'flatten skew function', I am setting a critical skew level of +/- 0.9 (i.e. only skew levels in excess of 0.9 or less than -0.9 will be applied a log transformation to). In addition, all the features that are log-transformed are printed at the end of the function to ensure the user can visually check if, by any chance, any of the features with values potentially close to zero have been transformed (above all the 'CHG_PCT_1D' and the 'CHG_PCT_5D' features).

The next preprocessing step is the scaling. For every feature in the dataset, we scale all the data to be in a given range. This range by default is `[0,1]`, but for example for LSTM we will use the range `[-1,1]`, as this is the range of the `tanh` function which is used as activation function in the input activation and output layer.

It is very important to perform features scaling, as the objective functions of some of the classifiers (like `Random Forest` or `MLP` and `LSTM`) will not work properly and will struggle to converge to a solution of the optimization problem.

In the project, the scaling is performed via the `scale()` function, which is built upon the `MinMaxScaler` in `sklearn`.

The last preprocessing step consists in removing the last (i.e. the most recent) row of the dataset, as we do not have a label from this observation (it is in the future for the period we are considering). We also shift the 'y' column of the dataset to obtain the set of labels. By shifting this

array by one day forward, we are trying to predict the outcome of the next trading day. The 'y' column is calculated in the spreadsheet as the sign of the 'CHG_PCT_1D', so it reflects if the market went up or down on a given trading day.

Implementation

All of the algorithms except `LSTM` are implemented in `sklearn`. `LSTM` instead uses `Keras` with `Tensorflow` backend.

The main step of the implementation is represented by the `train_test_model` function. This function is used to train and test all classifiers except the `LSTM` which uses its own train&test function. The `train_test_model` function has four main components: 1) it performs the `Walk-Forward` split, i.e. at the beginning takes the initial training set (which for the Oil market is the first/oldest 250 trading days), 2) it trains the a generic `sklearn` classifier to the training set; 3) calculates the prediction for the test set, which is composed of only the next trading day (i.e. the train set represents the *past days*, and the test set represents *today*). Finally, 4) the function keeps looping one step (i.e. trading day) ahead at a time, and includes the newly acquired information into the training set. It then refits to the training set and predicts the next day outcome.

As I wrote above, each `sklearn` algorithm is performed both in Walk-Forward and in Static Validation mode. The Static validation simply fits the model once for all on the first half of the available data, and then tries to predict all the subsequent labels without incorporating any new information. The Static validation is unrealistic: we always want to make new information available to a classifier and, potentially, we would want the classifier to disregard this new information if it is not useful. We check also the performance of the algorithms in Static Validation as a possible confirmation of the unpredictability of market sentiment, in accordance with the EMH.

As anticipated, the `LSTM` model is implemented in Walk-Forward validation only. Its `Keras` implementation is essentially the same as the `train_test_model` for `sklearn` classifiers (i.e. it follows the same walk-forward process as the `train_test_model` function).

As the `Random Forest` classifier is quite reach in terms of parameters, we perform an optimization over the parameters set and extract the features for the best and the worst (in terms of accuracy score) Random Forest classifier.

Let's look at the implementation details more closely.

- **Gaussian Naive Bayes**. In this case we just use the standard `sklearn` implementation without specifying prior probabilities for the classes (this is justified from the fact that on average the number of up trends in the market were roughly the same as the down trends)

- **Random Forest**. We start from the basic `sklearn` implementation, which uses `10` estimators, the `gini` criterion as the loss to minimize (i.e. the algorithm will try to minimize the Gini impurity), `max_features = auto`, i.e. equal to `sqrt(number of features)` and `inpurity split` (the threshold for early stopping in the tree growth) of `1e-7`.
  We later a parameter optimization over: `n_estimators` (over the range `[5,10,20]`), `criterion` (`gini` vs `entropy`), `max_features` (over the range `[None, auto, log2]`) and `inpurity split` (either `1e-7` and `1e-4`). We

then extract the 5 five features which are the best on average (i.e. across the test set) for the best classifier and the worst classifier (see the 'Results' section.

- **MLP**. After some manual fine-tuning, I have settled on a network with 3 hidden layers, all with size `100`. I am using the `LBFGS` solver instead of `Stochastic Gradient Descent` or `Adam`, given that the size of the dataset is relatively small and the convergence is quite fast. `LBFGS` stands for **L**imited memory **B**royden-**F**letcher-**G**oldfarb-**S**hanno algorithm, it is an optimizer of the quasi-Newton methods type. I am using the `relu` activation function. In the Walk-Forward validation mode I have set `alpha` of `1e-2`, `tol=1e-4` and I am setting `warm_start=True` so that the algorithm can rely on the previous time step trained weights to allow for faster convergence (it is also a way to keep some memory as moving along the time series). In the static validation mode, `alpha` is `1e-4`, `tol=1e-3` and `warm_start=False`. This parameters choice comes from some manual trials, and I have settled on this based on the accuracy score performance (see the 'Results' section)

The reason why I did not investigate the MLP deeper is because the main neural network we want to implement is the `LSTM`.

- **LSTM**. For this method I am implementing a *stateful* model, i.e. the network will start from the previously trained weights across sequential iterations (similar to the `warm_start=True` feature of the `MLP`). The main features to explore here are the combinations of the number of neurons (i.e. layers used in the network) and number of epochs used for training. One neuron is composed of four gates: 1) the Input activation gate; 2) the Input gate; 3) the Forget gate; 4) and the Output gate. The first three gates concur to produce a state, which is then combined with the Output gate to produce an output. Each epoch is a forward-backprop iteration. I am exploring `30` combinations of number of neurons and epochs in total. For the number of neurons: `[1,2,3,10,50]`; for the number of epochs: `[1,5,10,100,1000,3000]`.

A batch_size of `1` is used given that the model is stateful, therefore only `1` batch of data has to be used at each iteration and the model will retain information about that batch and assess by itself how to maintain it within its weights.
We use the `binary cross-entropy` loss function given that we have a classification problem, and the efficient `adam` optimizer.
As an activation we use the `softmax` activation function, which returns probabilities of a given data row to be classified as either an up-trend or a down-trend. If the probability is above 50%, we assign the point to label 1 (up-trend), otherwise to label 0 (down-trend).

Difficult parts of the implementation. The two most difficult parts of the implementation were in a) the scale function (which implements the `sklearn` MinMax scaler) and b) the `LSTM` train procedure (which is mainly composed of the `fit_lstm` and the `train_test_lstm` functions). The `scale` function needs to distinguish whether we are in Forward Walk or Static validation mode. If we are in Static validation mode in fact, we can scale already the whole test set based on the scaling applied to the train set. In Walk-Forward validation instead, we can scale only one test set point at a time. This is coded in the "`If`" block of the function, which leads to a different usage of the `Numpy` "reshape" function.
The difficult part of the `LSTM` train process instead was to handle the *Stateful* property of the network. To make the network Stateful in fact, we need to process only batch of data at a time (the "statefull" property of the model in fact decides how to preserve information for each single batch/time step). After training the model on the initial train set, we need to train the stateful network on each new train sample (which constitutes a new batch for training). After every epoch of training we reset the states of the `LSTM`. I had to distinguish between the first run of the training procedure (where we have all the past info available) and the subsequent training points (which come one by one as we move along the time series). This leads to a different usage of

the Numpy `expand_dims` function, which re-shapes the dimension of the training array according to which of the training phases we are running (this is implemented by the last "`if`" block of the `fit_lstm` function).

Refinement

A refinement has been introduced in the final part of the project, in terms of metrics. In fact, despite the fact that the accuracy_score is a good metric for the pure classification problem, in a financial environment we are interested in that when we are wrong and, say, we predict the market will go up, the market does not actually performs `-10%`, or vice versa.

We therefore introduced the *modified accuracy*, a metric that register a score proportional to the realized percentage performance of the market on a given trading day.
The `modified_accuracy` function implements this logic.

IV. Results

Model Evaluation and Validation

This table shows all the accuracy scores and the modified accuracies scores of the sklearn algorithms we implemented:

Sklearn algos	**NB**	**NB_2**	**NN**	**NN_2**	**RF**	**RF_2**
acc	0.514056	0.538153	0.53012	0.570281	0.518072	0.534137
mod_acc	-3.78	-92.98	5.18	-2.54	-80.94	-175.04

The appendix '_2' indicates the Static validation mode for the algorithm. 'acc' stays for accuracy, 'mod_acc' stands for modified_accuracy. The algorithms in the columns are: "Naïve Bayes" (NB), "MLP Neural Network" (NN), and "Random Forest" (RF).
It is very interesting to observe that they all beat both the coin-flip Naïve predictor and the persistence forecast model. **BUT**, they managed to beat them by a very small margin. Also, it is worth noticing that all the classifiers perform better in Static Validation mode, and we expected this to be a sign of failure in consistently predicting the market trend. In particular, it would seem that the sklearn models fail to successfully incorporate new information.
However, if look at the modified accuracy, the Static validation model perform very poorly, and we have some grounding to defend the need for more complex models, in particular the MLP Neural Network, which is the only one with a positive modified accuracy.

If we now look at the LSTM, the picture looks like this:

LSTM set	Accuracy	Modified Accuracy
e3000n1	0.542168675	10.72
e100n2	0.53815261	-12.98
e3000n2	0.53815261	-100.34
e100n50	0.530120482	-49.72
e1000n1	0.530120482	2.00
e3000n3	0.522088353	15.80
e1000n50	0.522088353	-55.72
e1000n3	0.522088353	-22.42
e1000n2	0.522088353	-25.42
e100n10	0.518072289	-20.78
e3000n10	0.514056225	-79.60
e3000n50	0.510040161	-76.84
e1n1	0.506024096	-378.52
e1000n10	0.502008032	-25.04
e10n2	0.497991968	-251.78
e5n1	0.497991968	-416.94
e5n10	0.497991968	-191.78
e1n3	0.489959839	-350.32
e100n3	0.485943775	-1.80
e1n50	0.485943775	-304.36
e5n3	0.481927711	-362.66
e1n2	0.477911647	214.10
e5n50	0.477911647	-78.94
e10n1	0.477911647	-388.56
e10n3	0.477911647	-319.16
e1n10	0.469879518	-340.22
e10n50	0.453815261	-40.70
e100n1	0.453815261	-52.42
e10n10	0.453815261	-126.92
e5n2	0.437751004	-311.22

In the first column, we first indicate the number of epochs and then the number of neurons. So, for example, 'e5n10' means that we have used 5 epochs and 10 neurons for training.
We can see that the best classifier is "e3000n1" and that in general we have some benefits in terms of accuracy if we increase the number of epochs.
However, it is extremely interesting to see that most of classifiers perform poorly in terms of modified accuracy (only 4 out of 30 are positive), even though the best classifier ("e3000n1") has a modified accuracy of 10.72, which beats both the sklearn classifiers and the persistence forecast (which has a modified accuracy of 2.42).

This other table shows better some other relevant statistics of the performance of LSTM classifiers:

	acc	mod_acc
count	30.000000	30.000000
mean	0.497858	-138.084667
std	0.028132	161.972272
min	0.437751	-416.940000
25%	0.477912	-309.505000
50%	0.497992	-77.890000
75%	0.522088	-23.075000
max	0.542169	214.100000

Here we can see that the average accuracy of the LSTM classifiers we have implemented is 49.78% (which looks quite disappointing). Also, the average modified accuracy is about -138, a heavy loss! This suggests the conclusion that fine-tuning the parameters is crucial and even with a well-trained and complex model like LSTM there can be bad results in terms of performance.

Grid Search for Random Forest and Features Extraction

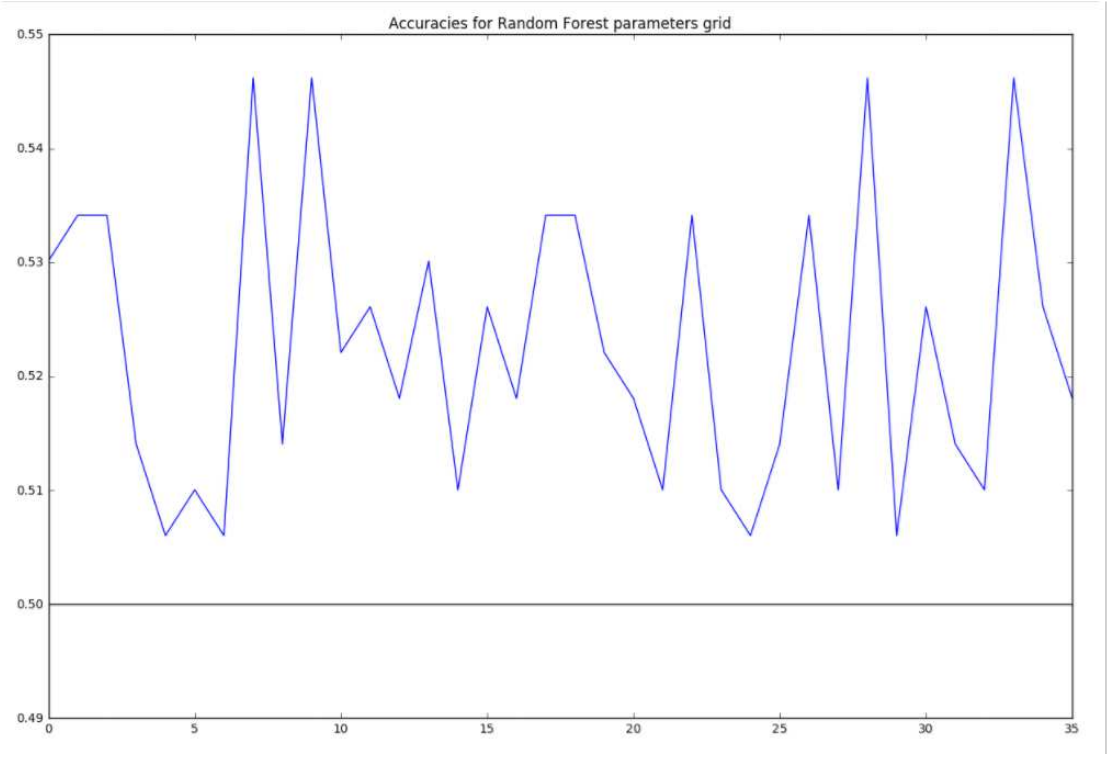
It is interesting to perform a deeper analysis for the Random Forest parameters, as this classifier as a considerably large number of parameters (especially if we compare it with Naïve Bayes). The parameters we optimize are:

`n_estimators` (over the range `[5,10,20]`),
`criterion` (`gini` vs `entropy`),
`max_features` (over the range `[None, auto, log2]`) and
`inpurity split` (either `1e-7` and `1e-4`).

I am collecting accuracy score for each combination (that is why I did not use the `sklearn GridSeeachCV`, but I implemented one myself).
These are the best and worst parameters combination I have found out of 36 combinations):

```
Random Forest best params: (10, 'entropy', None, 0.0001). Accuracy: 54.62%
Random Forest worst params: (5, 'gini', 'log2', 1e-07). Accuracy: 50.60%
```

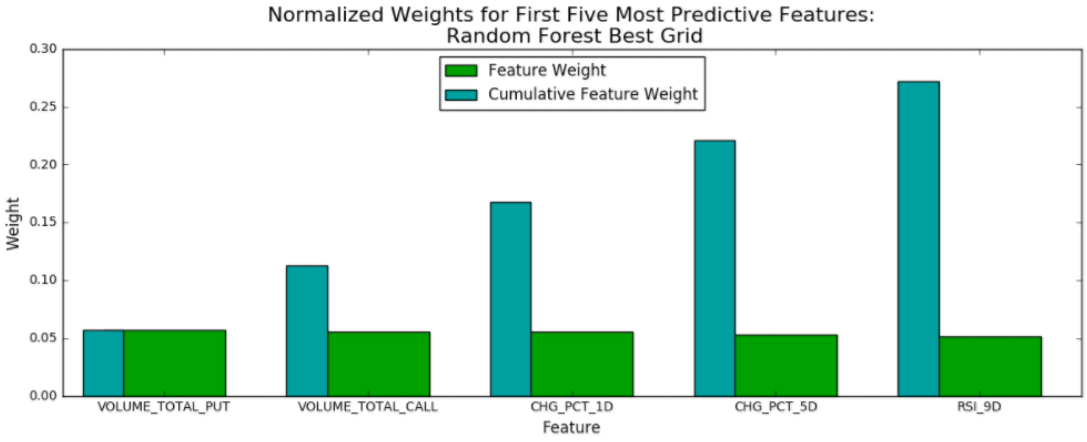
It is interesting to observe that both the best and worst have an accuracy score above 50%.
If we check the global performance of all the parameters we can draw the following plot:



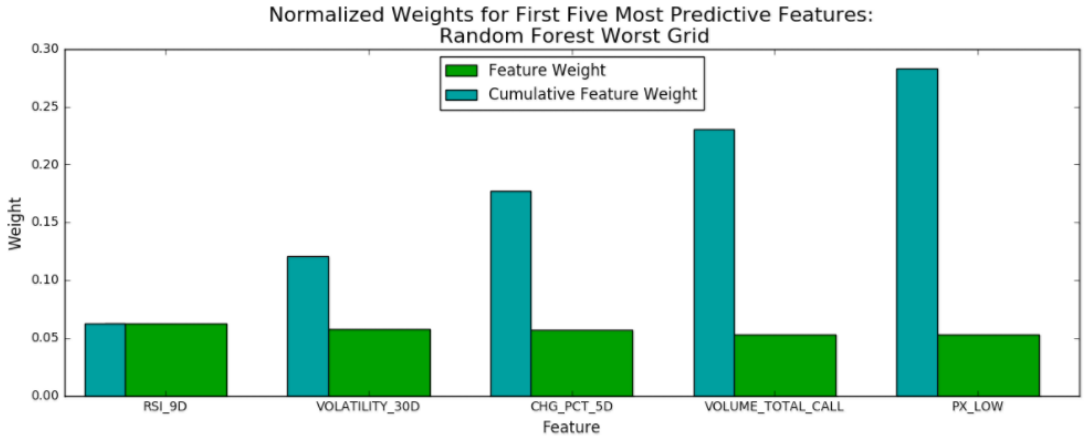
The black line represents the accuracy of the coin-flip (which is 50%). The blue line instead represents all the accuracy scores for each combination of parameters starting from (5, 'gini', None, 1e-7) to (20, 'entropy', log2, 1e-4).
The point that it is worth noticing here is that all of the accuracies are above 50%, which could be interpreted as a sign of robustness of the Random Forest classifier for the problem at hand.

We can extract the 5 most important features (on average across the test set time series) for the best and worst set of parameters for Random Forest:

Best Random Forest Classifier: 5 most important features:



Worst Random Forest Classifier: 5 most important features:



We can see that the 5 best features are quite similar, which is what we could have expected given that the difference in accuracy score is quite small for the best and worst classifiers.
For the best classifier we have: 1) 'VOLUME_TOTAL_PUT', 2) 'VOLUME_TOTAL_CALL', 3) 'CHG_PCT_1D', 4) 'CHG_PCT_5D' and 5) 'RSI_9D'.
For the worst instead we have: 1) 'RSI_9D', 2) 'VOLATILITY_30D', 3) 'CHG_PCT_5D', 4) 'VOLUME_TOTAL_CALL', and 5) 'PX_LOW'.
For both the best and the worst, the cumulative feature weight of the 5 most important features does not exceed 30%. This means that there is no particular set of components which shines particularly among the others (the 5 most important features are also quite close with each other). Therefore there does not seem to be the need to exclude certain features in favor of others.

V. Conclusion

Reflection

We have implemented 3 `sklearn` classifiers and a `LSTM` model in Keras to build a classifier to consistently predict the market sentiment for commodity futures and in particular we focused on the Crude Oil Market.
From the results above, we can state that, even though we have managed to beat the benchmarks with an accurate tuning of the parameters, we have found a high variance in the various classifiers. Therefore we cannot claim that the results we obtain managed to beat the market consistently.
In the appendix at the end of the project, I am reporting the table results for other commodity markets (Corn, Wheat, Gold, Coffee, and Soybeans): they all point out the same verdict, even when they manage to achieve a good accuracy score, they do not perform consistently.

We can say that the various classifiers did not beat the market consistently because of the results we have found from the modified accuracy.
Let's think of a real-world scenario: we want to invest in the Oil market, and we build the classifiers above. We select the classifier with the highest accuracy score (most likely in Walk-Forward validation, given that we want something with a good performance in a real-world scenario). Then we start investing, and we end up with the results from the modified accuracy. Now, in the case of the Oil market, we would have chosen the LSTM with 1 neuron and 3000 epochs, and we would have ended up with a 10.72 modified performance, which could be seen as a positive result given that the market performance between 10Apr2015 and 10Apr2017 was

negative 43%.
However, the high variance we have among the various classifiers could raise the objection that the whole process of predicting a market trend is purely random, and it is equivalent of predicting the flip of a coin without any knowledge of the physical environment where the flip occurs.

On a more personal level, the most difficult part of the project was to handle the time series nature of the data. In fact, in the training procedures I had to handle the time series carefully, especially in the Walk-Forward validation, where you have to re-train on every new piece of information you get from the market. Coding-wise, the most interesting aspect was the `LSTM` implementation, as it was really a big step forward for me from the subjects covered in the Lectures. `LSTM` models (and in general Recurring Neural Networks, **RNN**s) are the true bleeding edge of Machine Learning nowadays.

Finally, let's look at what potential improvements we could bring in to get stronger results.

Improvement

There are at least two major improvements we can think about.

The first improvement concerns the time steps frequency. Nowadays financial markets are very sophisticated and multiple players trade in fractions of seconds (a popular account of the High-Frequency Trading revolution is the famous Michael Lewis's book 'Flash Boys: A Wall Street Revolt'). It is therefore unrealistic to expect to be able to produce forecasts for time frames like one or more days in such fast-paced environments.

In practice, the main development of this analysis would be to use, say, hourly data instead of daily data for training and prediction.

Like in the field of weather forecast for example, where we know that a 1-day or 3-hours forecast is way more reliable than a 1 week one, it makes sense also for financial markets to increase the frequency of observations by shortening the time frames used for training and testing.

The second improvement is broader and consists in enlarging the scope of the analysis. As we saw in the definition of modified accuracy, in a trading environment what matters most is not whether the predictions had good accuracy *per se*, but whether the investment decisions based on such predictions lead to good results (i.e. in cash USD…).
Therefore, it is more important to get a good prediction when the market shows a significant movement rather than when the market trades flat around a certain level.

One way to incorporate a prediction on the magnitude of movements could be to run regression algorithms in parallel with the classification algorithms in this project.
This could be achieved by using, in `sklearn`, the Random Forest Regressor, the MLP Regressor, and in Keras the LSTM model with `mean_squared_error` as a loss instead of `binary_cross_entropy`.

Alternatively, we could maintain the classification setup, are introduce classes for movements, say, larger than 1%, 2%, 3% in both directions. We could then extract log probabilities (we can do that for Random Forest, for the MLP and for LSTM in Keras taking the output of the `softmax` function, which would replace the `sigmoid` activation we have in the Boolean class classification problem of the project).

APPENDIX – RESULTS FOR OTHER COMMODITIES

The results of this appendix were obtained by running the same notebook from the Oil market analysis (selecting the proper market in the file_to_load variable from the commos_dict dictionary). I have used exactly the same parameters used from the Oil market analysis. Therefore, some of these parameters may not result fully optimized for the specific market, but serve solely as a comparison for what results we would achieve if we expanded the classifiers of choice from the Oil market to other commodities markets. We report the basic statistics about the `sklearn` models and the `LSTM` model for the following markets: 1) Corn; 2) Wheat; 3) Coffee (Arabica); 4) Soybeans; and 5) Gold.
The results for these other commodities are similar to those of the oil market: we did not find an algorithm to consistently predict market sentiment in these markets. In particular, there is a high variance in the results, with classifiers that perform well in terms of standard accuracy score, but poorly in terms of modified accuracy.

1) Corn market

a) Performances of `sklearn` classifiers:

	NB	NB_2	NN	NN_2	RF	RF_2
acc	0.497992	0.502008	0.506024	0.46988	0.477912	0.526104
mod_acc	65.070000	80.970000	-0.130000	55.39000	-54.110000	-18.210000

b) Performances of `LSTM`:

```
LSTM set | Accuracy        | Modified Accuracy

e3000n1  |  0.530120481928  |  -29.83
e100n2   |  0.522088353414  |  -3.59
e3000n50  |  0.518072289157  |  -4.07
e1000n50  |  0.518072289157  |  -22.21
e1n50  |  0.5140562249  |  135.19
e1000n10  |  0.506024096386  |  -21.91
e3000n2  |  0.506024096386  |  -16.43
e100n10  |  0.502008032129  |  19.61
e100n50  |  0.502008032129  |  21.71
e10n2  |  0.502008032129  |  119.49
e1000n3  |  0.502008032129  |  -37.11
e3000n3  |  0.493975903614  |  -12.29
e100n3  |  0.493975903614  |  18.71
e3000n10  |  0.489959839357  |  -32.39
e1000n1  |  0.489959839357  |  -10.65
e1n3  |  0.489959839357  |  -30.07
e5n10  |  0.4859437751  |  112.87
e100n1  |  0.481927710843  |  -69.07
e5n50  |  0.477911646586  |  74.29
e5n1  |  0.473895582329  |  133.77
e1n1  |  0.473895582329  |  83.63
e1000n2  |  0.473895582329  |  -30.53
e1n10  |  0.469879518072  |  243.81
e1n2  |  0.465863453815  |  -54.29
e10n1  |  0.457831325301  |  49.45
e10n50  |  0.453815261044  |  -4.99
e10n3  |  0.449799196787  |  140.05
e5n3  |  0.437751004016  |  110.65
e10n10  |  0.433734939759  |  6.55
e5n2  |  0.413654618474  |  -7.71
```

c) Summary statistics on LSTM:

	acc	mod_acc
count	30.000000	30.000000
mean	0.484337	29.421333
std	0.027936	74.096781
min	0.413655	-69.070000
25%	0.470884	-22.135000
50%	0.489960	-3.830000
75%	0.502008	81.295000
max	0.530120	243.810000

2) Wheat market

a) Performances of `sklearn` classifiers:

	NB	NB_2	NN	NN_2	RF	RF_2
acc	0.459677	0.46371	0.491935	0.471774	0.495968	0.475806
mod_acc	187.920000	256.80000	-38.580000	186.660000	-105.180000	158.740000

b) Performances of `LSTM`:

LSTM set	Accuracy	Modified Accuracy
e1n2	0.540322580645	-282.86
e5n1	0.536290322581	-307.38
e5n3	0.524193548387	-158.68
e3000n10	0.524193548387	-56.68
e1000n50	0.524193548387	-68.86
e100n10	0.520161290323	-31.1
e1n50	0.516129032258	-86.2
e1n1	0.516129032258	-110.78
e1000n10	0.512096774194	-62.72
e10n1	0.508064516129	-230.22
e1000n3	0.504032258065	-29.18
e100n2	0.504032258065	-21.42
e10n2	0.5	-153.16
e1n3	0.495967741935	-220.26
e1000n2	0.495967741935	-55.24
e5n2	0.491935483871	-202.92
e10n3	0.491935483871	-151.82
e5n10	0.491935483871	-134.66
e1n10	0.483870967742	-39.76
e3000n1	0.483870967742	-39.7
e3000n50	0.483870967742	9.72
e3000n3	0.483870967742	-81.72
e100n50	0.483870967742	-11.94
e5n50	0.479838709677	-115.4
e3000n2	0.479838709677	-42.94
e100n1	0.475806451613	-78.44
e1000n1	0.471774193548	-35.92
e100n3	0.471774193548	-29.54
e10n10	0.463709677419	-125.12
e10n50	0.431451612903	-63.54

c) Summary statistics on `LSTM`:

	acc	mod_acc
count	30.000000	30.000000
mean	0.496371	-100.614667
std	0.023496	81.677672
min	0.431452	-307.380000
25%	0.483871	-147.530000
50%	0.493952	-73.650000
75%	0.515121	-39.715000
max	0.540323	9.720000

3) Coffee market (Arabica)

a) Performances of `sklearn` classifiers:

	NB	NB_2	NN	NN_2	RF	RF_2
acc	0.487903	0.524194	0.455645	0.471774	0.451613	0.455645
mod_acc	-58.440000	-243.640000	46.160000	-231.980000	18.480000	-219.120000

b) Performances of `LSTM`:

LSTM set	Accuracy	Modified Accuracy
e3000n1	0.548387096774	78.7
e3000n2	0.520161290323	22.9
e1000n10	0.520161290323	3.8
e1n1	0.520161290323	-88.38
e3000n3	0.520161290323	-47.0
e10n1	0.512096774194	302.16
e1000n2	0.495967741935	62.28
e3000n10	0.491935483871	16.86
e5n10	0.491935483871	115.18
e5n2	0.491935483871	48.48
e1n3	0.487903225806	-121.1
e1000n3	0.479838709677	29.64
e1n2	0.479838709677	210.48
e3000n50	0.475806451613	-10.84
e5n50	0.475806451613	86.08
e1n50	0.475806451613	1.6
e10n10	0.475806451613	40.82
e1000n1	0.471774193548	35.18
e10n50	0.471774193548	105.68
e100n3	0.467741935484	25.04
e100n2	0.467741935484	50.18
e1000n50	0.467741935484	21.32
e100n50	0.463709677419	33.82
e100n10	0.463709677419	40.06
e5n3	0.459677419355	34.32
e100n1	0.45564516129	106.94
e1n10	0.451612903226	-166.08
e5n1	0.451612903226	84.48
e10n3	0.451612903226	156.88
e10n2	0.41935483871	89.0

c) Summary statistics on LSTM:

	acc	mod_acc
count	30.000000	30.000000
mean	0.480914	45.616000
std	0.027017	89.648737
min	0.419355	-166.080000
25%	0.464718	17.975000
50%	0.475806	37.620000
75%	0.491935	85.680000
max	0.548387	302.160000

4) Soybeans market

a) Performances of `sklearn` classifiers:

	NB	NB_2	NN	NN_2	RF	RF_2
acc	0.536585	0.520325	0.536585	0.54878	0.495935	0.487805
mod_acc	-90.200000	-239.440000	-36.760000	-202.70000	-97.200000	-127.380000

b) Performances of `LSTM`:

LSTM set	Accuracy	Modified Accuracy
e1n10	0.565040650407	-230.96
e5n3	0.540650406504	-169.54
e5n10	0.540650406504	-142.4
e10n2	0.540650406504	-148.16
e1000n50	0.536585365854	-13.62
e5n1	0.536585365854	-204.98
e5n2	0.536585365854	-184.04
e1000n10	0.532520325203	1.32
e10n50	0.528455284553	-77.56
e5n50	0.524390243902	-97.28
e1n50	0.524390243902	-191.44
e1n1	0.520325203252	-117.42
e3000n10	0.516260162602	-52.3
e10n10	0.512195121951	-102.5
e10n1	0.512195121951	-65.42
e10n3	0.508130081301	-146.88
e1n3	0.508130081301	-57.12
e1000n2	0.508130081301	-3.68
e3000n3	0.50406504065	11.02
e100n2	0.5	-21.76
e3000n2	0.49593495935	-34.74
e1000n1	0.49593495935	-1.12
e3000n50	0.49593495935	-54.48
e100n50	0.49593495935	-29.96
e100n1	0.483739837398	-82.88
e100n10	0.479674796748	-31.92
e3000n1	0.471544715447	-38.02
e1n2	0.459349593496	177.56
e100n3	0.459349593496	-9.42
e1000n3	0.410569105691	-1.36

c) Summary statistics on `LSTM`:

	acc	mod_acc
count	30.000000	30.000000
mean	0.508130	-70.702000
std	0.031252	84.145688
min	0.410569	-230.960000
25%	0.495935	-136.155000
50%	0.510163	-55.800000
75%	0.531504	-15.655000
max	0.565041	177.560000

5) Gold market

a) Performances of `sklearn` classifiers:

	NB	NB_2	NN	NN_2	RF	RF_2
acc	0.459677	0.516129	0.532258	0.504032	0.512097	0.483871
mod_acc	-42.920000	-116.220000	14.460000	26.340000	-57.480000	-1.520000

b) Performances of `LSTM`:

LSTM set	Accuracy	Modified Accuracy
e1n1	0.552419354839	-90.24
e100n10	0.54435483871	-11.22
e1n10	0.536290322581	-142.06
e3000n50	0.528225806452	10.36
e1000n1	0.528225806452	-27.0
e100n50	0.520161290323	-14.06
e5n1	0.516129032258	-149.56
e5n2	0.516129032258	-138.7
e1000n50	0.512096774194	3.8
e3000n3	0.512096774194	-21.86
e3000n1	0.508064516129	-0.72
e10n2	0.508064516129	-119.4
e1n50	0.5	-101.52
e1000n10	0.5	-10.4
e100n1	0.5	-34.32
e3000n2	0.491935483871	17.18
e5n3	0.487903225806	-104.48
e1000n3	0.483870967742	1.0
e100n3	0.479838709677	-13.2
e10n1	0.479838709677	-85.9
e1n3	0.475806451613	-89.14
e3000n10	0.471774193548	15.0
e10n3	0.471774193548	-78.58
e100n2	0.471774193548	-3.6
e5n50	0.467741935484	-47.34
e1000n2	0.467741935484	3.78
e10n50	0.463709677419	-40.88
e5n10	0.459677419355	-77.08
e1n2	0.45564516129	-24.84
e10n10	0.447580645161	-41.0

c) Summary statistics on LSTM:

	acc	mod_acc
count	30.000000	30.000000
mean	0.495296	-47.199333
std	0.027737	51.154992
min	0.447581	-149.560000
25%	0.471774	-88.330000
50%	0.495968	-30.660000
75%	0.515121	-5.300000
max	0.552419	17.180000