Stock Price Prediction Base on Double Top Pattern

A multiclass classification problem

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Executive Summary

The goal of this project is to build a prediction model that make use of stock chart pattern, in particular double top to predict the next movement of stock price if it will decrease further, increase, or stay still within the next 10 days. If successful, traders can use this prediction model to make a data driven decision on their next trade.

To achieve this goal, we will create our own dataset first. This can be done by determining the minima and maxima of the time series dataset for every stock from various industry. Then, we will refer to it to detect the double top stock chart pattern. There are 5 points/prices that consists of maxima and minima that forms the pattern, these will become the descriptive features that we will use to predict the target feature which is the movement of stock price within the next 10 days. We also include the indexes of the start and end of the pattern, as well as the industry of the stocks where the pattern occurs.

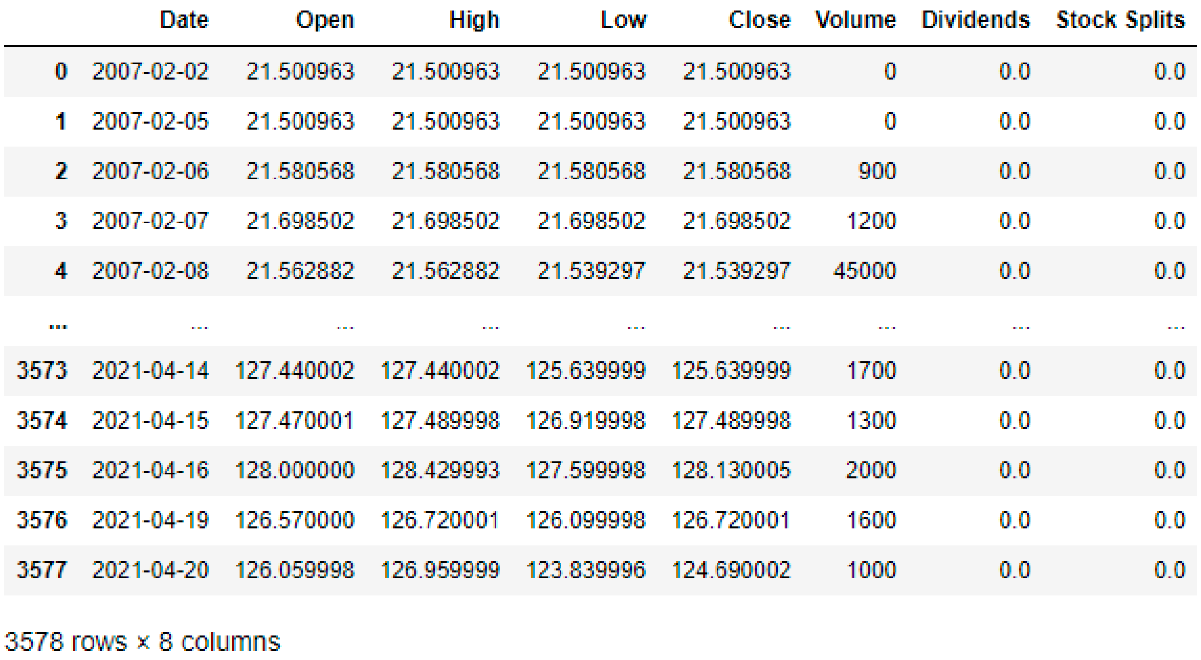
Now that we have the dataset. We will perform data exploration to visualize the double top pattern and verify the multicollinearity of the descriptive features because obviously they are correlated to each other since each are part of double top pattern. Moreover, we performed also feature engineer to get additional features that could help increase the predictive accuracy of the model.

After data exploration, we proceed to predictive modelling. Note that the target feature consists of 3 levels. Thus, we will fit multiclass models to our dataset such as multiclass KNN, multinomial

logistic regression, multiclass SVM etc.. Fortunately, this can be done simultaneously by using pycaret machine learning library, moreover it automatically split the dataset which we set to 80/20, and further perform data exploration such as normalization, in which we set it as minmax scaler, one hat encoding for nominal feature (industry). And as a result, the model the produces the highest F1 score is the gradient boosting classifier, a sequential ensemble approach with 0.5217 score. This implies that with 52.17% accuracy, we can predict the movement of stocks prices within 10 days after the double top stock chart pattern happen.

Raw Data

Historical dataset of stock prices for various industry web scrape from yahoofinance.com.



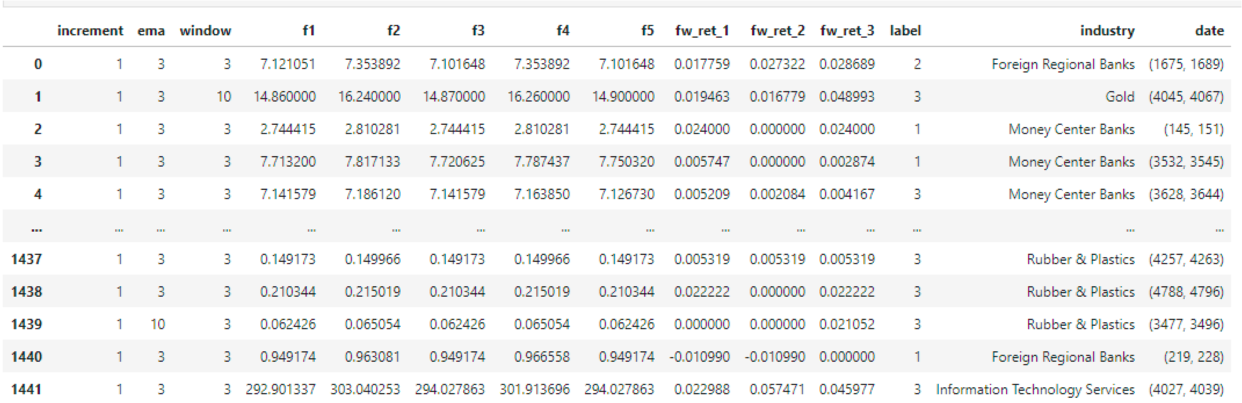
	Date	Open	High	Low	Close	Volume	Dividends	Stock Splits
0	2007-02-02	21.500963	21.500963	21.500963	21.500963	0	0.0	0.0
1	2007-02-05	21.500963	21.500963	21.500963	21.500963	0	0.0	0.0
2	2007-02-06	21.580568	21.580568	21.580568	21.580568	900	0.0	0.0
3	2007-02-07	21.698502	21.698502	21.698502	21.698502	1200	0.0	0.0
4	2007-02-08	21.562882	21.562882	21.539297	21.539297	45000	0.0	0.0
...	...	...	...	...	...	...	...	...
3573	2021-04-14	127.440002	127.440002	125.639999	125.639999	1700	0.0	0.0
3574	2021-04-15	127.470001	127.489998	126.919998	127.489998	1300	0.0	0.0
3575	2021-04-16	128.000000	128.429993	127.599998	128.130005	2000	0.0	0.0
3576	2021-04-19	126.570000	126.720001	126.099998	126.720001	1600	0.0	0.0
3577	2021-04-20	126.059998	126.959999	123.839996	124.690002	1000	0.0	0.0

3578 rows × 8 columns

Data Description

It contains a target feature (label) that have 3 levels, decrease "1", neutral "2", increase "3" and 7 descriptive features in which 5 of it (f1, f2, f3, f4, f5) consist of minima and maxima that forms a double top stock chart pattern, 1 is the date or indexes for start and end of the pattern lastly, industry of the stock where the pattern occur.

However, before arriving at this dataset, web scraping of stocks historical dataset for various industries at https://finance.yahoo.com/ are performed (see above table), then closing price from it was utilize. Moreover, minima and maxima of time series dataset for every stock were determined. Next, detection of double top stock chart pattern by setting threshold for the minima and maxima that forms the pattern, and lastly, determine its corresponding target feature by comparing the highest maxima or lowest minima within the pattern and the maximum or minimum prices within the next 10 days after the pattern is observed. Target is labeled increase "2" if the maximum price within the next 10 days is greater than the highest maxima within the pattern, decrease "0" if the minimum price within the next 10 days is lesser than the lowest minima within the pattern, neutral "0" if neither or both happens.



	increment	ema	window	f1	f2	f3	f4	f5	fw_ret_1	fw_ret_2	fw_ret_3	label	industry	date
0	1	3	3	7.121051	7.353892	7.101648	7.353892	7.101648	0.017759	0.027322	0.028689	2	Foreign Regional Banks	(1675, 1689)
1	1	3	10	14.860000	16.240000	14.870000	16.260000	14.900000	0.019463	0.016779	0.048993	3	Gold	(4045, 4067)
2	1	3	3	2.744415	2.810281	2.744415	2.810281	2.744415	0.024000	0.000000	0.024000	1	Money Center Banks	(145, 151)
3	1	3	3	7.713200	7.817133	7.720625	7.787437	7.750320	0.005747	0.000000	0.002874	1	Money Center Banks	(3532, 3545)
4	1	3	3	7.141579	7.186120	7.141579	7.163850	7.126730	0.005209	0.002084	0.004167	3	Money Center Banks	(3628, 3644)
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1437	1	3	3	0.149173	0.149966	0.149173	0.149966	0.149173	0.005319	0.005319	0.005319	3	Rubber & Plastics	(4257, 4263)
1438	1	3	3	0.210344	0.215019	0.210344	0.215019	0.210344	0.022222	0.000000	0.022222	3	Rubber & Plastics	(4788, 4796)
1439	1	10	3	0.062426	0.065054	0.062426	0.065054	0.062426	0.000000	0.000000	0.021052	3	Rubber & Plastics	(3477, 3496)
1440	1	3	3	0.949174	0.963081	0.949174	0.966558	0.949174	-0.010990	-0.010990	0.000000	1	Foreign Regional Banks	(219, 228)
1441	1	3	3	292.901337	303.040253	294.027863	301.913696	294.027863	0.022988	0.057471	0.045977	3	Information Technology Services	(4027, 4039)

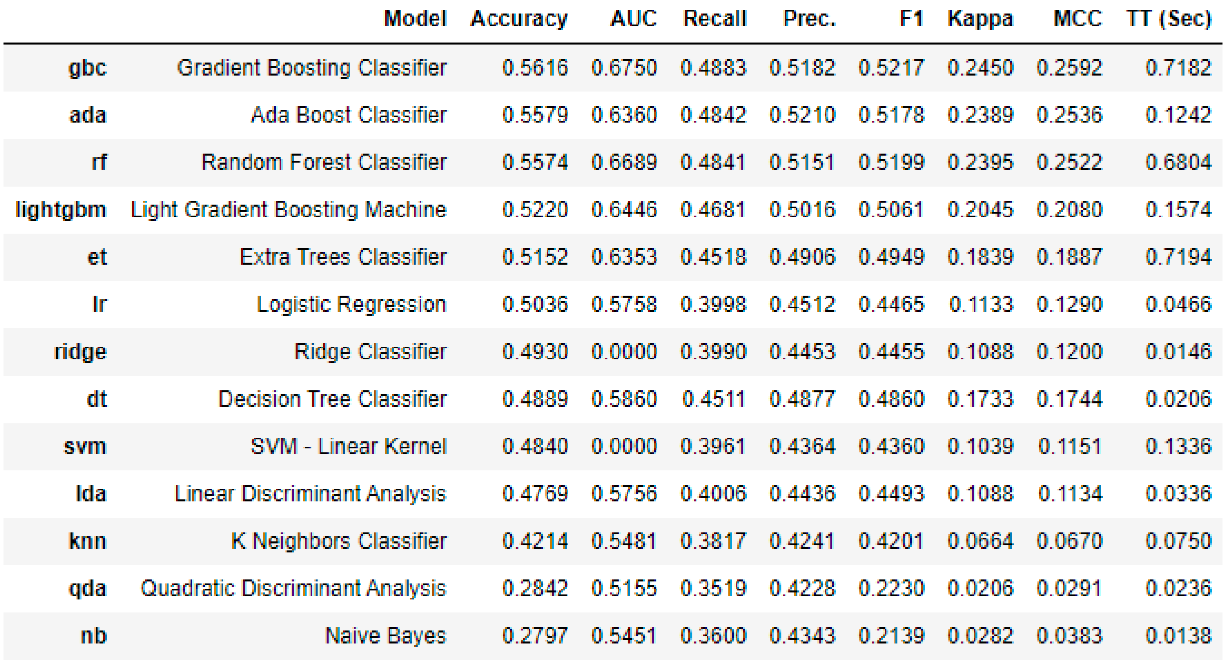
Data Exploration

In here, we have done feature engineer. Created 3 additional descriptive features, which are the absolute differences between f1 and f3, also between f3 and f5, then we took the average of the values from f1 to f5. These features were named d1, d2, and averages respectively. These additional features will help increase the predictive accuracy of the model built later on.

Model selection

The dataset we have consists of quantitative features and a single categorical feature which is the target feature. The target feature contains multiple levels. Therefore, we will fit several models that are multiclass to our dataset, in particular multiclass KNN, multinomial logistic regression, multiclass SVM etc. to find the best predictive model of this project. Fortunately, we can fit these models to our dataset simultaneously using pycaret machine learning library.

Moreover, pycaret also automatically normalized then splits dataset if specified, do one hat encoding for nominal features, perform cross validation, tuned hyperparameter for every model etc.. In our case, we specify the normalization method as minmax scaler then split it to 80% training set and 20% testing set, then let it perform 5 fold cross validation with 10 repetition.



	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
gbc	Gradient Boosting Classifier	0.5616	0.6750	0.4883	0.5182	0.5217	0.2450	0.2592	0.7182
ada	Ada Boost Classifier	0.5579	0.6360	0.4842	0.5210	0.5178	0.2389	0.2536	0.1242
rf	Random Forest Classifier	0.5574	0.6689	0.4841	0.5151	0.5199	0.2395	0.2522	0.6804
lightgbm	Light Gradient Boosting Machine	0.5220	0.6446	0.4681	0.5016	0.5061	0.2045	0.2080	0.1574
et	Extra Trees Classifier	0.5152	0.6353	0.4518	0.4906	0.4949	0.1839	0.1887	0.7194
lr	Logistic Regression	0.5036	0.5758	0.3998	0.4512	0.4465	0.1133	0.1290	0.0466
ridge	Ridge Classifier	0.4930	0.0000	0.3990	0.4453	0.4455	0.1088	0.1200	0.0146
dt	Decision Tree Classifier	0.4889	0.5860	0.4511	0.4877	0.4860	0.1733	0.1744	0.0206
svm	SVM - Linear Kernel	0.4840	0.0000	0.3961	0.4364	0.4360	0.1039	0.1151	0.1336
lda	Linear Discriminant Analysis	0.4769	0.5756	0.4006	0.4436	0.4493	0.1088	0.1134	0.0336
knn	K Neighbors Classifier	0.4214	0.5481	0.3817	0.4241	0.4201	0.0664	0.0670	0.0750
qda	Quadratic Discriminant Analysis	0.2842	0.5155	0.3519	0.4228	0.2230	0.0206	0.0291	0.0236
nb	Naive Bayes	0.2797	0.5451	0.3600	0.4343	0.2139	0.0282	0.0383	0.0138

Since this project aims to predict stock prices given double top stock chart pattern for trading purposes. Both false negative and false positive are crucial. That is, in the case of false negative, if we predict a decrease in price after the pattern then decided to sale the stocks because we won't get any more profit however, it actually increases, then we just lose the opportunity to earn more.

On the other hand, in the case of false positive, if we predict an increase in price after the pattern then decided to buy stocks so we can sale it during the increase however, it actually decreases, then we just lose some money. Also, the target feature has imbalanced classes. Therefore, we will emphasize the F1 score over accuracy and any other performance metrics for this project to measure the predictive power of the model built.

The above output shows the list of predictive performance for several models after we fit it to our data. Notice that the model that produces the highest F1 score is the Gradient descent classifier, a sequential ensemble approach, with 0.5217 score. This imply that the model we built can predict the target feature given f1, f2, f3, f4, f5, dateF, dateE, and industry with 52.17% accuracy.

Moreover, we will further interpret other performance metrics but this is just for better understanding of the predictive model performance. After all, we already interpreted F1 score, the appropriate performance metric for this project.

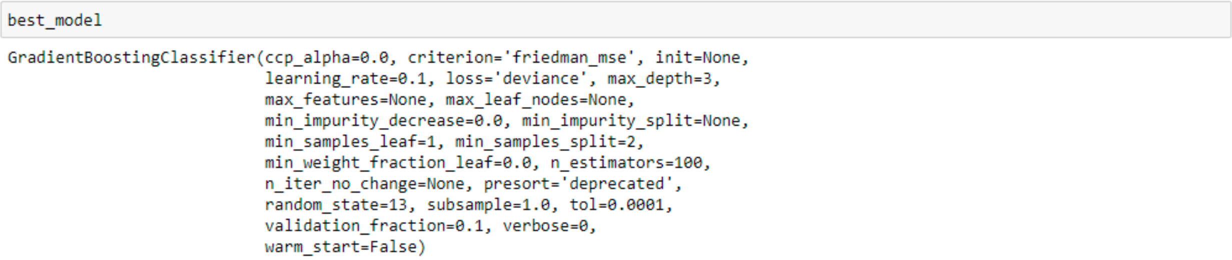
Now, notice that the model that produces the highest accuracy is still Gradient boosting classifier with value 0.5616, followed by Ada boost classifier with value 0.5579, both are sequential ensemble approach. These implies that the models we built can predict the target feature given f1, f2, f3, f4, f5, dateF, dateE, and industry with 56.16% and 55.79% accuracy respectively.

Ada Boost Classifier also produces the highest Precision with value 0.5210. This suggest that for the number of predictions that the model made, 52.19% of it are correct. Whereas, Gradient boosting classifier produces the highest AUC and Recall (Sensitivity) with values 0.6750 and 0.4883 respectively. AUC value suggest that the model have 67.50% accuracy to predict the target feature that will or will not occur. And recall value imply that, for the target feature that should occur, we predicted 48.83% of it.

Conclusion and Recommendation

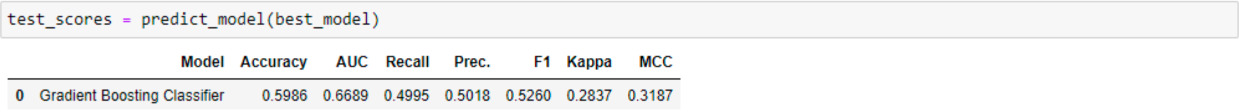
The dataset created consists of target feature with 3 levels (decrease/1, neutral/2, increase/3) and 7 descriptive features, in which 5 of them (f1, f2, f3, f4, f5) forms a double stock chart pattern and the other two are indexes of the start and end of the pattern. After we tried to fit several multiclass models on this dataset, we found out that its accuracy is less than 50%. Thus, we performed feature engineer by taking the absolute difference between f1 and f3, f3 and f5, and get the sum of f1 to f5. These 3 additional descriptive features actually helped the predictive model we built to increase its accuracy from below 50% to a little bit higher than 50%. The predictive model that produces this result is the gradient boosting classifier, a sequential ensemble approach that gives an F1 score of 51.19%. This only imply that the predictive model built can predict the movement of the stock prices given double top stock chart pattern with 51.19% accuracy.

Evaluate predictive accuracy of the model built



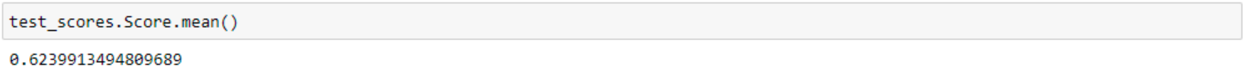
```
best_model
```

```
GradientBoostingClassifier(ccp_alpha=0.0, criterion='friedman_mse', init=None,
                           learning_rate=0.1, loss='deviance', max_depth=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=100,
                           n_iter_no_change=None, presort='deprecated',
                           random_state=13, subsample=1.0, tol=0.0001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
```



```
test_scores = predict_model(best_model)
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	Gradient Boosting Classifier	0.5986	0.6689	0.4995	0.5018	0.5260	0.2837	0.3187



```
test_scores.Score.mean()
```

```
0.6239913494809689
```

The predictive model built when use for test set, gives us a predictive accuracy of 62.40%. This suggest that we predicted the movement of stock prices given new queries of double top stock chart pattern (test set) with 62.40% accuracy.