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Finance Machine Learning: Meta-Labeling Application

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ABSTRACT
Meta-Labeling is a technique that uses the predictions of a classifier to label the data to improve the performance of the classifier. In this work, it has been applied the Meta-Labeling technique to the problem of predicting the direction of the next day's return of a stock, and evaluate if you take or pass the bet. It has been compared the results on three different labeling techniques. The results show that the Meta-Labeling process has improved the precision rate, which is the objective of the process. However, the recall rate has decreased. On backtesting, the strategy with the Meta-Labeling process outperformed the stock for the triple barrier method. Despite that the others methods has not shown significant difference between each other on the machine learning metrics. In addition, the bollinger bands and trend following has presented same results on the backtesting process.

INDEX TERMS data processing, data sampling, machine learning, labeling

I. INTRODUCTION

RECENT researches started to use artificial intelligence and machine learning techniques in asset pricing and market trend forecasting to increase investment profitability [1]. Nevertheless, the use of machine learning techniques in financial markets is still a challenge, due to variables complexity and noise signals, and strategies have been developed to deal with this problem, such as the use of labeling techniques, which are used to identify the trading opportunities in the data [2].

In addition to the labeling techniques, the use of meta-labeling techniques is also an additional resource to improve the performance of machine learning models. A primary model is fed from the labeled data with a signal to buy or sell a position. Nonetheless, this model is not perfect, and it can generate false signals. To overcome this problem, it is possible to apply a meta-labeling step, which is a secondary model that filters the primary model signals. Moreover, this technique could include signals from exogenous sources [3].

Labeling techniques as trend following, mean reversion add information to the data. However, these techniques depends on a proper evaluation of the data, which is a challenge in financial markets [4]. To reduce the noise in the data, other aggregate methods could be applied, instead the traditional time bars. With the combination of these techniques, could generate relevant inputs to improve the performance of the machine learning models, in especial, the meta-labeling techniques.

Meta-labeling is a technique that uses the output of a primary model, in which, seeks to maximize the model's recall (capturing correctly all positive trading opportunities) as well as its precision (minimizing the false positive rate) and generate a new label for the data to be used in a secondary model [5]. This technique has opportunities to explore the practical applications due to a limited volume of researches on this topic [6] [7] [8] [9].

This work aims to analyze the chronological sampling statistical characteristics, the performance of some labeling techniques in the stock market, and investigate the potential benefit of meta-learning techniques when combined with these techniques. The remainder of this paper is organized as follows. Section 2 presents the fundamentals on the data processing for featuring engineering and machine learning evaluation. Section 3 describes the methodology used in this work. Section 4 presents the results and discussion. Finally, Section 5 presents the conclusions and future works.

II. FUNDAMENTALS

The fundamental idea of this work is to apply machine learning technique to predict the direction of the next tick in the market. To elaborate this pipeline, some discussions over the data processing are necessary, which includes the discussion over the chronological sampling, the labeling techniques, and the concepts on meta-labeling steps.

A. CHRONOLOGICAL SAMPLING

Although the labeling techniques aggregate information to the data, some pitfall can occur depending on the technique on chronological sampling [4]. Normally, the time bars are, nonetheless, market do don process information at a constant interval [5]. Moreover, time bars generally exhibit poor statistical properties. To mitigate it, it can be applied some other strategy, as Dollar bars, and Volume bars, which tend to exhibit more stable sampling and its returns are more normally distributed.

The volume bars are generated by counting the number of shares traded in a given time interval. The dollar bars are generated by counting the total dollar amount of shares traded in a given dollar quantity.

The aggregation on bars have some advantages, such as the reduction of the noise on the data, and the reduction of the computational cost. However, it can also have some disadvantages, such as the loss of information, and the loss of the chronological order [10].

Moreover, the bet on the price move normally comes after some event as such as a structural break, an extracted signal, or microstructural phenomenal. Therefore, one useful event-based sampling method consists of sampling the data after detect a shift in the mean value of a measured quantity away from a target value, which is called the CUSUM filter, a quality-control method [10].

Consider IID observations $\{y_t\}_{t=1,\ldots,T}$ arising from a locally stationary process. We define the cumulative sums:

$$S_t = \max\{0, S_{t-1} + y_t - E_{t-1}[y_t]\} \tag{1}$$

with boundary condition $S_0 = 0$. This procedure would recommend an action at the first t satisfying $S_t \geq h$, for some threshold h (the filter size) [10]. The filter is set up to identify a sequence of upside divergences from any reset level zero. In particular, the threshold is activated when

$$S_t \geq h \Leftrightarrow \exists \tau \in [1, t] \mid \sum_{i=\tau}^{t} (y_i - \mathrm{E}_{i-1}[y_t]) \geq h \tag{2}$$

This concept of run-ups can be extended to include run-downs, giving us a symmetric CUSUM filter:

$$\begin{gathered} S_t^+ = \max\left\{0, S_{t-1}^+ + y_t - \mathrm{E}_{t-1}[y_t]\right\}, S_0^+ = 0 \\ S_t^- = \min\left\{0, S_{t-1}^- + y_t - \mathrm{E}_{t-1}[y_t]\right\}, S_0^- = 0 \\ S_t = \max\left\{S_t^+, -S_t^-\right\} \end{gathered} \tag{3}$$

The CUSUM sample a bar t if and only if $S_t \geq h$, at which point S_t is reset [10]. Therefore, the CUSUM filter is a method that can be used to trigger and sample the data, and it is a method that can be used to detect some microstructural phenomenal in the data.

B. TRIPLE BARRIER LABELING

Labeling in Finance generally labels observation using the fixed-time horizon method. However, this method is not suitable for all cases, due to the fact of time bars not exhibiting good statistical properties, and the fact that the same threshold is applied regardless of the observed volatility. An approach to mitigate this problem is the triple barrier labeling, which is a method that labels observations based on the first barrier reached [10].

For the fixed horizontal method, considers X as a feature matrix with m rows, $X_{i i=1,\cdots,m}$, drawn from some bars with index $t = 1, \cdots, T$, where $m \leq T$. The triple barrier method labels the i-th observation as y_i according to the following rule:

$$y_i = \begin{cases} 1 & \text{if } R_{t_{i,0}, t_{i,0+h}} > v \\ 0 & \text{if } |R_{t_{i,0}, t_{i,0+h}}| \leq v \\ -1 & \text{if } R_{t_{i,0}, t_{i,0+h}} < -v \end{cases} \tag{4}$$

where $R_{t_{i,0}, t_{i,0+h}}$ is the return from the observation i, which $R_{t_{i,0}, t_{i,0+h}} = \frac{P_{t_{i,0+h}} - P_{t_{i,0}}}{P_{t_{i,0}}}$, where $P_{t_{i,0}}$ is the price at time $t_{i,0}$, and v is the predefined threshold constant.

On three barriers, each of which reflects a particular aspect of the reality of investing in the markets. The first upper horizontal barrier is defined by the "profit-taking" threshold. The second lower horizontal barrier is defined by the stop-loss threshold. These two barriers are a dynamic function of the estimated volatility. The third, vertical barrier acts as an expiration limit. It is defined in terms of the number of bars elapsed since the position was taken.

The figure 1 illustrates the triple barrier labeling method.

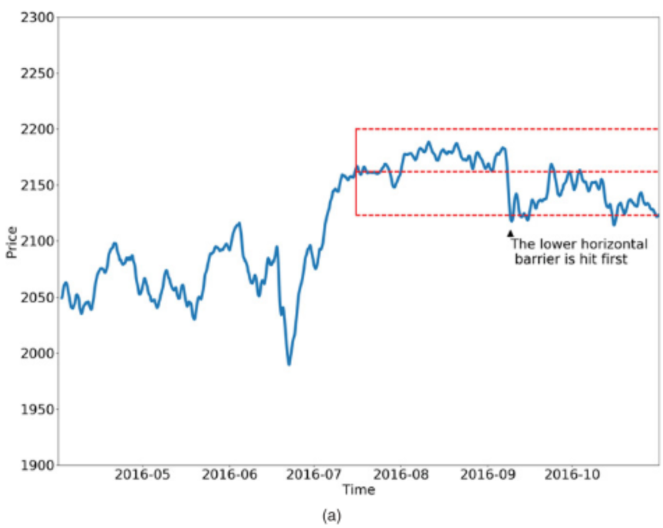

FIGURE 1. Triple barrier labeling method with lower horizontal hit [3].

In chart (a) we can see that the lower horizontal barrier is first reached, a -1 value is returned. In chart (b) the path never reaches the horizontal and triggers a 0 label when the vertical barrier is reached [3].

(b)

FIGURE 2. **Triple barrier labeling method with vertical horizontal hit [3].**

C. TREND FOLLOWING

The trend following strategy concerns the idea of two moving averages, with different time windows, and when the short moving average crosses the long moving average, it is a signal to buy, and when the short moving average crosses the long moving average, it is a signal to sell.

For example, a slow 200 days moving average and a fast 50 days moving average are used. When the fast moving average crosses the slow moving average from below, it is a signal (1) of buying the position, and when the fast moving average crosses the slow moving average from above, it is a signal of (-1) of selling the position. The figure 3 illustrates the trend following strategy.

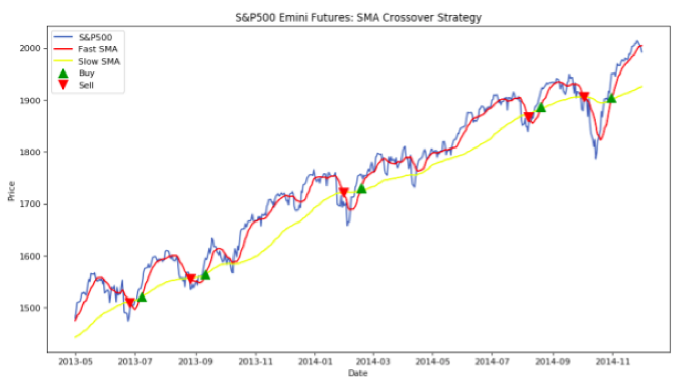

FIGURE 3. **Trend following strategy [3]**

where the red signals are to close the position, and the green signals are to open the position.

D. MEAN REVERSION

The Bollinger Bands strategy is a mean-reversion strategy that uses the Bollinger Bands indicator to generate signals. The Bollinger Bands indicator consists of a middle smoothing mean average (SMA) line and two outer bands, which are the standard deviation of the SMA times a threshold. The strategy is based on the assumption that the price will return to the mean [3].

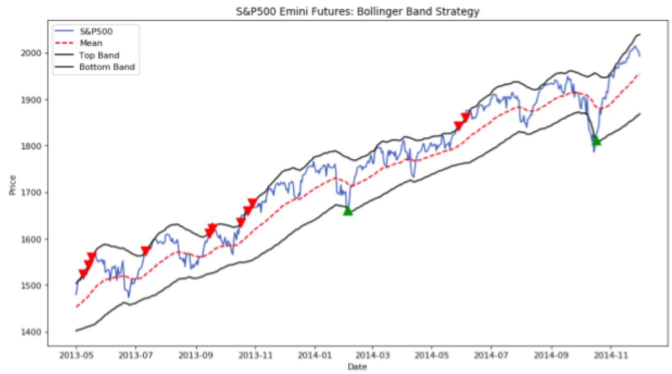

FIGURE 4. **Bollinger Bands strategy [3]**

The signals are long and short, long when the price touches the lower band and short when the price touches the upper band.

E. META-LABELING

At first, meta-labeling on finance has been proposed by Marcos Lopez de Prado [10], which considers a primary model signal, in addition to these primary model features to predict the label with maximum precision after a minimum recall evaluation [3]. As definition, although the proximity with ensemble learning, it is not a pure ensemble learning method, because it does not combine the primary model with the secondary model to identify the best machine learning fit model. Actually, it uses the secondary model to filter the primary model signals [11].

The overall process of meta-labeling is illustrated in the figure 5.

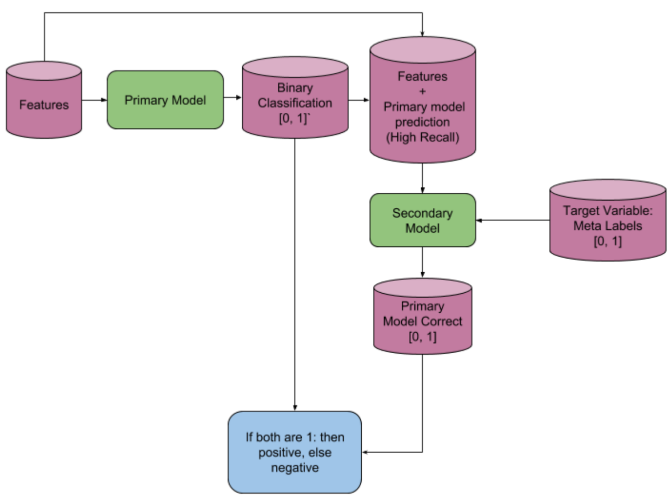

FIGURE 5. **Meta-labeling process [3]**

Therefore, the meta-labeling process is a two-step process. The first step is to train a primary model, which is a model that predicts the label, with exogenous signals or not. The second step is to train a secondary model, which is a model that filters the primary model signals.

On the first step, an evaluation on Receiver Operating Characteristic (ROC) curve is performed to find the best threshold to filter the primary model signals with maximum acceptable recall. Then, the secondary model is trained with the prediction of the primary model to ensure that the precision of the primary model is maximized and as consequence maximize the f-1 score.

III. METHODOLOGY

The data used in this work are the tick prices of IBM stocks for comprehension purpose, due to the data availability for this study. The analysis period is spread over a period of 03-01-2000 to 27/03/2023. On figure 6, it is possible to see the IBM adjusted stock price evolution over the period of analysis.

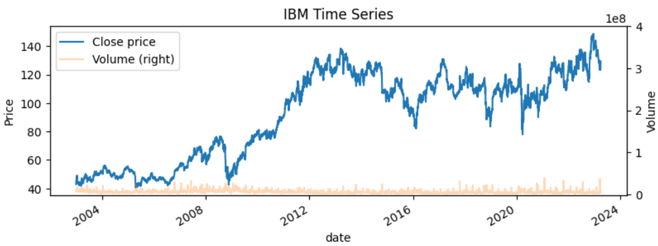

FIGURE 6. IBM stock price evolution.

The features consist of the opening price, closing price, highest price, lowest price, adjusted close, volume (OHLCV) and technical analysis indicators selected from the labeling methods after the CUSUM events. It is performed three labeling methods for comparison: the triple barrier method (TBM), and the combination of TBM with the mean-reversion method and the trend following method, which are considered as exogeounous information added to the data.

The OHLCV are evaluated in terms of their returns distribution, with an evaluation on the information frequency depending on the aggregation as dollar bars, volume bars and time bars, with an aggregation of 10^9 dollars, 10^7 shares and 3 days, respectively. On CUSUM events, it was considered a threshold of one standard deviation of the exponantial weighted mean (EWM) of 50 days of daily return volatilty, the percentage change of the price.

The TBM considers 5 days for vertical barrier, one standard deviation for upper and lower barrier, in addition of minimum daily return of 0.5%. The mean-reversion method considers two standard deviations for EWM of 50 days. The trend following method considers the fast series as 50 days EWM and the slow moving average as 200 days EWM.

The time series is divided into two sets: 80% for training and 20% for testing. On the training set, it is performed a blocked k-fold cross-validation. The blocked k-fold cross-validation, is a technique to evaluate the performance of a model, which is similar to the cross-validation, with the intention of avoiding the leakage of information due to the time series nature of the data. The figure shows the blocked k-fold cross-validation technique [12].

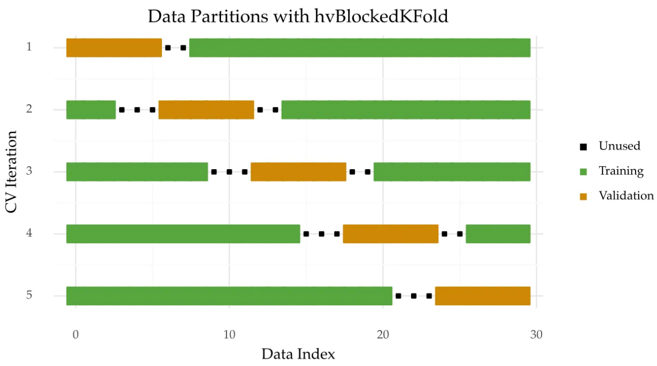

FIGURE 7. Blocked k-fold cross-validation [12].

The cross-validation gap k-fold is performed by splitting the data into k folds, where $k - b - a$ folds are used for training and a folds after the testing fold are blocked, and b folds before the testing fold are blocked. This process is repeated k times, where each fold is used for testing once [12]. For this work, $k = 13$, $a = 1$ and $b = 2$.

The primary and secondary models are ensemble machine learning, with a bagging technique, which is a random forest with 1000 estimators and 2 depth levels and cross-entropy loss function. The cross-entropy loss function is used to measure the performance of the classification model, which are for the primary model, the target is buy or sell decision, and for the secondary model, the take or pass the bet.

Python language is used to create the prediction system. The performance of the system is measured by its accuracy, precision and f1-score.

For the financial analysis of backtesting, the model is trainded with train set and it is performed a validation on test set. With the resutls, calculations are performed to obtain the annualized financial metrics, the mean return, mean standard deviation, Sharpe ratio, maximum drawdown for the test set considering just long strategy. In addition, the results are compared with a market index as S&P 500, to evaluate the performance of the system.

IV. RESULTS AND DISCUSSION

On the evaluation of the data, it is performed an information frequency analysis with an aggregation dollars, volume and time. The figure 8 shows the aggregated data on months for each aggregation technique with a moving average of 15 days.

It is observed on that the volume aggretation vary more than the others, nonetheless, the dollar aggretation tends to follow the volume. Therefore, it is possible to conclude information quantity per period is note the same on each aggregation technique, which induce to a different statistical

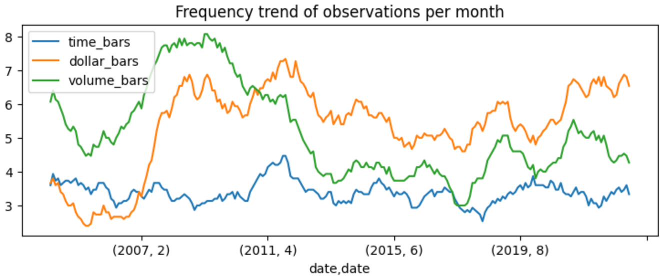

FIGURE 8. **Frequency of the data on each aggregation technique.**

information on the retuns of the stock. On the figure 9, the volatility of the data is evaluated.

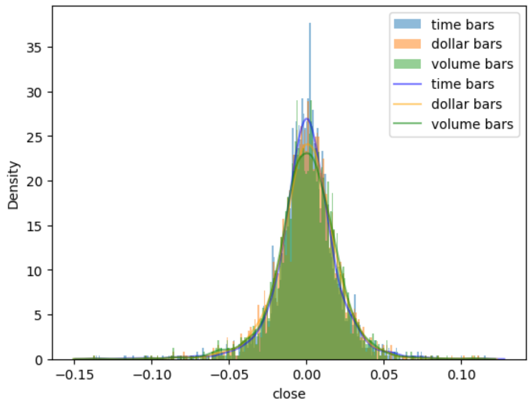

FIGURE 9. **Density of the data on each aggregation technique.**

The time aggregation shows a higher concentration of the returns, meanwhile, the dollar and volume are more normally distributed. Despite the concentration in the mean, all of them shows a long tail on both sides, which indicates a high volatility on the returns.

Due to the volume of data on the stock available, it was preferred to use the raw data with time bars. Therefore, on the labeling process, the data is labeled with the raw data on all the time series. For the trend following strategy, which considers the crossing of a fast and slow moving time series the labeling process, the resutl is observed on the figure 10.

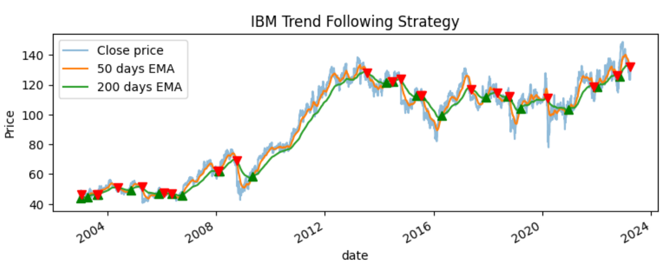

FIGURE 10. **Trend Following labeling.**

The buy or sell action is considered on the shift of the label, therefore, when the signal for appears, the side of the investment could be considered to shift, given the option a long and short position. These positions with the fast and slow series are included on the features for the meta-labeling process.

For the mean reversion strategy, the labeling is observed on the figure 11, which is based on the Bollinger Bands indicator, when touches the bands, the signal is considered.

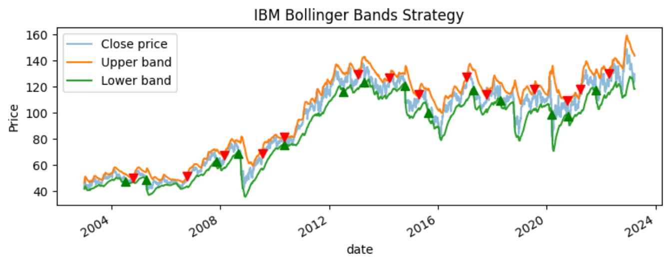

FIGURE 11. **Bollinger Bands labeling.**

The side for long and short positions on this strategy could be also considered as a buy and sell signal, and orienting the strategy for just one side, only long or only short. Moreover, the bands, and the side are included on the features for the meta-labeling process.

These two strategies are combined with the the triple barrier method, which sample the data from a trigger upto touch on a barrier, which could be a profit taking or stop loss. The trigger event is the CUSUM, which from each point, the data is sampled upto the barrier. The figure 12 shows the trigger events for the CUSUM method.

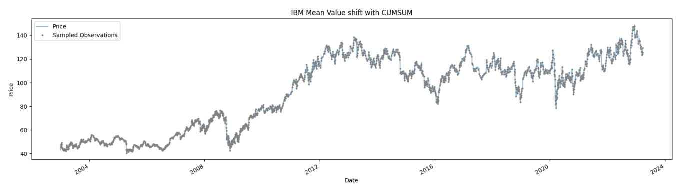

FIGURE 12. **CUSUM events.**

With the TBM, the data is sampled and it is obtainded the side and size of the bet. The side considers the touch on the barriers, in which, the vertical barrier touch returns positive if has a profit, and negative if is a loss. On vertical barrier, the size of return is the value when it has the touch, meanwhile, the horizontal barriers touch returns the size of the return given the limit value of the barrier. The size of the bet is the return value between the trigger and the barrier touch, which actually means that the size is an all win acceptance on the bet.

For understanding the meta labeling process, it is performed an evaluation on the TBM, and no additional features included, and considering the test position 8 on the k-fold. As consequence gap consideration on the data on the test position, the positions 6,7 and 9 are blocked for the training process.

With the features of OHLCV, and labels of the side from the TBM, the data is trained with a primary model of random forest classifier. It is plot a ROC curve for the model, which is observed on the figure 13.

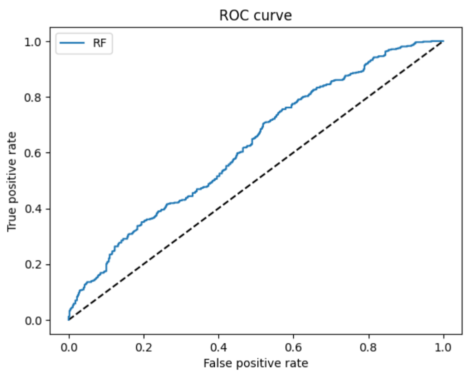

FIGURE 13. ROC curve for the primary model.

The accuracy is 0.55, which means that the model is not good for the classification. However, primary model is used to maximize the positive rate, therefore a threshold is applied to the model which maximize the recall. The figure 14 shows the confusion matrix for the model, considering this threshold on the testing fold.

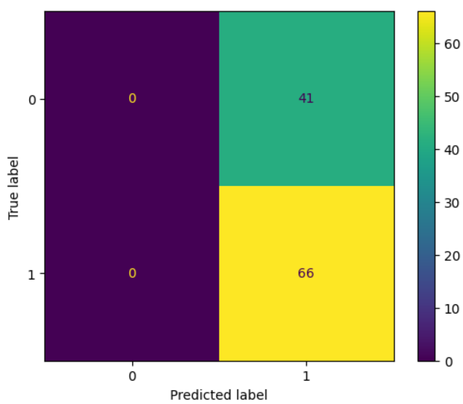

FIGURE 14. Confusion matrix for the primary model.

The confusion matrix shows that all the data is classified as positive, which means that the model is not good for the classification, which, ensures that all positive labels are correclty labeled. After performing the meta-labeling process, by concatenating the primary model result with the features and training a secondary model, on the same targets, the confusion matrix on the testing fold is observed on the figure 15.

The confusion matrix shows the improvement on the classification, with a precision rate passing from 0.62 to 0.68, and a recall rate passing from 1.0 to 0.32. The objective of the meta-labeling process is to improve the precision rate, which is achieved with the secondary model.

Performing the cross validation among the three strategies (TBM, TBM+bollinger bands, and TBM+trend following) and plotting the box plot comparing the primary model with the secondary model for the testing fold, the figures 16, 17, 18 and 19 are obtained.

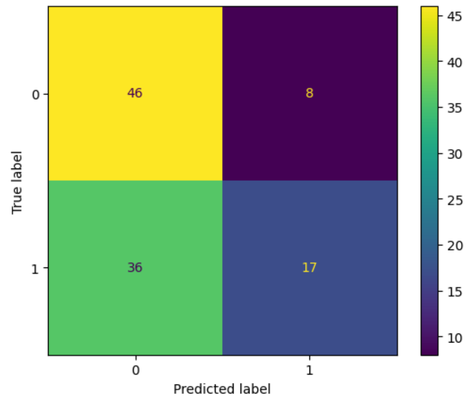

FIGURE 15. Confusion matrix for the meta-labeling model.

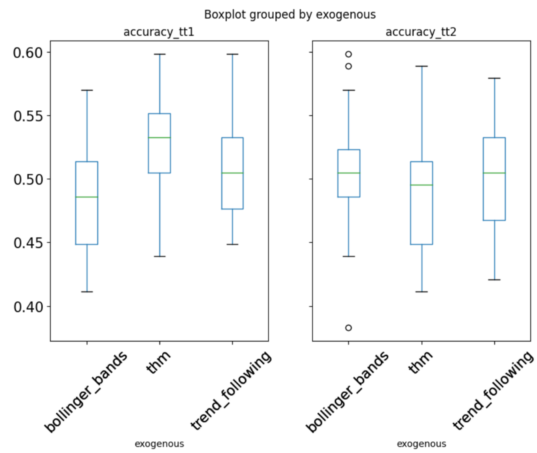

FIGURE 16. Accuracy for the primary and secondary model.

Evaluating the box plots, it is observed no significant difference between the strategies, except that the bollinger bands has presenter a higher deviation on the metrics with many outliers. Other observation is that all the models have decreased the recall and f1 score mean in comparison from the primary model to the secondary model, which means that the meta-labeling process has improved the precision rate.

To evaluate the performance of the models, it is performed a backtesting with along only strategy, which is observed on the figure 20.

The main observations of the figure 20 are that the bollinger bands series is has shown exactly same results as the trend following. All strategies out perform the IBM series, in spite of under performing the market index. The horizontal lines on the series means periods of no trading, as consequence of long only strategy.

The annualized financial metrics of the strategies are observed on the table 1.

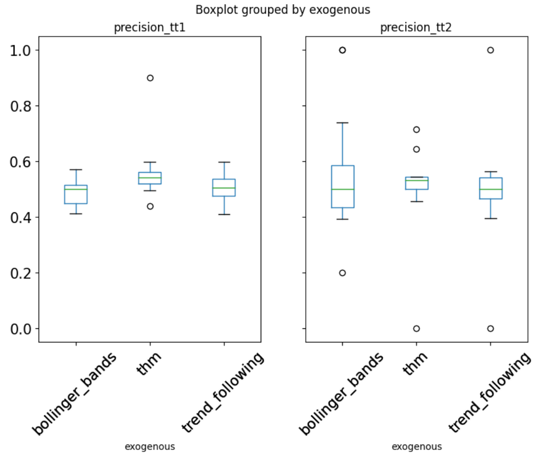

FIGURE 17. Precision for the primary and secondary model.

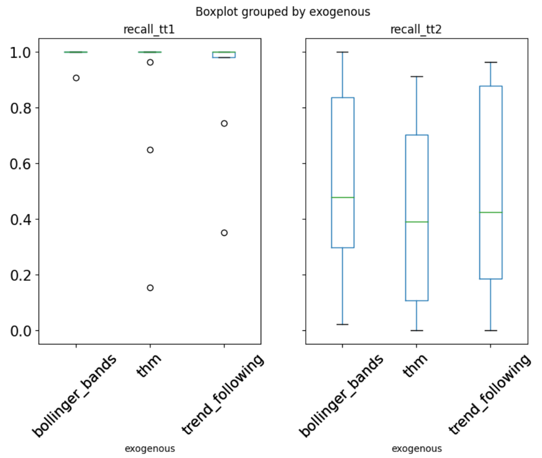

FIGURE 18. Recall for the primary and secondary model.

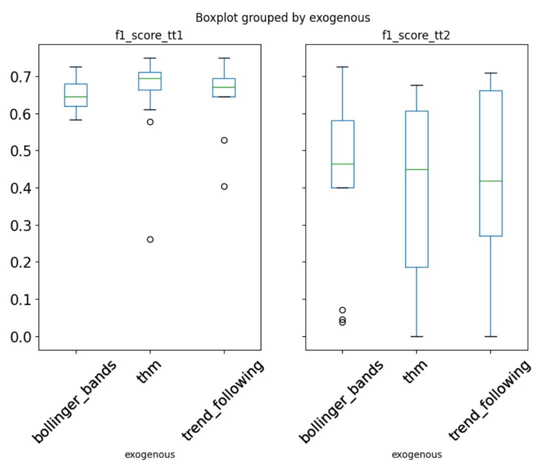

FIGURE 19. F1 score for the primary and secondary model.

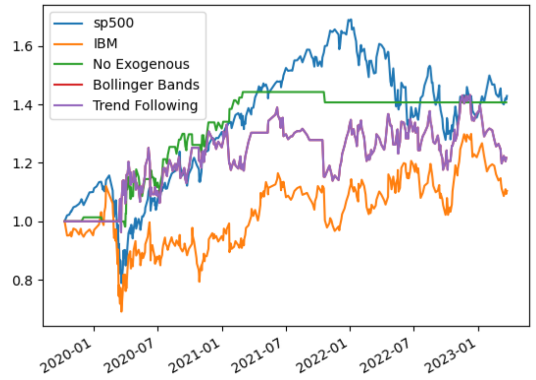

FIGURE 20. Backtesting process.

TABLE 1. Financial metrics for each strategies.

	TBM	Bollinger Bands	Trend Following
mean return	0.017	0.013	0.013
risk	0.172	0.373	0.373
sharpe ratio	1.529	0.570	0.570
max drawdown	-0.078	-0.180	-0.180

From the table, it is observed that only TBM outperform others on the sharpe ration, however, it is possible to infer that it is consequence of long periods of not trading, which reduces significantly the risk. Nonetheless, the strategy has shown the lower max drawdown, which means it has better decisions on the trading process when compared to the others.

V. CONCLUSION

Meta-Labeling is a technique that uses the predictions of a classifier to label the data to improve the performance of the classifier. In this work, it has been applied the Meta-Labeling technique to the problem of predicting the direction of the next day's return of the IBM stock, and evaluate if you take or pass the bet. The results show that the Meta-Labeling process has improved the precision rate, which is the objective of the process. However, the recall rate has decreased, which means that the model is not good for the classification.

On the backtesting process, it is observed that the strategy with the Meta-Labeling process outperformed the stock for the TBM. Despite that the others methods has not shown significant difference between each other on the machine learning metrics. In addition, the bollinger bands and trend following has presented same results on the backtesting process.

Moreover, the analysis on the aggregation of time series, and volume of information has shown the frequency of information can change according to the technique aggregation of the time series. Dollar and volume aggregation has shown more normality distribution than the common time bars.

For future researches, the methods could be improved by using other features as market data, others machine learning models, or others aggregation techniques, and others labeling strategies.

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