Enhancing stock price prediction with time series similarity

Lior Sidi
Software and information system engineering
Israel, Be'er Sheva
liorsid@post.bgu.ac.il

ABSTRACT

Stock market prediction with forecasting algorithms is very common these days, most of current forecasting algorithms train only on data collected on a certain stock. Traders and investors using information on similar and non-similar stocks helps investors to improve trading and hedge portfolios. In this paper, we enrich the data of the predictor with similar stocks or patterns found as a professional trader would have done. During this research, we optimize a baseline model and came up with the following model configurations: gradient boosting regressor trained on 10 size time windows of the price rate of change with Symbolic Aggregate approXimation (SAX) transformation. Then we enhance the optimized baseline with similar stocks instances for training. We test different similarities functions for selecting the top stocks for enhancing the baseline model. We found co-integration based similarity to have the best improvement on baseline model. Finally, we compare the enhanced model with the baseline model that train only on the target stock and a random enhanced model that add random stocks for training. We evaluate the models with seven S&P stocks from different industries on five fold over five years period. The enhanced model had significantly better results with 0.55 mean accuracy and 19.782 mean profit compare to the baseline and the random enhanced model with 0.52 and 0.54 mean accuracy, 6.66 and 15.02 mean profit (respectively)

KEYWORDS

ACM proceedings, LaTeX, text tagging

ACM Reference Format:
Lior Sidi. 2018. Enhancing stock price prediction with time series similarity. In *Proceedings of* . ACM, New York, NY, USA, Article 4, 14 pages. https://doi.org/

1 INTRODUCTION

Prediction of stock price or any financial equity is well-investigated subject for many researchers [10], traders and hedge funds. In an entire algo-trading framework, the stock prediction component collects information from different sources such as the market trading and news, the components goal is to feed the strategy component with feed on the next prices values. The strategy component is responsible to digest the information regarding the trader current position, risk parameters, losses and the price prediction to set actions for buying or selling certain finance equity.

Similarity analysis on time series data in the finance domain is used widely to cluster different equities into domains for manual exploration [20] [1] but also to identify correlated stocks for trading strategy [2] and for stock recommendation [17].

In this research, we investigate if a prediction model improves by adding similar stock during training and in prediction. Our two main research questions are "is enhancement of similar stock improve a model performance" and "which similarity configuration improve the model the most?"

In order to meet these questions we prepared a back-testing framework where we trained and optimized a prediction model with different time series processing, segmentation and modeling. In the Methods chapter, we describe the back-testing pipeline where we also explaining the different similarity function we used for finding the top stocks. In the Experiment setup chapter, we explain how we optimize and evaluate the back-testing process on S&P stocks. Finally, in the Experiment results chapter we compare between models that trained on similar stocks with models that trained only on the target stock or random stocks. The results show a clear advantage of models train on similar stocks with short horizon period (the next day) with mean profit of 19.87 and mean accuracy of 0.55.

2 RELATED WORK

In this research, we aim to improve stock prediction with a hybrid approach that combine stock similarity and classification. This section starts with an overview on the stock data representation and evaluation. Then we will review different appliances of stock similarities and clustering techniques. In the next method section, we will explain in detailed the methods that we will implement and evaluate in this paper.

2.1 Stock time series overview

Cavalcante et al. describes a two parts framework for financial trading forecasting; the first part deals with conventional forecasting aspects such as data preparation, algorithm choosing, model training and accuracy evaluation. The second part is responsible for financial forecasting aspects such as trading strategy and then profit evaluation.

In this section, we will explain the basic methodologies for stock time series forecasting.

2.1.1 Stock time series data

. A standard financial data is usually consist with aggregated data of the stock price for a certain period, the aggregations are usually high price, low price, opening price, closing price, trade volume, trading amount. Many papers also extract known technical indicators to identify trends and momentum in the stock price [21]. Table 1 cover the most important technical indicators.

One important aspect in the data preparation is defining the periods for prediction. a short horizon periods such as one day, one week and one month is more suitable for financial prediction with technical indicators [9].

2.1.2 Segmentation

. Time series representation and segmentation is a major part of many stock time series tasks, the goal is to reduce the dimensionality and complexity of the data and enable identification of technical patterns, clustering or prediction [6].

Each method combines different functionality for data manipulation such as normalization, discretization, transformation and dimensionally reduction (feature selection or instance selection). in the method chapter we will describe the segmentation methods we apply in this research.

2.1.3 Prediction

. forecasting proven to be well-suited for financial data modeling, sophisticated ML models such as artificial neural networks, SVM and genetic programming showed state of the art results in the field.[12] [9] [21]

Finnie et al. surveyed different techniques for time series forecast on financial data, they differentiate between machine learning technique, forecasting period and the input variables. They summarized with the noticed that the Artificial Neural Networks (ANNs) is a dominant machine learning technique. Nevertheless, Gerlein et al. demonstrate that also simple ML models such as decision tree, logistic regression, nearest neighbor and Naive Bayes showed good results as well. Therefore using simple forecast algorithms can be a good benchmark to evaluate different representation method and enrichments.

2.1.4 Evaluation

. Evaluating a stock time series predictor involve two type of evaluations, a conventional evaluation of the predictor with the accuracy measures such as mean absolute error, mean absolute percentage error, and root mean square error. The second is money evaluation which evaluate the profit for a certain trading strategy [6].

One of the most popular and yet simple strategy for evaluation is a Buy & hold strategy [10], the strategy simply buys a stock that will predicted to go up and sell it otherwise. Still any strategy shall apply a risk control mechanism such as stop loss[7].

2.2 Similarity and clustering on stock time series

Clustering in time series stock data serve many goals such as portfolios balancing, patterns discovery, Risk reducing, finding similar companies, prediction and recommendation. Applying a clustering model requires three key components: clustering algorithm, similarity definition and evaluation method [23].

Keogh and Kasetty address two types of clustering time series, the first is whole time-series clustering to cluster set of individual time series by their similarity, and the second is subsequence clustering to extract subsequences per time series such as sliding window. Aghabozorgi et al. also add time point clustering to cluster the points values in the time series.

The similarity and the clustering is highly effected by the segmentation and representation method applied, in his paper Keogh and Kasetty boldly claim that clustering of time-series subsequences with time window is meaningless unless only the significant motifs are considered.

In the rest of this section, we will explore the recent appliances of clustering on financial time series data per type of similarity distances

2.2.1 Numeric distance

. Aghabozorgi and Teh used different clustering methods to categorize companies based on their stock data similarity; they used basic Euclidean distance to find similarity in time points in a stock data. because Euclidean distance is not capable of identifying trends shapeliness they used Dynamic Time Warping (DTW) distance to find similarity in the stock data shape, DTW first introduced in the 1960s and still show similar results to more advance methods [8]. In general, DTW deals with unequal length and solves the local shift problem in the time series to find similar shapes between time series in different time phase axis.

Wang et al. applied DTW on foreign exchange (FX) market and use minimal spanning tree (MST) and hierarchical tree (HT) to cluster different currencies together. They strongly claimed that the usage of Pearson correlation coefficient (PCC) is not suitable for FX time series data because it is not robust to outliers and must have homogeneous, synchronous and equal length samples.

Jeon et al. searched for similar patterns in historic stock data with DTW and stepwise regression feature selection to improve predictions. the selected data set is used to train an artificial neural network (ANN). They evaluate their predictor with root mean square error (RMSE) and new evaluation that represent the target value with SAX and apply Jaro-Winkler similarity.

Caiado and Crato used generalize autoregressive conditional heteroskedasticity (GARCH) models to estimate the distance between stock time series volatilities. They used hierarchical clustering and multidimensional scaling technique to differentiate stock geographical markets. GARCH model assumes that the conditional variance is depended on a past linear volatility model, the GARCH model is lean with parameters and provide good representation of volatility for variety of processes. Their distance formulation consider the time series GARCH measurement combined with the sum of the series covariance-vector-estimation.

2.2.2 Symbolic distance

. Soon and Lee compared the numeric and symbolic representation for stock data similarity. For numeric representation, they use the original data with Euclidean distance and for symbolic representation, they used UP, DOWN and SAME symbols with number of matching symbols as distance. They found that opening, closing, highest and lowest prices of the stock are able to produce consistent results in similarity and demonstrate that under the representation and distances described above, the numeric distance was more consist then symbolic distance.

Aghabozorgi and Teh used Symbolic ApproXimation Aggregation (SAX) representation for dimensionality reduction, SAX method discrete stock continues representation with symbols per

Table 1: Technical indicators for stock time series

Technical indicator	description
relative strength index (RSI)	holds the magnitude of recent gains and losses over a specified time period
rate of change (ROC)	estimating the speed of change in a price
moving average convergence / divergence (MACD)	accumulating the relationship between two moving averages of prices
Sharpe ratio	calculating the risk of a certain period by subtracting the profits with the standard deviation

static data segment, they used k-Modes algorithm that suites categorical data. For the SAX distance measurement they develop APXDIST instead of MINDIST distance for symbolic distance [16] because MINDIST consider the neighbor symbols as zero, APXDIST distance also considering the global minimum and maximum symbols in the sequence.

Branco combined SAX and Shape Description Alphabet (SDA) representation with genetic algorithm to generate buy and sell signal, SDA representation calculate the amplitude difference between two adjacent points and represent it as a symbols. SAX is not capable of identify difference between segments that have same average value whereas the SDA identify trends and relation between adjacent points. For SAX, they use MINDIST and for SDA they use simple numeric subtraction between the relative representations.

Tamura et al. conducted time series classification based on SAX representation with Moving average convergence divergence (MACD) Histogram and applied 1 nearest neighbor (1NN) with extended Levinshtein distance that suites strings with SAX representation. MACD used widely in financial domains and consider the velocity and the acceleration of the time series, MACD calculate the difference between two exponential moving averages (EMA) with different window size. Tamura et al. used SAX to represent the original values and MACD values, and then they combined the values in an alternates order.

3 METHODS

As mentioned in the introduction chapter, the research main research questions are "do similar stocks can improve stock price prediction and which method shows the best performance?" In order to answer the research questions we implement a workflow that prepare the stocks data and manage the back-testing process, the workflow's generic implementation allows the evaluation of different methods configurations.

In this chapter we will describe the workflow's stages and methods we apply in this research, the workflow code is written in Python ans is available on GitHub: https://github.com/liorsidi/StockSimilarity. The workflow pipeline has four stages: Prepare fold data, process data, similar stocks enhancement and stock prediction.

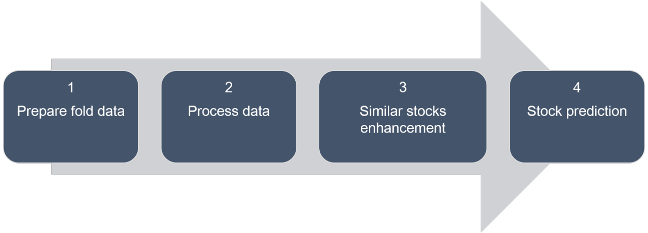


Figure 1: Workflow pipeline stages

3.1 Folds preparation

In this stage, the process split the data to n folds; the split separate the data to n equal width folds. Each fold contains a train data, a fold before the split and a test data, a fold after the split.

In order to keep the model relevant to the test data the system select only half of the test data near split point.

3.2 Data processing

The processing stage is responsible on the manipulating, modeling and feature extraction of the stocks data. The actions performed by this component are normalization (standardization), financial feature extraction (MACD, RSI, Price rate of change, volume, open close difference and trading volume), data segmentation (SAX or PCA) and data modeling (time points or time windows).

The component also responsible to train the normalization and segmentation processes on the each train fold data and apply it on the relevant test fold. Frthermore, this stage differentiate between univariate modeling with only one value and multivariate modeling with all the financial features. We apply time window modeling only for the univariate to reduce the size of dimensionality and eliminate overfitting. We also did not apply normalization on some financial features because their original raw values already normalized between ranges.

3.2.1 Standard normalization

. The standardization is used widely in normalizing financial data

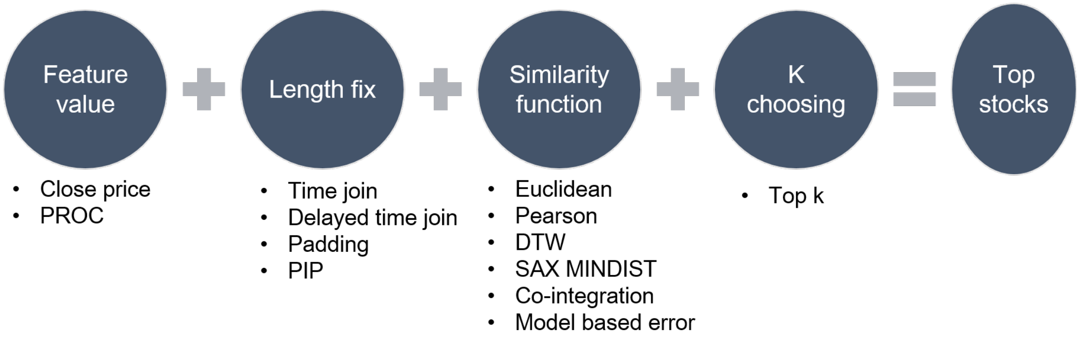


Figure 2: The different configurations for stock similarity

because the values of the stocks are random and therefore a normality assumption may be applied, furthermore the min max normalization is problematic in the filed because the stock values increases between different time periods and the max and minimum values also may change dramatically.

In this workflow, each time point value is normalize with elementary standardization function:

$$z = \frac{x - mean(X)}{std(X)}$$

3.2.2 Data modeling

. Time series data modeling can take place in various ways, each modeling represent the prediction record differently and expose different information regard the instance and its context.

- **Time Point** - This modeling address each time point separately without data of previous time points. Time Point representation allows adding complexity like feature extraction or join similar stocks values in the same point.
  Time point approach has several limitations, the first is a significant reduction of data when joining similar stocks on the same time point due to missing data, and the second limitation is the lack of contextual information from recent point therefore adding financial features that enrapture previous information such as exponential windows will be beneficial.
- **Time Window** - Represent each instance as a window of adjacent time point, this modeling allows the model to find relation between adjacent points, still this modeling enlarge the instance and harm the ability to add more features and stocks.
  When implementing this modeling we extract windows for each stock separately and do not join their values as applied in the time point modeling. From one hand the similar stocks data don't used in prediction, only in training. But from the other hand, the training data dramatically with similar stocks and improves the models.

3.2.3 Data segmentation.

- **Principals component analysis (PCA)** - creates a smaller representation of the dataset while maintaining its variance using eigenvector decomposition on the data covariance.
  The PCA produce principal component (PC) which is a linear combination of different features and acts as a new attribute. PCA is a common tool for data exploration and allow good reasoning of the data variance.
  in this research we set the PCA to produce 3 PCs from the entire data set to act as new attributes.
- **Symbolic ApproXimation Aggregation (SAX)** - A dimensionality reduction technique, it also allows distance measures to be defined on the symbolic approach that lower bounds euclidean distance [15].
  SAX involves performing two stages on the data: first, it transforms the original time-series into the appropriate piecewise aggregate approximation (PAA) representation.
  The PAA representation divides the series to parts (according to the given output length) and calculates each interval's mean value. Later it converts the PAA data into a string after normalization according to the given alphabet size. In this research, we use SAX representation while keeping the same word size as origin.

3.3 Similar stocks enhancement

The stock enhancement component apply the different functions for measuring the stock similarity, in figure 2 we describe the necessary configurations, the value for calculating the similarity, the fix the length function, the similarity functions and lastly the k top stocks are chosen.

The combination of the similar stocks is depends on the data modeling approach as explained in the previous data modeling section.

3.3.1 length fixing. Each instance (stock/equity) may miss different time points due to system error, vacation days, stock splitting or just because the stock have not founded.

When calculating distances between time series it's important to correlate them to have the same length size, in order to do this we implemented and examined the following fixing methods:

- **Time join** - a basic correlation between the stock based on the time, if one stock is missing a time point while the other is not the time point is eliminated (equivalent to inner join in SQL) this fixing is the most popular but may reduce the data substantially.

- **Delayed time join** - the same concept of the regular time join only on stock values are pushed t times points backward (delay), this correlation meant to identify if one stock indicated future behavior of the other one.
- **Padding** - basic padding fixing technique that adds a duplicate value in the beginning of the shorter series.
- **Perceptually important points (PIP)** - select the most important points in a series with the following steps: the first and the last points are set as PIP's. Then, the third PIP will be the point with the maximum distance to the first two PIP's. the forth PIP will be the point with the maximum distance between two adjacent PIPS, the a algorithm finish when achieving a predefined number of points.
  We use PIP in this project by applying it on each stock to find important time points (10 percent of original length) then we combined both PIPs and correlated the stock time points.

3.3.2 Similarity functions.

- **Euclidean distance** - A common indicator that measures the dissimilarity between time series comparing the observations at the exact same time. The Euclidean distance is a square root of the sum of the squared differences of each pair of corresponding points.
  The main limitation of this measure is its inability to identify shifting and trends in the data.
- **Pearson correlation coefficient** - A known measure of the linear correlation between two vectors, the coefficient is calculated by dividing the two series covariance with theirs standard deviation product, the correlation value range is between -1 and 1 for negative and positive correlation.
  Pearson has two major limitations regard stock prices correlation, the first is that it assume stationary behavior and the second is that it cannot deal non-linear behavior between series.
- **Dynamic Time Warping (DTW)** - A template matching algorithm in pattern recognition, DTW which can align sequences that vary in time or speed.
  DTW is an old technique but still very relevant in the financial similarity. In this research, we used python's implementation of DTW, based on Euclidean distance.
- **MINDIST** - In order to measure the similarity between the series in SAX representation we will use the MINDIST formula that defined by [15] and explained in figure 3. The main limitation of MINDIST in stock price series as mentioned by Liu and Shao because it does not address adjacent change in values. To fix this we tested MINDIST (and all other similarity functions as well) also on the price rate of change (PROC) to identify high increment of adjacent change.
- **Co-integration** - A statistical feature between multiple non-stationary time series, co-integration checks if there is a parameter that it's multiplication with one of the time series resolve with a constant spread between the non-stationary series.
  Stock prices are not necessarily stationary because their mean and standard deviation may change over time. Co-integration is used widely to compare similarity between stocks and may state that there is some relation between them [3].
  For testing series co-integration, we use co-integration python implementation of "stattools" library that test for co-integration behavior with Engle-Granger two-step co-integration test.
  We used the test P-value as a similarity measurement between the two series, a low p-value of the test means that the series are co-integrates thus they are similar.

$$MINDIST(G^{SAX}, H^{SAX}) = \sqrt{\frac{n}{w}}\sqrt{\sum_{i=1}^{w}(\text{dist}\ (G_i^{\ SAX}, H_i^{\ SAX}))^2}$$

Figure 3: MINDIST Equation - n is the number of window points, w the number of segments, Gi the value number i of series G transformed by the SAX method and the Hi the value number i of series H transformed by the SAX method.

3.4 Stock prediction

The prediction component train a regressor or a classifier model with the relevant algorithm. The model goal is to predict if the stock value will increase or decrease in a certain horizon.

Figure 4 explains how the system train and apply the classifier or the regressor model. For the classifiers the system train on the two classes in the traditional way. The regressors are trained to predict the next value but in prediction the system compare the predicted value to the current value and applied sign function (increase: 1, decrease: -1).

In this research, we choose to evaluate two ensemble algorithms that showed good results in the stock prediction domain: Random Forest and Gradient Boosting Tree. Both models has a classification and regression implementation in Scikit-learn (python library).

- **Random Forest** - Train t decision trees on different features and in prediction apply a majority voting on the results from all trees.
- **gradient boosting trees** - Train a chain of decision tree where each tree tries to predict the error of the previous tree, the model has a learning rate for summing the values from the tree chains.

4 EXPERIMENT SETUP

In order to evaluate if stocks similarity improves a baseline model we conduct two-step experiments (back testing) to evaluate different types of the system configurations. The first experiment goal is to come up with a processing pipeline and a baseline model. The second experiment is to evaluate how different stock similarity function influence on the baseline model. In figure 5 we mapped

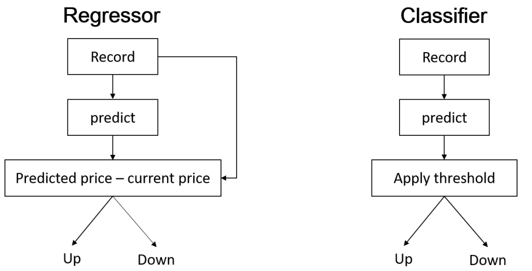


Figure 4: The training and appliance pipeline for classifiers and regressors models

the different configuration parameters the back-testing process will evaluate.

Our dataset contains historical daily data for all the S&P 500 stock market index companies during 2012 to 2017. The features given are date, open price, closing price, highest price, lowest price, volume and the short name of the stock. The S&P (Standard & Poor) is an American stock index of the largest companies listed in NYSE or NASDAQ, maintained by S&P Dow Jones Indices. It covers about 80 percent of the American equity market by capitalization.

We apply the evaluation process on stocks from different industries: Consumer (Disney - DIS , Coca Cola KO), Health (Johnson and Johnson - JNJ), Industrial (General electric - GE , 3M - MMM), Information technology (Google - GOOGL) and Financial (JP Morgan - JPM). The validation folds are set to five and prepared for each stock separately.

4.1 Experiment 1 - processing model evaluation

The experiment's goal is to evaluate basic processing and prediction model parameters to set a baseline model and processing configurations. The baseline settings are set in the next experiments to evaluate the similarity enhancement rather them model and processing tuning.

For processing, the experiment evaluates features (univariate or multivariate), segmentation methods (SAX, PCA or raw values), temporal modeling (time points or windows size 5 or 10). For stock prediction, the experiment evaluates the following configurations: prediction value (close price or price rate of change), horizon (next day, next 3 days or next week) and weighing instances per stock (applied only for the Euclidean similarity models).

To identify if stock similarity enhancements improve a baseline model we do not need to focus on improving the models with endless parameters tuning, but set recommended parameters to reduce the complexity of the experiments, the models recommended configuration: Random forest with 100 trees and gradient boosting with 0.02 learning rate. The first experiment also apply two basic stock similarity configurations: Euclidean similarity function on the price value with 10 similar stock compared to no enrichment of similar stocks.

4.2 Experiment 2 - Enhancement similarities evaluation

The second experiment evaluates the improvement each similarity functions parameters has on the baseline models defined in the first experiment.

For similarity parameters, the experiment evaluate similarity functions (co-integration, DTW, Euclidean, Pearson and SAX), length fixing functions, size of k similar stocks (10, 25, 50), similar value to compare (Close price or price rate of change).

The experiment will compare the best enhanced model with the best the non-enhanced model from the first experiment and with a model that randomly choose stocks for enhancement. The second comparison goal is to evaluate if the model's improvement is due to similarity enhancement and not due to general stock enrichment.

5 RESULTS

The evaluation metrics are Accuracy score and F1 score; we calculate each metric per class (increase / decrease) and average it to one score. For profit evaluation we implement a simple buy and hold algorithm that apply long or short position regarding the model price prediction. We also measure the risk of the strategy with Sharp ratio.

For visualizing the experiments results we use Tableau software to export graphs and tables based on CSV results from the pipeline python implementation.

5.1 Experiment 1 - processing model evaluation

The first stage of experiment one is to evaluate which processing configuration will resolve with best accuracy, F1 score, profit and low risk.

5.1.1 *Processing configuration evaluation*

. In figure 5 we present the different configuration and metrics of the data processing configuration and in figure 7 we emphasizes the profit difference per configuration. The best overall performance configurations is univariate modeling with SAX transformation. Furthermore, SAX transformation showed best results with all other configurations. Each metric in the figure is the mean of 1680 examples (7 different stocks, 5 folds, 3 different horizons, 2 predictions values, 4 type of models and 2 type of K top stocks)

5.1.2 *Prediction models evaluation*

. in the next step of the experiment we evaluate the predictions parameters, from the results in figure 8 we can observe that the overall performance for predicting rate of change price (PROC) is higher than predicting the closing price (the columns of price rate of change is all green with only positive mean profits).

The classification models have good accuracy results but their standard deviation is high and results with negative profit and high risk, the performance of the next day prediction horizon is higher than other horizons probably due to the fact of efficient market hypothesis. For model performance, we witness an interesting behavior between the regressors and the classifiers, the classifiers

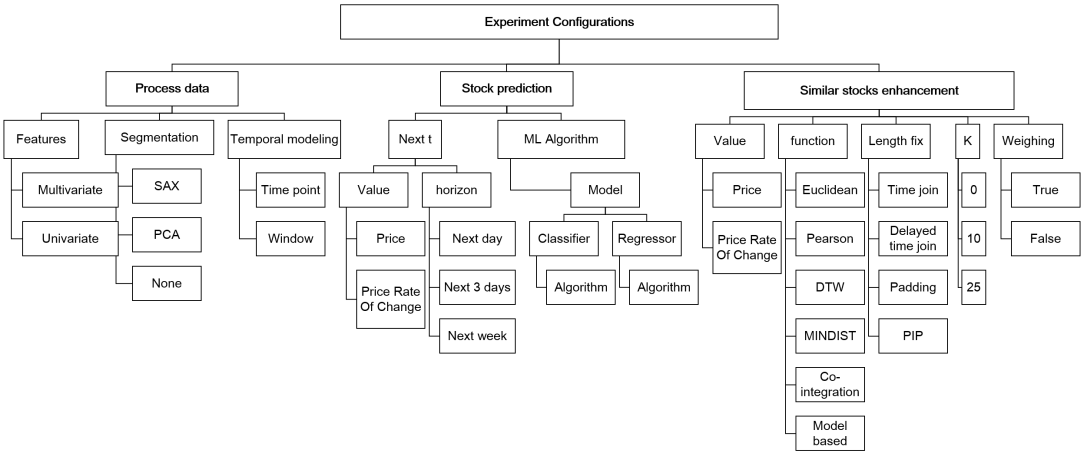
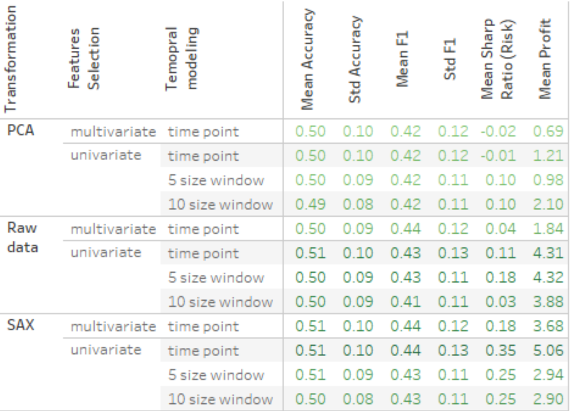


Figure 5: A configuration tree of all the setup to be optimize and evaluate in workflow pipeline

had the best accuracy for predicting the closing price whereas the regressors failed. However, the classifiers also meet negative mean profit and the regressors did not, probably because of the prediction inconsistency (high standard deviation) and threshold calibration. From the results, we see a slight but not significant advantage of the Gradient boosting trees over the Random forest models.



Transformation	Features Selection	Temopral modeling	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (Risk)	Mean Profit
PCA	multivariate	time point	0.50	0.10	0.42	0.12	-0.02	0.69
	univariate	time point	0.50	0.10	0.42	0.12	-0.01	1.21
		5 size window	0.50	0.09	0.42	0.11	0.10	0.98
		10 size window	0.49	0.08	0.42	0.11	0.10	2.10
Raw data	multivariate	time point	0.50	0.09	0.44	0.12	0.04	1.84
	univariate	time point	0.51	0.10	0.43	0.13	0.11	4.31
		5 size window	0.50	0.09	0.43	0.11	0.18	4.32
		10 size window	0.50	0.09	0.41	0.11	0.03	3.88
SAX	multivariate	time point	0.51	0.10	0.44	0.12	0.18	3.68
	univariate	time point	0.51	0.10	0.44	0.13	0.35	5.06
		5 size window	0.51	0.09	0.43	0.11	0.25	2.94
		10 size window	0.50	0.08	0.43	0.11	0.25	2.90

Figure 6: Experiment 1 processing parameters results - transformation function, features and temporal modeling. (rows - configuration , columns - metrics and color - profit scale)

As a part of experiment one, we also evaluate the models that train on top 10 similar stocks calculated with simple Euclidean distance alongside models that trained only on the target stock. In figure 9 the results showed that the model without the similarities has better results.

From this experiment results we conclude that the best processing and prediction parameters for the next experiment will be SAX transformation only on the price rate of change value (univariate), the price rate of change will be also the prediction value.

We did not witness any significant results for the temporal modeling and prediction models and horizon prediction configurations, therefore in the next experiment will apply all these configurations as well.

5.2 Experiment 2 - Similarity enhancement evaluation

The second experiment train the models with the processing suggested from experiment one and apply the similarity enhancement configurations as follows: similarity function, similarity value, top k stock to choose and the stock length fixing.

In this section we present the evaluation figures only on profit, we found the accuracy and profit to correlates, the full results are in the appendix A.

5.2.1 *Similarity functions evaluation*

. The results from figure 10 map the metrics for top K stock and similarity stocks (rows) over the similarity value used for calculating the similarity. Each cell in the table is a mean of 1680 instances (7 stocks, 5 folds, 3 horizons, 4 models, 4 fixing length techniques). The results shows a clear advantage of the co-integration and the SAX MINDIST similarities, price rate of change as similarity value and selecting top 50 stock. These combinations lead to mean accuracy of 0.53 and mean profit of more than 9.55 (SAX) and 9.81 (co-integration). The results already shows a significant improvement from the baseline model presented in figure 9.

In figure 13b we evaluate the length fixing functions of the best similarity configuration: the 50 top stocks with high SAX or co-integration similarity on price rate of change. Time join for fixing have the best results with profit of 15.67 (co-integration) and 14.85 (SAX).

In figure 12 we present the final results of these similarity with the best performing processing and modeling configurations: a gradient boosting regressor trained on the price rate of change with SAX transformation and 50 top stocks with co-integration similarity. The model have average mean of next day value with 19.87.

5.2.2 *Random stock enhancement comparison*

. Finally, we compare the results from the enhanced model with models that we enhanced with random 50 and 100 stocks. As described in 12 the random enhanced model also had significant better results than the baseline model presented in the first experiment. the random models improves as the horizon rise and the amount of random stocks are selected, this phenomena can be explained by the fact that the S&P stocks are known to have similar behavior and can contribute the predictions because many investors and ETFs buys or sell the index stocks all together causing the prices to behave similarly.

For horizon of the next day, the co-integration stock similarity has significant higher profit from the random 100 stocks with 19.78 and 16.21. From the other hand, the random model is significantly more profit in the long horizons. The long horizon performance is a result of the same phenomena explained above regard the S&P stocks. Nevertheless, the co-integration based model is more accurate in terms of accuracy score and F1 score then the random 100 model with accuracy between 0.542 - 0.55 and F1 score between 0.448 - 0.459. The random 100 model had less accurate results with accuracy score between 0.526 - 0.535 and F1 score between 0.437 - 0.443 (these detailed results are in appendix A).

We further investigate the profit behavior of the co-integration model and the random 100 model in order to understand the model profitable behavior. In figure 11 we plot the profit value over time for each stock (x axis) in each of the five folds evaluated (y axis), the models predict the next day value and then the simple buy and hold strategy is applied, the color represent each of the two models. From the plots, we identify the co-integration model (orange color) to be more profitable in most stock's folds except JPM stock.

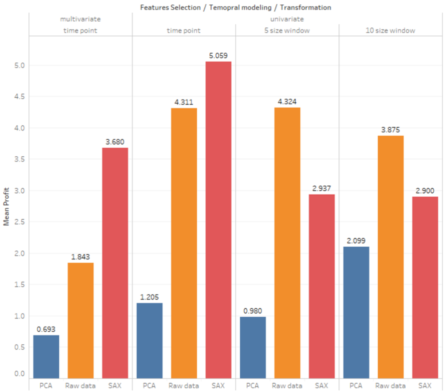
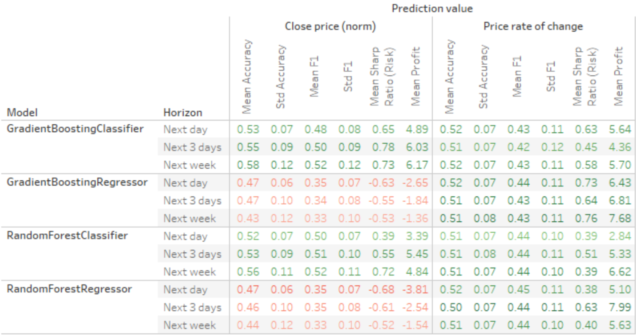


Figure 7: Experiment 1 processing parameters results - mean profit values per transformation configuration

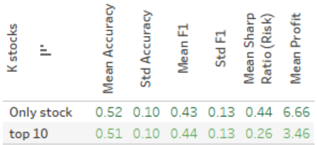
6 CONCLUSIONS

In this paper, we focus on improving prediction models on stock data with similar stocks; the process of enhancement is not straightforward and require several data processing phases. We design a pipeline for applying back-testing for all processing and prediction configurations. We evaluate the configurations impact on the models profit and accuracy and found that



		Prediction value											
		Close price (norm)						Price rate of change					
Model	Horizon	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (Risk)	Mean Profit	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (Risk)	Mean Profit
GradientBoostingClassifier	Next day	0.53	0.07	0.48	0.08	0.65	4.89	0.52	0.07	0.43	0.11	0.63	5.64
	Next 3 days	0.55	0.09	0.50	0.09	0.78	6.03	0.51	0.07	0.42	0.12	0.45	4.36
	Next week	0.58	0.12	0.52	0.12	0.73	6.17	0.52	0.07	0.43	0.11	0.58	5.70
GradientBoostingRegressor	Next day	0.47	0.06	0.35	0.07	-0.63	-2.65	0.52	0.07	0.44	0.11	0.73	6.43
	Next 3 days	0.47	0.10	0.34	0.08	-0.55	-1.84	0.51	0.07	0.43	0.11	0.64	6.81
	Next week	0.43	0.12	0.33	0.10	-0.53	-1.36	0.51	0.08	0.43	0.11	0.76	7.68
RandomForestClassifier	Next day	0.52	0.07	0.50	0.07	0.39	3.39	0.51	0.07	0.44	0.10	0.39	2.84
	Next 3 days	0.53	0.09	0.51	0.10	0.55	5.45	0.51	0.08	0.44	0.11	0.51	5.33
	Next week	0.56	0.11	0.52	0.11	0.72	4.84	0.51	0.07	0.44	0.10	0.39	6.62
RandomForestRegressor	Next day	0.47	0.06	0.35	0.07	-0.68	-3.81	0.52	0.07	0.45	0.11	0.38	5.10
	Next 3 days	0.46	0.10	0.35	0.08	-0.61	-2.54	0.50	0.07	0.44	0.11	0.63	7.99
	Next week	0.44	0.12	0.33	0.10	-0.52	-1.54	0.51	0.07	0.44	0.10	0.40	5.63

Figure 8: Experiment 1 prediction parameters results - prediction model, Horizon and Value (rows - configuration, columns - prediction value with metrics and color - profit scale)



K stocks	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (Risk)	Mean Profit
Only stock	0.52	0.10	0.43	0.13	0.44	6.66
top 10	0.51	0.10	0.44	0.13	0.26	3.46

Figure 9: Experiment 1 basic similarity results - a comparison between a model with top 10 similar stocks with Euclidean distance and a model without similarity enhancement. for predictions parameters: prediction model, Horizon and Value (rows - configuration, columns - metrics and color - profit scale)

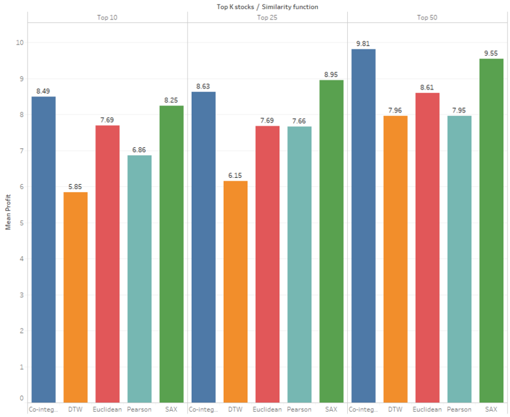


Figure 10: Experiment 2 similarity configurations - a profit comparison between similarity configurations

We came up with and optimized enhanced model with the following configurations: data processing of 10 size windows with the price rate of change SAX transformation. The predictor is a

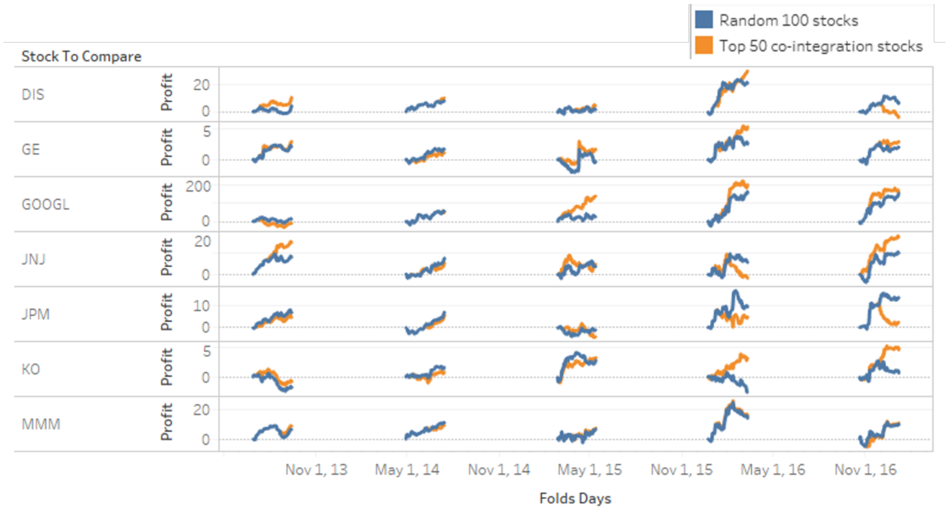


Figure 11: Experiment 2 folds profit per stock - a profit comparison between top 50 stocks from co-integration similarity (orange) and 100 random stock selection enhancement (Blue) for each stock (x axis) in different folds (y axis)

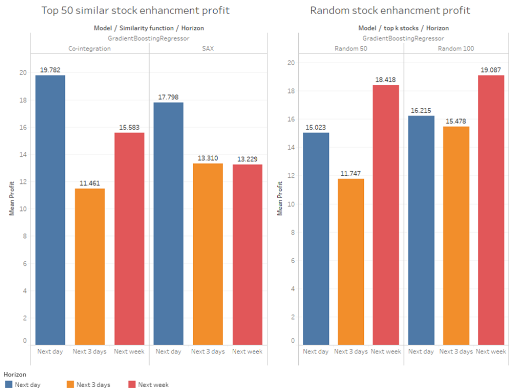


Figure 12: Experiment 2 random selection compare - a profit comparison between SAX and co-integration similarities on top 50 stocks and random stock selection

gradient boosting regressor with 0.02 learning rate and its training set is compound from the top 50 similar stocks found with co-integration similarity. We compared the enhanced model with and optimized baseline and random similarity model on seven stocks from different industries in five folds split over five years period.

The enhanced model had better results than the other models in terms of accuracy and profit. The mean accuracy of the enhanced model is 0.55 compare the 0.52 and 0.546 of the non-enhanced and random enhanced models (respectively). In terms of profit, the enhanced model showed high mean profit of 19.87 compare to 6.66 and 15.02 of the non-enhanced and random enhanced models.

During the research, we identify two limitations; the first regards the small data volume of the daily data set, because the scope of daily prices is not enough data to train a well-fitted model. We believe that applying the pipeline on intra-day data might improve the models because of the data volume, the in the intraday data has more similarities patterns that might be useful for intraday trading.

The second limitation regard the S&P stocks index in general, the index has two type of limitations, the first is that the index was mostly positive after the crisis of 2008; this behavior may affect the results in all the models evaluated. The other type is that the S&P stocks correlate to each other because traders usually buy the entire S&P index causing all the stocks to increase or decrease together. This kind of behavior eliminate some of the advantages a similarity measure might have because the stocks are already similar. In order to address these limitations we aim to apply the pipeline on other investing instruments like crypt-currency and commodities (Gold, Oil, silver etc.). We believe that the similarity pipeline on other datasets where most of the items do not correlate will have dramatically better results than in this research.

For future work, we suggest on some improvements, the most straightforward is to apply an ensemble similarity model on the different similarity measurements to combine the advantage of each method. Another improvement is to use deep learning models; we assume that the similarity enhancement will increase the training dataset and will improve deep learning models that require much more data for training.

REFERENCES

[1] Saeed Aghabozorgi, Ali Seyed Shirkhorshidi, and Teh Ying Wah. 2015. Time-series clustering - A decade review. *Information Systems* 53 (2015), 16–38. https://doi.org/10.1016/j.is.2015.04.007

[2] Saeed Aghabozorgi and Ying Wah Teh. 2014. Stock market co-movement assessment using a three-phase clustering method. *Expert Systems with Applications* 41, 4 PART 1 (2014), 1301–1314. https://doi.org/10.1016/j.eswa.2013.08.028

[3] Carol Alexander and Anca Dimitriu. 2003. Equity Indexing , Cointegration and Stock Price Dispersion : A Regime Switching Approach to Market Efficiency. *ISMA Centre Discussion Papers in Finance* 44, 2 (2003), 29.

[4] Tiago Branco. [n. d.]. Pattern analysis in stock markets optimized by genetic algorithms using modified SAX. ([n. d.]), 1–10.

[5] Jorge Caiado and Nuno Crato. 2007. A GARCH-based method for clustering of financial time series: International stock markets evidence. *Munich Personal RePec Archive* 2074 (2007).

[6] Rodolfo C. Cavalcante, Rodrigo C. Brasileiro, Victor L.F. Souza, Jarley P. Nobrega, and Adriano L.I. Oliveira. 2016. Computational Intelligence and Financial Markets: A Survey and Future Directions. *Expert Systems with Applications* 55 (2016), 194–211. https://doi.org/10.1016/j.eswa.2016.02.006

[7] T Chande. 1997. *Beyond Technical Analysis*. 143 pages. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Beyond+Technical+Analysis#2

[8] H Ding, G Trajcevski, P Scheuermann, X Wang, and E J Keogh. 2008. Querying and mining of time series data: experimental comparison of representations and distance measures. *Proc. of the VLDB Endowment* 1, 2 (2008), 1542–1552. https://doi.org/10.1145/1454159.1454226

[9] Cain Evans, Konstantinos Pappas, and Fatos Xhafa. 2013. Utilizing artificial neural networks and genetic algorithms to build an algo-trading model for intra-day foreign exchange speculation. *Mathematical and Computer Modelling* 58, 5-6 (2013), 1249–1266. https://doi.org/10.1016/j.mcm.2013.02.002

[10] Gavin Finnie, Bjoern Krollner, Bruce Vanstone, and Gavin Finnie. 2010. Financial time series forecasting with machine learning techniques : A survey. *European Symposium on Artificial Neural Networks ESANN2010* April (2010). http://works.bepress.com/bruce_vanstone/17

[11] Eduardo A. Gerlein, Martin McGinnity, Ammar Belatreche, and Sonya Coleman. 2016. Evaluating machine learning classification for financial trading: An empirical approach. *Expert Systems with Applications* 54 (2016), 193–207. https://doi.org/10.1016/j.eswa.2016.01.018

[12] Yong Hu, Kang Liu, Xiangzhou Zhang, Lijun Su, E. W.T. Ngai, and Mei Liu. 2015. Application of evolutionary computation for rule discovery in stock algorithmic trading: A literature review. *Applied Soft Computing Journal* 36 (2015), 534–551. https://doi.org/10.1016/j.asoc.2015.07.008

[13] Seungwoo Jeon, Bonghee Hong, and Victor Chang. 2017. Pattern graph tracking-based stock price prediction using big data. *Future Generation Computer Systems* (2017). https://doi.org/10.1016/j.future.2017.02.010

[14] Eamonn Keogh and Shruti Kasetty. 2002. On the need for time series data mining benchmarks. *Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '02* (2002), 102. https://doi.org/10.1145/775047.775062

[15] Jessica Lin, Eamonn Keogh, Stefano Lonardi, and Bill Chiu. 2003. A symbolic representation of time series, with implications for streaming algorithms. *Proceedings of the 8th ACM SIGMOD workshop on Research issues in data mining and knowledge discovery - DMKD '03* (2003), 2. https://doi.org/10.1145/882085.882086

[16] Wei Liu and Liangshan Shao. 2009. Research of SAX in Distance Measuring for Financial Time Series Data. 70572070 (2009), 935–937.

[17] Binoy B. Nair, P. K.Saravana Kumar, N. R. Sakthivel, and U. Vipin. 2017. Clustering stock price time series data to generate stock trading recommendations: An empirical study. *Expert Systems with Applications* 70 (2017), 20–36. https://doi.org/10.1016/j.eswa.2016.11.002

[18] Lay Ki Soon and Sang Ho Lee. 2007. An empirical study of similarity search in stock data. *Conferences in Research and Practice in Information Technology Series* 84, Aidm (2007).

[19] Keiichi Tamura, Tatsuhiro Sakai, and Takumi Ichimura. 2016. Time Series Classification using MACD-Histogram-based SAX and Its Performance Evaluation. (2016), 2419–2424.

[20] Qiang Tian, Pengjian Shang, and Guochen Feng. 2016. The similarity analysis of financial stocks based on information clustering. *Nonlinear Dynamics* 85, 4 (2016), 2635–2652. https://doi.org/10.1007/s11071-016-2851-9

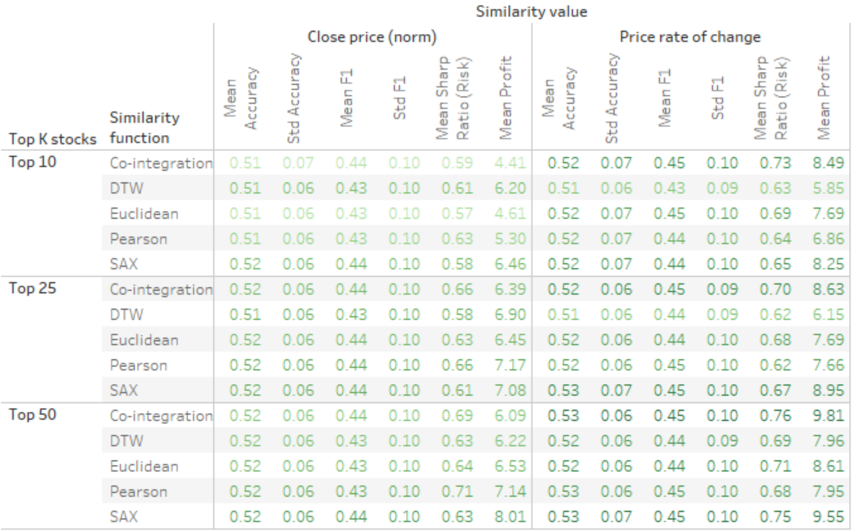
[21] Bruce Vanstone and Gavin Finnie. 2009. An empirical methodology for developing stockmarket trading systems using artificial neural networks. *Expert Systems with Applications* 36, 3 PART 2 (2009), 6668–6680. https://doi.org/10.1016/j.eswa.2008.08.019

[22] Gang Jin Wang, Chi Xie, Feng Han, and Bo Sun. 2012. Similarity measure and topology evolution of foreign exchange markets using dynamic time warping method: Evidence from minimal spanning tree. *Physica A: Statistical Mechanics and its Applications* 391, 16 (2012), 4136–4146. https://doi.org/10.1016/j.physa.2012.03.036

[23] T. Warren Liao. 2005. Clustering of time series data - A survey. *Pattern Recognition* 38, 11 (2005), 1857–1874. https://doi.org/10.1016/j.patcog.2005.01.025

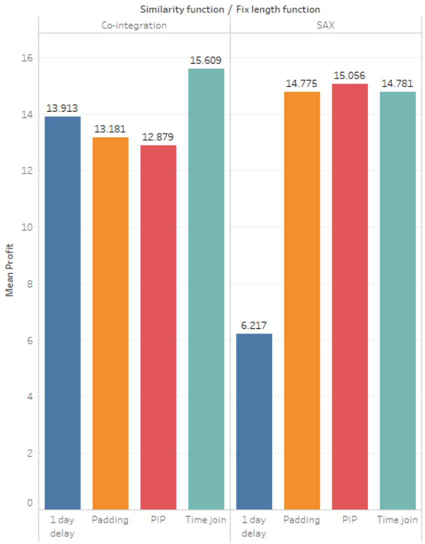
7 APPENDIX A - SIMILARITY CONFIGURATION EVALUATIONS

In this appendix, we collect the full evaluations per similarity configuration; these results address in the experiments results chapter.

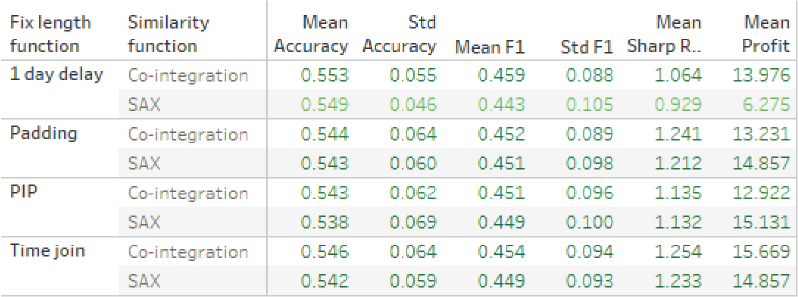


		Similarity value											
		Close price (norm)						Price rate of change					
Top K stocks	Similarity function	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (Risk)	Mean Profit	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (Risk)	Mean Profit
Top 10	Co-integration	0.51	0.07	0.44	0.10	0.59	4.41	0.52	0.07	0.45	0.10	0.73	8.49
	DTW	0.51	0.06	0.43	0.10	0.61	6.20	0.51	0.06	0.43	0.09	0.63	5.85
	Euclidean	0.51	0.06	0.43	0.10	0.57	4.61	0.52	0.07	0.45	0.10	0.69	7.69
	Pearson	0.51	0.06	0.43	0.10	0.63	5.30	0.52	0.07	0.44	0.10	0.64	6.86
	SAX	0.52	0.06	0.44	0.10	0.58	6.46	0.52	0.07	0.44	0.10	0.65	8.25
Top 25	Co-integration	0.52	0.06	0.44	0.10	0.66	6.39	0.52	0.06	0.45	0.09	0.70	8.63
	DTW	0.51	0.06	0.43	0.10	0.58	6.90	0.51	0.06	0.44	0.09	0.62	6.15
	Euclidean	0.52	0.06	0.44	0.10	0.63	6.45	0.52	0.06	0.44	0.10	0.68	7.69
	Pearson	0.52	0.06	0.44	0.10	0.66	7.17	0.52	0.06	0.45	0.10	0.62	7.66
	SAX	0.52	0.06	0.44	0.10	0.61	7.08	0.53	0.07	0.45	0.10	0.67	8.95
Top 50	Co-integration	0.52	0.06	0.44	0.10	0.69	6.09	0.53	0.06	0.45	0.10	0.76	9.81
	DTW	0.52	0.06	0.43	0.10	0.63	6.22	0.52	0.06	0.44	0.09	0.69	7.96
	Euclidean	0.52	0.06	0.43	0.10	0.64	6.53	0.52	0.06	0.44	0.10	0.71	8.61
	Pearson	0.52	0.06	0.43	0.10	0.71	7.14	0.53	0.06	0.45	0.10	0.68	7.95
	SAX	0.52	0.06	0.44	0.10	0.63	8.01	0.53	0.07	0.45	0.10	0.75	9.55

(a) Experiment 2 similarity configurations - a full metrics comparison between similarity configurations

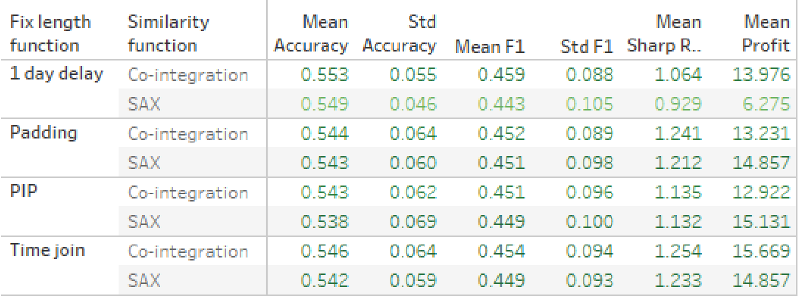


(b) Experiment 2 length fixing functions - a profit comparison between different fixing functions on top similarity configurations



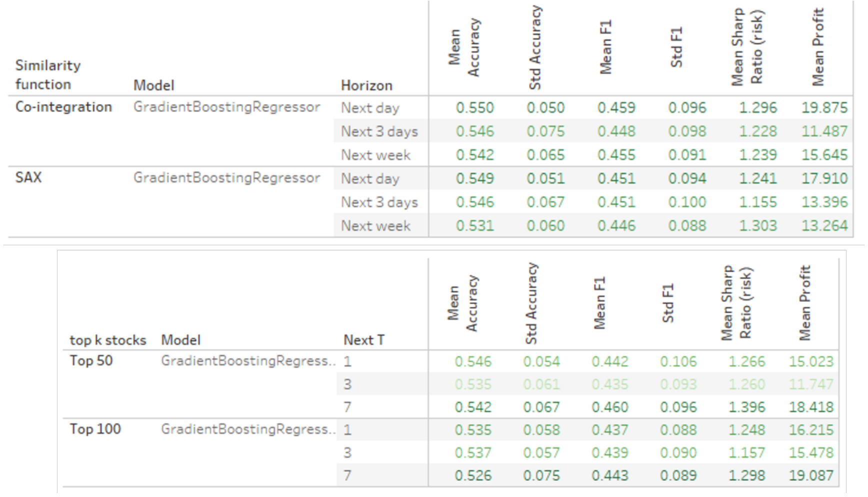
Fix length function	Similarity function	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp R..	Mean Profit
1 day delay	Co-integration	0.553	0.055	0.459	0.088	1.064	13.976
	SAX	0.549	0.046	0.443	0.105	0.929	6.275
Padding	Co-integration	0.544	0.064	0.452	0.089	1.241	13.231
	SAX	0.543	0.060	0.451	0.098	1.212	14.857
PIP	Co-integration	0.543	0.062	0.451	0.096	1.135	12.922
	SAX	0.538	0.069	0.449	0.100	1.132	15.131
Time join	Co-integration	0.546	0.064	0.454	0.094	1.254	15.669
	SAX	0.542	0.059	0.449	0.093	1.233	14.857

(a) Experiment 2 length fixing functions - a full metrics comparison between different fixing functions on top similarity configurations



Fix length function	Similarity function	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp R..	Mean Profit
1 day delay	Co-integration	0.553	0.055	0.459	0.088	1.064	13.976
	SAX	0.549	0.046	0.443	0.105	0.929	6.275
Padding	Co-integration	0.544	0.064	0.452	0.089	1.241	13.231
	SAX	0.543	0.060	0.451	0.098	1.212	14.857
PIP	Co-integration	0.543	0.062	0.451	0.096	1.135	12.922
	SAX	0.538	0.069	0.449	0.100	1.132	15.131
Time join	Co-integration	0.546	0.064	0.454	0.094	1.254	15.669
	SAX	0.542	0.059	0.449	0.093	1.233	14.857

(b) Experiment 2 length fixing functions - a full metrics comparison between different fixing functions on top similarity configurations



Similarity function	Model	Horizon	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (risk)	Mean Profit
Co-integration	GradientBoostingRegressor	Next day	0.550	0.050	0.459	0.096	1.296	19.875
		Next 3 days	0.546	0.075	0.448	0.098	1.228	11.487
		Next week	0.542	0.065	0.455	0.091	1.239	15.645
SAX	GradientBoostingRegressor	Next day	0.549	0.051	0.451	0.094	1.241	17.910
		Next 3 days	0.546	0.067	0.451	0.100	1.155	13.396
		Next week	0.531	0.060	0.446	0.088	1.303	13.264

top k stocks	Model	Next T	Mean Accuracy	Std Accuracy	Mean F1	Std F1	Mean Sharp Ratio (risk)	Mean Profit
Top 50	GradientBoostingRegress..	1	0.546	0.054	0.442	0.106	1.266	15.023
		3	0.535	0.061	0.435	0.093	1.260	11.747
		7	0.542	0.067	0.460	0.096	1.396	18.418
Top 100	GradientBoostingRegress..	1	0.535	0.058	0.437	0.088	1.248	16.215
		3	0.537	0.057	0.439	0.090	1.157	15.478
		7	0.526	0.075	0.443	0.089	1.298	19.087

(c) Experiment 2 random selection compare - a full metrics comparison between SAX and co-integration similarities on top 50 stocks and random stock selection

8 APPENDIX B - STOCK SIMILARITY EXPLORATIONS

In this appendix, we describe the manual exploration we conducted on the similarity results we conducted. In order to reason the similarity function we tested if the similarity function can group stocks in the same industry.

In Figure 15 each row is a target stock, the bin graph contains the similar stocks found in a certain rank and the color is represent the sector count. for example, in Disney target function, the first bin is all dark blue that represent the consumer sector, the same sector of the Disney stock. That means all the similarity functions choose the most similar stock from the same sector as Disney, this is not a surprise because all similarities choose Disney itself for as the first stock. If we continue with the y-axis we can see how the target stock sector is dominant in the beginning and then spread. This means that the similarities find a relationship between the stocks behavior and their sector.

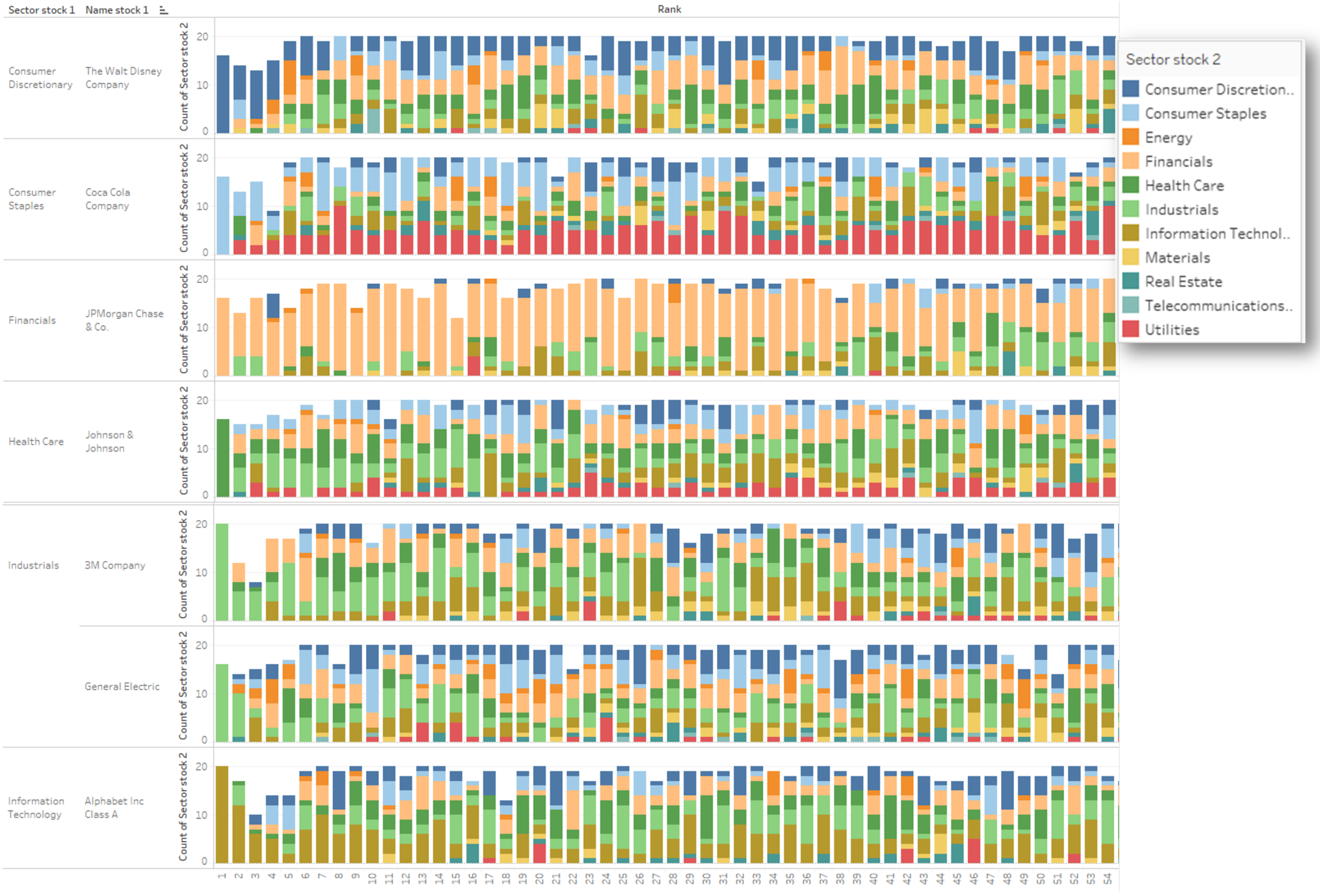


Figure 15: Target stock sector spread per rank

In figure 16 we demonstrate a confusion matrix between the target stock and the sector for the top 10 similar stocks found per similarity values (horizon) and similarity function (vertical). For example, the Pearson and close proc (Price rate of change) on the coca cola stock found that all top 10 similar stocks belongs to the same sector as coca cola, consumer staples. the stocks and sectors are arrange in a way that each stock is correspond to its relevant sector, meaning that if the diagonal is all dark green with 10 value, the similarity function found the stocks similar to its sector's stocks.

In figure 16 we describe which stocks found most similar to the target stocks, for example, in the coca cola stocks, the similarities functions found Pepsi to be the most similar.

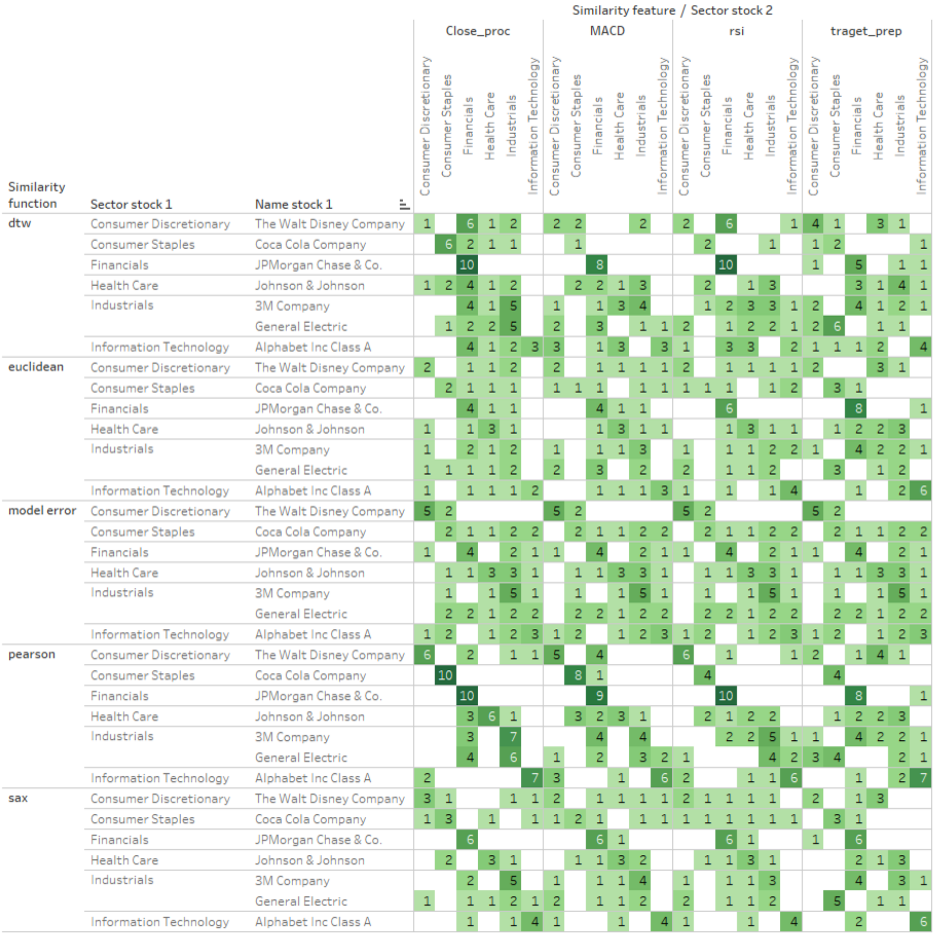


Figure 16: Target stock and sector confusion matrix for top 10 stocks per similarity function (vertical) and similarity value (horizontal)

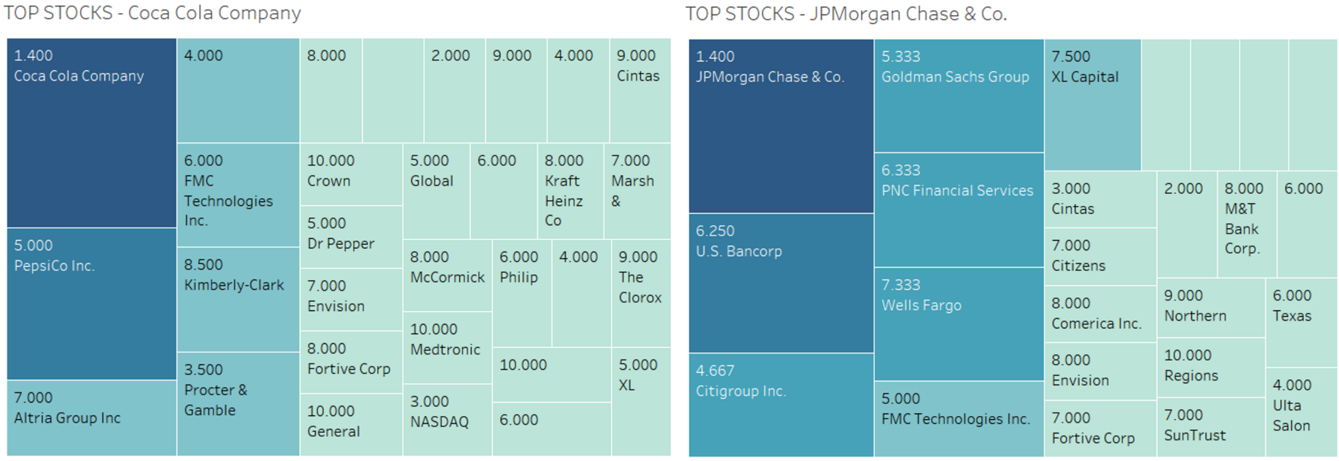


Figure 17: Coca cola and JP Mrgan Top stocks chosen