International Journal of Smart Computing and Artificial Intelligence
International Institute of Applied Informatics
2023, Vol. 7, No. 2, IJSCAI827

Asset Allocation Method Based on Sentiment Signals and Causal Information using Multi-asset Classes

Rei Taguchi *, Hiroki Sakaji *,
Kiyoshi Izumi*, Yuri Murayama*

Abstract

In this study, we demonstrate the usefulness of financial text for asset allocation with multi-asset classes, including stocks and bonds, by creating polarity indexes for several types of financial news through natural language processing. We performed clustering using a change-point detection algorithm on the created polarity indexes. We also constructed a multi-asset portfolio using an optimization algorithm and rebalanced it based on the detected change points. The results show that the proposed asset allocation method performed better than the comparison method, suggesting that polarity indexes can be useful in constructing asset allocation methods with multi-asset classes.

Keywords: Financial news, MLM scoring, causal inference, change-point detection, risk-parity portfolio

1 Introduction

1.1 Background

In this study, we propose that financial texts can be useful for tactical asset allocation methods using a multi-asset class. This can be accomplished using natural language processing and statistical causal inference to create rebalancing signals. Numerous studies have been conducted on investment techniques using machine learning. In particular, there is a growing body of research on asset allocation, including the derivation of investment signals and calculation of investment ratios [1,2]. In this study, we focus on the point at which portfolio prices change rapidly due to external factors, that is, the point of regime change. Regimes in finance theory are the invisible market states, such as expansion, recession, bulls, and bears. Some studies attempted to capture market alpha by incorporating these regime changes into investment strategies [3,4]. We will delve one step further and focus on measuring future regime changes. In this study, we specifically draw on the studies presented in [5]. If the information on future regime changes (i.e., future changes in the market environment) is known, active management with a higher degree of freedom becomes possible. However, because there are certain limitations in calculating future regimes using only traditional

* The University of Tokyo, School of Engineering, Tokyo, Japan

financial time-series data, we construct an investment strategy based on a combination of alternative data that has attracted attention in recent years in addition to multi-asset financial time series data.

1.2 Hypothesis

Considering Section 1.1, the following hypotheses are developed to calculate the point of change in future regimes:

- Multi-asset portfolios can ensure high returns while hedging risk by switching strategies in response to points of change in the polarity index.

1.3 Contributions

The investment strategy using the financial text proposed in this study is expected to generate better performance than the comparative strategy. This is done by generating polarity indexes from the financial text using natural language processing techniques, identifying the precedence of the generated polarity indexes using statistical causal inference, calculating the regime change points of the polarity indexes using change point detection techniques, and rebalancing the portfolio using multiple mathematical optimization models according to the change points. The contributions of this study is as follows.

- We demonstrate that the estimation of regime change points using financial text is effective in active management and propose a highly expressive asset allocation framework for multi-asset class.

2 Related Works

2.1 Asset allocation using machine learning

Studies in this area include the following: a two-stage deep learning model for a forecast-based exchange-traded fund (ETF) portfolio management method [6], a portfolio management method that considers the long-term dependence of time-series variation using mean-variance models and LSTM [7], and a model for portfolio optimization by optimizing XGBoost with the improved firefly algorithm (IFA) [8]. There is also a method of designing portfolios based on information on the predicted distribution by constructing a network that predicts the distribution of the residual term of returns [1], an evolutionary computational model that mimics the role of a trader called the trader-company method [2]. The novelty of this study differs from the above studies in that it uses natural language processing techniques in the framework of asset allocation.

2.2 Creation of economic index using text mining

Studies in this area include EcoRevs and a new architecture using long short-term memory (LSTM) [9], along with a study of polarity index creation using newspaper articles, economic trend surveys, and bi-directional LSTM [10]. In addition, research has been conducted on the creation of economic indexes using rate information from analyst reports [4, 11–13]. The novelty of this study is that the masked language model (MLM) score was used to create a polarity index and index the tone of financial texts.

2.3 Causal inference and its applications

Causal structure learning algorithms can be classified into three clusters. The first includes constraint-based approaches that use conditional independence tests to establish the existence of an edge between two nodes [14, 15]. The second includes a score-based method that uses several search procedures to optimize a particular score function [16–18]. The third includes structural causal models that represent variables at specific nodes as a function of their parents [19–23]. The following are example applications of statistical inference in the financial field. Studies have been conducted on the construction of networks that link causal relationships regarding the performance among firms, also known as causal chains [24, 25]. This study is novel in that it uses a vector autoregression linear non-gaussian acyclic model (VAR-LiNGAM) to empirically analyze the lead-lag relationship between stock portfolios and polarity indicators created from financial texts.

2.4 Time series change point detection and its applications

In time-series data, temporal non-independence must be explicitly addressed because of the existence of temporal correlations among the data. For example, several studies have applied change-point detection algorithms to financial time-series analyses [26–28]. This study is novel in that it uses a binary segmentation search, a highly expressive change-point detection algorithm, to estimate economic regimes.

3 Method

This section provides an overview of the MA-SSAAM proposed in this study. Studies on which this framework is based have been presented in [5]. We extend this study to the case of multi-asset portfolio optimization. The following is an overview of the MA-SSAAM.

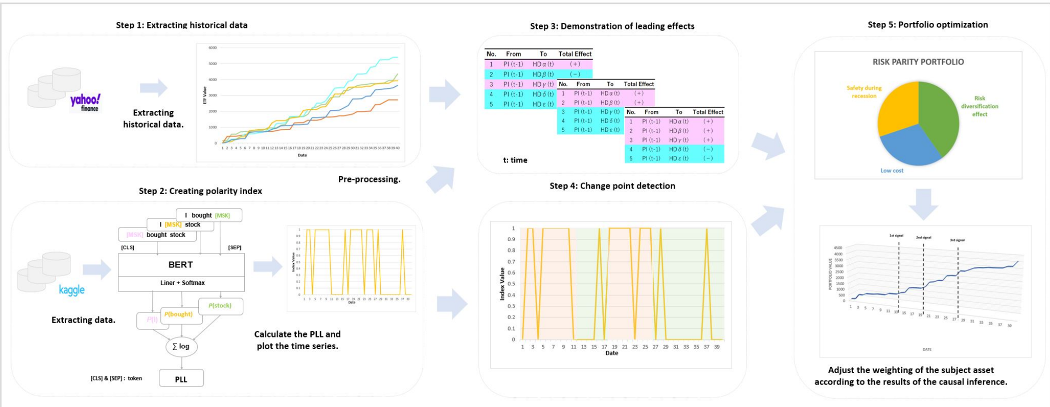


Figure 1: Framework of the proposed method

The architecture used in this study is shown in Figure 1.

3.1 Extracting historical data

Obtain historical time series data from data sources daily. Historical time-series data were obtained from the data sources. Details of the data sources to be used are described below;

however, for the allocation of multi-class assets in this study, multiple financial instrument data were used. Data sources were unified.

3.2 Creating polarity index

Score financial news titles using MLM scoring. In addition, quartiles are calculated from the same data, and a three-value classification of positive, negative, and neutral is performed according to the quartile range. The calculated values are aggregated daily. In this study, we used pseudo-log-likelihood scores (PLLs) to create polarity indexes. PLLs are probabilistic language models that correspond to MLMs proposed by [29]. Because MLMs are pretrained by predicting words in both directions, they cannot be handled by conventional probabilistic language models. However, PLLs can determine the naturalness of sentences at a high level because they are represented by the sum of the log-likelihoods of the conditional probabilities when each word is masked and predicted. Token ψ_t is replaced by [MASK], and the past and present tokens $\Psi_{\backslash t} = (\psi_1, \psi_2, ..., \psi_{|\Psi|})$ are predicted. Ψ refers to sentences, t represents time, Θ is the model parameter, and $P_{\mathrm{MLM}}(\cdot)$ denotes the probability of each sentence token. The BERT [30] was used for MLM.

$$\mathbf{PLL(\Psi)} := \sum_{t=1}^{|\Psi|} \log_2 P_{\mathrm{MLM}}(\psi_t | \Psi_{\backslash t}; \Theta) \tag{1}$$

For preprocessing, [31] was used to remove the stop words. For lines with the same sentences, one sentence was deleted. The financial news text with PLLs was scored one sentence at a time after pre-processing. The scores were summed daily for data scored one sentence at a time. Quartile ranges were calculated for the summed scores. Table 1 illustrates the polarity classification method.

Table 1: Polarity Classification Method

Classification Method	Sentiment Score
3rd quartile $>$ PLLs	1 (positive)
1st quartile $\leq$ PLLs $\leq$ 3rd quartile	0 (neutral)
1st quartile $<$ PLLs	-1 (negative)

If the polarity index created here is used with the financial time-series data in the next step, it should be aligned with the date of the financial time-series data. If there was a missing date on the polarity index side, the polarity index was filled with the median value.

3.3 Demonstration of leading effects

We use statistical causal inference to demonstrate whether financial news has leading effects on a stock portfolio using the polarity index created. The VAR-LiNGAM algorithm is used. In this study, we used VAR-LiNGAM to demonstrate the precedence. VAR-LiNGAM is a statistical causal inference model proposed by [32]. The causal graph inferred by VAR-LiNGAM is as follows:

$$\mathbf{x}(t) = \sum_{\tau=0}^{T} \mathbf{B}_\tau \mathbf{x}(t-\tau) + \mathbf{e}(t) \tag{2}$$

Algorithm 1 Window Sliding Segmentation

Input: signal $y = \{y_t\}_{t=1}^{T} (1 \leq t \leq T)$, cost function $c(\cdot)$, half window width w_h, peak search procedure PKSearch.

Initialize: $Z \leftarrow [0, 0, ...]$ a T-long array filled with 0.

for $t = w_h, ..., T - w_h$ **do**
  $p \leftarrow (t - w_h)..t$
  $q \leftarrow t..(t + w_h)$
  $r \leftarrow (t - w_h)..(t + w_h)$
  $Z[t] \leftarrow c(y_p) + c(y_q)$
end for

$L \leftarrow$ PKSearch (Z)

Output: set L of estimated breakpoint indexes.

where $\mathbf{x}(t) = (x_1(t), ..., x_n(t))^\top$ is the vector of the variables at time t and τ is the time delay. $\top$ denotes the transposition, n denotes the number of coefficients, and T represents the maturity date. In addition, $\mathbf{B}_\tau$ is a coefficient matrix that represents the causal relationship between the variables $\mathbf{x}(t-\tau) = (x_1(t-\tau), ..., x_n(t-\tau))^\top$. $\mathbf{e}(t) = (e_1(t), ..., e_n(t))^\top$ denotes a disturbance term. VAR-LiNGAM was implemented using the following procedure:

- First, a vector auto-regressive (VAR) model was applied to the causal relationships among variables from lag time to the current time.
- Second, for the causal relationships among variables at the current time, LiNGAM inference was performed using the residuals of the VAR model above.

This study confirms whether financial news precedes stock portfolios.

3.4 Change point detection

Verify that the polarity index has leading effects. Calculate the regime change point of the polarity index using the change point detection algorithm. The window sliding segmentation algorithm is used here. Window sliding segmentation [33, 34] is a fast approximation algorithm for computing the discrepancy between two adjacent windows that slide along the signal y. The entire algorithm is described in Algorithm 1. The notation of the algorithm is as follows [35]. Window sliding segmentation measures the discrepancy between the most recent past (left window) and most recent future (right window). Once the discrepancy curve is computed, a peak search is performed to determine the change-point index. The complete algorithm for window-sliding segmentation is presented in this section. Z is the score list, and PKSearch (Z) is the peak search procedure. The main benefits of window-sliding segmentation are its low complexity and ease of implementation.

3.5 Optimization algorithm

Portfolio optimization is performed based on the change points created. A constrained risk parity approach is used for portfolio optimization. Risk-parity portfolios have attractive characteristics that make them an appropriate choice for investors who wish to diversify their investments. Instead of allocating capital evenly across all assets in the investment universe, risk parity portfolios allocate total risk evenly across assets. In this study, we minimized the logarithmic barrier function proposed in [36]. The optimization problem is formulated as follows:

$$\min_{w>0} f(w) = w^{\top}\Sigma w - \sum_{i=1}^{n} \ln w_i \tag{3}$$

The domain of the objective function f for this problem is the interior of the nonnegative orthant $\mathbb{R}^n_+ = \{\boldsymbol{x} \in \mathbb{R}^n : \boldsymbol{x} \geq \mathbf{0}\}$. This optimization problem is sometimes referred to as the logarithmic penalty formulation because the term $-\sum_{i=1}^{n} \ln w_i$ is the logarithmic barrier function. Assume n is the investment-risk assets. Let w_i denote the ratio of asset i to the total invested assets, and define the portfolio as an n-dimensional vector $w = (w_1, w_2, ..., w_n)$. The symbol $\top$ denotes the transposition. The standard deviation of the rate of return on asset i is σ_i, the correlation coefficient between the rates of return on asset i and asset j is ρ_{ij}, and the covariance matrix of the rates of return on all assets is as follows: Covariance σ_{ij} of assets i and j is given by $\sigma_{ij} = \sigma_i \sigma_j \rho_{ij} (i \neq j)$.

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & & \sigma_{2n} \\ \vdots & & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{pmatrix} \tag{4}$$

The optimization conditions for the optimization problem are as follows.

$$\nabla f(x) = 2\Sigma w - w^{-1} = 0 \tag{5}$$

$w^{-1} = (\frac{1}{w_1}, \frac{1}{w_2}, ..., \frac{1}{w_n})$ denotes the vector of reciprocals of vector w.

Conversely, the relative risk contribution (RRC) of an asset is defined as the ratio of the risk contribution of that asset to the overall portfolio risk. This is given as follows:

$$RRC_i = \frac{w_i(\Sigma w)_i}{w^{\top}\Sigma w} \tag{6}$$

Note that we can write each element of the optimality condition in an equivalent form as follows:

$$2(\Sigma w)_i - \frac{1}{w_i} = 0 \Leftrightarrow w_i(\Sigma w)_i = \frac{1}{2}, i = 1, ..., n \tag{7}$$

If these conditions hold, we obtain the following:

$$RRC_i = \frac{w_i(\Sigma w)_i}{w^{\top}\Sigma w} = \frac{1/2}{n/2} = \frac{1}{n} \tag{8}$$

We showed that the optimality conditions for the optimization problem are equivalent to the risk parity conditions given above.

This study attempts to integrate sentiment signals and causal information into risk-parity portfolios. The causal information calculated by VAR-LiNGAM is reflected in the risk parity portfolio. The relationship between sentiment signals and causal information is illustrated in Figure 2. In this study, the region flanked by the signals is referred to as the regime.

Based on the sign of the overall effect in the VAR-LiNGAM, the weights of the subject assets in the risk parity portfolio are adjusted based on the sign of the overall effect of

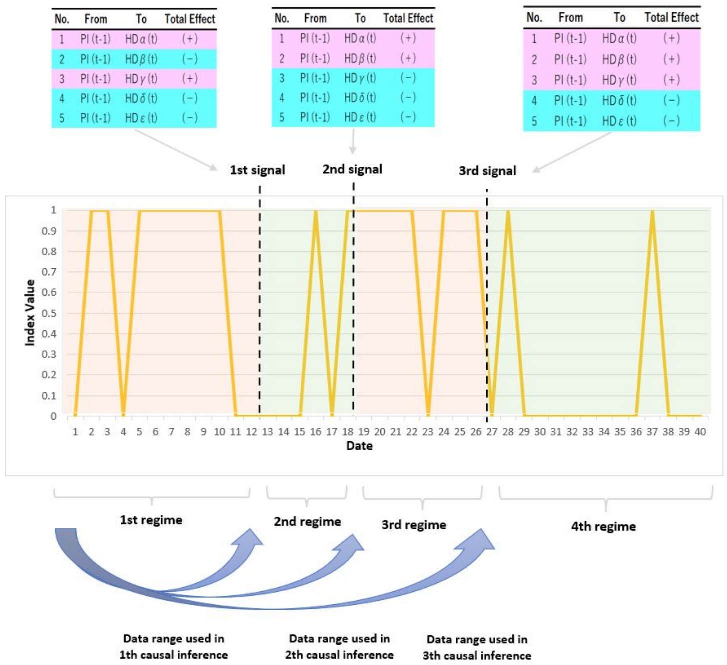


Figure 2: Relationship between sentiment signals and causal information

VAR-LiNGAM. In this study, we refer to this as a sentiment regime strategy. This can be categorized as follows: n denotes the number of assets. Additionally, n is represented by $n = l + m$.

- **Sentiment regime strategy 1:** The algorithm from the start until reaching signal 1 is a risk parity portfolio with no weighting adjustment. In this case, the weight vector is $w = (w_1, w_2, ..., w_n)$.

- **Sentiment regime strategy 2:** In regimes where the economy is improving, that is, regimes where the polarity indicator has a high percentage of values of 1, a two-stage weighting adjustment is performed. In this case, a risk parity portfolio is first created using vector $w = (w_1, w_2, ..., w_l)$, and then an additional weight vector $w^{adj} = (w_1^{adj}, ..., w_m^{adj})$ is adjusted to the target asset based on the results of causal inference. In this case, all components of ω^{adj} should have the same ratio.

- **Sentiment regime strategy 3:** In regimes and cases where the economy is downwards, i.e., where the polarity indicator has a high percentage of 0 values, the constraint is removed and the portfolio is a normal risk parity portfolio. In this case, the weight vector is $w = (w_1, w_2, ..., w_n)$.

The portfolio optimization method in this study is a combination of the sentiment regime strategy and regular periodic rebalancing.

Type	Name	Details
News	CNN	CNN News Headlines
	HFN	Historical Financial News Titles
	ONI	Onion Article Titles
ETF	SPY	SPDR S&P 500 ETF
	QQQ	PowerShares QQQ ETF
	GLD	SPDR Gold Shares
	EMB	iShares JP Morgan USD Em Mkts Bd ETF
	AGG	iShares Core US Aggregate Bond ETF

Table 2: Data overview

4 Experiments & Results

4.1 Preparation for back-testing

The polarity index is presented in Section 3.2. Financial news data were preprocessed before creating the polarity index. Both financial news and ETF data are in daily units; however, to match the period, if there are blanks in either, lines containing blanks are dropped. Once the polarity index is created in Section 3.2, the next step is to create a stock portfolio by adding the ETFs' adjusted closing prices. Next, we use VAR-LiNGAM in Section 3.3 to perform causal inference. Python library ruptures [35] were used. The results for VAR-LiNGAM show that the polarity index has a leading edge in the equity portfolio. The LiNGAM Python library [32] was used. Python libraries vectorbt [37], Riskfolio-Lib [38], PyPortfolioOpt [39], and FinRL [40] were used for back testing.

4.2 Dataset description

In this study, we calculate the signal for portfolio rebalancing and tactical asset allocation to actively go for an alpha based on the assumption that financial news has precedence over the portfolio. Two types of data were used. The period for these data was from January 2017 to December 2019.

- **News:** We used the daily historical financial news archive provided by Kaggle[1], a data analysis platform.
- **ETF:** We used the daily ETF data provided by Yahoo! Finance[2]. Additional historical data was used when conducting back testing (Section 4.1).

A summary of the data used in this study is shown in Table 2.

4.3 Scenarios for back-testing

The assumptions made for each algorithm are as follows. This condition set has been confirmed to be valid to a certain degree in [5].

- Regular rebalancing is timed every 30 days.

[1] https://www.kaggle.com/
[2] https://finance.yahoo.com/

- MA-SSAAM is a strategy that combines periodic rebalancing and sentiment regimes. The start of the sentiment regime strategy is to align with the breaking point of the regular balance.

- The number of change points [3] for change point detection (Section 3.4) was set at 3.

The main algorithms proposed in this study are as follows:

- **MA-SSAAM:** This is the proposed method in this study (Section 3) and is based on [5]. In this study, several results with different parameters are described.

The benchmarks are as follows:

- **BM (RPP):** This optimization is the RPP [36]. This is a benchmark model that removes the effects of causal inference in Section 3.3 and change point detection in Section 3.4 from MA-SSAAM.

- **BM (RPP+MV):** This optimization is a combination of RPP [36] and mean-variance model (MV) [41]. If the signal calculated by Section 3 is in a downtrend, RPP is used; if it is in an uptrend, the mean-variance model is used. This benchmark model removes the effects of causal inference in Section 3.3 from MA-SSAAM.

Portfolio theory-based methods are as follows:

- **MV:** This optimization is based on a mean-variance model [41]. The model considers only the mean and variance of the portfolio's rate of return.

- **CVaR:** This optimization is based on a conditional value at risk (CVaR) [42]. CVaR represents the average loss of a portfolio within a probability level; minimizing CVaR is an investment technique that minimizes the expected loss.

- **EVaR:** This optimization is based on an entropic value at risk (EVaR) [43]. EVaR is a risk indicator that represents the upper limit of VaR and CVaR.

- **CDaR:** This optimization is based on a conditional drawdown at risk (CDaR) [44]. CDaR is a drawdown-based risk measure. Its optimization framework is similar to CVaR optimization.

The reinforcement-based methods are as follows:

- **DDPG:** This optimization [40] is based on a deep deterministic policy gradient (DDPG). DDPG [45] is a model-free deep reinforcement learning algorithm. It obtains higher reward amounts with fewer trials in complex tasks where the action space is highly dimensional.

- **A2C:** This optimization [40] is based on an advantage actor-critic (A2C). A2C [46] is a distributed deep reinforcement learning based on actor-critic. A2C employs synchronous processing, which keeps the GPU load low.

[3] This is a pre-set parameter in ruptures. Note that this does not necessarily mean that the set number of changes will be detected, and in some cases, fewer change points may be detected.

- **PPO:** This optimization [40] is based on a proximal policy optimization (PPO). PPO [47] is a simplified algorithm with clipped surrogate objective and adaptive KL penalty.
- **SAC:** This optimization [40] is based on a soft actor-critic (SAC). SAC [48–50] is a method that adds a policy entropy term to the conventional objective function to allow for more diverse search.

4.4 Evaluation for back-testing

The evaluation indicators are defined as follows:

- **TR:** Total Return (TR) refers to the total return earned from an investment in an investment product within a given period. It is defined as follows, where P_{Start} is the price at the start, P_{End} is the price at the end, and D is dividends received during the period.

$$\mathbf{TR} = \frac{P_{Start} - P_{End} + D}{P_{Start}} \tag{9}$$

- **AR:** Annualized Return (AR) is the rate of return on an investment generated during the year. It is defined as follows, where n is the days during the period.

$$\mathbf{AR} = (\mathbf{TR} + 1)^{\frac{252}{n}} - 1 \tag{10}$$

- **AV:** Annualized Volatility (AV) represents the rate of price volatility of financial assets generated during the year. It is defined as follows, where N is the number of elements, R_i is the i th return, and $\hat{R}$ is the average return.

$$\mathbf{AV} = \sqrt{252} \times \sqrt{\frac{\Sigma_{i=1}^{N}(R_i - \hat{R})^2}{N-1}} \tag{11}$$

- **MDD:** Maximum Drawdown (MDD) refers to the rate of decline from the maximum asset. It is defined as follows. Here, V_{Peak} is the peak value before the largest drop, and V_{Lowest} is the lowest value before the largest drop.

$$\mathbf{MDD} = \frac{V_{Peak} - V_{Lowest}}{V_{Peak}} \tag{12}$$

- **SR:** Sharpe Ratio (SR) is an indicator that measures whether the investment has made a return commensurate with the risk taken. It is defined as follows, where R_f is the risk free rate. The risk-free rate is assumed to be 0 for this study.

$$\mathbf{SR} = \frac{\mathbf{AR} - R_f}{\mathbf{AV}} \tag{13}$$

- **CR:** Calmar Ratio (CR) is an indicator of whether higher returns are associated with higher risk. Here, R_f is the risk free rate. The risk-free rate is assumed to be 0 for this study.

$$\mathbf{CR} = \frac{\mathbf{AR} - R_f}{\mathbf{MDD}} \tag{14}$$

- **TE:** Tracking Error (TE) represents the difference between the portfolio return and benchmark return. It is defined as follows, where function $Var(\cdot)$ represents the variance, R_p is the portfolio return, and R_b is the benchmark return.

$$\mathbf{TE} = \sqrt{252} \times \sqrt{Var(R_p - R_b)} \tag{15}$$

- **IR:** Information Ratio (IR) represents how much more return is earned in relation to the risk considered in the tracking error. It is defined as follows. Here, N is the number of elements, R_p is the portfolio return, and R_b is the benchmark return.

$$\mathbf{IR} = \frac{R_p - R_b}{\mathbf{TE}} \tag{16}$$

4.5 Results of Back-testing

In this study, the following metrics were employed to assess portfolio performance.

The time-series plot of total returns at the end of each month is shown in Figure 3.

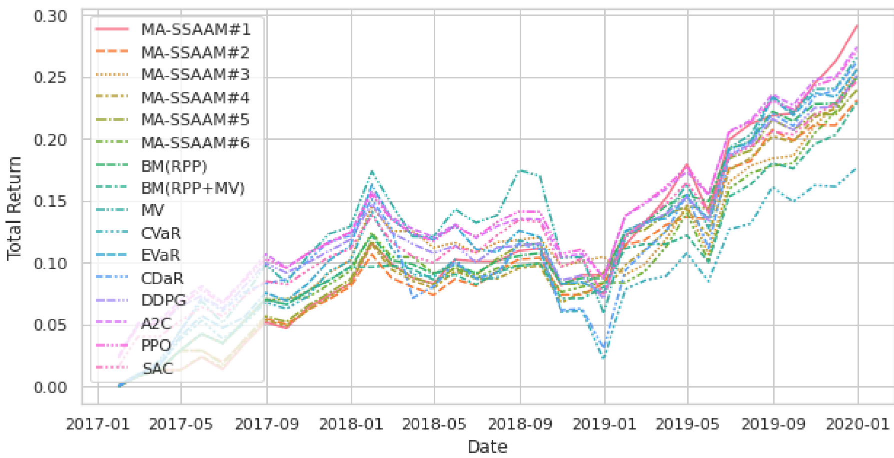


Figure 3: Total return

The results of the back-testing are presented in Table 3 [4]

Figure 4 illustrates the operational efficiency of the benchmark, Figure 4a shows the tracking error against BM (RPP), Figure 4b shows the tracking error against BM (RPP), Figure 4c shows the information ratio against BM (RPP+MV), and Figure 4d shows the information ratio against BM (RPP+MV).

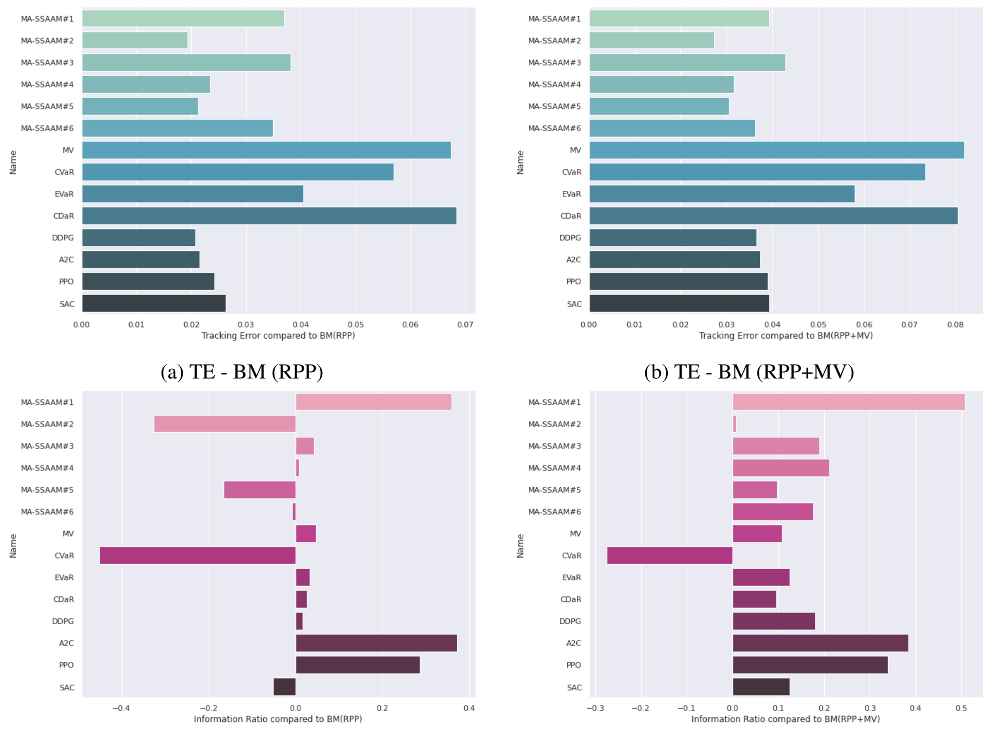
5 Discussion

The overall trend in the proposed method in Table 3 is well-balanced, with high values for AR, SR, and CR. In particular, the value of CR is high, indicating that this is a stable operational strategy. In addition, MA-SSAAM #1 and #3, which are methods using CNN, have particularly stable AR and CR. This indicates that the performance of this method can be enhanced using more formal text sources.

[4]Reinforcement learning used additional ETF data from January 2008 through December 2016 as training data.

Type	Name	Parameter	AR [%]	AV [%]	MDD [%]	SR	CR
Proposed Method	MA-SSAAM #1	news = cnn, adj-weight = 0.3	**9.97**	6.65	5.52	1.50	1.81
	MA-SSAAM #2	news = hfn, adj-weight = 0.3	7.90	**4.87**	4.90	1.62	1.61
	MA-SSAAM #3	news = oni, adj-weight = 0.3	8.72	6.42	7.05	1.36	1.24
	MA-SSAAM #4	news = cnn, adj-weight = 0.2	8.57	5.69	6.14	1.40	1.51
	MA-SSAAM #5	news = hfn, adj-weight = 0.2	8.18	5.31	5.43	1.54	1.51
	MA-SSAAM #6	news = oni, adj-weight = 0.2	8.54	5.94	6.60	1.44	1.29
Benchmark Method	BM (RPP)	weight_bounds = (0.01, 1)	8.56	5.03	6.24	**1.70**	1.37
	BM (RPP+MV)	weight_bounds = (0.01, 1)	7.85	4.69	**4.21**	1.67	**1.86**
Portfolio Theory	MV	significance_level = 0.05	8.65	10.84	17.11	0.80	0.51
	CVaR	significance_level = 0.05	5.59	9.59	17.13	0.58	0.33
	EVaR	significance_level = 0.05	8.56	8.20	13.02	1.04	0.66
	CDaR	significance_level = 0.05	8.53	10.67	17.07	0.80	0.50
Reinforcement Learning	DDPG	batch_size = 128, learning_rate = 0.001	8.53	6.35	11.16	1.34	0.76
	A2C	batch_size = 128, learning_rate = 0.0002	9.36	6.50	10.53	1.44	0.89
	PPO	batch_size = 128, learning_rate = 0.001	9.24	6.67	10.58	1.39	0.87
	SAC	batch_size = 128, learning_rate = 0.0003	8.36	6.39	10.46	1.31	0.80

Table 3: Back-testing



(a) TE - BM (RPP)

(b) TE - BM (RPP+MV)

(c) IR - BM (RPP)

(d) IR - BM (RPP+MV)

Figure 4: Comparison of each method against benchmarks

The proposed method was compared with the benchmark methods. Comparing BM (RPP) and MA-SSAAM, SR tends to be higher for BM (RPP), whereas AR tends to be relatively higher for MA-SSAAM. BM (RPP) is a risk parity portfolio strategy often used for the allocation of multi-class assets, but the CR values are relatively higher for MA-SSAAM. Comparing BM (RPP+MV) and MA-SSAAM, MDD was lower in BM (RPP+MV). BM (RPP+MV) can be interpreted as MA-SSAAM without the causal inference effect, but because the AR of MA-SSAAM outperforms that of the BM (RPP+MV), the causal inference effect has a return-enhancing effect. The comparison of BM (RPP) and MA-SSAAM showed the same trend as BM (RPP+MV). Here, BM (RPP) can be interpreted as dropping change-point detection and causal inference effects from MA-SSAAM. Conversely, comparing BM (RPP+MV) and BM (RPP), BM (RPP+MV) had a lower MDD and AR. This result indicates that the introduction of change point detection has a risk-hedging effect against a significant market, and does not differ from the hypothesis (Section 1.2).

The proposed method is compared with portfolio theory. Overall, the MA-SSAAM metric outperforms portfolio theory; MDD is particularly higher for portfolio theory, making it a relatively high-risk strategy for multi-class asset allocation. However, MA-SSAAM and portfolio theory have similar results for AR. In addition, the CVaR's AR is low and that of MDD is high, making it comparatively inferior to other operational results. In particular, MDD was almost three times larger than MA-SSAAM #1. This point should be considered in the future as a secondary result of this study.

The proposed method was compared with other methods using reinforcement learning. Overall, AR and MDD were higher for the reinforcement learning method. The method using reinforcement learning has a high risk and high return compared with MA-SSAAM. In addition, the performance of the method using reinforcement learning may vary depending on the amount of teacher data; therefore, it is necessary to search for best practices when using this method in the future. The most important feature of MA-SSAAM is its ability to minimize MDD. However, there is room for further research on maximizing returns. We believe that methods using reinforcement learning can compensate for this. In future research, we intend to consider this and make the MA-SSAAM framework more robust.

Considering the tracking errors computed for the two benchmarks in Figure 4, MA-SSAAM shows a similar trend in Figure 4a and 4b. This indicates that change-point detection and causal inference do not significantly affect return divergence. However, the information ratio of MA-SSAAM shows a different trend in Figures 4c and 4d. In Figure 4c, the MA-SSAAM information ratio is low, with some MA-SSAAM information ratios being negative. In contrast, in Figure 4d, all MA-SSAAM information ratios are positive. This indicates that the values improve when BM (RPP+MV) or change-point detection is included, indicating that the efficiency of active operations is higher when the change-point detection effect is included.

6 Conclusion & Future Work

In this study, we demonstrate the usefulness of financial texts for asset allocation with portfolios comprising multiclass assets. This was accomplished using natural language processing and change-point detection techniques to create polarity indicators that signal rebalancing. In the future, we intend to further enhance this framework in portfolio management, including hedging strategies using virtual currencies and other highly volatile instruments, real estate, options, and credit derivatives. We confirmed the effectiveness of this approach by examining available textual data, such as reports and financial statements published by central banks.

Acknowledgment

This work was supported by JST-Mirai Program Grant Number JPMJMI20B1, Japan, and JST, PRESTO Grant Number JPMJPR2267, Japan. The authors would like to thank Professor Shohei Shimizu for lending their expertise on the application of VAR-LiNGAM. The authors declare that the research was conducted without any commercial or financial relationships that could be construed as potential conflicts of interest.

References

[1] Kentaro Imajo, Kentaro Minami, Katsuya Ito, and Kei Nakagawa. Deep portfolio optimization via distributional prediction of residual factors. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(1):213–222, May 2021.

[2] Katsuya Ito, Kentaro Minami, Kentaro Imajo, and Kei Nakagawa. Trader-company method: A metaheuristics for interpretable stock price prediction. In *Proceedings of the 20th International Conference on Autonomous Agents and MultiAgent Systems*, AAMAS '21, page 656–664, Richland, SC, 2021. International Foundation for Autonomous Agents and Multiagent Systems.

[3] Takahiro Komatsu and Naoki Makimoto. Linear rebalancing strategy for multi-period dynamic portfolio optimization under regime switches. *Journal of the Operations Research Society of Japan*, 61(3):239–260, 2018.

[4] Rei Taguchi, Hikaru Watanabe, Hiroki Sakaji, Kiyoshi Izumi, and Kenji Hiramatsu. Constructing equity investment strategies using analyst reports and regime switching models. *Frontiers in Artificial Intelligence*, 5, 2022.

[5] Rei Taguchi, Hiroki Sakaji, and Kiyoshi Izumi. Ssaam: Sentiment signal-based asset allocation method with causality information. In *2022 IEEE International Conference on Big Data (Big Data)*, pages 2363–2366, 2022.

[6] Hyungbin Yun, Minhyeok Lee, Yeong Seon Kang, and Junhee Seok. Portfolio management via two-stage deep learning with a joint cost. *Expert Systems with Applications*, 143:113041, 2020.

[7] Wuyu Wang, Weizi Li, Ning Zhang, and Kecheng Liu. Portfolio formation with preselection using deep learning from long-term financial data. *Expert Systems with Applications*, 143:113042, 2020.

[8] Wei Chen, Haoyu Zhang, Mukesh Kumar Mehlawat, and Lifen Jia. Mean–variance portfolio optimization using machine learning-based stock price prediction. *Applied Soft Computing*, 100:106943, 2021.

[9] Tomoki Ito, Kota Tsubouchi, Hiroki Sakaji, Tatsuo Yamashita, and Kiyoshi Izumi. Contextual sentiment neural network for document sentiment analysis. *Data Science and Engineering*, 5(2):180–192, 2020.

[10] Hiroki Sakaji, Ryota Kuramoto, Hiroyasu Matsushima, Kiyoshi Izumi, Takashi Shimada, and Keita Sunakawa. Financial text data analytics framework for business confidence indices and inter-industry relations. In *Proceedings of the First Workshop on Financial Technology and Natural Language Processing*, pages 40–46, 2019.

[11] Rei Taguchi, Hikaru Watanabe, Masanori Hirano, Masahiro Suzuki, Hiroki Sakaji, Kiyoshi Izumi, and Kenji Hiramatsu. Market trend analysis using polarity index generated from analyst reports. In *2021 IEEE International Conference on Big Data (Big Data)*, pages 3486–3494, 2021.

[12] Masahiro Suzuki, Hiroki Sakaji, Kiyoshi Izumi, Hiroyasu Matsushima, and Yasushi Ishikawa. Forecasting net income estimate and stock price using text mining from economic reports. *Information*, 11(6), 2020.

[13] Masahiro Suzuki, Hiroki Sakaji, Kiyoshi Izumi, and Yasushi Ishikawa. Forecasting stock price trends by analyzing economic reports with analyst profiles. *Frontiers in Artificial Intelligence*, page 103, 2022.

[14] Biwei Huang, Kun Zhang, Jiji Zhang, Joseph D Ramsey, Ruben Sanchez-Romero, Clark Glymour, and Bernhard Schölkopf. Causal discovery from heterogeneous/nonstationary data. *J. Mach. Learn. Res.*, 21(89):1–53, 2020.

[15] Peter Spirtes, Clark N Glymour, Richard Scheines, and David Heckerman. *Causation, prediction, and search*. MIT press, 2000.

[16] David Maxwell Chickering. Optimal structure identification with greedy search. *Journal of machine learning research*, 3(Nov):507–554, 2002.

[17] David Heckerman, Dan Geiger, and David M Chickering. Learning bayesian networks: The combination of knowledge and statistical data. *Machine learning*, 20(3):197–243, 1995.

[18] Biwei Huang, Kun Zhang, Yizhu Lin, Bernhard Schölkopf, and Clark Glymour. Generalized score functions for causal discovery. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining*, pages 1551–1560, 2018.

[19] Peter Bühlmann, Jonas Peters, and Jan Ernest. Cam: Causal additive models, high-dimensional order search and penalized regression. *The Annals of Statistics*, 42(6):2526–2556, 2014.

[20] Patrik Hoyer, Dominik Janzing, Joris M Mooij, Jonas Peters, and Bernhard Schölkopf. Nonlinear causal discovery with additive noise models. *Advances in neural information processing systems*, 21, 2008.

[21] Jonas Peters, Joris M. Mooij, Dominik Janzing, and Bernhard Schölkopf. Causal discovery with continuous additive noise models. *Journal of Machine Learning Research*, 15(58):2009–2053, 2014.

[22] Shohei Shimizu, Patrik O Hoyer, Aapo Hyvärinen, Antti Kerminen, and Michael Jordan. A linear non-gaussian acyclic model for causal discovery. *Journal of Machine Learning Research*, 7(10), 2006.

[23] Shohei Shimizu, Takanori Inazumi, Yasuhiro Sogawa, Aapo Hyvärinen, Yoshinobu Kawahara, Takashi Washio, Patrik O Hoyer, and Kenneth Bollen. Directlingam: A direct method for learning a linear non-gaussian structural equation model. *The Journal of Machine Learning Research*, 12:1225–1248, 2011.

[24] Kiyoshi Izumi, Hitomi Sano, and Hiroki Sakaji. Economic causal-chain search and economic indicator prediction using textual data. In *Proceedings of the 3rd Financial Narrative Processing Workshop*, pages 19–25, 2021.

[25] Kiyoshi Izumi and Hiroki Sakaji. Economic causal-chain search using text mining technology. In *International Joint Conference on Artificial Intelligence*, pages 23–35. Springer, 2019.

[26] Sayantan Banerjee and Kousik Guhathakurta. Change-point analysis in financial networks. *Stat*, 9(1):e269, 2020.

[27] VASILE GEORGESCU. Online change-point detection in financial time series: challenges and experimental evidence with frequentist and bayesian setups. In *Methods For Decision Making In An Uncertain Environment*, pages 131–145. World Scientific, 2012.

[28] Reza Habibi. Bayesian online change point detection in finance. *Financial Internet Quarterly*, 18(1):27–34, 2022.

[29] Julian Salazar, Davis Liang, Toan Q. Nguyen, and Katrin Kirchhoff. Masked language model scoring. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2699–2712, Online, July 2020. Association for Computational Linguistics.

[30] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2019.

[31] Steven Bird, Ewan Klein, and Edward Loper. *Natural Language Processing with Python*, Juni 2009.

[32] Aapo Hyvärinen, Kun Zhang, Shohei Shimizu, and Patrik O Hoyer. Estimation of a structural vector autoregression model using non-gaussianity. *Journal of Machine Learning Research*, 11(5), 2010.

[33] Alexandre Lung-Yut-Fong, Céline Lévy-Leduc, and Olivier Cappé. Distributed detection/localization of change-points in high-dimensional network traffic data. *Statistics and Computing*, 22(2):485–496, 2012.

[34] Céline Lévy-Leduc and François Roueff. Detection and localization of change-points in high-dimensional network traffic data. *The Annals of Applied Statistics*, pages 637–662, 2009.

[35] Charles Truong, Laurent Oudre, and Nicolas Vayatis. Selective review of offline change point detection methods. *Signal Processing*, 167:107299, 2020.

[36] Petter N. Kolm, Reha Tütüncü, and Frank J. Fabozzi. 60 years of portfolio optimization: Practical challenges and current trends. *European Journal of Operational*

Research, 234(2):356–371, 2014. 60 years following Harry Markowitz's contribution to portfolio theory and operations research.

[37] Oleg Polakow. vectorbt (1.4.2), 2022.

[38] Dany Cajas. Riskfolio-lib (3.0.0), 2022.

[39] Robert Andrew Martin. Pyportfolioopt: portfolio optimization in python. *Journal of Open Source Software*, 6(61):3066, 2021.

[40] Xiao-Yang Liu, Hongyang Yang, Qian Chen, Runjia Zhang, Liuqing Yang, Bowen Xiao, and Christina Dan Wang. Finrl: A deep reinforcement learning library for automated stock trading in quantitative finance. *arXiv preprint arXiv:2011.09607*, 2020.

[41] Harry Markowitz. Portfolio Selection. *Journal of Finance*, 7(1):77–91, March 1952.

[42] Stanislav Uryasev and R Tyrrell Rockafellar. Conditional value-at-risk: optimization approach. In *Stochastic optimization: algorithms and applications*, pages 411–435. Springer, 2001.

[43] Dany Cajas. Entropic portfolio optimization: a disciplined convex programming framework. *Available at SSRN 3792520*, 2021.

[44] Alexei Chekhlov, Stanislav Uryasev, and Michael Zabarankin. Portfolio optimization with drawdown constraints. In *Supply chain and finance*, pages 209–228. World Scientific, 2004.

[45] Timothy P. Lillicrap, Jonathan J. Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning, 2015.

[46] Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning, 2016.

[47] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms, 2017.

[48] Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor, 2018.

[49] Tuomas Haarnoja, Aurick Zhou, Kristian Hartikainen, George Tucker, Sehoon Ha, Jie Tan, Vikash Kumar, Henry Zhu, Abhishek Gupta, Pieter Abbeel, and Sergey Levine. Soft actor-critic algorithms and applications, 2018.

[50] Tuomas Haarnoja, Sehoon Ha, Aurick Zhou, Jie Tan, George Tucker, and Sergey Levine. Learning to walk via deep reinforcement learning, 2018.