Enhancing Portfolio Efficiency with Mean-Shift Clustering

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Abstract.

Mean-Shift Clustering, an unsupervised learning algorithm, facilitates the grouping of objects sharing similar characteristics without assuming a predefined number of clusters during the calculation. In the context of portfolio formation, investors seek groups of stocks across diverse sectors to construct a well-diversified portfolio, aiming to minimize risk. The aims of this paper are to provide an overview of how Mean-Shift Clustering can be applied to portfolio construction and highlight the advantages and benefits of using Mean-Shift in comparison to traditional methods This research employs the Mean-Shift Clustering algorithm to cluster IDX80 stocks based on expected return variance and average sales volume. The Mean-Shift Clustering algorithm yields five clusters for IDX80, of which four clusters are identified as optimal portfolios using mean variance. Evaluating the portfolios based on the Sharpe index value, portfolio 3, comprising BRIS, DMMX, ENRG, ESSA, HRUM, MDKA, and SMDR, emerges as the most optimal among the considered portfolios.

Keywords: Mean Shift Clustering, Optimal Portofolio, Mean-Variance Method.

1 Introduction

Portfolio construction is the process of investing in different types of asset classes and financial products, keeping market types and risks, diversification needs, fund management efficiency, risk tolerance, investment time horizon, and long-term and short-term financial goals in mind [1]. The purpose is to strategically allocate capital to improve portfolio returns. A well-structured portfolio ensures long-term returns and profit maximization for investors. It balances risks and safeguards investors from direct or indirect market fluctuations. It facilitates diversification by helping an investor place their capital in various assets like stocks, bonds, real estate, commodities, etc. Strategic portfolio construction enables compounding, controls market exposure, brings investment discipline, and facilitates liquidity management [2], [3].

The process of portfolio construction involves identifying suitable assets, analyzing associated risks, implementing a suitable asset allocation strategy, choosing a solid

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management approach, making mindful investments, and ensuring consistent monitoring for portfolio performance optimization [1]. Traditional and modern are two well-known portfolio construction techniques [1]. Investors face several challenges while making investment decisions. It also involves investment style selection, portfolio balancing, emotional decision-making, market fluctuations handling, etc. Overcoming these challenges is crucial to earn good returns. One of the most popular investment options is stocks, which are motivated by capital gain and dividends that will be received annually [3]. To obtain a maximum profit, investor will construction a portfolio that contains a collection of financial assets that aims to reduce risk by allocating a number of funds to alternative investments or stock diversification.

Efficient portfolio construction is crucial for risk management and maximizing returns. Kangari [4] emphasizes the importance of diversification in construction project portfolios, while Brunel [5] introduces a tax-efficient model for multi-investment portfolios. Deng [6] and Canbaz [7] both highlight the significance of practical constraints and interdependencies in global and project portfolios, respectively. Korzeniewski [8] and Gaenore [9] propose clustering-based and efficiency-based techniques for stock and asset allocation, respectively. Herold [10] and Ivanyuk [11] focus on the role of qualitative forecasts and algorithmic models in portfolio construction. These studies collectively underscore the need for a systematic and comprehensive approach to portfolio construction.

In this pursuit, mean shift clustering has emerged as a powerful algorithm in unsupervised machine learning. By rapidly identifying patterns and groupings within vast datasets, mean shift clustering enables investors to discern underlying structures in stock market trends. Given the ever-changing nature of market conditions, timely decision-making is essential. Utilizing mean shift clustering, investors can quickly adapt their portfolios to capitalize on emerging opportunities or mitigate risks. The algorithm's ability to identify clusters based on the mean-shift procedure provides a nuanced understanding of stock dynamics, allowing for the construction of portfolios that align with current market sentiments. In an environment where every moment counts, mean shift clustering offers a strategic advantage, enabling investors to make informed choices and optimize their stock portfolios in response to evolving market conditions. Thus, mean shift clustering is a valuable tool for investors seeking to navigate the complexities of the stock market. Mean shift clustering is a powerful algorithm in unsupervised machine learning that helps investors discern underlying structures in stock market trends. Identifying clusters based on the mean-shift procedure, enables investors to construct portfolios that align with current market sentiments. Utilizing mean shift clustering can offer a strategic advantage for investors to respond to evolving market conditions and optimize their portfolios.

In this paper, we provide an overview of how Mean-Shift Clustering can be applied to portfolio construction and highlight the advantages and benefits of using Mean-Shift in comparison to traditional methods. We also present real-world examples showcasing the application of Mean-Shift Clustering in portfolio construction using IDX80 stocks price data.

2 Literature Review

A range of studies have explored the application of clustering algorithms in portfolio management. Zhan [12]and Burney [13] both demonstrate the potential of these algorithms in reducing portfolio risk and improving optimization. This is further supported by Zhang [14], who shows that clustering can enhance portfolio stability and returns. The use of clustering algorithms for risk-adjusted portfolio construction is also highlighted by León [15], who found that these algorithms can produce more stable portfolios with smaller volatilities. Subekti [16] and Goetzmann and Wachter [17]both emphasize the role of clustering in improving the reliability and performance of portfolios. However, the specific clustering algorithms used in these studies vary, with some focusing on correlation clustering [12], fuzzy granularity-based clustering [13] and ant colony optimization [16].

Several studies have also demonstrated the effectiveness of mean-shift clustering in optimal portfolio construction. León [15] and Massahi [18] both found that clustering algorithms, including mean-shift, produced more stable portfolios with smaller volatilities. This was further supported by Korzeniewski [8], who applied mean-shift clustering to construct a well-diversified stock portfolio. The use of mean-shift clustering in portfolio management was also shown to improve Sharpe ratios and portfolio weight stability [14]. Additionally, Tayali [19] and Begušić [20] both found that mean-shift clustering, when integrated into the mean-variance portfolio optimization model, outperformed other clustering methods and improved out-of-sample portfolio performance. Khedmati [21] further extended this by proposing an online portfolio selection algorithm using mean-shift clustering, which demonstrated better efficiency compared to existing algorithms.

3 Portfolio Construction and Clustering Algorithm

3.1 Mean Variance

The optimal portfolio is a combination of assets that provides maximum return with minimum risk [9]. The theory proposed by Harry Markowitz (1952) states that in the formation of the optimal portfolio is done by maximizing the mean as expected return or minimizing variance as risk. How to form an optimal portfolio with the mean variance method. The covariance variance of the return is given by

$$\sigma_{ij} = \frac{1}{T-1}\sum_{t=1}^{T}\left(R_{i,t} - E(R_i)\right)\left(R_{j,t} - E(R_j)\right) \tag{1}$$

where $R_{i,t}$ is the return of the stock price calculated by finding the difference between the two natural log prices at the end and beginning of the period and can be calculated using equation, $E(R_{i,t})$ is the expected return obtained by calculating the average value of stock returns during the observation period with equation. The covariance variance matrix is given by

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \cdots & \sigma_{2n} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \cdots & \sigma_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \sigma_{n3} & \cdots & \sigma_{nn} \end{bmatrix}$$

Our objective is to minimize the risk of the portfolio, $\boldsymbol{\sigma_p^2} = \boldsymbol{\omega}^{\mathbf{T}}\boldsymbol{\Sigma}\boldsymbol{\omega}$ with respect to the expected return and the weight $\boldsymbol{\omega}$. By applying mean-variance method, see [22], [23], the optimal weight is given by

$$\boldsymbol{\omega} = \frac{\boldsymbol{\Sigma}^{-1}\mathbf{1}}{\mathbf{1}^{T}\boldsymbol{\Sigma}^{-1}\mathbf{1}}$$

where ω is the stock weight, Σ^{-1} is the inverse of the variance-covariance matrix, $\mathbf{1}$ is an $n \times 1$ matrix of $\mathbf{1}$, and $\mathbf{1}^{T}$ is the transpose matrix of 1. The performance of portfolio is measured by considering the return and risk factors of the portfolio in its calculation. The method developed by William Sharpe bases its calculations on the concept of the capital market line as a benchmark. If a portfolio has a higher Sharpe index value then this portfolio is considered better when compared to similar portfolios. The Share index is calculated by

$$S_p = \frac{E(R_p) - R_f}{\sigma_p} \tag{2}$$

where R_f is the fix rate of return proposed by the Bank of Indonesia.

3.2 Mean Shift Clustering

Mean-Shift Clustering is a type of non-parametric unsupervised learning algorithm used to group data based on similar characteristics without using cluster assumptions. Clustering in this algorithm is defined as a condition where all data points that point to the same mode will be part of the same cluster. A mode is the local maximum point of a density [24].

The mean shift starts by defining windows with predefined bandwidth at each point (or random locations) in the feature space. The centers of the windows form the initial estimates of the densest regions. For each window, we compute the center of mass that is equal to the weighted mean (average) for all data points inside the window. After that, we shift each window to its center of mass. The algorithm will keep calculating the means and shifting the windows until convergence, i.e., the mean shift vectors ≈ 0 [25]. The mean shift vector is given by

$$M_h(y_0) = \left[\frac{\sum_{i=1}^{nx} w_i(y_0)x_i}{\sum_{i=1}^{nx} w_i(y_0)}\right] - y_0 \tag{3}$$

Using h bandwidth and dataset $D = (x_1, x_2, x_i, \dots, x_n)$ where $x_i \in \mathbb{R}^d$ and $d \geq 2$ as the input, we can get number of clusters as the output for this algorithm. The detail of this algorithm, readers may refer to [25].

3.3 Clustering Factors and Data Standarization

In general, investors will pay attention to the return and risk of a stock before starting an investment. Return is the result of investment while risk is the deviation from the results received with the expected [11]. Not only that, the volume of stocks is also a concern of investors because the volume of stocks includes the number of stocks bought and the number of stock sold during a certain period so that it shows how much interest people have in investing in these stocks.

In applying mean shift clustering to stock clustering, the expected return value, variance, and average stock volume will be used as clustering factors. With this, it is expected that the algorithm will be able to provide clusters containing a collection of stocks that have the potential to provide profits for investors. The expected return of a stock is the return that investors expect in the future, the variance indicates the risk of the stock, and the average stock volume is the average of the stock's buying and selling activities.

Data standarization is a stage that is carried out if there are differences in values with a large scale in the variables studied. Data standarization can use the Z-score calculation to convert each variable to a standard value. The Z-score calculation is done by finding the difference between the data and the average value then divided by the standard deviation of each research variable [26]. Z-score standarization is calculated using equation (4)

$$z = \frac{x_i - \bar{x}}{s} \tag{4}$$

where x_i is the i data, x_i is the mean of the data, and s is the standard deviation.

4 Method and Result

4.1 Collecting Data and Preprocessing

The data used are stocks that are consistently listed on IDX80 during the period January 1, 2020 - November 10, 2022. Historical stock data is obtained through the yahoo finance website. The expected return value, variance, and average trading volume of each stock are calculated. They are all used as input for the mean shift clustering algorithm. The standardization is needed to reduce the variability of the data using equation (4).

4.2 Result

Based on Indonesia Stocks Exchange, there are only 75 stocks that consisten in IDX80 during the period observation, it shows in Table. 1.

Table 1. Stocks Consisten in IDX80 During Period Observation

AALI	BBTN	ERAA	JPFA	SIDO	BBNI
ACES	BFIN	ESSA	JSMR	SMDR	EMTK

ADHI	BMRI	EXCL	KLBF	SMGR	ISAT
ADRO	BRIS	GGRM	LPPF	SMRA	PWON
AGII	BRMS	HEAL	LSIP	SRTG	WIKA
AKRA	BRPT	HMSP	MAPI	TBIG	BBRI
AMRT	BSDE	HRUM	MDKA	TINS	ENRG
ANTM	BTPS	ICBP	MEDC	TKIM	ITMG
ASII	CPIN	INCO	MIKA	TLKM	SCMA
ASSA	CTRA	INDF	MNCN	TOWR	WSKT
ARTO	DMMX	INDY	PGAS	TPIA	
BACA	DOID	INKP	PTBA	UNTR	
BBCA	DSNG	INTP	PTPP	UNVR	

4.3 Mean Shift Clustering

After doing the preprocessing data, all the data will inputed to the mean shift clustering algorithm and give 5 cluster as the output show in Figure 1, list of stocks in each cluster it shows in Table. 2.

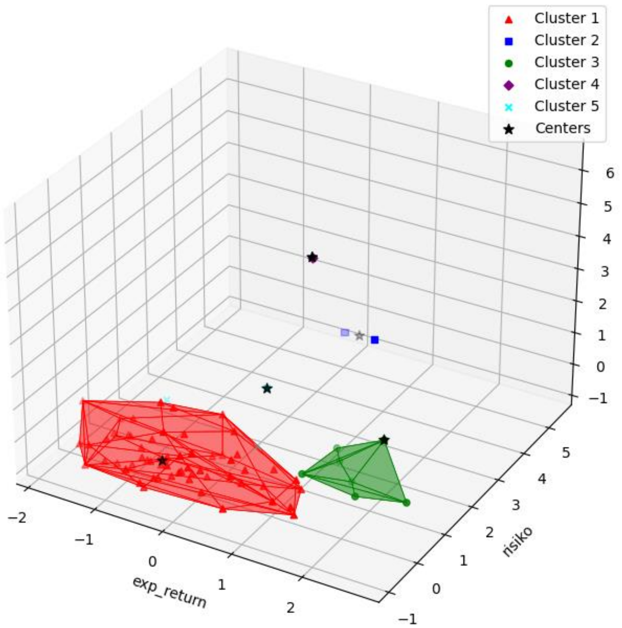

Fig. 1. Plot Clastering by Mean Shift Clustering

Table 2. List of Stocks in Each Cluster

Cluster	List of Stocks

Cluster 1	AALI, ACES, ADHI, AGII, AKRA, AMRT, ASII, ASSA, BACA, BBCA, BBNI, BBTN, BFIN, BMRI, BRPT, BSDE, BTPS, CPIN, CTRA, DOID, DSNG, EMTK, ERAA, EXCL, GGRM, HEAL, HMSP, ICBP, INCO, INDF, INDY, INKP, INTP, ISAT, ITMG, JPFA, JSMR, KLBF, LPPF, LSIP, MAPI, MEDC, MIKA, MNCN, PGAS, PTBA, PTBA, PTPP, PWON, SCMA, SMGR, SMRA, SRTG, TBIG, TINS, TKIM, TLKM, TOWR, TPIA, UNTR, UNVR, WIKA, WSKT
Cluster 2	ARTO, SIDO
Cluster 3	BRIS, DMMX, ENRG, ESSA, HRUM, MDKA, SMDR
Cluster 4	BRMS
Cluster 5	ADRO, ANTM, BBRI

Stocks that are in the same cluster have similar expected return values, variance, and average stocks volume, which means that mean shift clustering is able to group IDX80 stocks into a cluster where each stock has similar characteristics. Based on the results of the cluster formed, each cluster is formed into an optimal portfolio with the mean variance method. Among all the clusters formed, cluster 4 is ignored because the cluster contains only 1 stock member which means it does not comply with the definition of a portfolio consisting of a collection of assets. Furthermore, cluster 1 refers to as portfolio 1, cluster 2 refers to as portfolio 2, cluster 3 refers to as portfolio 3, and cluster 5 refers to as portfolio 4.

4.4 Optimal Portfolio Construction

The optimal portfolio formation will be carried out by the mean variance method, where this method will maximize the mean as the expected return and minimize the variance as the risk so as to obtain maximum profit [22]. Table 3 shows the optimal weight of each stock in each portfolio.

Table 3. Optimal Portfolio Construction

Portofolio 1							
Stocks	Weight	Stocks	Weight	Stocks	Weight	Stocks	Weight
AALI	-1%	BSDE	7%	INDY	-1%	PTBA	-2%
ACES	6%	BTPS	1%	INKP	-4%	PTPP	2%
ADHI	-3%	CPIN	1%	INTP	-3%	PWON	-2%
AGII	1%	CTRA	0%	ISAT	-1%	SCMA	-5%
AKRA	4%	DOID	-1%	ITMG	5%	SMGR	-3%
AMRT	6%	DSNG	9%	JPFA	-1%	SMRA	-2%
ASII	2%	EMTK	5%	JSMR	1%	SRTG	4%
ASSA	0%	ERAA	3%	KLBF	3%	TBIG	-1%
BACA	3%	EXCL	-4%	LPPF	1%	TINS	0%
BBCA	12%	GGRM	4%	LSIP	-6%	TKIM	-1%

BBNI	-5%	HEAL	12%	MAPI	4%	TLKM	10%
BBTN	-1%	HMSP	-1%	MEDC	-1%	TOWR	5%
BFIN	3%	ICBP	10%	MIKA	6%	TPIA	11%
BMRI	-2%	INCO	-1%	MNCN	7%	UNTR	2%
BRPT	-6%	INDF	6%	PGAS	-2%	UNVR	6%
WIKA	-5%	WSKT	3%				
Portofolio 2							
ARTO	91%	SIDO	9%				
Portofolio 3							
BRIS	8,64%	DMMX	14%	ENRG	17%	ESSA	6%
HRUM	17%	MDKA	23%	SMDR	15%		
Portofolio 4							
ARTO	25%	ANTM	10%	BBRI	64%		

The percentage number in the weight column indicates how much money should be invested in the stock. A positive percentage indicates that the investor should invest that percentage, while 0% and negative percentages indicate that the investor should not invest in the stock. For example, assume an investor has an investment capital of USD1000 and will invest in portfolio 2, then the amount of funds that must be invested in ARTO is USD910 and in SIDO is USD90.

4.5 Portfolio Perfomance

Calculation of portfolio performance is carried out to determine whether the portfolio formed has been able to meet the investment objectives that investors want to achieve [11]. Portfolio performance is calculated with the Sharpe index, which is a method for measuring portfolio performance by taking into account the return and risk factors of the portfolio in its calculation. The following is a table of sharpe index results from each portfolio formed based on the results of cluster mean shift clustering.

Table 4. Portfolio Perfomance

Portfolio	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
Sharpe Index	-0,152564148	-0,017105211	0,029572905	-0,063211386

The calculation of the Sharpe index of each portfolio has different results, this is due to differences in the combination and number of shares in each portfolio and also the distribution of the weight of each share in each portfolio. Porto 1, 2, and 4 have negative values, this indicates that the benefits obtained by investors when investing in these portfolios are not comparable to the risks borne, so investors are advised not to invest in these portfolios and choose porto 3 which has a positive sharpe index value. Because, a positive sharpe index value indicates that the amount of risk borne by investors will be proportional to the benefits received.

5 Conclusion

Mean shift clustering is able to help investors to choose a combination of stocks that have the potential to provide investors with maximum profits. With three factors that investors consider in choosing a combination of stocks, mean shift clustering results in 5 Clusters with a combination of stocks that have similar characteristics but only 4 cluster that formed to optimal portfolio. After each cluster is formed as an optimal portfolio with the mean variance method and using the sharpe index value as a portfolio performance counter, the results show that portfolio 3 with a combination of 7 stocks is able to provide maximum profit for investors. The division of stock weights in portfolio 3 includes: Bank Syariah Indonesia Tbk (BRIS) by 8.64%, Digital Mediatama Maxima Tbk (DMMX) by 14%, Energi Mega Persada Tbk (ENRG) by 17%, ESSA Industries Indonesia Tbk (ESSA) by 6%, Harum Energy Tbk (HRUM) by 17%, Merdeka Copper Gold Tbk (MDKA) by 23%, and Samudera Indonesia Tbk (SMDR) by 15%.

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