Executive Summary:
APS1051 Final Project – ETF Clustering

Sebastian Tampu (1004928572)

I. Introduction

In the domain of investment management, the ability to identify high-performing ETFs is crucial. This project aims to apply clustering techniques to classify ETFs based on their returns and volatility, enhancing the selection process for rotational momentum strategies. It focusses on the discovery of ETFs like the 21 sector ETFs and 7 government bond ETFs previously proposed in class. Utilizing historical ETF data, I investigated the effectiveness of hierarchical clustering and k-means clustering in identifying ETFs with similar performance characteristics. The primary goal was to find these similar ETFs and the secondary objective was to evaluate their performance.

II. Methodology

A. *Data Collection*

Historical ETF data was sourced from Yahoo Finance, covering the period from January 30, 2016, to January 30, 2020. This dataset includes both the original sector and government bond ETFs as well as additional ETFs to broaden the scope of the analysis. Some of the choices are of personal interest.

B. *Clustering Techniques*

Two primary clustering techniques were employed. The first was hierarchical clustering. This method forms clusters based on the similarities in returns and volatility, visualized through a dendrogram. The second method, k-means clustering, creates clusters by partitioning the data into a predefined number of clusters, allowing for a comparative analysis with hierarchical clustering.

C. *Rotational Momentum Program*

The rotational momentum program was implemented to evaluate different parameter configurations. The Sharpe ratio surface program was not utilized to find these optimal parameters as the testing for final performance was not meant to be rigorous. The primary goal was simply to find the similar ETFs, while performance was secondary. As such, the grid search method sufficed. The parameters tested were:

- *Lookback Periods:* Ranged from 10 to 55 days with intervals of 5 days.
- *Holding Periods:* Ranged from 2 to 24 weeks with intervals of 2 weeks, all ending on Friday.
- *Weights:* Various more random combinations of weights for short-term returns, long-term returns, and volatility.

III. Results

The analysis of the ETFs using both hierarchical clustering and k-means clustering demonstrated the effectiveness of these methods in identifying ETFs with similar performance characteristics to the original sector and government bond ETFs. Graphs representing both clustering results are not included in this report due to their size. They will be submitted along with the paper and seen in the accompanying slideshow presentation.

A. *Clustering Results.*

Hierarchical clustering resulted in a silhouette score of 0.668, indicating strong clustering quality. The ETFs within each cluster were closely related in terms of returns and volatility, while those in different clusters were clearly distinct. This method was particularly effective in identifying new ETFs that shared similar characteristics with the original ETFs. For example, IEF and PFF were grouped together due to their sensitivity to interest rates, despite one focusing on government bonds and the other on preferred stocks. Similarly, IEZ, USO, and XOP were clustered based on their exposure to the energy sector, though they target different aspects of the oil industry. Another notable pair, SMH and SOXX, highlighted the close relationship within the semiconductor sector. These findings underscore the utility of hierarchical clustering in identifying ETFs with similar risk-return profiles, even across different market segments.

K-means clustering produced a silhouette score of 0.643, which, although slightly lower than that of hierarchical clustering, still indicates good clustering quality. The results were generally consistent with those from hierarchical clustering, reinforcing the robustness of the k-means approach. However, it's worth noting that only one of the three clusters was well grouped, suggesting that using more clusters or centroids might have better arranged the others. For example, ETFs like BIL and SHV, and TIP and BIV remained close to each other, like their positions in the hierarchical clustering, reflecting their shared characteristics in terms of risk and returns. In contrast, KRE and KBE, which were closely grouped with IBB in the hierarchical cluster, were now further apart, with KBE even positioned in a different cluster altogether. This indicates some divergence in sector-based ETFs when using k-means clustering. Despite these differences, k-means effectively identified broad market ETFs such as QQQ and DIA for their alignment with the original sector ETFs and grouped sector-specific ETFs like XLK, XLE, XLF, and XLV in the same cluster. Additionally, it captured the relationships between emerging market ETFs like IEMG and EEM and identified real estate and precious metals ETFs, such as REZ, XLRE, GLD, and SLV, highlighting the method's ability to categorize ETFs across diverse asset classes while maintaining connections to the original set.

B. Best Parameters

The optimal configuration for the rotational momentum strategy was identified by testing various combinations of lookback periods, holding periods, and weight distribution. The best-performing configuration yielded a Sharpe Ratio of 1.342, reflecting a strong balance between returns and risk.

This optimal setup included a lookback period of 25 days, providing sufficient historical perspective to capture performance trends without extending the observation window excessively. The holding period was set at 2 weeks, specifically ending on Friday, which proved effective in leveraging rotational momentum., This allowed for timely portfolio adjustments to maintain optimal exposure to outperforming ETFs. The weights were allocated as 0.4 for short-term returns, 0.2 for long-term returns, and 0.4 for volatility. The weighting schemes emphasized the importance of short-term returns and volatility management, contributing to an overall enhancement in the performance of the ETF portfolio. While the issue of returns is secondary to clustering for this project, showing the final figures is still important. As seen in Fig. 1, the portfolio achieves around a four-fold return in a four-year period, indicating good returns, made better considering the low risk.

Hierarchical clustering produced well-defined clusters, supported by a strong silhouette score. K-means clustering, while slightly less precise, confirmed the robustness of the analysis by identifying similar ETFs. Both methods highlighted ETFs across various asset classes, including fixed income, broad market exposure, and specific sectors, showing their potential to complement or replace the original ETFs in a rotational momentum strategy. In the future, different measures, along with volatility and returns, could be used to develop even more meaningful groups and find new patterns.

The project, as a secondary task, also involved evaluating different parameter configurations to determine the most effective approach for implementing the new ETFs. The configuration with the highest Sharpe Ratio of 1.342 included a 25-dat lookback period, a 2-week holding period, and weights of 0.4 for short-term returns, 0.2 for long-term returns, and 0.4 for volatility. These parameters probed effective in capturing momentum while managing risk.

Overall, these finding offer practical insights for investors looking to refine their ETF selection process and improve the effectiveness of their rotational momentum strategies. The analysis underscores the importance of careful parameter selection and the use of clustering techniques in identifying ETFs that can enhance portfolio performance and support informed investment decisions.

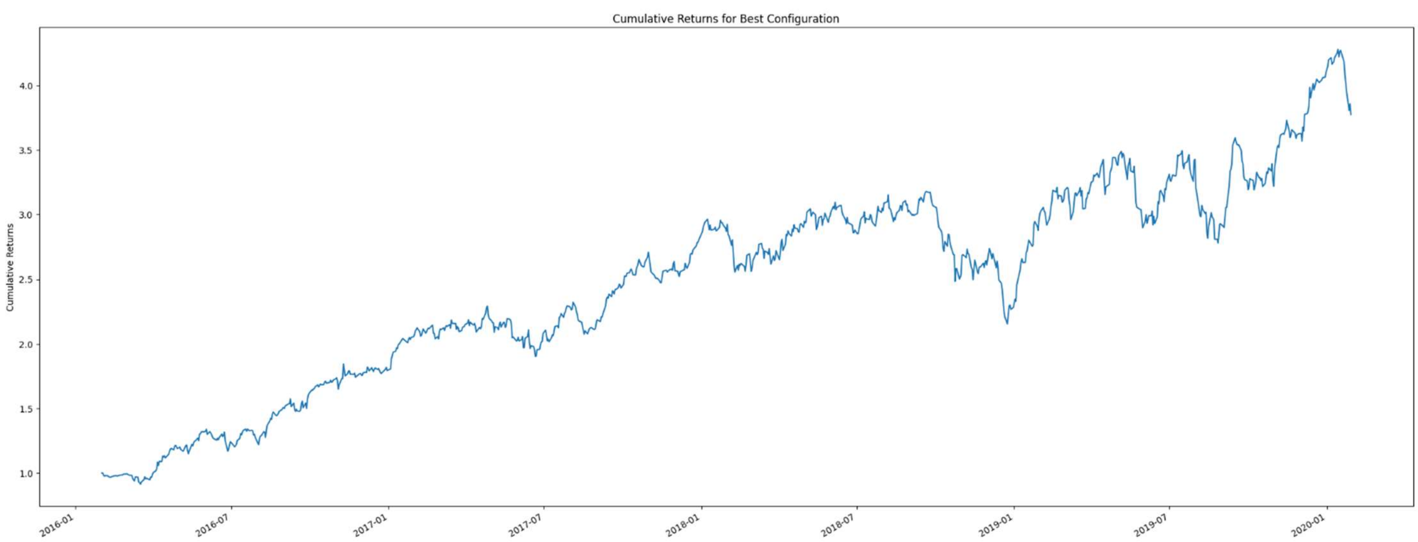

Fig. 1 Cumulative returns for the best portfolio configuration from January 2016 to January 2020.

IV. Conclusion

In conclusion, identifying ETFs that align with a rotational momentum strategy is important for optimizing investment portfolios. This project used hierarchical and k-means clustering techniques to analyse historical ETF data, identifying new ETFs with performance characteristics like those of the original sector and government bond ETFs. By grouping ETFs based on returns and volatility, the clustering methods identified a range of alternatives that could potentially enhance portfolio diversification and performance.