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Title: Regime-Based Dynamic Portfolio Optimization

1. Introduction

Financial markets are characterized by regime shifts, where asset return behaviors change due to macroeconomic conditions, investor sentiment, and structural market dynamics. Traditional approaches for identifying these shifts, such as moving averages, volatility measures, and Markov-switching models (Ang & Bekaert, 2002; Kritzman et al., 2012) are usually slow to respond to sudden market fluctuations. Similarly, econometric models such as ARCH/GARCH are effective in tracking volatility clustering (Campbell, Lo, & MacKinlay, 1997) but lack the ability to classify distinct market regimes effectively. As financial markets become increasingly complex, there is a growing need for adaptive, data-driven methods that can dynamically classify market conditions and adjust investment strategies accordingly.

This project proposes using unsupervised machine learning techniques, specifically K-Means clustering, Gaussian Mixture Models (GMM), and Hidden Markov Models (HMM), to classify stock market regimes and optimize asset allocation. Unlike traditional rule-based methods, machine learning models offer greater flexibility and adaptability, allowing them to detect regime transitions in real-time.

2. Literature Review

The concept of market regime classification has been explored in various financial studies. Ang & Bekaert (2002) and Kritzman et al. (2012) applied Markov-switching models to identify regime changes in asset prices and risk premia. These models demonstrated that return distributions and volatilities differ significantly between market states, providing strong justification for regime-based investing. However, a major limitation of these approaches is their reliance on fixed probability transition matrices, which do not fully account for unexpected market events or shifts in macroeconomic fundamentals.

In addition, unsupervised learning methods, such as K-Means and GMM, can detect hidden structures within market data without requiring predefined labels. Notable works include Chen & Tsang (2018) and Nystrup et al. (2017). Momentum-based investing has also been widely studied in the context of regime-dependent performance. Daniel & Moskowitz (2014) highlight how momentum strategies fail during market reversals due to time-varying beta, leading to significant drawdowns. While their work provides insights into regime-dependent risks, it lacks a predictive component, focusing instead on retrospective analysis. Our research builds upon this by incorporating real-time regime detection models that adjust momentum exposure dynamically. Similarly, Mayo & Zhu (2019) introduced correlation networks for regime classification, but their approach is constrained by its reliance on fixed asset relationships rather than adaptive clustering techniques.

In the domain of portfolio optimization, Costa & Kwon (2020) introduced a Regime-Switching Factor Model for Mean-Variance Optimization, providing a structured framework for regime-aware investing. While their approach is mathematically rigorous, it struggles with real-time regime detection and parameter estimation challenges. Our project refines this model by enhancing computational efficiency and integrating machine learning for adaptive portfolio management, ensuring more accurate investment decisions.

Suárez-Cetrulo, Quintana, and Cervantes (2023) review machine learning applications in financial prediction under regime changes, emphasizing technical analysis and the limitations of traditional models in handling non-stationary data. Their focus on supervised learning contrasts with our emphasis on unsupervised methods like K-Means and GMM for regime classification. Similarly, Mayo and Zhu (2019) explore market regime classification using correlation networks, though their approach may be less flexible than our clustering techniques. Zhang and Li (2023) propose a dynamic portfolio optimization model based on regime-based firm strength, aligning with our goal of adaptive portfolio strategies but differing in their reliance on regime-switching models rather than machine learning-driven classification.

3. Expected Innovation

We are looking to introduce several key innovations that distinguish it from existing market classification and portfolio optimization models. First, our model adapts real-time market conditions, ensuring greater flexibility and responsiveness. Secondly, we incorporate macro-financial indicators such as inflation, interest rates, and GDP growth into market segmentation. Third, our project extends portfolio optimization beyond equities, introducing a multi-asset strategy that includes stocks, bonds, commodities, and cryptocurrencies. Lastly, we explore alternative clustering methods beyond conventional financial models. We aim to integrate these innovations via an interactive web-based dashboard that outperforms traditional regime-classification and asset allocation models.

4. Research Objectives and Approach

This project seeks to develop a data-driven, machine learning-powered system that classifies market regimes and optimizes portfolio allocation dynamically. The first objective is to build an unsupervised learning model that segments stock market conditions into distinct regimes, such as bull, bear, and neutral markets. Unlike traditional econometric models, our approach will use K-Means, GMM, and HMM to allow real-time classification and adapt to new market trends as they emerge. The second objective is to integrate macroeconomic variables into the regime classification process, improving the model's interpretability. The final objective is to develop a dynamic portfolio optimization framework that adjusts asset allocation based on the detected market regime.

5. Implementation plan

TASK	ASSIGNED TO	PROGRESS	DAYS	START	END
Define project scopes	Trang/Jia/Roshan	100%	7	2/17/25	2/24/25
Data collection & preprocessing	Trang/Jia/Roshan/Goodness/Daniel	43%	14	2/24/25	3/10/25
Regime Classifications & Portfolio Optimization	Trang/Jia/Roshan/Goodness/Daniel	0%	22	3/10/25	4/1/25
Dashboard Development	Trang/Jia/Roshan/Goodness/Daniel	0%	12	4/1/25	4/13/25
Testing and validation	Trang/Jia/Roshan/Goodness/Daniel	0%	5	4/13/25	4/18/25

6. Measure of success, risk & payoff, and cost

If successful, this project will provide a data-driven framework for dynamic portfolio optimization that can be practically applied by retail investors to enhance risk-adjusted returns through market regime classification. The impact will be measured by evaluating whether the model accurately identifies historical market regimes, such as the 2008 financial crisis and the COVID-19 crash, using clustering validation as a mid-term checkpoint. At the end of the project, success will be assessed by comparing the Sharpe ratio of our portfolio strategy against those in the literature review. If our approach consistently outperforms traditional and existing machine learning-based strategies, it will be considered effective. The primary risks include model limitations, such as potential inaccuracies in detecting regime shifts, and underperformance of the investment strategy in unpredictable market conditions. However, the payoff is the development of a robust, adaptable investment framework that can be used by retail investors for real-time decision-making. The cost of implementation is minimal to zero, as it primarily relies on open-source financial data and computational tools. Progress will be tracked through back testing experiments, evaluating risk-adjusted returns, and conducting user testing on the interactive dashboard to ensure usability and accuracy.

7. Conclusion

In conclusion, this high-performance investment strategy project will bridge the gap between machine learning and practical investment strategies by proposing an interactive dashboard will provide investors with real-time, data-driven recommendations, enabling adaptive risk management in changing market conditions.

References

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