A Hidden Markov Model Framework for Identifying Risk-On and Risk-Off States in the US Equities Market

Motivation

Global financial markets represent intricate and interconnected ecosystems influenced by diverse elements such as macroeconomic indicators, geopolitical events, investor behavior, and market sentiment. Navigating these complexities is crucial for investors, portfolio managers, and traders who strive to maximize returns and minimize risk. Identifying prevailing market conditions—often characterized as either "risk-on" or "risk-off" regimes—allows investors to adapt their strategies dynamically, enhancing their decision-making and performance.

In a "risk-on" environment, markets demonstrate higher risk appetite, with investors typically favoring equities, emerging markets, and other growth-oriented assets. Conversely, a "risk-off" regime indicates heightened risk aversion, prompting shifts toward safer assets such as bonds, gold, or defensive sectors. Timely detection and accurate classification of these market states are therefore instrumental in strategic asset allocation, optimized risk management, and informed algorithmic trading decisions.

This exercise aims to leverage historical price data to classify market conditions systematically into these two distinct regimes. By developing a robust classification model, we aim to provide clear, actionable insights into market sentiment and volatility shifts, empowering stakeholders to make informed, strategic choices aligned with prevailing market dynamics. The analysis will be carried out using Hidden Markov Model (HMM) and Gaussian Mixture Model (G MM) and a comparison between these two models will be carried out.

Dataset

We'll use S&P 500 as the main underlying data to classify the risk-on and risk-off regime and the data will be retrieved from Yahoo Finance's python API from 2000-2023. Once we have the prices, we'll calculate the log returns and 5-day moving average of the price series. We will be using S&P 500 log returns as the main feature in our model.

Gaussian Mixture Models (GMM)

GMM assumes that the observed market data is generated by a mixture of several Gaussian distributions. Each distribution represents a different market regime. The model estimates the parameters (mean, covariance) of each Gaussian distribution and assigns a probability to each observation belonging to one of these components.

Days are grouped into regimes based on the statistical characteristics of the market (risk-on and risk-off regime).

Hidden Markov Models (HMM)

HMM takes a slightly different approach by considering that the market evolves over time and that the current market regime depends on the previous one. It posits that there are unobserved states corresponding to different market regimes that influence the observed data. It estimates the statistical properties of the observations in each state and how likely the market is to stay in the same state or switch to a different one from one day to the next.

The value-add of HMM is we gain insight into both the statistical properties of each regime and the dynamics of how regimes change over time. This sequential dependency can be very helpful, as market regimes tend to persist for a period before transitioning**.**

Methodology

Firstly, we fit both Hidden Markov Models (HMM) and Gaussian Mixture Models (GMM) using a generic parameter initialization function. The implementation of HMM is carried out using hmmlearn and scikit-learn package on Python. Next, we use a grid search routine for both models to optimize hyperparameters based on the Information Coefficient, ensuring that the selected models best capture the dynamics of the data.

For evaluation, the dataset is split into training and testing subsets, with a feed-forward testing strategy that retrains models as new data arrives. In our feed-forward test we retrain both models on a rolling window and refit every 100 trading days.

Lastly, we backtested this regime classification using a simple buy/ sell strategy using the signals and compared it against the buy-and-hold strategy of S&P 500.

Hyper-parameters Tuning

To optimize the hyperparameters of our model, we set up a grid search process systematically explores combinations of these hyperparameter values by iterating over every possibility defined in our parameter grid.

We will evaluate the set of parameters based on Pearson correlation coefficient. because it provides a straightforward and interpretable measure of the linear relationship between the predicted regime signal and the actual market returns. Once the grid search is completed, we select the best set of parameters with highest correlation coefficient to use in our models.

In-Sample Training Results

Before we look at the results, it is important to emphasize the 2007–2009 financial crisis and the COVID-related market downturn in February 2020. The aim of this regime detection prototype is to recognize these events along with any other significant market downturns.

The interpretation of each state involves subjective judgment, informed by domain expertise and additional empirical analysis. We could also utilize summary statistics to help classify the regimes. In our context, we will use period of known market crashes to help identify the risk-on/ risk-off states, in addition to summary statistics.

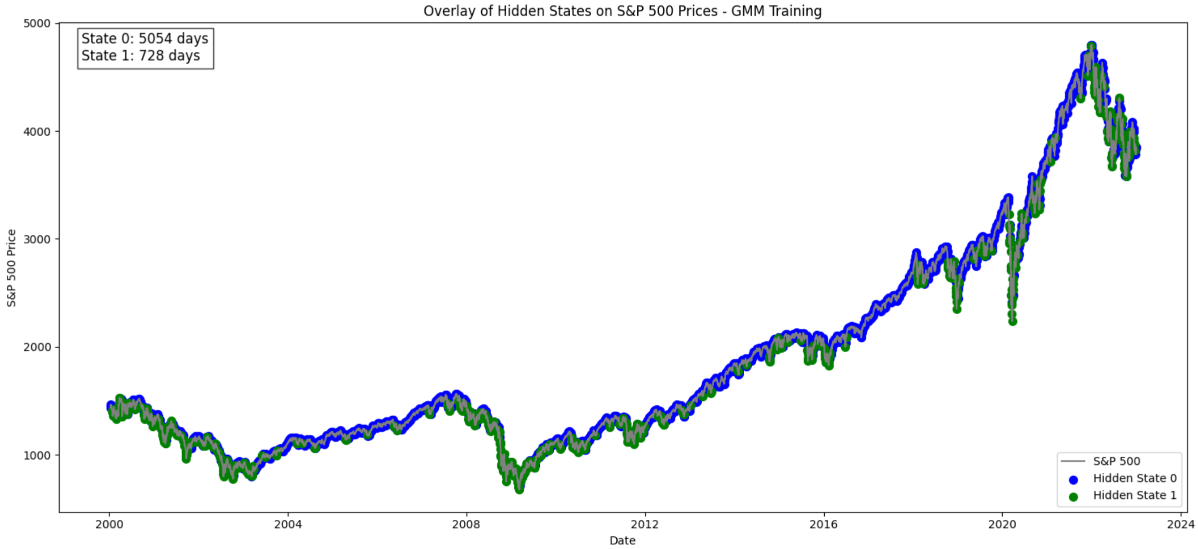

Figure 1: GMM Training

Figure 1 shows the hidden states predicted by the GMM. The model classified 728 observations as hidden state 1, which we attributed to the crash period as we notice more green layers during the market downturns such as 2008 and 2020. GMM successfully identifies major drawdowns, though it lacks temporal coherence in state transitions

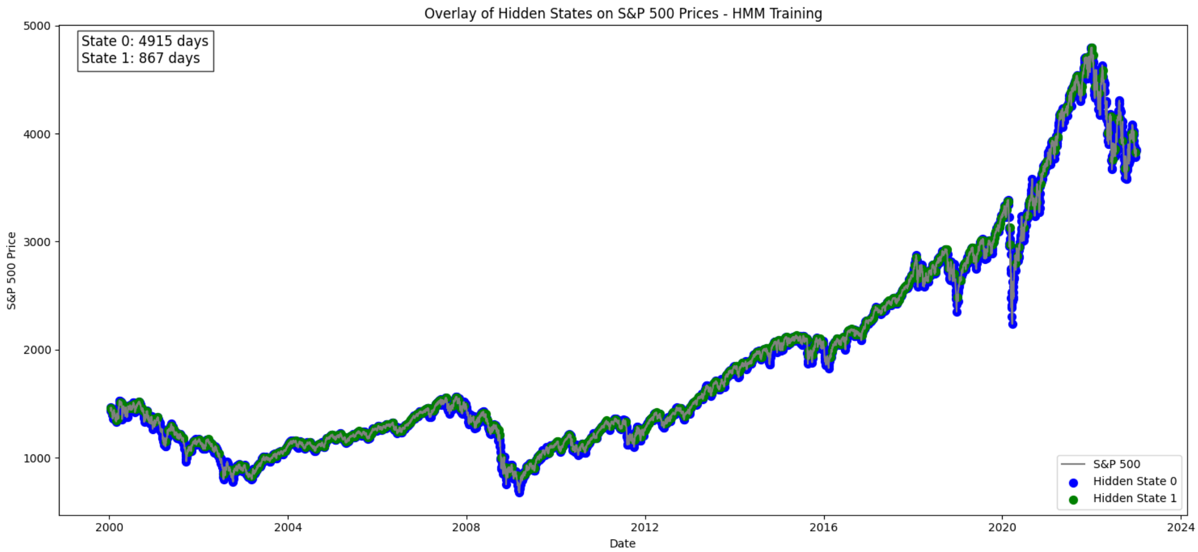

Figure 2: HMM Training

Figure 2 presents the distribution of hidden states predicted by HMM. HMM could identify both financial and COVID crashes, as well as (with some lags) the volatile period starting after January 2022. Overall, the HMM classification closely mirrors the GMM's regime assignments during major crashes but enforces longer regime durations.

Out-of-Sample Feed Forward Testing

Here, we implement feed-forward testing where we train on the first 70% of the dataset, and then, for each new observation in the remaining 30%, the model predicts the corresponding hidden state. Importantly, the prediction for each day is based on all information available up to that day. This demonstrates how a model would process incoming data point by point.

We apply feed-forward training and out-of-sample testing to the GMM and HMM models. The objective is to better simulate a real-time environment in which the model is continually updated with new data, rather than being fixed after a single training phase. Our model re-fits the model every 100 days, using all data seen so far as long as a minimum amount of data is available

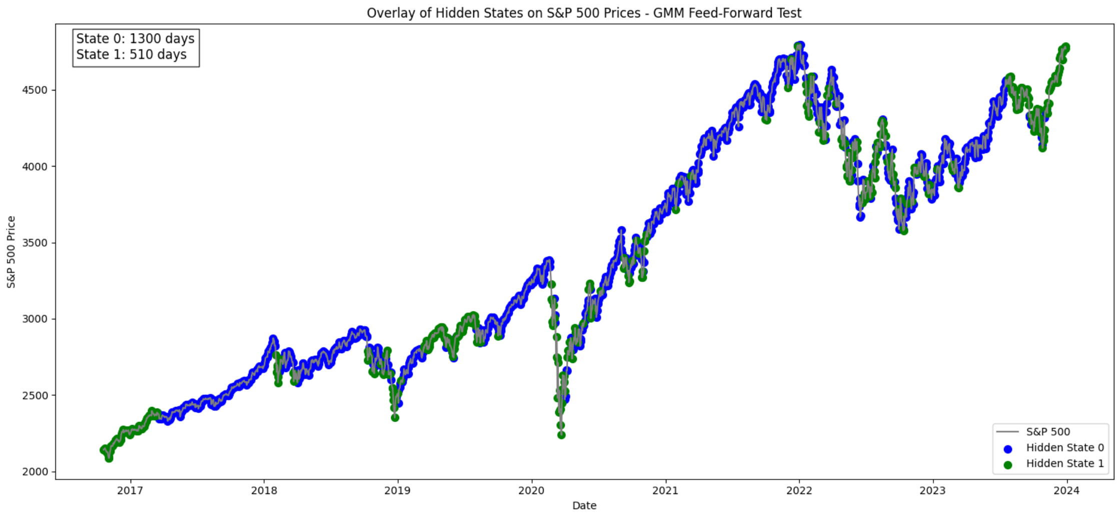

Figure 3: GMM Feed-Forward Test

In GMM Feed-Forward Test, the GMM occasionally misclassifies the prevailing regime, most notably in early 2017 and again in late 2023 by reacting solely to contemporaneous market features. We also observe more state changes because GMM assigns states based on the current features alone, without considering the previous state, which can lead to more frequent state changes. This lack of temporal continuity results in a higher-than-desirable turnover of inferred regimes and can obscure longer-term trends.

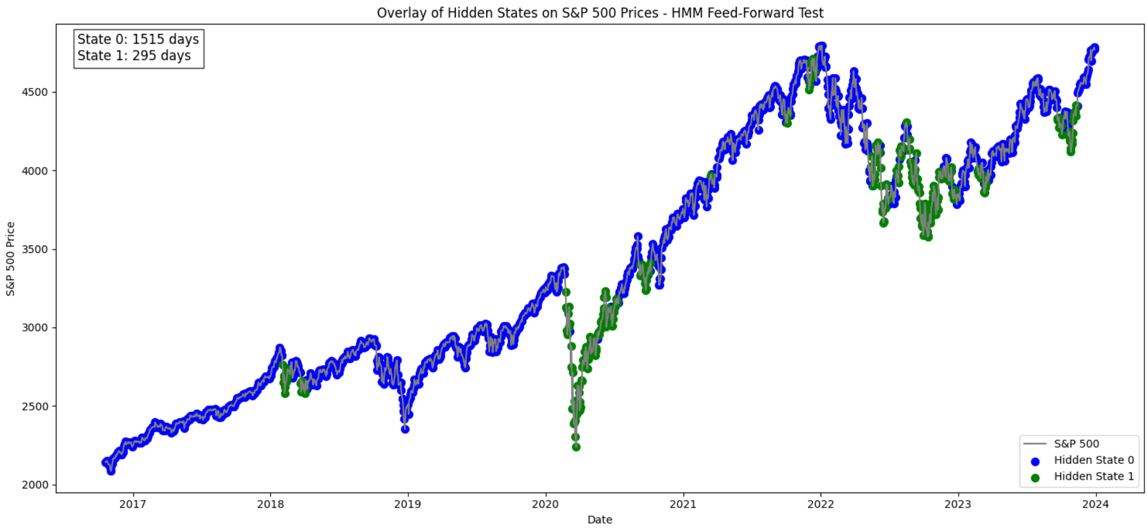

Figure 4: HMM Feed-Forward Test

On the other hand, the HMM model exhibits better performance as shown in Figure 4, accurately identifying significant market downturns, particularly those associated with the financial crisis and the COVID-induced market decline. Additionally, the continuity of states in this plot appears more stable, with transitions occurring less frequently. Maintaining state continuity is crucial, as it ensures that actionable signals remain consistent, preventing frequent fluctuations that could hinder decision-making. This is because transition probabilities capture the likelihood of staying in or switching states over time, which tends to maintain state continuity, making regimes appear more stable and persistent.

Implementation of strategy

Now, we'll implement a simple trading strategy using the signals from the HMM model. In the feed-forward test above, we see that state 1 is associated with high volatility and market downturn and state 0 is the normal state. In our simple strategy, we will go long S&P in state 0 and go short the S&P in state 1. The signals are shifted by one day to prevent look-ahead bias.

The daily outcomes, computed as the product of these positions and the S&P 500's log returns, are cumulated and exponentiated to simulate the evolution of wealth, starting with an initial value of $1. We normalize S&P and contrast our strategy to S&P 500.

We see in Figure 5 that using the buy/ sell signals helps us achieve better performance. This outperformance appears to be driven in part by the model's ability to switch between long and short positions, particularly around early 2020 when the strategy's wealth spikes upward as it captures the downside move during the COVID-driven market collapse.

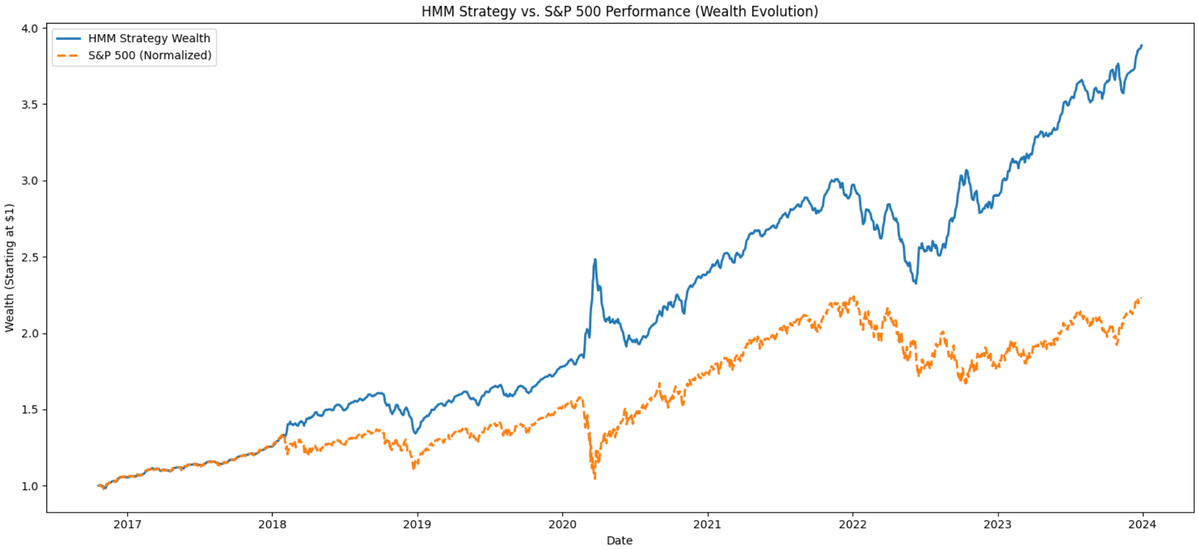

Figure 5: Model Performance

Conclusion and areas of improvement

In conclusion, the regime-switching models demonstrate promising capabilities in capturing market dynamics by effectively identifying shifts between distinct market states. However, while the results are encouraging, further improvements such as incorporating transaction costs, refining hyperparameter optimization, and implementing robust risk management are essential to validate the models' real-world applicability. Overall, these findings provide a solid foundation for exploring advanced dynamic asset allocation strategies. We can also add more features into our model such as oil prices, 10Y yields to introduce more features into our model. We can also expand our grid for our hyper-parameters tuning as well.

References:

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