Modeling Financial Market Regimes with Hidden Markov Models

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# Abstract

This paper presents a comprehensive methodology for identifying and forecasting latent financial market regimes using Hidden Markov Models (HMMs). Our approach begins with the construction of a feature set that captures both momentum and volatility across multiple time horizons, two factors widely recognized in the literature for their predictive capacity in market behavior (Jegadeesh & Titman, 1993; Corsi, 2009). The HMM is configured with multivariate Gaussian emissions to model these features, allowing the system to infer unobserved market states over time. Following state inference, regime sequences are evaluated for stability using transition metrics to ensure robust classification. Forecasting is performed by propagating the inferred state through the model’s transition dynamics, yielding a probabilistic outlook over a forward horizon.

To enhance the practical utility of these regime classifications, we perform hierarchical clustering on recent regime sequences across assets, revealing groups of assets that behave similarly under market conditions. These clusters are used to structure the portfolio construction process, where we aggregate forecasted regime probabilities and apply category-based weight adjustments to form a diversified and regime-aware portfolio. This multi-layered approach is grounded in prior research on regime-switching models (Hamilton, 1989; Ang & Bekaert, 2002) and has been demonstrated to outperform static asset allocation strategies, particularly in non-stationary market environments (Maheu & McCurdy, 2000; Guidolin & Timmermann, 2007).

By integrating statistical modeling, stability diagnostics, forecast propagation, and cluster-based asset grouping, this framework provides a comprehensive tool for understanding and acting on market regimes. The result is a principled, interpretable system for allocation decisions that adapts to the evolving dynamics of financial markets.

# 2. Conceptual Overview of the HMM in Finance

Understanding the theoretical foundations of Hidden Markov Models (HMMs) is essential before applying them to financial regime detection. HMMs offer a principled approach to modeling time-series data where the system dynamics are governed by unobserved states. This capability aligns well with financial markets, where investors observe returns, volatility, and other indicators without direct access to the true market regime. By treating market regimes as latent states and observed financial variables as emissions from those states, the HMM provides a probabilistic structure that captures both temporal dependencies and structural shifts in financial behavior.

## 2.1. What Is an HMM?

A Hidden Markov Model is a statistical model composed of hidden states and observable outputs. Each state represents a latent condition that influences the observable financial data. The model consists of three main components: the initial state distribution, the state transition matrix, and the emission probabilities. Formally, at each time step t, the system resides in a state S\_t ∈ {1, ..., K}, and emits an observation x\_t, typically drawn from a multivariate normal distribution N(μ\_{S\_t}, Σ\_{S\_t}). The transition between hidden states is governed by a Markov chain, where the probability of moving from one state to another depends only on the current state, not the sequence of previous states. A Hidden Markov Model consists of a system that evolves through a set of hidden states, each of which generates observable data according to a probability distribution. In the context of financial modeling, the hidden states represent latent market regimes, and the observed data include indicators such as asset returns and volatility. The model estimates the likelihood of being in a particular state, the probabilities of transitioning from one state to another, and the distribution of observations given each state.

## 2.2. Application to Financial Markets

In the context of finance, the hidden states of the HMM are interpreted as unobservable market regimes such as bullish, bearish, or neutral. These regimes manifest through observable financial indicators like asset returns and volatility. Empirical studies have shown that regimes differ in their statistical properties, particularly in the mean and variance of returns. By engineering features such as momentum and volatility from price series, and modeling their joint distribution within the HMM framework, we can learn the structure and dynamics of these regimes. Once trained, the HMM infers the most likely regime for each time point and helps forecast future regime probabilities based on the learned transition dynamics. The HMM is especially well-suited for financial data due to its ability to model regime-switching behavior. In this application, hidden states can be interpreted as market conditions such as bullish (characterized by high momentum and low volatility), bearish (marked by declining returns and rising volatility), or neutral (indeterminate or transitioning phases). To capture these characteristics, we use engineered features that reflect momentum and volatility dynamics. These features are then used to train the HMM to identify and label time periods according to the underlying market regime.

# 3. Supporting Literature

A strong foundation in previous research validates the approach taken in this study. Hidden Markov Models have a well-established presence in both theoretical and applied finance, particularly for modeling non-stationary, regime-switching dynamics that traditional linear models struggle to capture. In this section, we review foundational work that has informed the structure and application of the model presented here.

## 3.1. HMMs in Financial Regime Analysis

The seminal work by Hamilton (1989) introduced Markov-switching models in the context of macroeconomic cycles, demonstrating that observed fluctuations in output could be better understood through latent regimes. This concept has since been extended to asset markets, where returns and volatilities also exhibit regime-like behaviors. Guidolin and Timmermann (2007) provided empirical evidence that portfolio strategies adjusted to regime changes improve performance. Ang and Bekaert (2002) further advanced this by incorporating regime switches into international asset pricing models, improving the explanatory power for global equity returns. The use of regime-switching models in economics began with Hamilton (1989), who introduced Markov-switching autoregressive models for business cycle analysis. Building on this, Guidolin and Timmermann (2007) showed that asset allocation can be optimized by incorporating regime-dependent dynamics. Similarly, Ang and Bekaert (2002) demonstrated that regime-switching models provide improved explanations for time-varying risk premia and return predictability in global equity markets.

## 3.2. Volatility and Momentum as Regime Signals

The selection of momentum and volatility as primary features is supported by extensive empirical work. Jegadeesh and Titman (1993) showed that momentum is a persistent anomaly that can be exploited across markets and time periods, indicating it reflects more than transient noise. Corsi (2009) introduced long-memory models that account for the persistent and clustered nature of volatility, which makes it an excellent candidate for differentiating between regimes. Ding, Granger, and Engle (1993) showed that volatility exhibits autocorrelation at multiple horizons, making its historical patterns a predictive signal for future market behavior. Momentum and volatility are widely recognized as important indicators of market state. Jegadeesh and Titman (1993) found momentum strategies to be robust anomalies in return predictability, while Corsi (2009) developed long-memory models to better capture volatility clustering. Ding, Granger, and Engle (1993) provided additional support for volatility modeling by showing that volatility exhibits persistence across time horizons, reinforcing the case for dynamic regime modeling.

## 3.3. Practical Implementations

Beyond theory, numerous practical applications confirm the viability of HMMs in real-world financial modeling. Lo, Mamaysky, and Wang (2000) applied HMMs to identify technical patterns in asset prices, showing that such probabilistic models outperform heuristic-based rules. Maheu and McCurdy (2000) used HMMs to segment financial time series into bull and bear markets, offering superior forecasting accuracy compared to GARCH models. Mitra and Mitra (2011) demonstrated how HMM-based state predictions can be used as inputs to dynamic asset allocation, enhancing portfolio performance during transitional market conditions. Applications of HMMs have extended to pattern recognition in asset prices, as explored by Lo, Mamaysky, and Wang (2000). In forecasting applications, Maheu and McCurdy (2000) showed that HMMs outperform traditional GARCH models in identifying bull and bear markets. Mitra and Mitra (2011) integrated HMMs into portfolio optimization, demonstrating their utility in constructing regime-aware investment strategies.

# 4. Mathematical Formulation and Data Pipeline

This section outlines the technical implementation of the model, including the transformation of raw price data into engineered features, the mathematical formulation of the HMM, and the procedures for inference, forecasting, and evaluating model stability. This pipeline enables both classification of market regimes and prediction of future conditions using a structured statistical approach.

## 4.1. Input Data

The raw input to the model consists of historical adjusted closing prices, denoted as , where . These prices serve as the basis for calculating derived features that are more informative for regime detection.

## 4.2. Feature Engineering

To model latent states, we construct a feature vector for each time step. This vector includes two key features: momentum and volatility. Momentum is calculated as the average of compounded returns over 3, 6, 9, and 12-month windows. Volatility is measured as the standard deviation of daily returns over 1-month and 3-month rolling windows. To make volatility comparable across time and assets, it is normalized between zero and one.

**Daily returns:**

**Momentum:**

Where is the adjusted closing price at time , and is the lookback window in trading days (3, 6, 9, and 12 months).

**Volatility:**

Rolling standard deviations:

Normalized volatilities:

Combined volatility:

## 4.3. HMM Specification

The HMM consists of hidden states , a transition matrix defining probabilities of moving between states, and an initial state distribution . Each state emits a vector drawn from a multivariate normal distribution with state-specific mean and covariance . This generative structure allows the model to probabilistically infer which latent regime most likely generated the observed feature at each time point.

**State transition probability:**

**Emission probability (Gaussian):**

## 4.4. Inference and Forecasting

Inference involves estimating the most likely sequence of hidden states that generated the observed data. This is typically done using the Viterbi algorithm, which maximizes the joint posterior over the hidden state sequence. Once the model is trained and the states are inferred, forecasting involves computing the future distribution of states by raising the transition matrix to the power of the number of forecast steps and applying it to the current state vector.

**Most likely sequence of states (Viterbi):**

**Forecasting future state distribution after steps:**

Where is the state distribution at time , and is the transition matrix.

## 4.5. Stability Evaluation

To assess the quality of the model, we evaluate the stability of the inferred state sequences. This involves calculating the transition rate, defined as the ratio of state changes to total time steps. Models with high instability (frequent switching) are penalized and may trigger retraining. The stability check helps ensure the regime sequences are meaningful and not driven by noise.

**Transition rate:**

Where is the number of regime changes and is the total number of time steps.

# 5. Portfolio Construction via Clustering and Forecast Aggregation

The portfolio construction process builds on the output of the HMM-based regime classification and forecast. It leverages hierarchical clustering to group assets that share similar regime behavior and constructs a regime-aware portfolio with weights influenced by cluster structure and forecast distributions.

## 5.1. Hierarchical Clustering of Regime Sequences

Each asset's recent regime sequence is treated as a time series of categorical states. These state labels are converted into numerical sequences using label encoding to facilitate quantitative analysis. All sequences are aligned to a common length (typically 252 trading days) to ensure comparability. Pairwise Euclidean distances are calculated to measure similarity between sequences, and Ward’s linkage method is used to generate a hierarchical clustering tree. Cutting the tree at a predefined threshold partitions the assets into distinct clusters that exhibit similar regime behaviors.

## 5.2. Forecast Distribution Aggregation by Cluster

After clustering, the next step is to aggregate the regime forecast distributions from all assets within a cluster. Each asset's HMM provides a probability distribution over future regimes, which are mapped to common categories (Bullish, Neutral, Bearish) based on the model's state labels. Within each cluster, these probabilities are summed and normalized to produce a representative outlook for the entire cluster. This outlook determines the weight each cluster receives in the final portfolio.

## 5.3. Weighting and Asset Selection

Within each cluster-category pair, a two-step allocation procedure is followed. First, clusters receive weights in proportion to their contribution to each regime category (e.g., how much of the total Bullish probability is explained by Cluster 1). Second, assets within a cluster are filtered to remove those with excessive Bearish probability (greater than 15%). The remaining assets are assigned weights based on their relative Bullish strength. If no eligible assets remain in a cluster, its weight is redistributed to the rest of the portfolio in proportion to existing allocations.

## 5.4. Final Portfolio Construction and Visualization

The portfolio weights across all selected assets are normalized to ensure the total adds to one. These weights are then visualized using a pie chart, offering an intuitive view of the allocation. The final portfolio reflects a structured integration of forecasted regime strength, cluster similarity, and individual asset outlook, resulting in a forward-looking, risk-aware investment allocation.

# 6. Use Cases and Implications

The proposed HMM-based framework offers a robust toolkit for both investment professionals and researchers seeking to understand and exploit financial regime dynamics. One critical application lies in tactical asset allocation, where identifying regime shifts early enables proactive adjustment of risk exposure. For example, moving into defensive assets when the model forecasts a transition to a bearish regime can protect capital and reduce drawdowns. Conversely, during stable bullish regimes, the model supports increased risk-taking and equity exposure.

In risk management, this approach improves upon traditional volatility-based methods by offering a multi-dimensional, probabilistic view of regime behavior. The incorporation of forecast distributions allows practitioners to plan under uncertainty and assign confidence levels to scenario analyses. Moreover, because the model generates interpretable regime labels and assigns them to historical periods, it can also be used retrospectively to study the behavior of assets under different market conditions, informing better strategic decisions.

Beyond investment management, this framework contributes to academic finance by operationalizing theoretical concepts such as regime-switching and behavioral clustering. By integrating market structure, feature transformation, state modeling, and data-driven portfolio construction, this model illustrates how machine learning methods can be rigorously applied to uncover latent patterns in complex financial systems. This modeling framework enables investors and analysts to identify hidden market regimes and adjust asset allocations accordingly. It supports tactical asset allocation by signaling regime shifts, enhances risk management by identifying unfavorable conditions in advance, and provides a principled basis for portfolio diversification through cluster-based structuring. Additionally, the probabilistic forecasting capability extends the utility of the model into strategic planning and scenario analysis.

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