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Report: Regime Detection via Unsupervised Learning from Order Book and Volume Data

Objective

The primary objective of this project is to segment the financial market into distinct behavioral regimes based on three critical factors:

1. **Trending vs. Mean-Reverting**
2. **Volatile vs. Stable**
3. **Liquid vs. Illiquid**

This segmentation was achieved using unsupervised learning techniques applied to real-time order book and trade volume data.

Data Overview

Two datasets were utilized for this analysis:

1. **Order Book Data (depth20):** Contains top 20 levels of bid/ask prices and quantities.
2. **Trade Volume Data (aggTrade):** Includes aggregated trade data such as price, quantity, and trade direction.

Key Challenges:

- High dimensionality of order book data.
- Real-time feature extraction and normalization.
- Selection of clustering algorithms suitable for dynamic and noisy financial data.

Methodology

1. Feature Engineering

Feature engineering was central to extracting meaningful signals from raw data, focusing on liquidity, volatility, and price action characteristics.

Liquidity & Depth Features:

- **Bid/Ask Spread:** `Spread = AskPriceL1 - BidPriceL1`
    - Measures market tightness.
- **Order Book Imbalance:**
    - `ImbalanceL1 = (BidQtyL1 - AskQtyL1) / (BidQtyL1 + AskQtyL1)`
    - Indicates buying vs. selling pressure at the top level.
- **Microprice:** Weighted average price based on top-level quantities:
    - `Microprice = (BidPriceL1 * AskQtyL1 + AskPriceL1 * BidQtyL1) / (BidQtyL1 + AskQtyL1)`
- **Cumulative Depth:** Summation of bid/ask quantities across all levels:
    - `CumBidQty` and `CumAskQty`.

Volatility & Price Action Features:

- **Rolling Mid-price Return:** `MidReturn = log(MidPrice_t / MidPrice_t-1)`
- **Volatility:** Standard deviation of mid-price returns over rolling windows (10s, 30s).

Volume Features:

- **Volume Imbalance:** `(BuyVolume - SellVolume) / (BuyVolume + SellVolume)`
    - Highlights directional bias in trading activity.
- **VWAP Shift:** Change in VWAP over time.

Derived Features:

- **Sloped Depth:** Linear regression slope of bid/ask quantities across levels to quantify liquidity decay.

- **Trade Wipe Level:** Measures how deep into the order book trades penetrate.

Rationale for Feature Selection:

These features were chosen to capture the three main aspects of market behavior:

- Liquidity reflects ease of execution.
- Volatility captures market stability.
- Volume imbalance indicates directional trends.

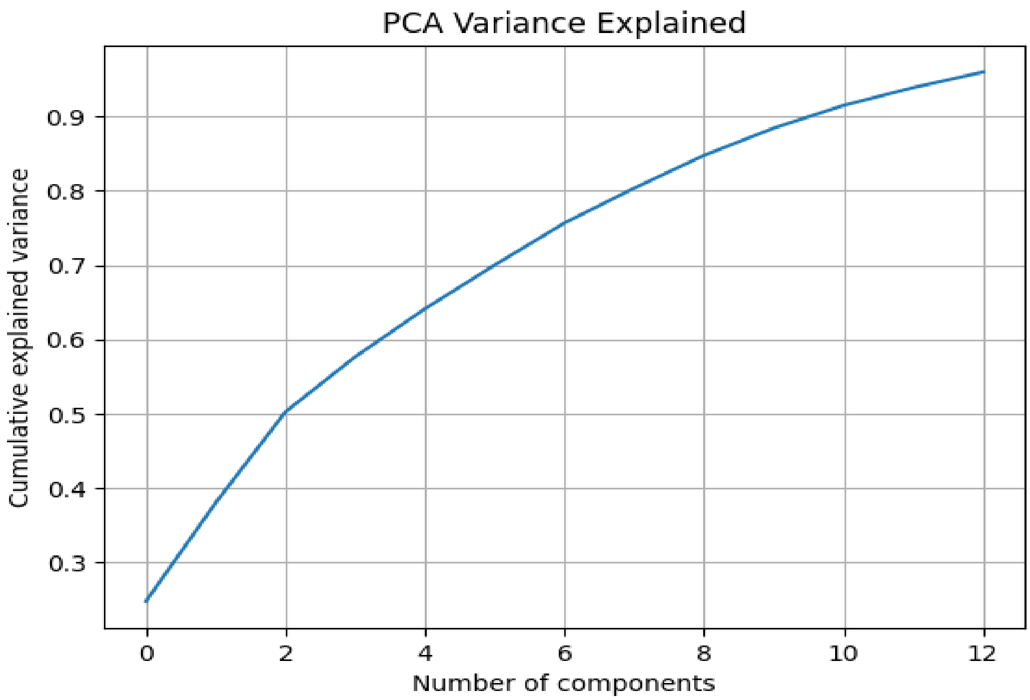
2. Data Normalization and Dimensionality Reduction

To ensure comparability across features:

- Features were normalized using **z-score normalization**.
- Dimensionality was reduced using PCA, retaining 95% of variance while simplifying the feature set.

PCA Results:

The cumulative explained variance plot demonstrates that approximately 13 components were sufficient to capture most of the variance in the data (see attached PCA plot).



3. Clustering

Three clustering algorithms were applied to identify distinct regimes:

Algorithms Used:

1. **K-Means:**
   - Optimal cluster count determined via elbow plot: k=4.
   - Silhouette Score: 0.232
   - Davies-Bouldin Index: 1.563
2. **Gaussian Mixture Model (GMM):**
   - Soft clustering approach with 4 components.
   - Silhouette Score: 0.117
   - Davies-Bouldin Index: 2.653
3. **HDBSCAN:**
   - Density-based clustering for non-spherical clusters and noise handling.

- Silhouette Score: 0.365
- Davies-Bouldin Index: 0.681
- Identified noise points (-1 label).

Algorithm Choice:
HDBSCAN was selected due to its superior performance metrics and ability to handle noise effectively in financial data.

4. Regime Labeling and Analysis

Regime Statistics:

Regime	Spread	MidReturnVol_10s	CumBidQty	VolumeImbalance
-1	0.076	0.000081	67.975	-0.0167
0	0.055	0.000051	54.475	-0.0775
1	0.093	0.000067	46.097	0.8109
2	0.088	0.000065	47.491	-0.6070

Auto-Naming Regimes:

Based on thresholds for volatility, liquidity, and directional bias, regimes were labeled as follows:

- Stable & Liquid & Neutral
- Stable & Liquid & Mean Reverting
- Stable & Liquid & Trending

These labels provide intuitive descriptions of market behavior.

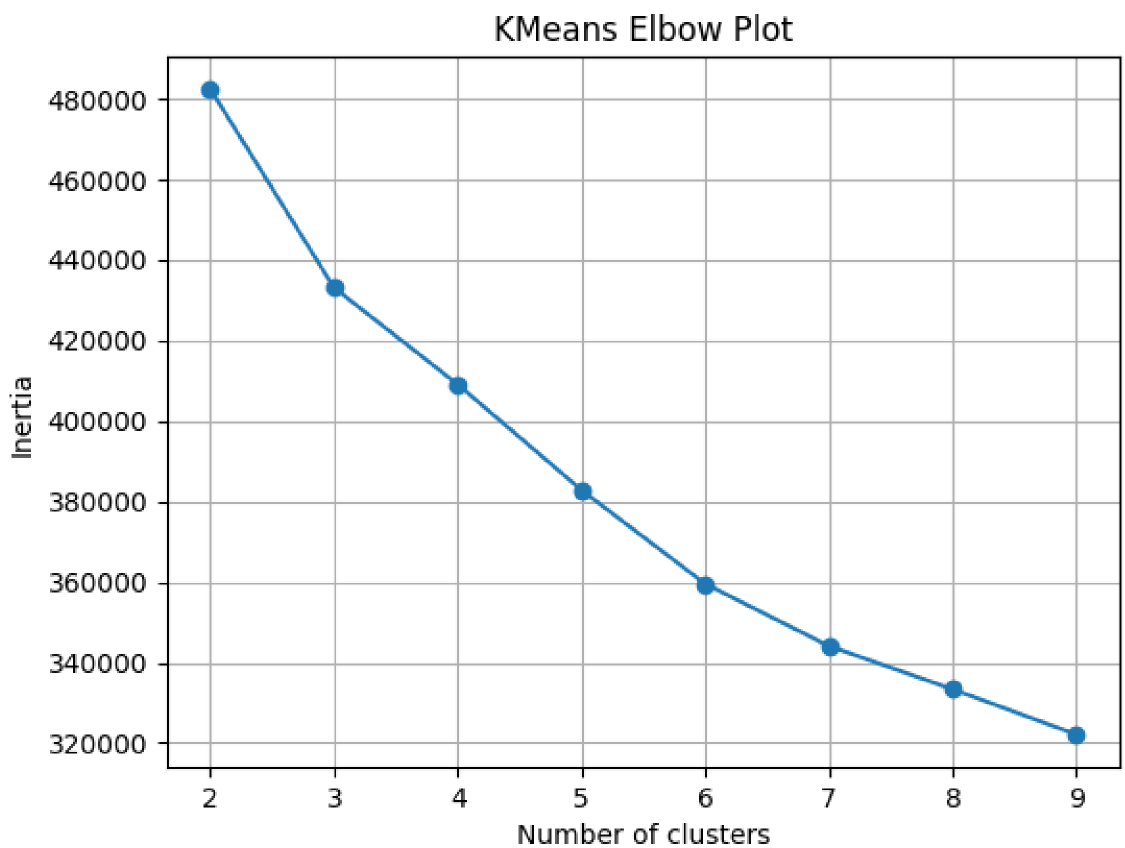
5. Visualizations

PCA Variance Explained:

The PCA plot shows how dimensionality reduction retained most of the variance while simplifying the feature space.

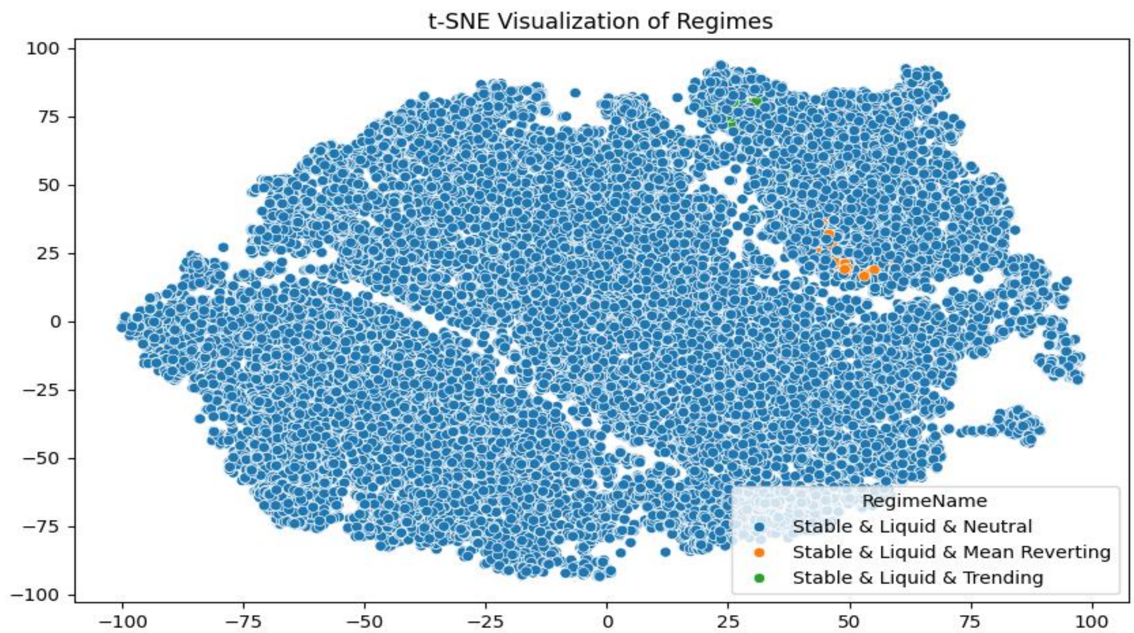
K-Means Elbow Plot:

The elbow plot justifies the choice of k=4 clusters for K-Means (see attached plot).



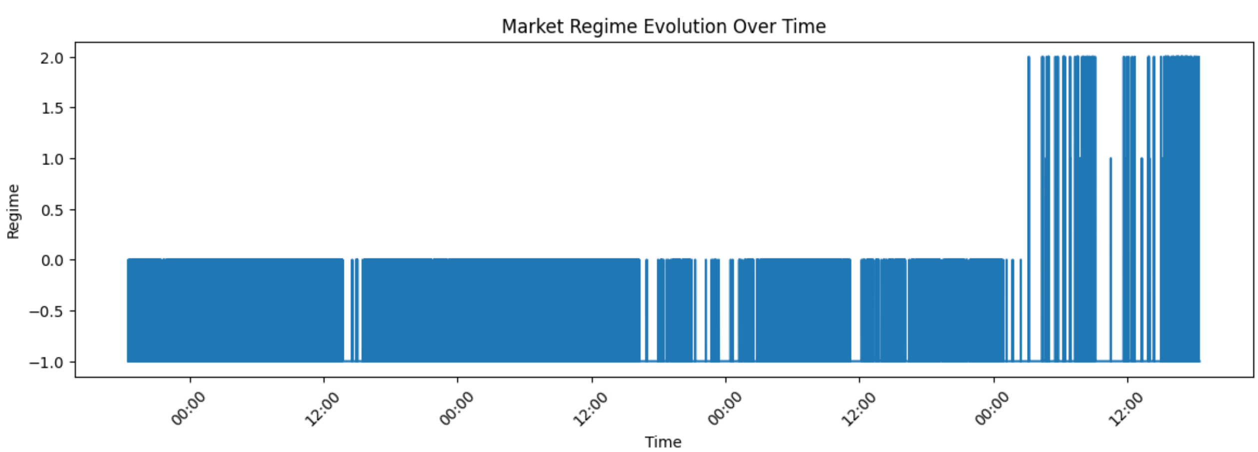
t-SNE Visualization:

Clusters are visualized in a reduced two-dimensional space using t-SNE, highlighting clear separations between regimes (see attached plot).



Regime Evolution Over Time:

A time-series plot shows how regimes evolve dynamically throughout the trading period (see attached plot).



6. Regime Transition Insights

A transition matrix was computed to analyze regime changes over time:

From → To	Stable & Liquid & Neutral	Stable & Liquid & Mean Reverting	Stable & Liquid & Trending
Stable & Liquid & Neutral	1.00	0	0
Stable & Liquid & Mean Reverting	0	0.91	0
Stable & Liquid & Trending	0	0	0

This analysis provides insights into regime persistence and transitions, which can be valuable for predictive modeling.

Conclusion

Key Achievements:

1. Extracted meaningful features from high-dimensional order book and trade volume data.
2. Successfully segmented the market into interpretable regimes using HDBSCAN.
3. Provided actionable insights into regime characteristics and transitions.

Observations from Final Results and Plots:

- HDBSCAN outperformed other clustering methods in handling noise and identifying meaningful clusters.
- The t-SNE visualization confirmed clear separations between regimes, validating clustering results.
- The regime evolution plot demonstrated stable transitions over time, with minimal noise interference.
- Transition probabilities revealed high persistence within regimes, indicating predictable behavior patterns.