RozReturns Capital

Assignment -- Ujjwal Bisaria

Problem Statement:

Regime Detection via Unsupervised Learning from Order Book and Volume Data

Objective:

Segment the market into distinct behavioural regimes depending on 3 factors:

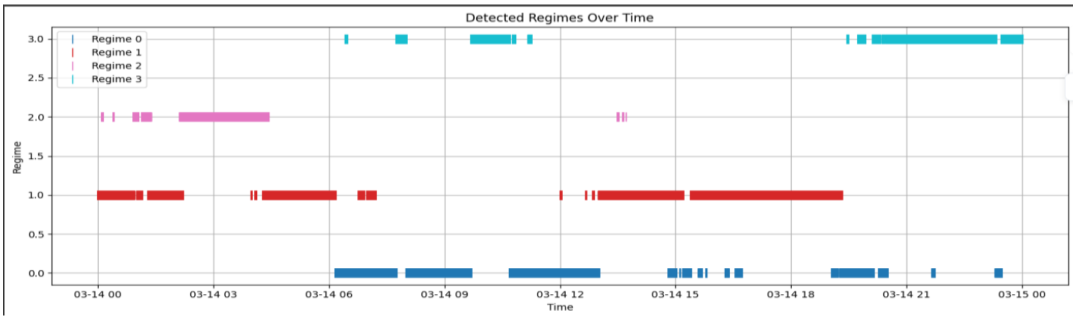
1)Trending vs Mean-Reverting

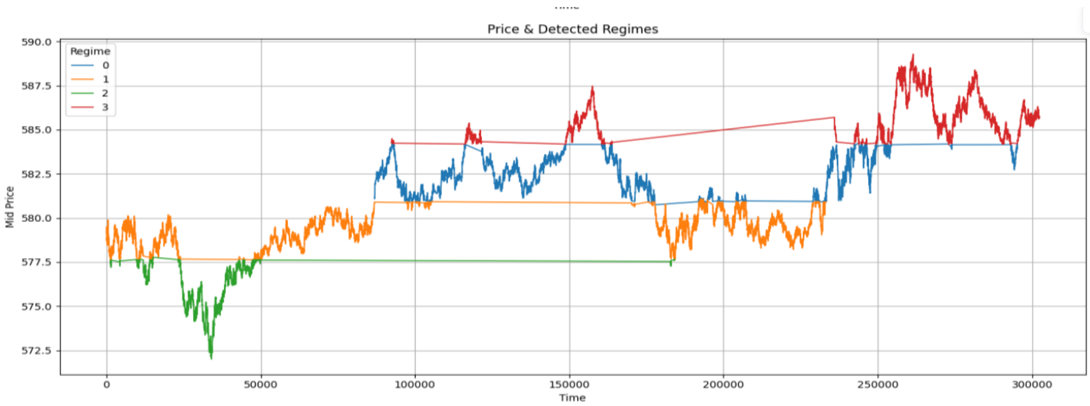
2)Volatile vs Stable

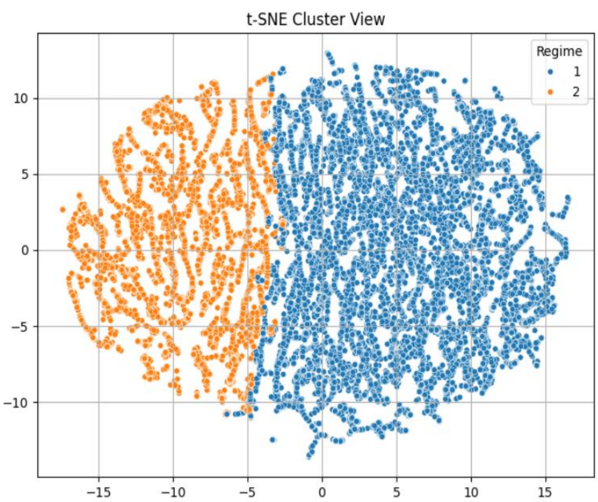
3)Liquid vs Illiquid

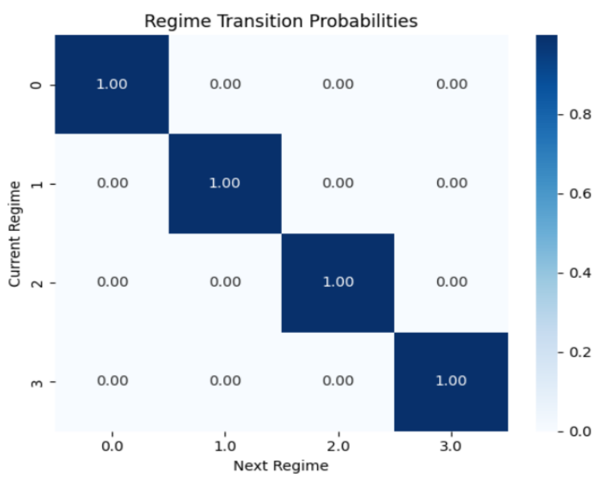
Results:

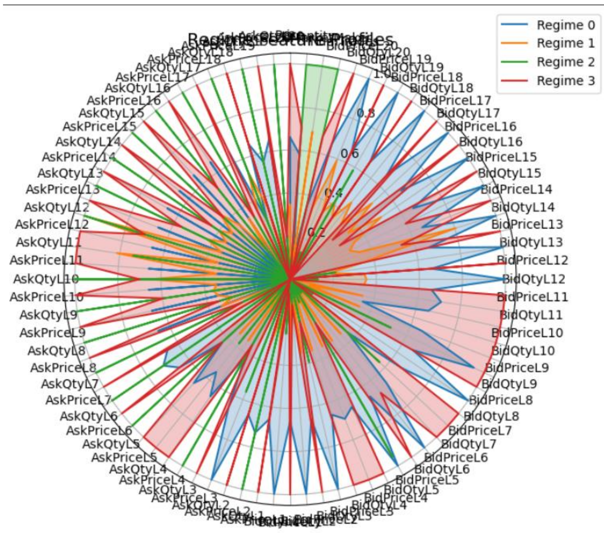
Only used the Data of Day-1(14th Date)









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From Regime 0 most likely transitions to:
  → Regime 0.0 with probability 0.998
  → Regime 1.0 with probability 0.001

From Regime 1 most likely transitions to:
  → Regime 1.0 with probability 0.998
  → Regime 0.0 with probability 0.001

From Regime 2 most likely transitions to:
  → Regime 2.0 with probability 0.997
  → Regime 1.0 with probability 0.003

From Regime 3 most likely transitions to:
  → Regime 3.0 with probability 0.999
  → Regime 0.0 with probability 0.001
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Conclusions and Observations:

1. Regime Identification and Market Behavior

1) The model successfully identified **four distinct market regimes**.
2) **Regime 0 and Regime 1** dominate most of the market activity.
3) **Regime 0** typically represents steady or mildly upward price movements.
4) **Regime 1** is associated with sharp upward trends and high volatility.
5) **Regime 2** appears during periods of **downward or volatile bearish trends**.
6) **Regime 3** occurs occasionally, likely reflecting **low-activity or unstable market periods**.

2. Price Movements and Regimes

1) The **price vs. detected regimes plot** shows how market prices move differently under each regime.
2) Clear segmentation in price trends aligns with specific regimes, indicating that each regime captures a **unique market state**.
3) The model's regime labeling appears consistent with actual price movement patterns.

3. Cluster Visualization (t-SNE Results)
1) The **t-SNE cluster view** demonstrates that the regimes are **well-separated in feature space**.
2) Data points naturally cluster together based on their assigned regime, confirming the **model's ability to distinguish different market conditions**.

4. Regime Transition Probabilities
1) The transition probability matrix shows extremely high diagonal values, indicating that the market tends to stay in the same regime for extended periods.
2) Transitions are rare — when they do happen, they mostly occur between Regime 0 and Regime 1, reflecting the **dominance of these two regimes**.
3) **Minimal transitions to Regime 2 and Regime 3**, suggesting those market conditions are less frequent.

5. Feature Importance Across Regimes
1) The feature importance radar chart reveals that different market features influence regime detection differently.
2) In Regime 0, various bid and ask prices and quantities have a balanced impact.

3) In Regime 1, specific bid price levels play a more dominant role.
4) This indicates that market behavior changes significantly across regimes, and the model is effectively capturing these differences.

6. Practical Implications

1) The persistence of regimes and rare transitions suggest that it's possible to develop regime-specific trading strategies.
2) Since the model identifies which variables are most important in each regime, traders and analysts can focus on those key indicators for decision-making.
3) These results also offer insights for risk management by highlighting when the market is likely to stay stable and when it might shift to a high-volatility state.