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Blockhouse Work Trial

1 Feature Engineering Reasoning

Reasoning for including features in part 1.

1.1 Trade Duration

Measures the time taken to execute a trade from order placement to completion, providing insights into market liquidity and execution efficiency. Longer durations may indicate inefficiencies or high competition for liquidity, while shorter durations suggest efficient execution and ample liquidity. Understanding trade duration can help identify bottlenecks in the trading process, allowing for improvements in order execution strategies.

1.2 Market Sentiment Score

Utilizes NLP to gauge the sentiment from news articles and social media, providing a real-time indicator of market sentiment. Positive sentiment can precede price increases, while negative sentiment might predict declines, aiding in anticipating market movements. Incorporating market sentiment scores into trading algorithms can enhance predictive accuracy and improve decision-making.

1.3 Order Cancelation Rate

High cancellation rates can indicate uncertain or volatile market conditions, as traders frequently adjust their orders in response to rapidly changing prices. Reflects the aggressiveness or hesitancy of traders, providing insights into their confidence and strategy adjustments. Monitoring order cancellation rates helps in assessing the reliability of market conditions and the stability of trading environments.

1.4 Order Execution Speed

Measures the speed at which orders are executed, offering insights into the efficiency of the market and the effectiveness of the execution strategies. Faster execution speeds typically correlate with higher market liquidity, while slower speeds can indicate liquidity constraints or execution difficulties. Tracking order execution speed can reveal the efficiency of trading infrastructure and highlight areas for technological enhancements.

1.5 Order to Trade Ratio

High OTR values indicate that many orders are placed but fewer are executed, suggesting high competition or cautious trading behavior. Low OTR values imply efficient order execution and better utilization of liquidity, providing a gauge of how much of the order flow actually translates into trades. Evaluating the order to trade ratio aids in understanding market dynamics and can guide the development of more effective trading strategies.

2 Summary of Two New Papers

2.1 Constrained Portfolio Liquidation in a Limit Order Book Model by Aurelien Alfonsi, Alexander Schied, and Antje Schulz

The paper "Constrained Portfolio Liquidation in a Limit Order Book Model" by Aurélien Alfonsi, Alexander Schied, and Antje Schulz focuses on optimizing the placement of market orders to minimize expected liquidity costs. The mathematical model for optimal portfolio liquidation in a limit order book (LOB) with resilience aims to minimize the expected liquidity costs of buying a given amount of shares X_0 over a specified time period [0,T]. The model considers a linear price impact, γ, and an exponential decay of the price impact with a time-dependent resilience rate, ρ. The cost function C(x), which is obtained by optimizing the total cost of a market order at time t, for the order sizes x is defined as:

$$C(x) = \sum_{i=0}^{N-1} (\gamma(\sum_{j=0}^{i} x_j + (\frac{1}{q} - \gamma) \sum_{j=0}^{i} x_j e^{-\int_{t_j}^{t_i} \rho_s ds}) x_i$$

where t represents the time intervals and q is the constant height of the LOB. The optimization problem includes the constraint that the sum of all order sizes must equal X_0:

$$\sum_{i=0}^{N-1} x_i = X_0$$

The model reduces to minimizing the quadratic cost function subject to these constraints. The solution involves computing the recovery factor:

$$e^{-\int_{t_j}^{t_i} \rho_s ds}$$

for the given resilience rate ρ_t.

2.2 Market Impact and Trading Profile of Hidden Orders in Stock Markets by Emilio Moro, et al.

The paper "Market Impact and Trading Profile of Hidden Orders in Stock Markets" by Esteban Moro et al. focuses on the empirical study of the market impact of hidden trading orders in stock markets. Market impact is the price change conditioned on initiating a trade of a given size and sign. Typically, a buy order increases the price, while a sell order decreases it. Hidden orders are large trading orders executed incrementally to minimize transaction costs. In this implementation, we calculate the market impact and slippage of hidden orders in stock markets using several mathematical models. The total volume V of a hidden order is calculated as the sum of the signed volumes of individual transactions:

$$V = \sum_{j=1}^{N} v_j$$

The volume fraction of market orders f_{mo} is determined by the ratio of market order volume to total volume:

$$f_{mo} = \frac{\sum_{j=1}^{N} v_{j,mo}}{\sum_{j=1}^{N} v_j}$$

where $v_{j,mo}$ is the traded volume through market orders.

The participation rate α is computed as the ratio of the hidden order volume to the total market volume:

$$\alpha = \frac{\sum_{j=1}^{N} v_j}{V_M}$$

where V_M is the total volume of the stock traded concurrently with the hidden order.

The market impact $R_i(t,T)$ is the log price change divided by the spread:

$$R_i(t, T) = \eta_i \frac{log(p_{i,\, i+T}/p_{i,t})}{s_i}$$

where η_i is +1 for buy orders and -1 for sell orders.

The market impact as a function of order size follows a power law:

$$R(N) = AN^{\delta}$$

with δ is the exponent typically found to be around 0.5, consistent with a square-root law for market impact.

Finally, the impact over time is modeled as:

$$R \propto \left(\frac{t}{T}\right)^{\beta}$$