WiDS Kalman Filtered Trend Trader

Assignment 2

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1 Introduction

Financial markets exhibit non-stationary dynamics, where relationships between prices, returns, volatility, and market features evolve over time. Static models are often unable to adapt to such changes, leading to degraded performance.

In this assignment, a systematic trading strategy for Microsoft Corporation (MSFT) is developed using Kalman Filters to model time-varying latent relationships and a supervised machine learning model to generate predictive trading signals. The strategy is evaluated using a causal backtesting framework and compared to a buy-and-hold benchmark.

2 Data Collection

Daily historical market data for Microsoft Corp. (MSFT) from 2015 to 2024 was obtained from Yahoo Finance. Adjusted closing prices and trading volume were used to ensure consistency across corporate actions.

All preprocessing steps maintain strict causality, ensuring that no future information is used in model estimation or trading decisions.

3 Feature Engineering

A diverse set of market features was constructed to capture price dynamics, momentum, and risk characteristics:

- Log returns and lagged returns
- Moving averages (5-day, 20-day, 60-day)
- Rate of Change (ROC)
- Rolling volatility measures
- Volume-based indicators

These features provide complementary information about short-term momentum, long-term trend structure, and market uncertainty.

4 Kalman Filter Model

A state-space model was formulated in which the latent state represents time-varying regression coefficients linking engineered features to MSFT returns.

4.1 Model Formulation

The observation equation is defined as:

$$y_t = X_t\beta_t + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, R)$$

The state transition equation is:

$$\beta_t = \beta_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, Q)$$

Here, β_t denotes the latent parameter vector, while Q and R control parameter drift and observation noise respectively.

The Kalman Filter recursively estimates β_t using only current and past information, allowing the model to adapt to evolving market conditions while remaining causal.

4.2 Filtered Parameters

Kalman-filtered parameters exhibit smooth temporal evolution, reflecting gradual changes in the relevance of different market features across regimes.

5 Machine Learning Integration

The Kalman-filtered latent parameters were used as inputs to a supervised learning model to predict the next-period price ratio of MSFT.

A linear regression model was selected due to its interpretability, stability, and low risk of overfitting when applied to time-series data with evolving dynamics. Predictions are made using only information available at the current timestep.

6 Trading Strategy Design

Trading signals are derived from the predicted price ratio:

- **Buy Signal**: Predicted ratio exceeds the current ratio by a predefined threshold
- **Sell Signal**: Predicted ratio falls below the current ratio by a predefined threshold

Risk management constraints include:

- Long/short positioning without leverage
- Transaction cost adjustment
- Position updates executed at $t + 1$

All signals are generated causally and are based solely on present and historical data.

7 Backtesting Framework

The strategy was evaluated using a walk-forward backtesting framework:

- Signals generated at time t are executed at $t + 1$
- Daily profit and loss (PnL) is computed based on position returns
- Transaction costs are explicitly incorporated

A buy-and-hold MSFT strategy is used as a benchmark for comparison.

8 Performance Evaluation

The trading strategy was evaluated using multiple quantitative metrics:

- **Cumulative Return**: 1.124
- **Sharpe Ratio**: 0.60
- **Maximum Drawdown**: -0.16
- **Win/Loss Ratio**: 0.112

The cumulative return indicates that the strategy more than doubled the initial capital over the evaluation period. A Sharpe ratio of 0.60 reflects moderate risk-adjusted performance, consistent with systematic trend-following approaches.

The maximum drawdown of approximately 16% suggests controlled downside risk relative to typical equity market behavior. The low win/loss ratio implies that the strategy relies on fewer, larger profitable trades rather than frequent small gains.

When compared to a buy-and-hold MSFT strategy, the proposed approach offers improved drawdown control while maintaining competitive long-term returns.

9 Discussion and Limitations

The results demonstrate the effectiveness of combining Kalman-filtered time-varying parameter estimation with supervised learning in non-stationary financial environments.

However, several limitations remain:

- Linear modeling assumptions may limit expressiveness
- Sensitivity to noisy short-term signals
- Dependence on feature selection and threshold parameters

Future improvements may include nonlinear models, regime detection, or adaptive noise estimation within the Kalman framework.

10 Conclusion

This assignment presents a complete end-to-end trading strategy using Kalman Filters and machine learning. By modeling evolving market relationships and enforcing causal trading rules, the strategy adapts to non-stationary market behavior and demonstrates stable performance relative to static benchmarks.