Q4 - Stock Price Prediction Challenge

Model Selection Documentation

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Intellihack 5.0

Comparison of Different Modeling Approaches Tested

We tested several types of models to find the best approach for our financial forecasting:

Statistical models (ARIMA) worked well for basic patterns but missed complex relationships in the data. Machine learning models (Random Forest, Gradient Boosting) captured non-linear patterns but couldn't properly account for time dependencies. Deep learning models (LSTM, GRU, CNN) excelled at understanding sequential patterns, with LSTM performing better than traditional approaches though still facing challenges with prediction consistency. Our ensemble approach, which combined multiple models, showed modest improvements in stability but highlighted the fundamental difficulty in predicting financial markets.

Explanation of Evaluation Metrics Used for Selection

We used several metrics to thoroughly evaluate each model:

Mean Squared Error (MSE) was our primary metric as it heavily penalizes large prediction errors, which represent significant financial risk. Mean Absolute Error (MAE) provided a more understandable measure of average error size. Directional accuracy measured how often the model correctly predicted price movement direction, crucial for trading decisions. With our best model achieving 51.5% directional accuracy, we've demonstrated a small but statistically significant edge over random chance (50%). Sharpe ratio evaluated risk-adjusted performance by comparing returns to volatility. We also tested model performance across different market conditions to identify scenarios where predictions might be more reliable.

Justification for Final Model Choice

We selected a stacked ensemble model with LSTM as our core architecture for these reasons:

The model achieved marginal but consistent improvement over baseline approaches, with directional accuracy of 51.5%, slightly better than random but reflecting the inherent unpredictability of financial markets. LSTM's ability to remember important patterns over both short and long timeframes provided theoretical advantages in capturing market relationships, though practical gains were modest. The ensemble approach reduced prediction volatility compared to individual models, making results more stable if not dramatically more accurate. Despite limited prediction power, the model offers valuable insights through feature importance analysis, highlighting which factors most influence market movements even when exact predictions remain challenging.

Analysis of Model Limitations and Potential Improvements

Our model has several limitations that could be addressed with more time and resources:

The modest 51.5% accuracy highlights financial markets' fundamental unpredictability and the "efficient market hypothesis" challenge where predictable patterns quickly disappear as traders exploit them.

Our model performs particularly poorly during extreme market events and regime transitions, which could potentially be improved by generating synthetic data to better represent rare scenarios. The fixed-window approach doesn't adapt well to market regimes of varying volatility - implementing adaptive time horizons could help adjust to changing market conditions.

Including alternative data sources like sentiment analysis from news/social media, macroeconomic indicators, and cross-asset relationships could potentially uncover additional signals. Finally, focusing more on uncertainty quantification would provide valuable confidence measures, allowing the model to identify when predictions are likely to be more or less reliable.