Causal Discovery in Stock Return

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Introduction

- Driven by a complex interplay of **economic conditions**, **corporate performance shocks**, and **investor anticipations**, the high volatility of financial markets challenges stock return forecasting, further amplified by recent **global policies** and **economic disruptions**. As a result, capturing both **long-term trends** and **external shocks** has become crucial in guiding the decisions of millions of investors.
- Traditional forecasting models struggle with **sudden market shifts** due to their reliance on historical patterns and predefined economic relationships. Meanwhile, despite better accuracy, deep learning-based models **lack interpretability**, which limits their adoption in high-stakes financial markets.

To enhance model transparency and reliability, we proposed a **hybrid** stock return prediction framework that 1) uses **PCMCI with DeepAR** for **causal feature selection** and **lag optimization** to better capture general daily trends and 2) leverages **CD-NOD** on real-**time macro-economic** and **company-level factors** with Random Forest to capture the effect of shock on stock price.

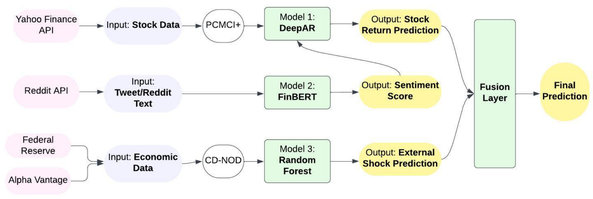
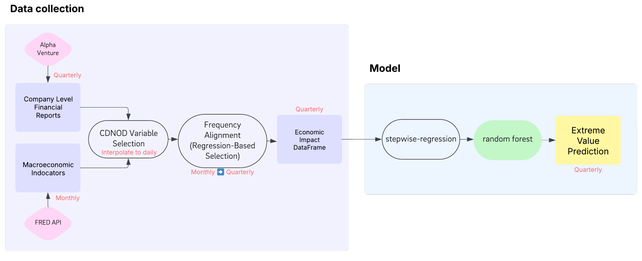


Fig. 1: Overview of the Proposed Stock Return Prediction Framework

Economic Impact Analysis Module



Data Collection

Microeconomic Data: Company quarterly reports from Alpha Vantage, including information on income statements, cash flow, and balance sheets

Macroeconomic Indicators: Monthly Economic data from FRED (CPI, GDP).

Data Pre-processing

Frequency Alignment: We first mapped each quarter to three monthly time-series vectors and then **regressed the monthly vector on the quarterly compound return**. Finally, we selecting the most representative month to aligned with company-level quarterly report via **hypothesis testing on the coefficients**.

Prediction Model:

A **Random Forest** model was applied to the integrated dataset to predict **extreme quarterly stock returns upon the release of company financial statements** in real time, to capture shocks driven by economic fluctuations and expectations.

CDNOD: Feature Selection from a Causal Len

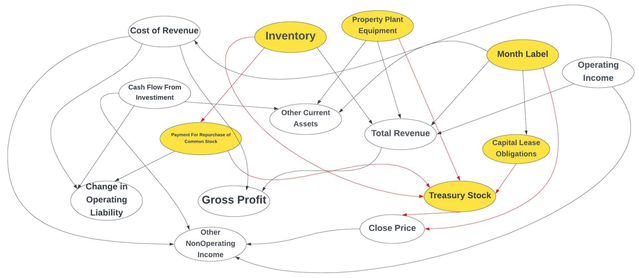


Fig. 3: Causal Graph for AT&T

Causal Feature Selection: After interpolating economic factors with daily stock prices, we applied **CD-NOD with monthly grouping** and **Fisher's Z-test at a 0.01 significance level** to capture causal relationships between factors and stock price shocks.

We define **impactful features** as those that (1) have a **direct edge** to stock price or (2) connect to stock price **through causal pathways** in the learned graph.

We further performed **pairwise regression** to assess each predictor's direct impact.

Stock Return Prediction Module

Data Collection & Pre-processing: Historical data of 6 companies (3 Tech, 3 Healthcare) from Jun 2020 to Feb 2025, including daily metrics of opening/closing price, high, low, and volume. We calculate Daily return as: $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$.

Causal Feature Selection: Applied PCMCI+ algorithm for causal feature selection, identifying 8 key covariates based on their causal impacts.

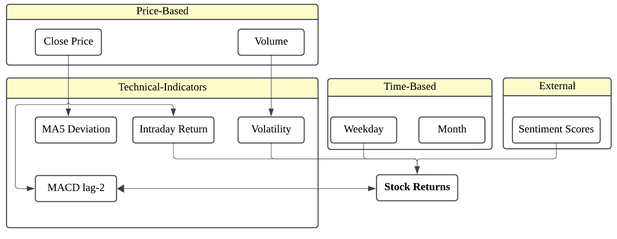


Fig. 4: Causal Structure of Stock Return Predictors after PCMCI Analysis

Model Architecture: The model integrates historical returns, technical indicators, and entity embeddings into a concatenated input tensor. An enhanced LSTM with skip connections and variational dropout enables robust gradient flow. The probabilistic output layer generates a Gaussian distribution of future returns, instead of just point estimates.

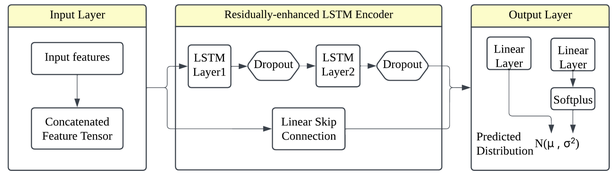


Fig. 5: DeepAR Model Pipeline

Sentiment Analysis Module

Model: FinBERT - Specialized NLP model for financial text sentiment analysis.
Data Collection & Pre-processing:

- AMZN, GOOG, CVS GitHub Tweet Dataset (June 2020 - May 2023).
- Collected Reddit posts and comments for additional sentiment data via API.
- Applied time-scaled linear interpolation for data smoothing.

Sentiment Scoring: Weighted FinBERT confidence levels with normalization to 0-1 range.

Fig. 6: Work Flow of Sentiment Analysis Module

Results

Evaluation Metrics: MAE, MAPE, RMSE, and Direction Accuracy.
In figure below, our model accurately captures overall market trends, with CVS stock price direction being predicted with 100% accuracy, while the AMZN model excels particularly in long-term forecasting with a long-term MAE of only $2.61.

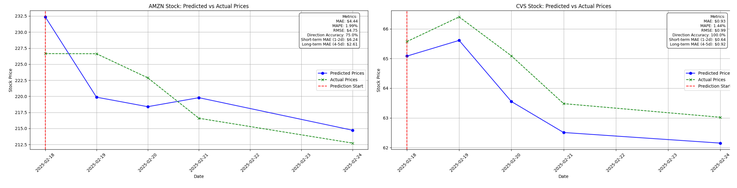


Fig. 7: Stock Price Prediction Performances

Remarks (Developing)

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References(Developing)