Developing a Hybrid AI model for Financial Market Prediction

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Research objectives

This research aims to deepen the understanding of stock market behavior by conducting an **ablation study** on a variety of modeling techniques and data sources.

The goal is to systematically evaluate the contribution of different input features and model architectures, including:

- traditional statistical approaches: **ARIMA** and **SARIMA.**
- machine learning methods: **MLR** with scaling and non-linear transformations combinations.
- deep learning architectures: **ANN** with different architecture complexity.
- probabilistic deep learning methods: **BNN** with different priors and complexity.

Research relevance

- Makes investment decision making process more informed and reliable.
- Reveals the efficiencies of different AI architectures with variety of market features.
- Provides a ready-to-use infrastructure for future contribution.

Core assumptions

Future **stock returns are inherently stochastic**, so modeling their full probability distribution provides more reliable forecasts compare to a single point estimate.

Deterministic view

- We expect **NVDA** to return 10 % next year.

Probabilistic view

- There is a 50 % probability that **NVDA** total return over the next 12 months will lie between 8 % and 12 %.

Incorporating **inputs beyond raw OHLC** helps models capture the true complexity of financial markets.

Baseline data

- Open
- High
- Low
- Close

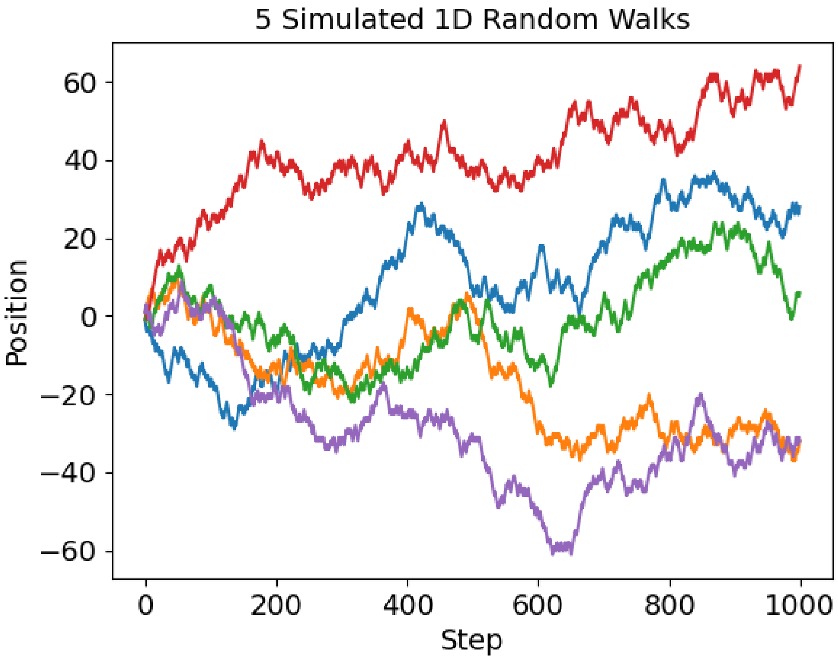
\+ Volume

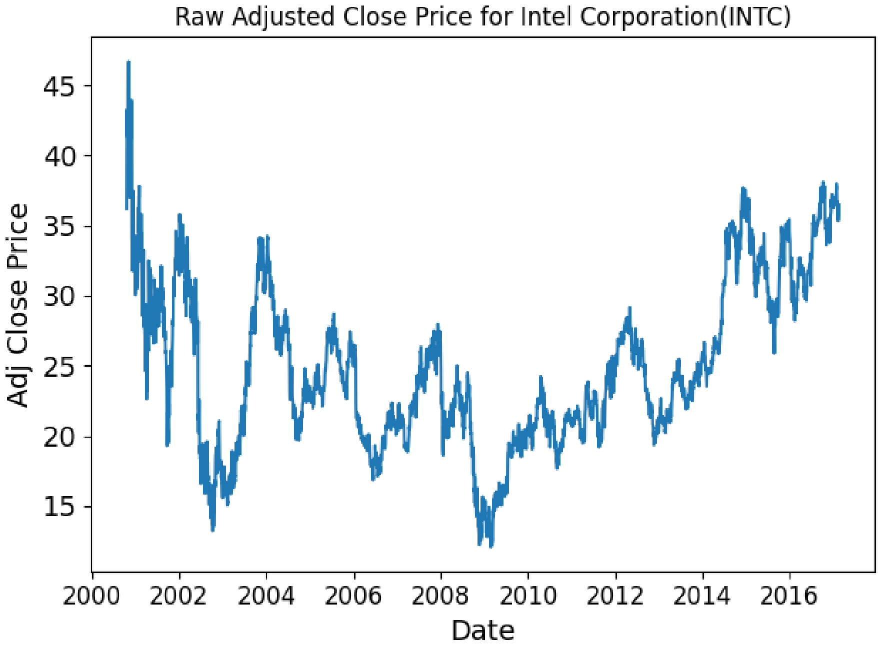
Extra data

- Datetime variables
- Macro data
- Technical indicators
- Rolling features
- Anomaly scores
- Sentiment scores

Random Walk Simulation vs. Stock Price Movement

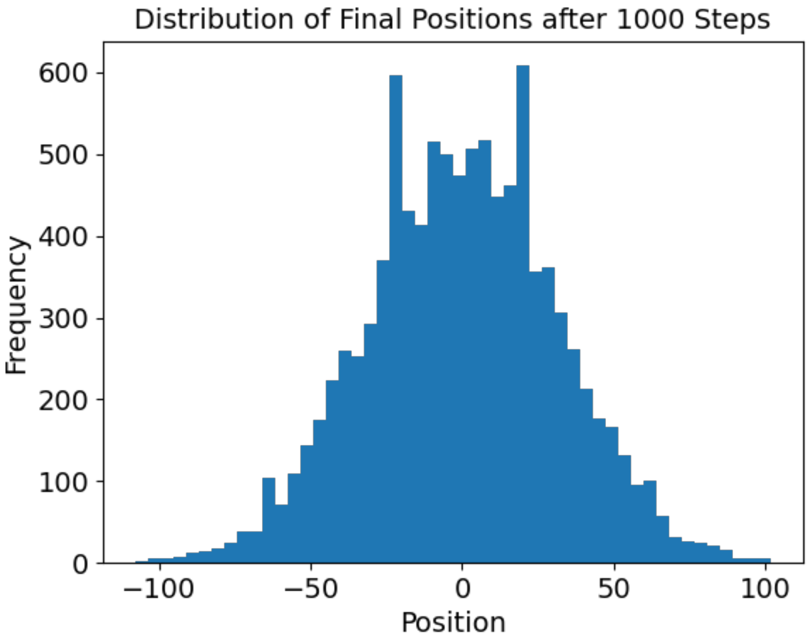
Random walk simulation offer a baseline for understanding stock price movements under uncertainty and noise:

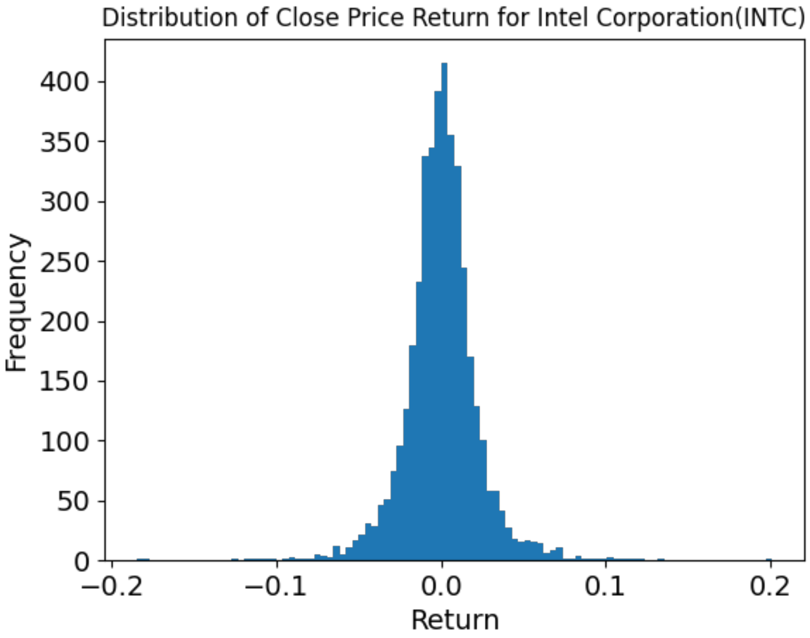




Random Walk Simulation vs. Stock Price Movement

There are quite a few similarities between *random walk simulation* and actual *close price return distributions*:





The Bayesian Brain

Domain space

Machine learning

$$p(x,y,\theta)$$

$$p(y|\theta,x)$$

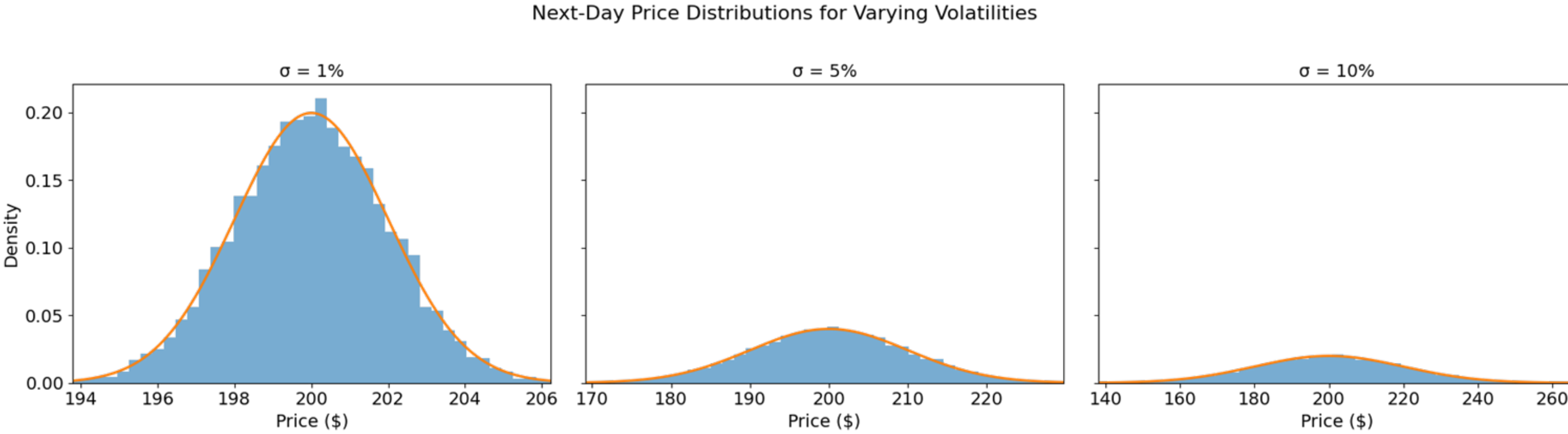
Inference

$$p(\theta|y,x) = \frac{p(y|\theta,x)p(\theta|x)}{\int p(y,\theta|x)d\theta}$$

- $p(\theta|y,x)$ - posterior
- $p(y|\theta,x)$ - likelihood

Volatility Simulation

Given the stock's current price of \$200 and σ (market volatility estimate), *what is the probability that its closing price on the next trading day will reach \$210?*



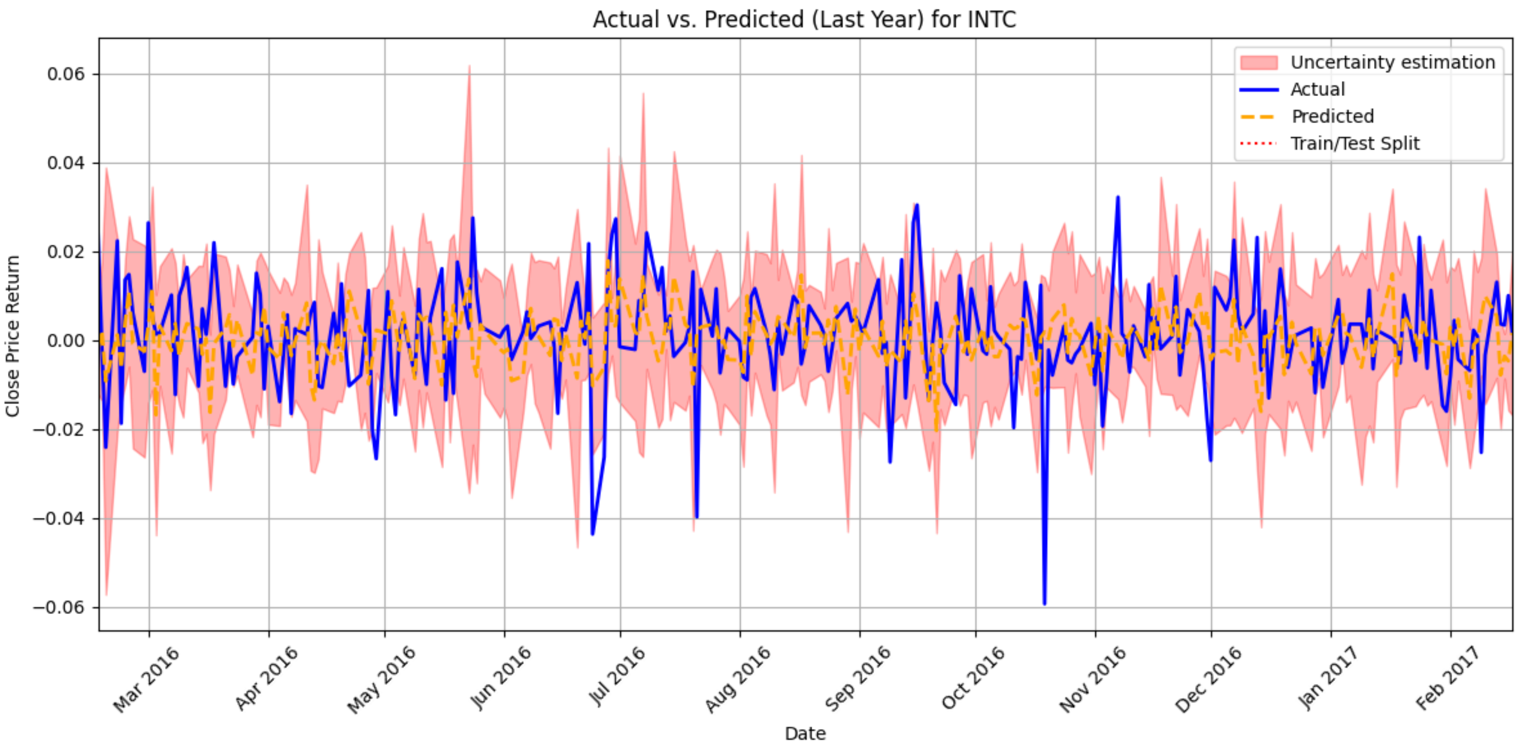
$\sigma = 1\%$: $z = 5.00$, P(price $\geq$ \$210) ~ **0**

$\sigma = 5\%$: $z = 1.00$, P(price $\geq$ \$210) ~ **0.16**

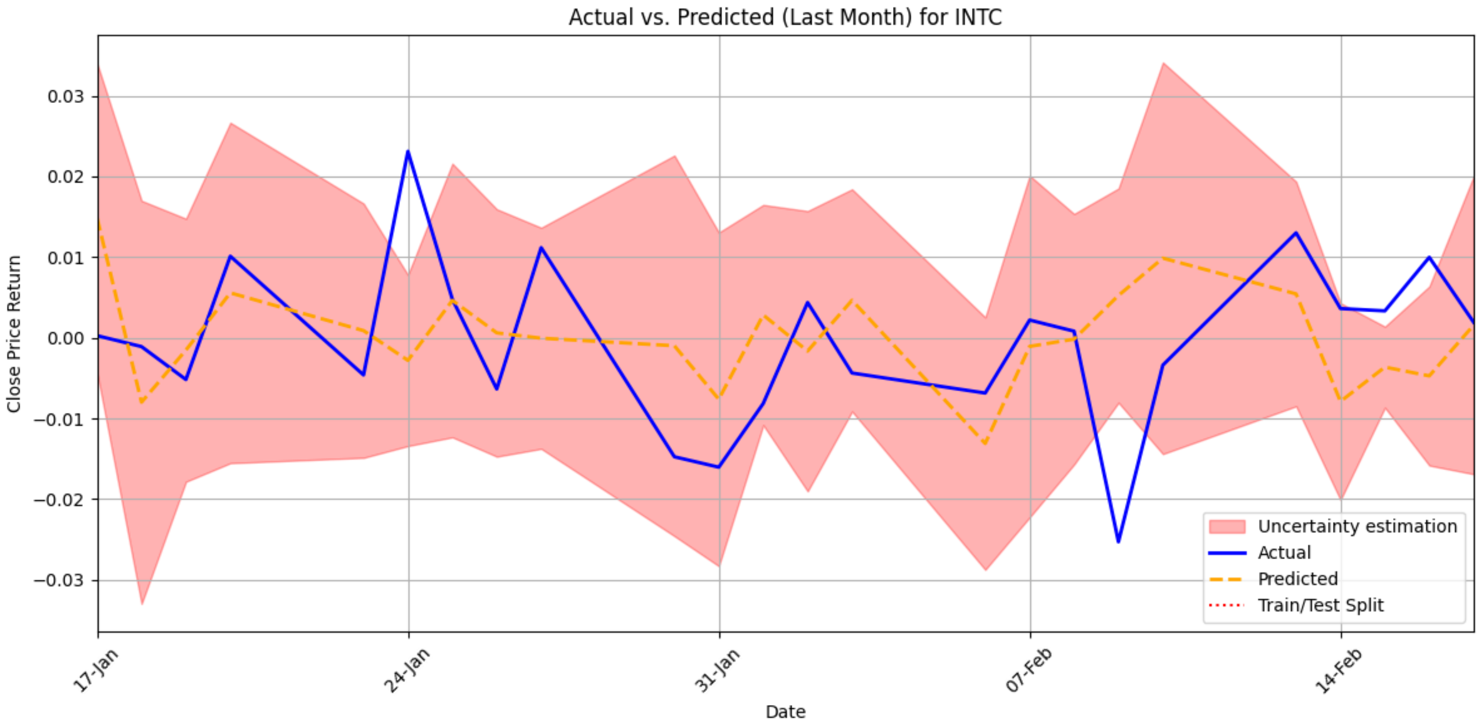
$\sigma = 10\%$: $z = 0.50$, P(price $\geq$ \$210) ~ **0.31**

"The **standard deviation σ is estimated** by defining a prior distribution and updating it using observed data through BNNs."

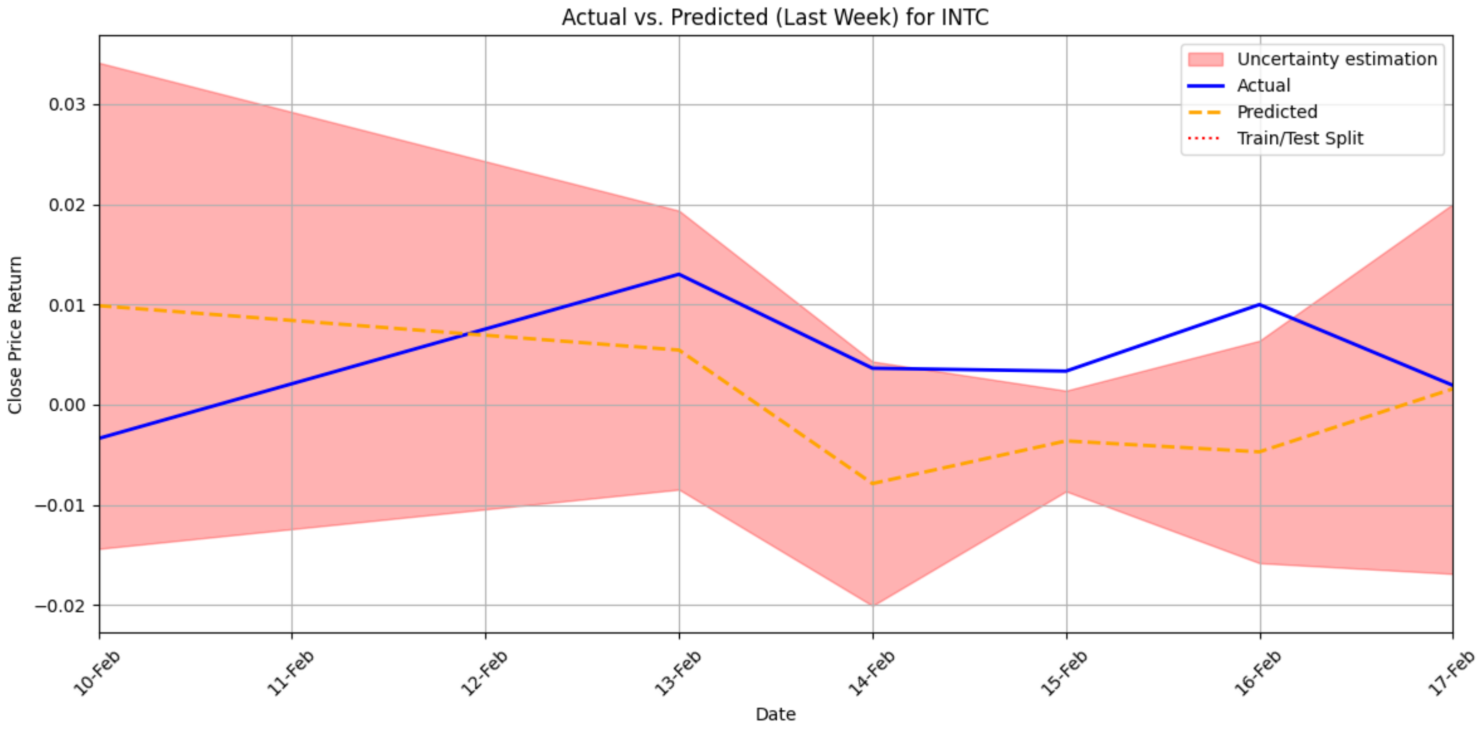
Estimated BNN Uncertainty - one year scope



Estimated BNN Uncertainty - one month scope

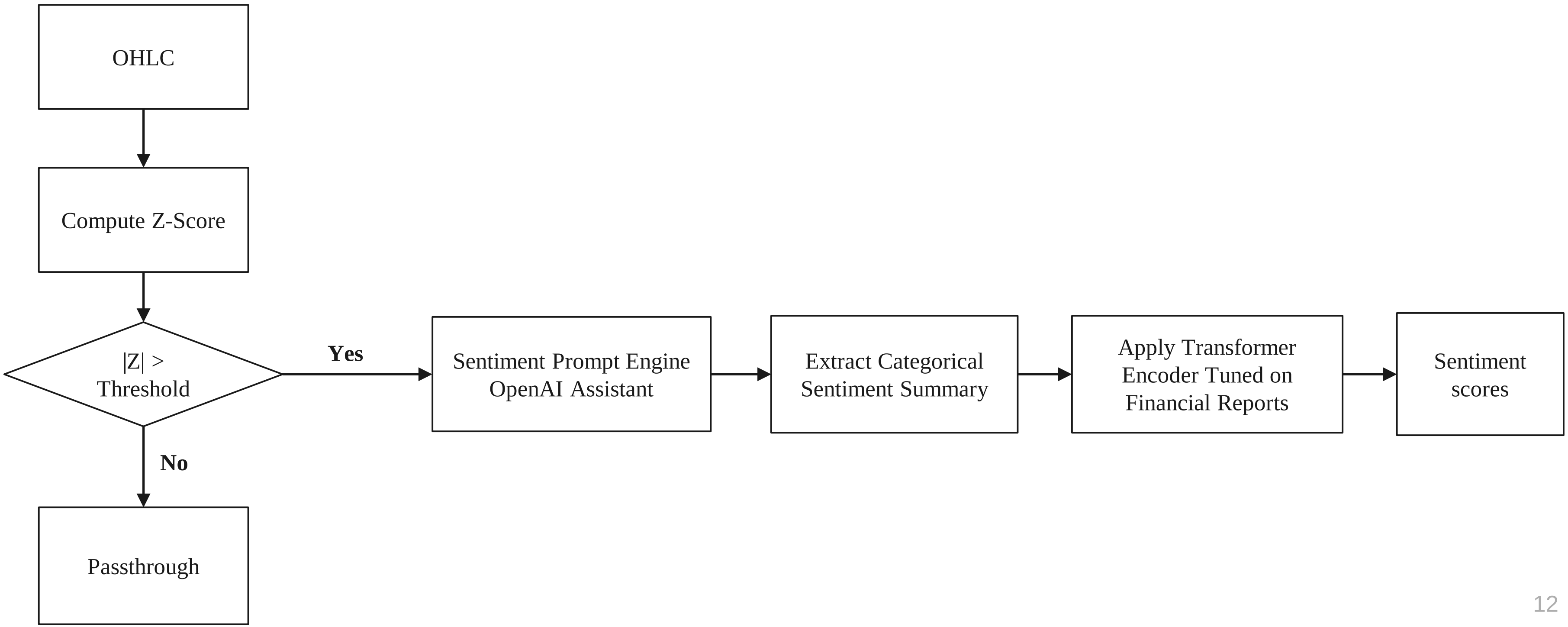


Estimated BNN Uncertainty - one week scope



Sentiment extraction flowchart

A Z-score pipeline that **detects significant price movements and extracts financial sentiment** using a transformer-based language model.



Ablation study design

To be able to test our two main assumptions, we have conducted a comprehensive ablation research, which includes

- 5 semiconductor stock assets
- 7 types of processed data
- **87 engineered features in total**
- 13 years of train and 4 years of validation data epochs
- **5 model architectures**
- 3 types of predictions

Let's take a look at the configured ML tracking setup !

Ablation study results

After experimenting with models complexity, scaling functions, non-linearity and probability distributions, *we have gathered the best results for Intel Corporation(INTC)*:

Model name & Sets of features	**Baseline**	**Macro**	**Extra**	**Mean Squared Error (MSE)**		
				1 day	3 days	5 days
Linear regression: Scaled: True, Nonlinear: False	✓	✓	✓	2.46e-05	9.94e-05	0.0001354
Linear regression: Scaled: True, Nonlinear: True	✓	✗	✗	0.0001236	0.0001504	0.0001709
Artificial Neural Network: Scaled: True	✓	✓	✓	0.0001794	0.0001680	0.0001690
Bayesian Neural Network: Scaled: True, Student-T	✓	✓	✓	0.0002310	0.0002146	0.0002104

Key Results & Takeaways

- *Linear regression* shows the best result in a short-term predictions, while *Artificial Neural Network* are the best in the middle-long term predictions.
- *Bayesian Neural Network* has been able to estimated the market volatility, hence the MSE for the actual targets remains roughly the same with other architectures.
- *Bayesian Neural Network* performs better on long-term predictions.

"Given volatility estimates and the ability to sample and compute predictive probabilities, Bayesian Neural Networks offer greater confidence in financial market predictions."

Future work

- **Improve BNN Complexity Handling:** Test alternative output distributions *(e.g. LogNormal*, *Laplace)* and experiment with different priors to improve uncertainty modeling.
- **Apply Advanced Time Series Methods:** Use *STL decomposition* to capture trend and seasonality.
- **Reduce Input Complexity:** Apply *feature importance algorithms* to identify and remove less relevant features.

Demo!