Long Short Trader Using Deep Learning

PO-237

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Agenda

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1. Motivation and goals
2. Data ingestion
3. Data processing and feature engineering
4. Model Architecture
5. Trading Strategy
6. Simulation Results
7. Next steps

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Motivation and Goals

Project Motivation

- Leverage deep learning frameworks to tackle the challenges of time series data in financial markets.
- Utilize a portfolio allocation strategy to maximize profits

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Motivation and Goals

Challenges and Learning

- Time Series Complexity: Adapting LSTMs for time series analysis, which included handling dependencies and trends.
- Training using Sliding Window: Mastering the sliding window approach to split data effectively for prediction intervals on a large, real-world dataset.
- New Deep Learning Framework: Learning PyTorch from scratch to implement LSTM models, which was both challenging and rewarding due to its flexibility and control over model architecture.

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Process Flow

Overview

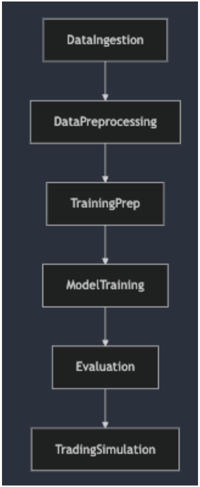

Figure: Process Flow

Data Ingestion

COMDINHEIRO API

Brazilian Stock Market

- Market data
- Fundamentalist Data

Total of 26 features

Data processing and feature engineering

- Challenges of data serialization and memory constraints
  - Solution: batch training
  - Stocks traded in parallel per time window
  - Model weights are updated after each time-window
- Creating target variable: return direction

$$T = \mathbb{1}(P_t - P_{t-1} > 0)$$

- Dealing with missing values: forward fill
- Validation with sliding window

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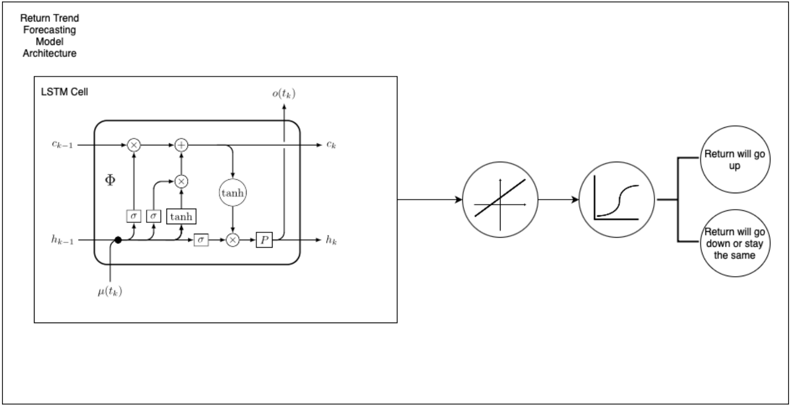


Figure: Model Architecture

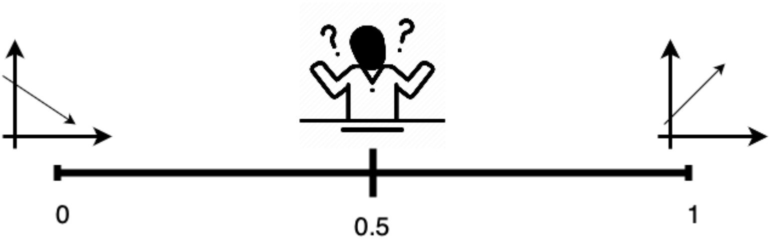


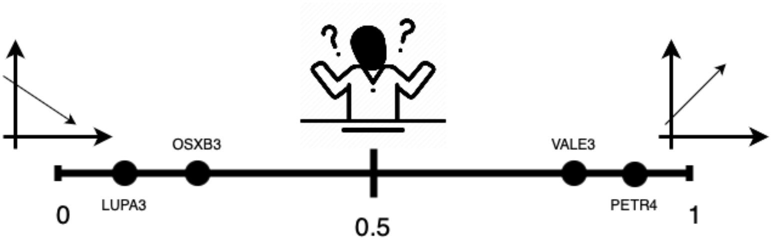
Figure: Model Output

Trading Strategy
Long Short Strategy

- New portfolio daily
- Long strategy: Choose 10 stocks with greater certainty of growth
- Short strategy: Choose 10 stocks with greater certainty of decrease
- Equal weight of the 20 stocks

Trading Strategy

Long Short Strategy



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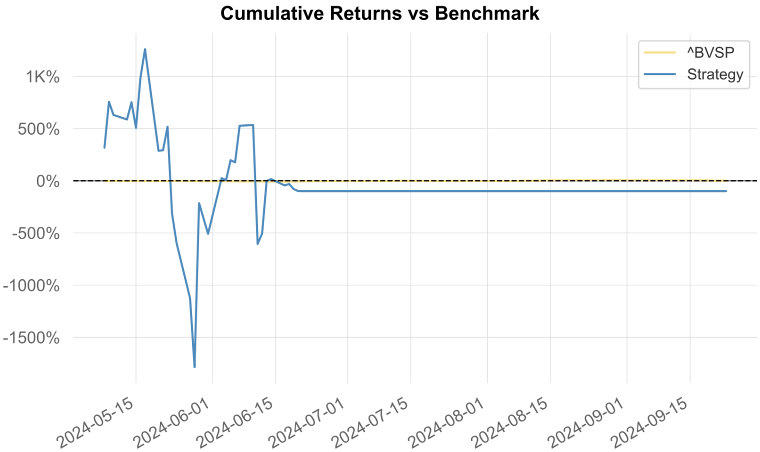
Context: simulated over 100 trading days



Simulation Results

Cumulative Returns Volatility Matched

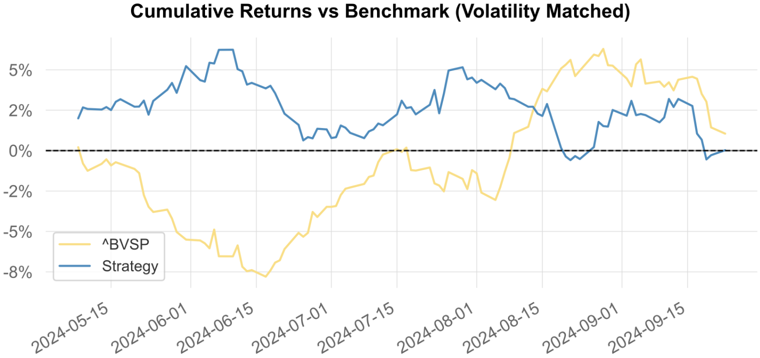


Figure: Cumulative Returns Volatility Matched

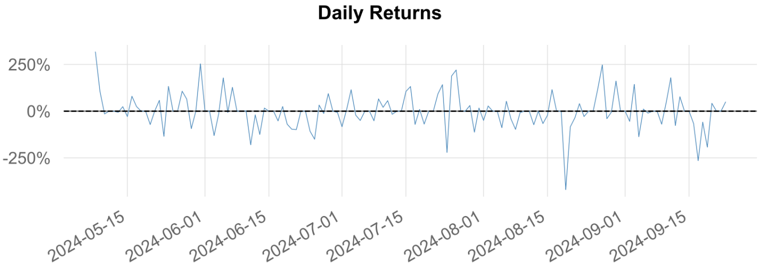


Figure: Daily Returns

Next Steps

Attempt:

- A different model architecture
- More feature engineering
- A different retraining frequency

References

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Thank you for listening!

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