IMPERIAL

Innovative Approaches to Asset Prediction: Combining Deep Learning with Financial Modelling

Project Plan

Author

C. Ioannidis

CID: 02533490

Supervised by

Prof. Pasquale Della Corte

Prof. Walter Distaso

Dr Lluis Guasch

A Thesis submitted in fulfillment of requirements for the degree of
Master of Science in Applied Computational Science and Engineering

Department of Earth Science and Engineering
Imperial College London
2024

Abstract

This project addresses the increasing complexity and volatility in financial markets through the development of advanced analytical tools. Leveraging the theoretical foundations established by Bryan Kelly and Kusuma, we propose refining Convolutional Neural Networks (CNNs) to enhance the prediction of financial asset behaviors. Key aspects of this research include:

- Exploring asset co-movements within and across different markets to better understand inter-market dependencies.
- Establishing a methodological framework integrating CNN architectures with candlestick chart data for simultaneous analysis of multiple financial assets.
- Developing a predictive model aimed at improving decision-making for multi-asset investment strategies.

Anticipated outcomes include enhanced predictive accuracy and deeper insights into global financial market dynamics. This research sets the stage for a comprehensive study on the interconnected nature of modern financial markets.

Declaration of Originality

I hereby declare that the work presented in this thesis is my own unless otherwise stated. To the best of my knowledge the work is original and ideas developed in collaboration with others have been appropriately referenced.

Copyright Declaration

Contents

1 Introduction

Contents

1.1 Literature review

Asset price prediction, vital for investors and policymakers, has traditionally relied on methods like Auto Regressive Integrated Moving Average (ARIMA), but recent advances in machine learning, particularly convolutional neural networks (CNNs), have shown promise in improving prediction accuracy. Kusuma et al. (2019) demonstrated that CNNs could effectively analyze historical stock data transformed into candlestick chart images, achieving high prediction accuracies for the Taiwanese and Indonesian stock markets [1]. Sezer and Ozbayoglu (2019) converted time-series stock data into 2-D bar chart images, using CNNs to identify trading signals, outperforming traditional strategies, especially in bear markets [2]. Zeng et al. (2021) introduced a video prediction model for economic time series, leveraging CNNs' ability to detect spatial patterns in image sequences, surpassing traditional methods like ARIMA and Prophet [3]. Jiang (2023) used OHLC charts with CNNs to forecast stock returns, highlighting the models' ability to capture intricate patterns and their scalability across different geographies and time scales [4]. These studies illustrate that CNNs, through innovative transformations of time-series data into image formats, significantly enhance asset price prediction accuracy, outperforming traditional methods and opening new avenues for integrating visual data representations in financial forecasting.

1

1.2 Problem description

This three-month project aims to enhance financial market prediction models by developing advanced Convolutional Neural Network (CNN) architectures. Focused on understanding asset co-movements within and across various markets, the project will gather and analyze time-series data from multiple asset classes using refined CNNs. The project will begin with the collection and preprocessing of data, followed by the development and iterative refinement of the predictive models. In the final month, the models will be tested in simulated environments to assess their predictive accuracy and applicability in real-world scenarios. This initiative is expected to offer significant insights into market dynamics, supporting more informed decision-making in financial investments and contributing to the field of financial analytics.

1.3 Objectives

The primary objective of this project is to advance the predictive capabilities of financial market models through the development and refinement of Convolutional Neural Network (CNN) architectures. By focusing on the analysis of asset co-movements within and across various markets, the project aims to uncover complex interdependencies that influence market behavior. This will enable more accurate predictions and effective risk management in volatile market conditions. Additionally, the project seeks to provide a deep understanding of the dynamics of asset interactions, which will assist investors and analysts in making more informed decisions regarding multi-asset investment strategies. Ultimately, the endeavor aims to contribute valuable insights and tools to the field of financial analytics, promoting a more nuanced understanding of global financial markets.

2 Progress to Date

Contents

2.1 Data access

2.1.1 Data Acquisition and Transition

The initial phase of the project utilizes publicly available financial data from Yahoo! Finance for preliminary model testing, providing foundational data handling and processing. As the project progresses, it will transition to the CRSP database, accessed through Imperial College London. This shift introduces enhanced depth and quality in financial metrics, supporting more detailed financial analyses and model accuracy.

2.1.2 Benefits and Impact of CRSP Data

Transitioning to CRSP data will broaden the historical perspective and enrich data granularity, which are crucial for analyzing asset co-movements and improving the robustness of financial models. Utilizing this high-quality dataset is expected to significantly enhance the predictive accuracy of the models by providing a deeper dataset for more effective training and detailed analysis.

2.2 Framework setup

2.2.1 Data Acquisition and Transformation

A systematic data acquisition process is implemented using Python scripts to automate data downloads, ensuring consistency and efficiency in initial data handling. Following acquisition, data is transformed into candlestick chart images, which are particularly effective for CNN applications, allowing the model to capture and learn from visual price movement patterns. This transformation process is integral to preparing the data for effective analysis.

2.2.2 Integration and Impact on Deep Learning Analysis

The transformed data is then integrated with Convolutional Neural Network (CNN) architectures, which are designed to interpret complex visual inputs from financial markets, thereby enhancing the model's analytical capabilities. This preprocessing strategy ensures that the CNNs operate efficiently and provides a scalable solution for handling large datasets and complex analyses, significantly improving the overall efficacy of the deep learning process.

2.3 Tools and Hardware

2.3.1 Current Setup and Planned Upgrades

The project currently operates on a CPU setup adequate for preliminary tasks but limited for scaling. Plans include an upgrade to High-Performance Computing (HPC) resources at Imperial College London, intended to accommodate increased computational demands and handle larger datasets. Alongside this upgrade, custom PyTorch scripts will be developed to effectively leverage multiple GPUs, enhancing training efficiency and model complexity management.

2.3.2 Impact of Upgraded Computational Resources

The transition to HPC and the utilization of GPUs are expected to significantly improve computational efficiency and reduce model training times. These enhancements are crucial for effectively processing the extensive datasets and supporting the advanced computational needs of complex neural network architectures, thereby enhancing the overall performance and scalability of the project.

3
Future Plan

Contents

3.1 Data collection

3.1.1 Data Acquisition and Scope

We will access the comprehensive CRSP database, which provides a wide range of financial metrics from major U.S. stock exchanges, governed by secure protocols to ensure data governance and confidentiality. The database offers detailed daily and monthly data spanning several decades, invaluable for analyzing long-term market trends and asset behaviors. This extensive coverage is crucial for exploring asset co-movements and market cycles under diverse economic conditions, forming a robust foundation for our analyses.

3

3.1.2 Preprocessing, Integration, and Model Training

Post-acquisition, the data undergoes rigorous preprocessing to remove inconsistencies and transform it into formats suited for deep learning applications, such as candlestick charts. The granularity of the CRSP data enhances the training phase of our CNN models, allowing for the identification of subtle patterns and correlations. This detailed approach is expected to significantly improve the predictive accuracy and depth of our analyses, enhancing financial decision-making capabilities.

3.2 Model refinement

3.2.1 Initial Configuration and Parameter Tuning

The initial stage of the project involves setting up the fundamental parameters of our Convolutional Neural Network (CNN) architectures, including layer structures, activation functions, and learning rates, based on established best practices and insights from prior research. This setup retains flexibility for modifications in response to preliminary testing outcomes. Concurrently, parameter tuning is a critical phase where the model's hyperparameters, such as the number of convolutional layers, filter sizes, dropout rates, and learning rates, are meticulously adjusted to enhance the model's accuracy and processing efficiency.

3.2.2 Iterative Testing and Validation

The robustness and reliability of the model are confirmed through iterative testing and validation. This process involves assessing the model across various scenarios, comparing its predictive outputs against actual market behaviors. Feedback from these evaluations is used to continuously refine the model, making necessary adjustments to improve predictive accuracy and address potential issues like overfitting or underfitting, thereby enhancing the model's overall stability and reliability.

3.3 Model evaluation

3.3.1 Evaluation Strategy and Benchmarking

To rigorously assess the effectiveness of our deep learning model in forecasting asset class co-movements, we plan to compare its performance against simple trading strategies such as buy-and-hold and moving average crossovers. These traditional strategies will serve as benchmarks to highlight the advanced capabilities of our model. This comparative analysis is aimed at validating the predictive capabilities of our model beyond conventional methods.

3.3.2 Performance Metrics and Statistical Significance

The evaluation will focus on key performance metrics including return on investment, Sharpe ratio, and maximum drawdown, providing a comprehensive view of both profitability and risk characteristics. Additionally, statistical tests will be conducted to ascertain the robustness of our findings, ensuring that any performance improvements are statistically significant and not due to random variations.

3.3.3 Practical Implications and Contributions

The outcomes of this evaluation will not only validate the effectiveness of our model but will also shed light on potential improvements to trading strategies in the financial markets. By demonstrating the practical benefits of our model, this research aims to contribute significantly to the evolution of financial analytics, providing actionable insights that can enhance market strategies and decision-making processes.

3.4 Strategy and Application

3.4.1 Project Overview, Strategy, and Data Handling

This research initiative aims to develop a deep learning model using Convolutional Neural Networks (CNNs) to analyze asset class movements through stacked image inputs. Integrating multiple asset classes within a single image allows the model to discern intricate co-movements among asset classes like stocks, bonds, commodities, and currencies, refining trading decisions. Data for this model will be processed to capture key financial metrics from various asset classes and prepared in image form to highlight significant market trends, with normalization and scaling ensuring consistency across asset types.

3.4.2 Analytical Methods and Predictive Decision-Making

The core of the model's predictive capability lies in its ability to interpret visual patterns from complex image data, leveraging CNN's robust feature extraction capabilities to decode collective asset responses to market dynamics. Upon development, the model will categorize assets into 'buy', 'hold', or 'sell', based on predicted movements, informing dynamic portfolio adjustments to optimize financial returns. This framework will evolve as the model matures and additional insights are integrated.

3.4.3 Model Evaluation, Optimization, and Future Implementation

The model's efficacy will be assessed through backtesting with historical image data, focusing on precision, recall, and F1-score to evaluate the accuracy of trading decisions.

Continuous refinement will include retraining with updated data and parameter adjustments. Subject to successful validation, the model is slated for real-time trading deployment, with future enhancements planned to integrate real-time data feeds and expand the range of asset classes and markets, enhancing the model's applicability and strategic utility in global financial markets.

Bibliography

[1] R. M. I. Kusuma, T.-T. Ho, W.-C. Kao, Y.-Y. Ou, and K.-L. Hua, *Using deep learning neural networks and candlestick chart representation to predict stock market*, 2019. arXiv: 1903.12258 [q-fin.GN].

[2] O. B. Sezer and A. M. Ozbayoglu, *Financial trading model with stock bar chart image time series with deep convolutional neural networks*, 2019. arXiv: 1903.04610 [cs.LG].

[3] Z. Zeng, T. Balch, and M. Veloso, *Deep video prediction for time series forecasting*, 2021. arXiv: 2102.12061 [cs.CV].

[4] J. Jiang, B. Kelly, and D. Xiu, "(re-)imag(in)ing price trends," *The Journal of Finance*, vol. 78, no. 6, pp. 3193–3249, 2023. DOI: 10.1111/jofi.13268. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.13268. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.13268.