Deep reinforcement learning networks for portfolio management using WaveCorr

M.Tech Term Project

in

Financial Engineering

by

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Declaration

I, hereby, declare that this project work of Deep reinforcement learning networks for portfolio management using WaveCorr is my own original work and has not been submitted before to any institution for assessment purpose. Further, I have acknowledged all sources used and have cited these in the reference section.

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Certificate

This is to certify that the work contained in this report entitled "Deep reinforcement learning networks for portfolio management using WaveCorr" is submitted by Mr. Subhadeep Paul (Roll. No.19EE3FP03) to the Vinod Gupta School of Management, Indian Institute of Technology Kharagpur, for the partial fulfillment of the requirements for the degree of Master of Financial Engineering. I hereby accord my approval of it as a study carried out and presented in a manner required for its acceptance in partial fulfillment for the Post Graduate Degree for which it has been submitted. The thesis has fulfilled all the requirements as per the regulations of the Institute and has reached the standard needed for submission.

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Date: April 24, 2024

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Subhadeep Paul

Abstract

This study investigates the impact of incorporating higher-order risk metrics, skewness, and kurtosis into a deep reinforcement learning (DRL) framework for portfolio management. We build upon WaveCorr, a state-of-the-art DRL model with permutation invariance for asset allocation. We extend WaveCorr by integrating skewness and kurtosis alongside traditional reward signals like return and volatility. Our objective is to analyze the influence of these higher moments on portfolio performance, particularly annual return.

We evaluate the enhanced model's performance across diverse market conditions by employing datasets from the US and Canadian markets. By comparing results with the original WaveCorr model, we aim to determine if considering higher-order risk metrics improves risk management capabilities while maintaining or enhancing returns. This study contributes to the field by exploring the potential of DRL for portfolio optimization with a more comprehensive risk perspective.

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Introduction

Deep reinforcement learning (DRL) has emerged as a powerful tool for tackling complex decision-making problems, including portfolio management. DRL models aim to learn optimal asset allocation strategies that balance risk and return within this domain. While significant progress has been made, existing models often rely primarily on reward signals based on mean and variance, potentially neglecting valuable information contained in higher-order risk metrics. This study addresses this gap by investigating the impact of incorporating skewness and kurtosis, alongside traditional reward signals, into a DRL framework for portfolio management.

The cornerstone of our work is WaveCorr, a recently proposed DRL architecture specifically designed for portfolio management. WaveCorr incorporates a novel convolutional neural network (CNN) architecture with "permutation invariant" properties. This ensures the model's performance remains consistent regardless of the order assets are presented within the data. While WaveCorr demonstrates superior performance to previous DRL models, it primarily focuses on mean and variance for risk assessment. Real-world markets exhibit complex return distributions, often deviating from a normal distribution. Higher-order moments, such as skewness and kurtosis, can offer valuable insights into these deviations.

Skewness measures the asymmetry of a distribution, indicating a potential bias towards positive or negative returns. Positive skewness suggests a higher probability of large positive returns, potentially appealing to some investors. On the other hand, negative skewness indicates a greater likelihood of significant losses. Kurtosis captures the "tailedness" of a distribution, reflecting the frequency and severity of extreme events. High kurtosis suggests a higher probability of both large gains and significant losses compared to a normal distribution.

By incorporating skewness and kurtosis into the reward function of the DRL model, we aim to achieve a more comprehensive understanding of risk. This could potentially lead to strategies that optimize returns and manage exposure to undesirable tail events such as significant losses. Our study addresses the following key questions:

- How does incorporating skewness and kurtosis alongside traditional reward signals influence the annual return of DRL-managed portfolios?
- Does including higher-order risk metrics improve the model's ability to navigate diverse market conditions?
- Can this approach enhance risk management capabilities while maintaining or potentially increasing returns compared to the original WaveCorr model?

To address these questions, we extend the WaveCorr architecture by integrating modules that calculate skewness and kurtosis for each candidate portfolio. We then incorporate these metrics alongside traditional return and volatility measures into the model's reward function. The enhanced model will be evaluated across various market datasets, including data from the US and Canadian markets. By comparing the performance of the extended model with the original WaveCorr, we aim to gain insights into the effectiveness of using higher-order risk metrics for DRL-based portfolio management. This study contributes to the field by exploring the potential of DRL for portfolio optimization with a more comprehensive risk perspective, potentially leading to more robust and adaptable investment strategies.

Literature Review

2.1 A Deep Increasing-Decreasing-Linear Neural Network for Financial Time Series Prediction, 2019

Problem: Conventional neural networks used for financial time series prediction have an inherent limitation. They experience a 1-step delay in their predictions compared to the actual data. This means the predictions are one step behind the real values.

Proposed Solution: The paper introduces a Deep Increasing-Decreasing Linear Neural Network (IDLN) architecture. Each layer of the IDLN is comprised of unique processing units called increasing-decreasing linear units. These units are specifically designed to address the 1-step delay issue.

Benefits: The IDLN architecture is intended to overcome the delay problem present in traditional methods, potentially leading to more accurate predictions in financial time series forecasting.

Future Research Directions: The paper doesn't explicitly mention future research directions, but some potential areas for exploration could include:

- Comparing IDLN's performance with more recent neural network architectures.
- Investigating how IDLN can be adapted to incorporate additional financial data or economic factors.
- Exploring the use of IDLN for time series prediction in other domains beyond finance.

2.2 A novel Deep Reinforcement Learning based automated stock trading system using cascaded LSTM networks, 2024

The paper proposes a novel stock trading system with a deep reinforcement learning (DRL) approach with cascaded Long Short-Term Memory (LSTM) networks.

Challenge: Traditional DRL methods designed for games aren't ideal for financial data. Stock data has unique characteristics like low signal-to-noise ratio and unevenness, which can lead to performance issues in these adapted models.

Proposed Solution: The authors address this challenge by proposing a DRL-based system with cascaded LSTMs (CLSTM-PPO Model). This model uses a two-stage LSTM approach:

- The first stage utilizes LSTM to extract important features from historical stock data (time series data).
- The extracted features are then fed into an agent for training. This agent represents the trading strategy within the reinforcement learning framework.
- Interestingly, the agent itself also employs another LSTM for further training on the reinforcement learning tasks.

Benefits: The paper claims that this cascaded LSTM approach helps capture hidden information within the stock data, leading to a more effective trading strategy.

Results: The authors tested their model on two datasets: DJI (US market) and SSE50 (Chinese market). Their findings suggest that the CLSTM-PPO model outperforms previous baseline models in terms of both cumulative returns and Sharpe ratio. Notably, the advantage was more significant in the SSE50 (emerging market) data.

This research introduces a novel DRL system with cascaded LSTMs for automated stock trading. The approach addresses the limitations of existing DRL methods in finance and demonstrates promising results, particularly in emerging markets.

2.3 A polynomial goal programming model for portfolio optimization based on entropy and higher moments, 2018

The paper proposes a new approach to portfolio optimization that considers not just mean and variance but also higher moments of returns (like skewness and kurtosis) and portfolio diversification measured by entropy.

Limitations of Traditional Model: Modern Portfolio Theory (MPT) primarily focuses on mean-variance optimization. This can be limiting if the return distribution isn't normal.

Higher Moments and Entropy: The paper incorporates higher moments of returns (skewness and kurtosis) to capture the potential for asymmetry and extreme events. Additionally, entropy is used as a diversification measure, aiming for a well-spread portfolio.

Polynomial Goal Programming: This technique is used to formulate the optimization problem. It allows for defining multiple goals (mean return, variance, skewness, kurtosis, entropy) and achieving them satisfactorily, even if not ideally.

Comparison of Entropy Measures: The paper explores the use of Shannon and Gini's Simpson entropy for diversification and analyzes their impact on portfolio selection.

Evaluation: The model is tested with real data to assess its effectiveness in creating efficient portfolios compared to traditional MPT approaches.

This research introduces a novel portfolio optimization method that considers a wider range of risk and diversification aspects alongside traditional return considerations. This can benefit investors seeking a more comprehensive approach to portfolio construction.

2.4 Clustering-based return prediction model for stock pre-selection in portfolio optimization using PSO+CNN+MVF, 2023

The paper discusses a novel approach to portfolio optimization that combines several techniques: clustering, machine learning, and optimization algorithms.

Problem: Portfolio optimization aims to select a set of stocks (assets) that maximizes returns while minimizing risk.

Proposed Method:

1. **Clustering:** The first step involves grouping stocks with similar characteristics using a clustering algorithm. This helps identify potential patterns in stock behavior.
2. **PSO-CNN+MVF Prediction:** Within each cluster, a machine learning model is employed to predict future returns. This model combines three techniques:
3. **Particle Swarm Optimization (PSO):** An optimization algorithm that helps find the best model parameters for prediction.
4. **Convolutional Neural Network (CNN):** A deep learning architecture that can effectively capture complex relationships from historical stock data.
5. **Multi-Variate Factor (MVF) Regression:** A statistical technique that considers various factors influencing stock prices.
6. **Portfolio Selection:** Based on the predicted returns, the model pre-selects a set of promising stocks. Then, a standard portfolio optimization algorithm can be used to determine the optimal allocation of capital among these pre-selected stocks.

Benefits: The authors claim that this approach offers advantages over traditional methods by:

- **Leveraging Clustering:** It considers the relationships between stocks, potentially leading to more informed predictions.
- **Machine Learning for Prediction:** The PSO-CNN+MVF model aims to capture complex patterns in historical data for better return prediction.

Overall, the paper presents a novel framework for portfolio optimization that integrates clustering, machine learning, and optimization techniques.

2.5 Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction, 2014

The paper compares two popular models for forecasting stock prices: ARIMA and Artificial Neural Networks (ANNs). There's an ongoing debate about which model is better, and this research aims to shed some light on that.

Problem Statement: Accurately predicting stock prices is challenging due to complex market dynamics. The paper acknowledges the ongoing debate about which model is best suited for this task: ARIMA or Artificial Neural Networks (ANNs).

Proposed Solution: The authors propose comparing the forecasting performance of ARIMA and ANN models using real stock data.

Results: The research suggests that ANNs outperform ARIMA models in general for stock price prediction. However, the paper highlights that previous studies have shown ARIMA to be effective in some cases.

Benefits: The research sheds light on the relative strengths of ARIMA and ANNs for stock price prediction. Understanding these advantages can help users choose the most appropriate model for their specific needs.

Future Research: The paper points to the potential benefits of combining ARIMA and ANNs in a hybrid approach. Additionally, it emphasizes the need for further investigation into how factors like data characteristics and desired prediction focus (price vs. direction) influence the optimal model choice.

2.6 Adopting a dendritic neural model for predicting stock price index movement. 2022

The paper "Adopting a dendritic neural model for predicting stock price index movement" explores a new approach to forecasting stock market movements using a dendritic neural model (DNM).

Motivation: Predicting stock prices is a challenging task due to the complex and dynamic nature of financial markets. Machine learning offers promising techniques for financial forecasting, and the study proposes DNM as a novel approach.

Core Idea: DNM mimics the structure and function of biological neurons, specifically focusing on the dendrites. Dendrites receive and integrate information from other neurons, similar to how the model would process historical stock price data.

Innovation: The researchers introduce a new training algorithm called scale-free differential evolution (SFDE) specifically for DNM. This algorithm aims to balance exploration (searching for new possibilities) and exploitation (refining existing solutions) during the training process.

Data and Analysis: The effectiveness of DNM-SFDE is evaluated on eight benchmark stock price indices from various markets. The model's performance is compared to other prevailing models.

Results: The study suggests that DNM trained with SFDE delivers superior forecasting accuracy compared to existing methods. This indicates that DNM may be a reliable tool for predicting stock price movements.

The paper also discusses how to prepare the data for DNM by reconstructing it into a higher dimensional phase space. This helps capture the complex relationships within the data. To determine the appropriate parameters for the model, the authors employ techniques like the maximum Lyapunov exponent to assess the chaotic properties of the financial data and methods like mutual information to calculate the time delay in the phase space.
Overall, the research suggests that DNM is a promising technique for stock price index prediction, particularly when combined with the SFDE training algorithm.

2.7 Deep learning with long short-term memory networks for financial market predictions, 2018

The paper "Deep learning with long short-term memory networks for financial market predictions" by Thomas Fischer and Christopher Krauss explores the potential of Long Short-Term Memory (LSTM) networks for predicting stock prices.

LSTM Networks for Sequence Learning: LSTMs are a type of recurrent neural network adept at handling sequential data. This makes them suitable for financial markets where data like historical prices comes in a specific order and understanding these sequences is crucial for predictions.

LSTM's Advantage in Financial Predictions: The paper argues that LSTM networks are under-utilized for financial time series forecasting compared to other methods. They believe LSTMs can capture complex patterns and temporal relationships within the data.

Evaluating LSTM Performance: The authors implement LSTM networks to predict the directional movements (up or down) of S&P 500 stocks from 1992 to 2015. Their LSTM model outperforms other memory-less classification methods like random forest and logistic regression.

Profitability Analysis: The study goes beyond just demonstrating superior performance. It delves into understanding why the LSTM model works. They discover that the LSTM strategy seems to be profitable for stocks with high volatility and short-term reversal patterns (where a price drop is followed by a rise, and vice versa).

LSTM vs. Simpler Strategies: Interestingly, the paper develops a basic rule-based strategy capitalizing on the short-term reversal phenomenon. This simpler strategy captures a portion of the returns achieved by the LSTM model, suggesting that the LSTM might be partially exploiting this well-known market behavior.

Overall, the paper highlights the potential of LSTM networks for financial market predictions while acknowledging that they may be benefiting from identifying pre-existing patterns like short-term reversals.

2.8 Aggregating multiple types of complex data in stock market prediction: A model-independent framework, 2019

The paper proposes a framework for incorporating various complex data types into stock market predictions. This framework is designed to be model-independent and can be used with different prediction models.

Motivation: The availability of diverse data in the financial sector, including numerical data (e.g., trading volume), time-series data (e.g., stock prices), and compositional data (e.g., investor sentiment from social media), presents an opportunity for more comprehensive stock market analysis. Traditional models might struggle to handle these different data types effectively.

Proposed Framework: The authors address this challenge by creating a framework that can handle multiple data types categorized as:

- Scalar data (single numerical values)
- Functional data (data represented by curves or functions, like time series)
- Compositional data (data where components add up to a constant, like proportions in a pie chart)

Model-Independence: This framework acts as an intermediary, transforming different data types into a format compatible with various prediction models. This allows researchers to leverage existing models without needing to modify them for each data type.

Application: The paper demonstrates the framework's effectiveness through simulations that predict the next day's opening price movement (up or down). They incorporate:

- Trading volume (scalar data)
- Intraday return series (functional data)
- Investor sentiment from social media (compositional data)

Benefits: The results show that the framework can effectively combine these diverse data sources, potentially leading to more accurate predictions. Interestingly, the study also reveals how the impact of specific data points (e.g., investor fear) can differ depending on market conditions (bullish vs. bearish). Overall, this research presents a framework that can improve stock market prediction by incorporating various complex data types into existing models. This paves the way for a more holistic understanding of the factors influencing stock prices.

2.9 Heuristic Learning in Intraday Trading under Uncertainty, 2015

The paper explores a new approach to intraday trading that leverages heuristic learning.

Background: Traditional economic models for trading often struggle with the complexities of intraday markets characterized by high frequency and constant change. These models also don't account for the prevalence of technical analysis used by many traders.

The Proposed Model: Bekiros proposes a heuristic learning model that mimics how traders learn and adapt in real time. This model incorporates factors like:

- Beliefs and preferences of the trader
- Expectations about market movements
- The ability to adjust trading rules based on new information (adaptive training)

Focus and Testing: The study focuses on the Euro (EUR) and US Dollar (USD) currency pair, a highly liquid market. The model's effectiveness is measured by its ability to predict price movements directionally. The performance is compared to various benchmarks, including:

- Other non-linear models
- A random walk (representing unpredictable price movement)
- A simple buy-and-hold strategy

Results and Significance: The research suggests that the heuristic learning model performs better than the benchmarks, even after considering transaction costs. This implies that some level of predictability may exist in intraday markets, potentially due to factors influencing market microstructure (how buy and sell orders interact). The findings challenge the notion of perfectly efficient markets and highlight the potential benefits of using heuristic learning approaches in intraday trading. Overall, this paper sheds light on a new way to model intraday trading by incorporating real-world trader behavior and learning mechanisms. It offers an alternative to traditional models and suggests that technical analysis might hold some value in navigating the uncertainties of intraday markets.

2.10 Novel volatility forecasting using deep learning–Long Short Term Memory Recurrent Neural Networks, 2019

The paper explores the idea of using Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs), a type of deep learning model, for forecasting volatility in financial markets.

Traditional methods: Traditionally, statistical models like Generalized Autoregressive Conditional Heteroskedasticity (GARCH) were used for volatility forecasting.

Deep learning approach: The paper argues that LSTM RNNs, a form of deep learning, might outperform these traditional methods. LSTMs are adept at handling sequential data, which is characteristic of financial time series. Their ability to learn long-term dependencies makes them suitable for capturing the complex dynamics of volatility.

Comparison with SVM: The study compares LSTM RNNs with Support Vector Regression (SVR), another popular technique. While SVR performed well for large-interval volatility forecasting, LSTM RNNs were found to be competitive.

Benefits of LSTM RNNs: The paper highlights the advantage of LSTM RNNs, particularly when dealing with big data. Their ability to handle many hidden layers and neurons with strong computational power (like GPUs) can potentially lead to more accurate volatility predictions compared to SVR, especially for specific financial instruments.

Results: Overall, the paper suggests that LSTM RNNs are a promising deep learning approach for volatility forecasting, potentially offering better accuracy than traditional methods.

It's important to note that this research is part of a larger discussion about the potential of deep learning in finance. While LSTM RNNs show promise, further research is needed to solidify their role in real-world financial applications.

2.11 Predicting Stock Returns and Volatility Using Consumption-Aggregate Wealth Ratios: A Non-linear Approach, 2015

The paper explores how the ratio of consumption to aggregate wealth (CAY) can be used to predict stock returns and volatility.

Background: Traditionally, researchers have looked at CAY as a predictor of stock returns. Essentially, a high CAY suggests lower future returns because consumers are already feeling wealthy and may not invest as much. Some studies considered a variant, CAYMS, which accounts for potential shifts in the relationship between CAY and returns.

Argument: The authors argue that the relationship between CAY and stock returns (and volatility) might not be linear. In simpler terms, the impact of CAY on returns may not be a constant increase or decrease.

Approach: They analyzed data from 1952 to 2013 to see if a non-linear relationship existed between CAY, stock returns, and volatility. They employed statistical tests to assess if CAY or CAYMS was a better predictor.

Findings: The study found evidence that the relationship between CAY and both stock returns and volatility is indeed non-linear. Interestingly, they discovered that the original CAY measure, not CAYMS, was a stronger predictor for both returns and volatility.

Significance: This research suggests that a more nuanced approach, considering the non-linearity, might be needed when using CAY to predict stock market performance. The finding that the original CAY is a stronger predictor than CAYMS calls for further investigation into the reasons behind it.

2.12 Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques, 2015

The paper investigates the application of machine learning techniques for predicting stock price movements in the Indian stock market.

Focus: Predicting the direction of movement (up or down) of stock prices and indexes.

Methodology:

- **Data preparation:** The study employs a technique called "Trend Deterministic Data Preparation" which likely involves transforming the raw stock price data into a format suitable for machine learning algorithms.
- **Machine Learning Techniques:** They explore various machine learning algorithms including Decision Trees, Support Vector Machines (SVM), Naive Bayes, and Artificial Neural Networks (ANNs).

Analysis: The models are trained on historical stock market data and evaluated for their effectiveness in predicting future price movements.

The paper likely compares the performance of these different machine learning techniques and determines which one achieves the most accurate predictions for the Indian stock market data used in the study. Overall, this paper explores the potential of machine learning for stock price prediction in the Indian market. By comparing different algorithms and data preparation techniques, it contributes to the ongoing research in this field.

2.13 Intelligent System for Time Series Forecasting, 2017

The paper proposes a method for improving time series forecasting using a combination of artificial neural networks and wavelet transforms.

- **Time Series Forecasting:** This refers to predicting future values based on historical data points in a time series.
- **Artificial Neural Networks (ANNs):** These are algorithms inspired by the structure of the human brain and are powerful tools for finding patterns in complex data.
- **Wavelet Transforms:** These are mathematical techniques for analyzing data at different scales, which can be helpful in separating signal from noise in time series.

The author argues that traditional methods for time series forecasting might not always be sufficient. Their approach involves:

- **Data Preprocessing:** The time series data is fed through a wavelet filter to remove noise and enhance the underlying signal.
- **Neural Network Training:** The preprocessed data is then used to train an artificial neural network. This network learns to identify patterns in the data and use them for prediction.

The paper likely discusses the benefits of this approach, such as improved accuracy and the ability to handle complex time series data. It might also compare this method to other forecasting techniques.

2.14 Evaluating multiple classifiers for stock price direction prediction, 2015

The paper investigates the effectiveness of various machine learning algorithms for predicting stock price movements.

Goal: The study aims to compare the performance of different classifiers in predicting whether a stock price will go up or down. Even small improvements in prediction accuracy can be significant in the financial world.

Methods: The researchers evaluate both individual classifiers (like Logistic Regression, Support Vector Machines, and K-Nearest Neighbors) and ensemble methods (like Random Forest and AdaBoost) that combine predictions from multiple models.

Data: They use historical stock data from a large number of European companies.

Evaluation: The authors assess the performance of each classifier using a metric called Area Under the ROC Curve (AUC). AUC measures how well a model can distinguish between positive and negative cases (upward vs. downward price movement).

Findings: The research suggests that Random Forests emerge as the top performer, followed by Support Vector Machines and other ensemble methods. Notably, individual classifiers like Logistic Regression and K-Nearest Neighbors show lower accuracy. Overall, the paper emphasizes the potential of ensemble methods for stock price direction prediction compared to single classifiers. It highlights the importance of considering various algorithms when building models for financial forecasting.

2.15 Forecasting price movements using technical indicators: Investigating the impact of varying input window length, 2017

The paper investigates how the choice of input window length affects the accuracy of forecasting price movements using technical indicators.

Technical indicators are mathematical calculations used by traders to analyze price charts and identify potential trading opportunities. The indicator's calculation often considers past price data within a specific time frame, known as the input window length. The study explores how this window length impacts the forecasting performance for different time horizons (how far into the future you're trying to predict).

Key findings:

- The best prediction accuracy is achieved when the input window length is approximately equal to the forecast horizon. This means using a similar timeframe of past data for calculating the indicator as the timeframe you're trying to predict.
- The study evaluates this pattern using various performance metrics like prediction accuracy, winning rate, return per trade, and Sharpe ratio.

Essentially, the paper highlights that the amount of historical data considered by a technical indicator should be relevant to the timeframe you're trying to forecast price movements for.

2.16 A Feature Weighted Support Vector Machine and K-Nearest Neighbor Algorithm for Stock Market Indices Prediction, 2017

The paper proposes a hybrid approach for predicting stock market indices. This approach combines two machine learning algorithms: Feature Weighted Support Vector Machine (FWSVM) and Feature Weighted K-Nearest Neighbor (FWKNN).

Techniques:

- **Feature Weighted Support Vector Machine (FWSVM):** This is a variation of the standard SVM algorithm that assigns weights to different features (data points) based on their importance in predicting the target variable (stock index). Features with a higher weight are considered more significant by the model.

- **Feature Weighted K-Nearest Neighbor (FWKNN):** Similar to FWSVM, this is a modified KNN algorithm where weights are assigned to neighboring data points. Points closer to the query point (data point for prediction) have a higher influence on the prediction.

The Hybrid Approach: The paper proposes using FWSVM to identify the most relevant features for predicting the stock index. Then, it utilizes FWKNN to make the actual prediction based on the weighted features identified by FWSVM. This combination aims to leverage the strengths of both algorithms:

- FWSVM helps focus on the most informative features, potentially leading to better predictions.
- FWKNN provides a way to incorporate similar historical data points into the prediction, potentially capturing trends and patterns.

Overall, the paper argues that this FWSVM-FWKNN combination can outperform traditional methods for stock market index prediction.

2.17 Stock Market One-Day Ahead Movement Prediction Using Disparate Data Sources, 2017

The paper proposes a system for predicting stock market movements one day in advance. This system is unique because it incorporates data from various sources, not just traditional financial data.

Key points:

- Disparate Data Sources: The system goes beyond using just historical prices and financial data. It explores incorporating "disparate" data sources, meaning information from different and potentially unrelated areas. This could include news articles, social media sentiment, or even economic indicators.
- Knowledge Base and Inference Engine: The system is designed as a financial expert system. It utilizes a "knowledge base" that stores the collected data from various sources. An "inference engine" then analyzes this data using artificial intelligence techniques.
- AI Techniques: The paper mentions three AI techniques used by the inference engine: it's not specified which ones, but they could involve machine learning algorithms or neural networks. These techniques would identify patterns or relationships between the different data sources and past stock movements.

- Prediction Accuracy: The authors claim their system achieves an accuracy of 85% in predicting the direction of the stock market's one-day movement (up or down). This is reportedly higher than previously documented results.

Results: The paper describes a novel approach to stock market prediction by leveraging a combination of traditional financial data and external information sources. Machine learning helps analyze these diverse data points to potentially improve the accuracy of short-term stock movement predictions.

2.18 Developing an approach to evaluate stocks by forecasting effective features with data mining methods, 2015

The paper proposes a novel method to assess stocks using data mining techniques.

Goal: The primary aim is to predict both future stock returns and associated risks. This allows investors to make more informed decisions by considering both potential gains and potential losses.

Method: The authors propose a three-stage approach:

- **Feature Identification:** This stage involves comprehensively identifying all potential features that might influence a stock's return and risk. Examples could include financial ratios, market trends, and economic indicators.
- **Prediction with Data Mining:** Various data mining techniques are applied to the identified features to forecast future returns and risks. The paper mentions exploring different techniques but doesn't specify which ones. Common data mining methods for financial forecasting include decision trees, regression analysis, and neural networks.
- **Feature Selection and Re-prediction:** Finally, the authors propose a hybrid algorithm that combines filter and wrapper-based feature selection methods. This helps identify the most important features for accurate prediction. Subsequently, the model re-predicts returns and risks using the selected features.

Benefits: The paper suggests that this method can be a valuable tool for effective feature selection and risk-return prediction in the stock market.

Limitations: The paper likely focuses on the theoretical framework of the approach. It would be beneficial to know:

- The specific data mining techniques employed.

- The effectiveness of the proposed method compared to existing approaches through validation on real-world data.

Overall, the paper presents an interesting approach for stock evaluation using data mining. By incorporating risk prediction alongside return forecasting, it can potentially aid investors in making informed investment decisions. However, further exploration of the specific methods and their effectiveness would be necessary for a more comprehensive understanding.

2.19 Proximal support vector machine based hybrid prediction models for trend forecasting in financial markets, 2016

The paper proposes a method for predicting stock market trends using a combination of techniques.

Challenge: Financial markets are complex and influenced by various factors, making accurate price prediction difficult. **Approach:**The authors use a hybrid model that combines:

- **Proximal Support Vector Machine (PSVM):** A machine learning algorithm for classification.
- **Feature Selection Techniques:** Methods to identify the most relevant factors (technical indicators) from a large pool for predicting trends.

Process:

- **Feature Selection:** The paper explores four different techniques (Linear Correlation, Rank Correlation, Regression Relief, and Random Forest) to choose the most important technical indicators from a set of 55.
- **PSVM Classification:** The chosen technical indicators are fed into a PSVM classifier to predict the future direction (upward or downward) of stock prices.

Evaluation: The performance of the models is evaluated on twelve stock indices from various markets using different metrics like accuracy and a newly proposed metric called Joint Prediction Error (JPE). The results show that all the hybrid models outperform the PSVM model alone.

Findings:

- The hybrid model that combines Random Forest for feature selection with PSVM (RF-PSVM) performs the best.

- This suggests that selecting informative technical indicators is crucial for accurate trend prediction.

Overall, the paper highlights the potential of combining feature selection techniques with PSVM for improved stock market trend forecasting.

2.20 Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies, 2017

The paper dives into the potential of deep learning for stock market analysis and prediction. The allure of deep learning lies in its ability to extract features from vast amounts of raw data automatically. This is particularly attractive for stock market prediction, where the complex interplay of factors can be difficult to pinpoint manually. Unlike traditional methods, deep learning doesn't require prior knowledge of specific predictors, allowing it to uncover hidden patterns in the data potentially.

Methodology: The authors outline a general framework for using deep learning in stock market analysis and prediction. This framework involves:

- **Data Preprocessing:** This includes collecting and preparing the data, often involving historical stock prices, financial ratios, and news sentiment.
- **Feature Extraction:** Deep learning can handle raw data, but pre-processing steps like Principal Component Analysis (PCA), autoencoders, or Restricted Boltzmann Machines (RBMs) can sometimes improve performance.
- **Deep Learning Model Selection and Training:** The paper explores various deep learning architectures like Recurrent Neural Networks (RNNs) and their variants like Long Short-Term Memory (LSTM) networks. These models are trained on the prepared data to learn complex relationships between the input features and the target variable (e.g., future stock prices).
- **Evaluation and Analysis:** The model's performance is assessed using metrics relevant to stock market analysis. The authors emphasize the importance of backtesting to ensure the model's effectiveness in real-world scenarios.

Data Representations: The paper highlights how data is represented can significantly impact the performance of deep learning models. They examine the effects of using different data representations on prediction accuracy, such as high-frequency intraday stock returns.

Advantages:

- **Promotes Deep Learning for Stock Analysis:** The paper brings attention to the potential of deep learning for analyzing complex financial data like stock prices. This method offers an alternative to traditional techniques by automatically extracting features from vast datasets.

- **Provides a Framework:** The outlined framework for using deep learning in stock market analysis offers a structured approach. It includes data pre-processing, optional feature extraction methods, deep learning model selection, evaluation, and backtesting, which helps researchers implement deep learning effectively.

- **Highlights Data Representation:** The paper emphasizes the importance of data representation in deep learning. Exploring different representations like high-frequency returns, it showcases how data formatting can influence the model's performance.

- **Case Studies for Practical Applications:** Including case studies demonstrates how deep learning can be applied to real-world stock market tasks like predicting returns and analyzing market structure.

Disadvantages:

- **Limited Scope on Prediction Accuracy:** While discussing deep learning's potential, the paper might not delve deeply into the limitations of these models for accurate stock price prediction.

- **Focus on Specific Techniques:** The paper focuses on a specific set of deep learning architectures like RNNs and LSTMs. It might not explore other potentially useful deep-learning models for stock market analysis.

2.21 Deep Reinforcement Learning Agent for S&P 500 Stock Selection, 2020

The paper proposes a method for using deep reinforcement learning to select stocks from the S&P 500 index.

The Problem: Traditional stock selection methods often rely on predicting future stock prices, which can be challenging. These methods might not consider diversification across different sectors, leading to higher risk.

Solution: A Deep Reinforcement Learning Agent

- The authors propose a reinforcement learning agent that learns through trial and error to choose an optimal portfolio of S&P 500 stocks.
- The agent receives data on past stock performance and financial ratios.
- It takes actions like buying, selling, or holding stocks and observes the resulting portfolio value.
- Over time, the agent learns to take actions that maximize its reward, which is typically linked to the portfolio's growth.

Findings:

- The research suggests that the reinforcement learning agent can outperform the S&P 500 regarding cumulative returns.
- The agent might exhibit risk-seeking behavior, requiring further development for a more balanced approach.

Overall, the paper explores the potential of deep reinforcement learning for stock selection and portfolio management. It highlights the ability of the agent to learn from vast amounts of data and potentially outperform traditional methods. However, further research is needed to address risk management and ensure the generalizability of these findings.

2.22 Stock trend prediction based on a new status box method and AdaBoost probabilistic support vector machine, 2016

The paper proposes a new method for predicting stock market trends using a combination of techniques:

- Status Box Method: This method moves beyond analyzing individual data points and instead considers a "box" containing a sequence of data points. This box reflects the trend over a short period, capturing more information than a single data point.
- AdaBoost: This is an algorithm used in machine learning to improve the accuracy of models by training multiple versions of a learning model (like a Support Vector Machine) and then combining their predictions.
- Probabilistic Support Vector Machine (SVM): SVMs are machine learning models that excel at classification tasks. In this case, the SVM will likely classify the status boxes into different categories representing uptrend, downtrend, or possibly even sideways movement. The probabilistic SVM extension provides probabilities associated with the classifications, allowing for more nuanced predictions.

By combining these techniques, the authors aim to achieve more accurate stock trend predictions than traditional methods relying solely on individual data points.

Findings:

- The status box method captures trend information over a short period, potentially providing a more comprehensive view than single data points.
- AdaBoost enhances the accuracy of the SVM model by combining predictions from multiple trained versions.
- The probabilistic SVM offers probabilities for trend classifications, allowing for a more flexible interpretation of the predictions.

2.23 Integrating principle component analysis and weighted support vector machine for stock trading signals prediction, 2018

The paper proposes a method for predicting stock trading signals using a combination of two techniques: Principal Component Analysis (PCA) and Weighted Support Vector Machine (WSVM).

Problem Formulation: The authors view stock price prediction as a classification problem. They aim to categorize future price movements into four classes: significant increase, slight increase, slight decrease, and significant decrease.

Data Preprocessing: The model likely uses historical data on various factors that might influence stock prices. These factors include technical indicators, economic variables, or investor sentiment measures. They likely employ PCA to address two issues with high-dimensional data:

- **The Curse of Dimensionality:** PCA reduces the number of features by identifying a smaller set of uncorrelated variables (principal components) that capture most of the information in the original data. This helps improve the efficiency of the model and avoid overfitting.
- **Irrelevant Features:** PCA can help remove irrelevant features from the data, focusing the model on the most important factors for prediction.

Weighted Support Vector Machine: After dimensionality reduction with PCA, the data is fed into a WSVM classifier. WSVM is a variant of SVM that assigns weights to different data points during training. In the context of stock prediction, these weights might be based on the magnitude of past price changes. For instance, periods with significant price movements might be given higher weights, influencing the model to pay closer attention to those instances.

Multi-class Classification: Unlike traditional SVMs that handle binary classification (buy or sell), WSVM here likely tackles a four-class problem (significant increase, slight increase, slight decrease, significant decrease).

By combining PCA for dimensionality reduction and WSVM for classification with weighted data points, the authors aim to create a more robust model for predicting stock trading signals.

2.24 Fusion of multiple diverse predictors in stock market ,2017

The paper explores the idea that combining forecasts from various predictors can lead to more accurate stock market predictions compared to relying on a single source.

Key points:

- **The Stock Market Challenge:** Predicting stock prices is inherently difficult due to the complex interplay of various factors.
- **Strength in Diversity:** The paper argues that using a multitude of diverse predictors, each capturing different aspects of the market can provide a more comprehensive picture.
- **Types of Predictors:** These predictors can encompass traditional financial data (price history, trading volume) and alternative data sources like news sentiment, social media trends, and economic indicators.
- **Fusion Techniques:** The paper likely explores different methods for combining the forecasts from these diverse predictors. This could involve techniques like averaging, voting or using more sophisticated machine learning models.
- **Potential Benefits:** By leveraging the strengths of various predictors and mitigating their weaknesses, the fusion approach might lead to improved prediction accuracy.

Overall, the paper highlights the potential benefits of combining diverse information sources for stock market prediction.

2.25 Forecasting daily stock market return using dimensionality reduction, 2017

The paper proposes a method to predict the direction (up or down) of daily stock market returns using a combination of dimensionality reduction techniques and artificial neural networks (ANNs).

Challenge: Accurately predicting daily stock market movements is notoriously difficult.

The Approach:

- **Dimensionality Reduction:** The authors use three techniques (PCA, FRPCA, and KPCA) to reduce the number of features in the financial data. This is done to address the issue of potentially redundant information in many financial datasets and improve the model's efficiency.

- **Artificial Neural Networks (ANNs):** ANNs classify the data into positive or negative daily returns after dimensionality reduction.

The Benefit: The paper argues that combining dimensionality reduction with ANNs can lead to more accurate daily stock return direction predictions than using either technique alone. Their findings suggest that PCA-based ANN models achieved the best results.

The Significance: This approach offers a data-driven method for potentially profiting from short-term market movements. The authors mention that their strategy resulted in significant risk-adjusted profits compared to benchmarks.

2.26 Predicting stock market index using fusion of machine learning techniques, 2015

The paper proposes a method for predicting the future values of a stock market index using a combination of machine learning techniques.

Challenge: Predicting stock prices is notoriously difficult due to the complex and dynamic nature of the market. The authors acknowledge the Efficient Market Hypothesis, which suggests that stock prices reflect all available information and thus cannot be consistently predicted. However, they explore techniques used by technical analysts who believe patterns in historical data can be used for forecasting.

Proposed Method: The researchers use a two-stage fusion approach. In the first stage, Support Vector Regression (SVR) is used to analyze the data. SVR is a machine learning algorithm suited for regression tasks. Next, different machine learning models are combined: Artificial Neural Network (ANN), Random Forest (RF), and another SVR. This creates three fusion models: SVR-ANN, SVR-RF, and SVR-SVR.

Data and Evaluation: The researchers test their approach on two Indian stock market indices: CNX Nifty and S&P Bombay Stock Exchange (BSE) Sensex. They use 10 years of historical data and compare the performance of the single-stage models (just ANN, RF, or SVR) to the three fusion models in predicting the index values for various timeframes (1-10 days, 15 days, and 30 days).

Conclusion: The paper's findings suggest that the fusion models outperform the single-stage models in predicting the stock market indices. This indicates that combining different machine-learning techniques can lead to more accurate predictions.

Overall, the paper contributes to exploring using machine learning for stock market prediction by demonstrating the potential benefits of combining different techniques.

2.27 A feature learning approach based on XGBoost for driving assessment and risk prediction, 2019

The paper proposes a framework for assessing driving behavior and predicting potential risks.

Goal: Develop a system to assess driver behavior and predict their risk of accidents.
Approach:

- **Feature Extraction:** It extracts many features (around 1300) from vehicle trajectory data. These features capture various aspects of driving behavior, providing a comprehensive view.

- **Learning-based Feature Selection:** Not all extracted features are equally important. This stage employs a learning algorithm to identify the most significant features for risk prediction.

- **Unsupervised Risk Rating:** Since labeling driving data as "risky" or "safe" can be expensive, the system uses unsupervised learning to group vehicles into clusters based on their extracted features. These clusters are then assigned risk levels.

- **Imbalanced Data Resampling:** Real-world driving data often has a class imbalance, with many more safe driving instances than risky ones. To address this, the system may undersample the safe category to create a more balanced dataset for the next stage.

- **XGBoost Classification:** The system utilizes XGBoost, a powerful machine learning model, to classify new driving behavior data points into different risk categories based on the selected features.

Benefits:

- This approach can improve driver safety by identifying high-risk drivers and providing targeted interventions.

- By leveraging unsupervised learning, the system can handle unlabeled data, making training more efficient.

The paper presents a promising framework for using XGBoost and feature learning to assess driving behavior and predict potential risks.

2.28 Forecasting daily stock trend using multi-filter feature selection and deep learning, 2021

The paper proposes a method for predicting daily stock price trends using feature selection techniques and deep learning models.

Multi-filter Feature Selection: Financial data can include many features, some of which might be irrelevant or redundant for predicting trends. This approach uses multiple feature selection methods to identify the most informative features that contribute to stock price movement.

Deep Learning: Deep learning models, particularly Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) networks, are well-suited for analyzing time series data like stock prices. These models can capture complex relationships between past and future price movements.

The Process:

- Collecting historical stock price data and other relevant financial indicators.
- Applying multiple feature selection techniques to identify the most useful features.
- Preprocessing the data for the deep learning model.
- Training an LSTM or similar deep learning model on the selected features and historical data.
- Evaluating the model's performance on predicting future stock price trends (up, down, or unchanged).

Benefits:

- Focusing the model on the most relevant data.
- Allowing the deep learning model to capture complex non-linear relationships in stock prices.

Overall, the paper contributes to research on using machine learning for stock price prediction by combining feature selection and deep learning techniques.

2.29 Prediction of stock price direction using a hybrid GA-XGBoost algorithm with a three-stage feature engineering process, 2021

This paper proposes a method for predicting stock price direction (up or down) using a combination of techniques:

- **Feature Engineering:** The authors develop a three-stage process to create features that might influence stock prices. This likely involves transforming existing data (e.g., historical prices, trading volume) into new features that are more informative for predicting direction.

- **Genetic Algorithm (GA):** This is an optimization technique inspired by biological evolution. The GA will be used to select the most relevant features from the engineered ones in the first stage.

- **XGBoost:** This is a machine-learning algorithm known for its effectiveness in gradient boosting. Here, XGBoost will likely use the selected features to learn a model that can predict whether the stock price will go up or down.

Overall, the paper combines feature engineering, feature selection, and machine learning to address a challenging task: predicting stock price movements.

2.30 Deep learning for stock prediction using numerical and textual information, 2016

The paper investigates the application of deep learning for predicting stock prices. They propose a method that leverages both numerical and textual information to improve prediction accuracy.
Goal: Develop a deep learning model to predict stock prices.
Uniqueness: The model incorporates both numerical data (e.g., historical prices) and textual data (e.g., news articles) for prediction.
Data: The authors used corporate announcements from Germany and the UK for the textual data.
Text Processing: They employed bigram analysis (considering sequences of two words) and feature selection techniques to extract relevant information from the text.
Deep Learning Model: The specific details of the deep learning model are not elaborated on in the summary you provided, but the paper likely describes a neural network architecture that can handle both numerical and textual inputs.
Overall, the research explores the potential of combining numerical and textual data with deep learning for stock price prediction.

2.31 Futuristic portfolio optimization problem: wavelet based long short-term memory, 2023

The paper proposes a novel approach to portfolio optimization that leverages machine learning to predict future stock prices. Here's a breakdown of the key ideas:
Traditional Portfolio Optimization: Classic portfolio optimization models like Markowitz's Modern Portfolio Theory (MPT) rely on historical data to estimate the risk and return of investment assets. This method assumes that historical trends will continue, which may not always be true.

Proposed Futuristic Method:

- **Data Preprocessing:** The authors gather historical stock price data for the assets being considered for the portfolio.
- **Wavelet Transform:** They employ a mathematical technique called wavelet transform to decompose the historical price data into different time scales. This helps extract features from the data that capture short-term and long-term trends.
- **Long Short-Term Memory (LSTM) Network:** An LSTM, a type of recurrent neural network, is used to analyze the wavelet-transformed data. LSTMs are adept at learning complex relationships in time series data, making them suitable for stock price prediction.
- **Predicting Future Returns:** The trained LSTM network is used to forecast the future closing prices of the stocks. This prediction serves as an estimate of the future returns for each asset.
- **Portfolio Optimization:** A portfolio optimization model (e.g., MPT) is then applied, but instead of using historical returns, the model incorporates the predicted future returns generated by the LSTM.

Benefits:

- The approach aims to improve portfolio performance by incorporating anticipated future trends into the optimization process.
- This method could potentially lead to a more efficient allocation of investment capital.

Limitations:

- The LSTM predictions' accuracy heavily influences the overall approach's effectiveness.
- Financial markets are inherently complex and unpredictable, making future price forecasts uncertain.

Overall, the research by Abolmakarem et al. presents a promising new direction for portfolio optimization by integrating machine learning for price prediction. However, further research is needed to validate its effectiveness and practical application in real-world scenarios.

2.32 WaveCorr: Deep reinforcement learning with permutation invariant convolutional policy networks for portfolio management, 2023

The paper proposes a novel approach to portfolio management using deep reinforcement learning (DRL). **Background:**

- Portfolio management involves making investment decisions to balance risk and return.
- DRL has emerged as a promising technique for complex decision-making problems.
- Existing DRL methods in portfolio management struggle to capture the dependencies between different assets (stocks, bonds, etc.).

Innovation:

- The paper introduces a new property called "asset permutation invariance" for policy networks in portfolio management.
- This property ensures the network's performance remains consistent regardless of the order assets are presented.
- WaveCorr, a convolutional neural network (CNN) architecture, is the first to incorporate this property.
- WaveCorr's design includes a special layer for processing asset correlations while preserving permutation invariance.

Benefits:

- WaveCorr outperforms existing DRL architectures in portfolio management experiments.
- It achieves significant improvements in both average annual return (3%-25%) and Sharpe ratio (over 200% increase).
- WaveCorr demonstrates increased stability in performance, even with different initial asset orderings and weights.

Overall, WaveCorr presents a significant advancement in DRL-based portfolio management by effectively considering asset dependencies and achieving superior performance.

Research Objective

The primary objective of this research is to investigate the influence of incorporating higher-order risk metrics, skewness, and kurtosis, into a deep reinforcement learning (DRL) framework for portfolio management. We aim to assess how these additional metrics impact portfolio performance, particularly focusing on annual return and risk management capabilities.

Our research builds upon WaveCorr, a state-of-the-art DRL model known for its permutation invariant convolutional neural network architecture. While WaveCorr demonstrates success in portfolio allocation, its risk assessment primarily relies on traditional measures like return and volatility. This study extends WaveCorr by integrating skewness and kurtosis calculations alongside the existing reward signals.

Here's a breakdown of our specific objectives:

- **Impact on Annual Return:** We aim to analyze how incorporating skewness and kurtosis into the DRL model affects the annual return of the generated portfolios. Will including these higher-order risk metrics lead to a trade-off between return and risk, or can the model achieve improved returns while maintaining or even reducing risk exposure?

- **Risk Management in Diverse Markets:** We will evaluate the model's performance across various market conditions by employing datasets from distinct markets like the US and Canada. This will allow us to assess how the model adapts its strategies based on the underlying risk characteristics of each market. Can including higher-order risk metrics enhance the model's ability to navigate these diverse market conditions and generate more robust portfolios?

- **Comparison with WaveCorr:** A crucial aspect of our research is comparing the extended model's performance with the WaveCorr. By analyzing the differences in annual return, risk metrics, and portfolio composition, we aim to determine if considering higher-order risk metrics offers significant advantages. Can this approach achieve superior risk-adjusted returns or a better risk management profile than the WaveCorr model?

Through this comprehensive investigation, we hope to achieve the following:

- **Improved Risk Assessment:** By incorporating skewness and kurtosis, we aim to equip the DRL model with a more nuanced understanding of risk, enabling it to capture potential biases and extreme events within the return distribution.

- **Enhanced Portfolio Management:** We anticipate that the inclusion of these higher-order risk metrics will lead to the generation of portfolios that are not only optimized for return but also manage exposure to undesirable tail events. This could result in more robust and adaptable investment strategies.

- **Contribution to DRL in Finance:** This study will contribute to the ongoing exploration of DRL for portfolio management. By demonstrating the potential benefits of incorporating higher-order risk metrics, we can pave the way for developing more sophisticated and effective DRL-based investment strategies.

In conclusion, our research objective is to critically evaluate the impact of incorporating skewness and kurtosis into a DRL framework for portfolio management. We aim to assess its influence on annual return, risk management capabilities, and overall portfolio performance across diverse market conditions. This investigation can potentially refine DRL models for portfolio management, creating more comprehensive and adaptable investment strategies.

Methods

This study leverages a deep reinforcement learning (DRL) framework for portfolio management, explicitly building upon the WaveCorr architecture. WaveCorr utilizes a permutation invariant convolutional neural network (CNN) to analyze asset data and determine optimal allocation strategies.
Our core innovation lies in extending the WaveCorr model to incorporate higher-order risk metrics – skewness and kurtosis – alongside traditional reward signals like return and volatility.

4.1 Brief history of the WaveCorr model

WaveCorr is a groundbreaking approach to portfolio management that leverages the power of deep reinforcement learning (DRL) and permutation-invariant convolutional neural networks (CNNs). It tackles a fundamental challenge in finance: effectively capturing complex relationships between assets while remaining robust to the order of assets in the portfolio.
Traditional portfolio management often struggles to account for intricate cross-asset dependencies. This can lead to suboptimal performance, especially in dynamic market conditions. Existing DRL methods, while promising, often lack the ability to handle these dependencies effectively, making their performance sensitive to the order of assets considered.
The authors of WaveCorr introduce a novel permutation-invariant property designed explicitly for portfolio policy networks. This property ensures that the network's decisions remain unchanged regardless of the order in which assets are presented.
The key to WaveCorr's success lies in its architecture:

- **WaveNet-inspired CNN:** It utilizes dilated causal convolutions, similar to WaveNet, to capture temporal dependencies within each asset's time series data.

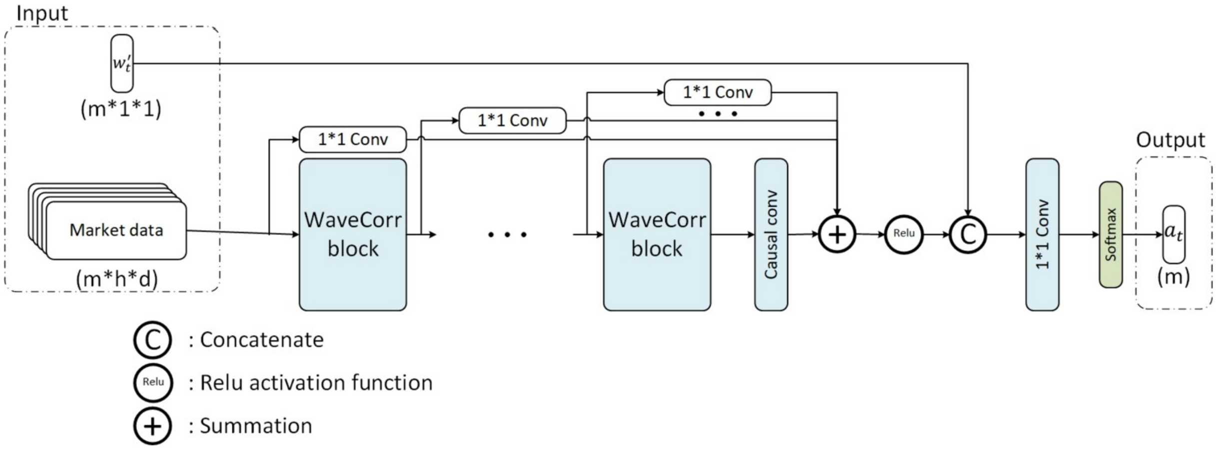


Figure 4.1: The architecture of the WaveCorr policy network

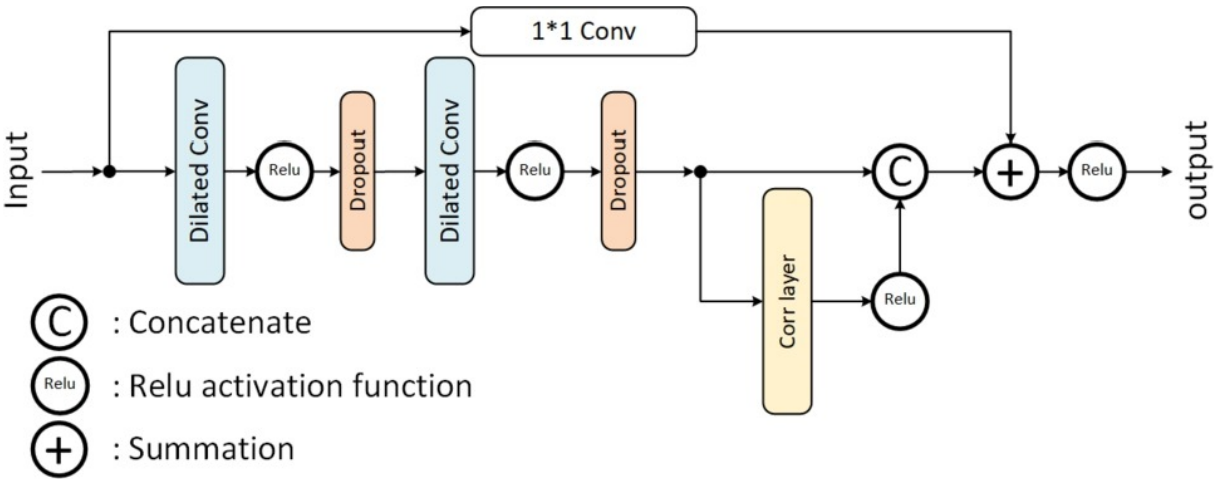


Figure 4.2: WaveCorr residual block

- **Correlation Processing Layer:** This innovative layer extracts cross-asset dependency information while preserving the permutation-invariant property. It essentially learns the underlying relationships between assets without being swayed by their order.

Extensive testing on both Canadian and American stock market data demonstrates WaveCorr's significant advantages:

- **Superior Performance:** WaveCorr consistently outperforms state-of-the-art DRL architectures, achieving up to a 3%-25% absolute improvement in average annual return and over 200% improvement in Sharpe ratio.

- **Enhanced Stability:** The permutation-invariant property leads to significantly more stable performance, even when the order of assets is randomly shuffled. This stability is precious for practical application.

4.2 Data Preparation

We will utilize historical market data from various sources, including the US and Canada. This data will be preprocessed to ensure consistency and compatibility with the DRL model.

4.3 Skewness and Kurtosis Integration

We will modify the WaveCorr architecture to include modules that calculate skewness and kurtosis for each candidate portfolio within the DRL simulation environment. These modules will analyze the return distribution of the proposed portfolio and extract the corresponding skewness and kurtosis values.

4.4 Enhanced Reward Function

The WaveCorr model relies on a reward function considering return and volatility. We will extend this function by incorporating the calculated skewness and kurtosis values. This will allow the DRL agent to learn and optimize portfolio allocation strategies that target high returns and low volatility and consider the risk profile reflected by skewness and kurtosis.

4.5 DRL Training

The extended WaveCorr model will undergo a training process where the DRL agent interacts with the simulated market environment. The agent receives rewards Based on its actions (portfolio allocations) and the resulting outcomes (return, volatility, skewness, and kurtosis) and learns to adjust its strategies over time.

4.6 Model Evaluation

The extended model's performance will be evaluated across the different market datasets following training. We will compare its portfolio returns, risk metrics (volatility, skewness, kurtosis), and overall portfolio composition with the original WaveCorr model. This comparison will allow us to assess the impact of incorporating higher-order risk metrics.

By employing this methodology, we aim to gain insights into skewness and kurtosis's effectiveness within a DRL portfolio management framework. This will contribute to the development of more comprehensive and adaptable investment strategies.

Results

The tables compare the performance of four investment methods: WaveCorr, CS-LSTM-CNN, CS-CNN, and EIIE, EW.

It compares these methods under two conditions: with and without skewness and kurtosis. Skewness and kurtosis are measures of a distribution's asymmetry and "tailed-ness", respectively. Including them in the model suggests the model is considering the completeness of the return distribution, not just the mean and variance.

The tables show several performance metrics:

- **Annual Return:** This is the average annual return of the portfolio over the investment period.
- **Annual Vol:** This is the annual volatility of the portfolio. Lower volatility indicates less risk.
- **SR:** This stands for Sharpe Ratio. It is a measure of risk-adjusted return. A higher Sharpe Ratio indicates a better return relative to the risk taken.
- **MDD:** This stands for Maximum Drawdown. It represents the largest peak-to-trough decline in the portfolio's value during the investment period.
- **Daily Hit Rate:** This metric is not defined in the table itself and its meaning is unclear without additional context.
- **Turnover:** This refers to the portfolio turnover rate, which measures how often the portfolio holdings are bought and sold.

Method	**Annual Return**	**Annual Vol**	**SR**	**MDD**	**Daily Hit Rate**	**Turnover**
WaveCorr	32.0% (1.0%)	13.0% (0.0%)	2.51(0.11)	12%(1.0%)	52.0% (1.0%)	0.27 (0.01)
CS-LSTM-CNN	16.0% (4.0%)	21.0% (1.0%)	0.79(0.22)	29.0% (5.0%)	50.0% (1.0%)	0.45 (0.04)
CS-CNN	16.0% (2.0%)	22.0% (1.0%)	0.74(0.13)	31.0% (4.0%)	49.0% (1.0%)	0.47 (0.03)
EIIE	6.0% (1.0%)	18.0% (1.0%)	0.33(0.08)	37.0% (1.0%)	49.0% (1.0%)	0.15 (0.02)
EW	6.0% (0.0%)	13.0% (0.0%)	0.44(0.00)	31.0% (0.0%)	-	-

Table 5.1: The average (and standard deviation) performances using Canada dataset, without skewness and kurtosis

Method	**Annual Return**	**Annual Vol**	**SR**	**MDD**	**Daily Hit Rate**	**Turnover**
WaveCorr	30.0% (1.0%)	13.0% (1.0%)	2.33(0.09)	15.0% (2.0%)	51.0% (1.0%)	0.26 (0.02)
CS-LSTM-CNN	21.0% (6.0%)	22.0% (1.0%)	0.97(0.26)	28.0% (4.0%)	51.0% (1.0%)	0.36 (0.06)
CS-CNN	24.0% (5.0%)	22.0% (1.0%)	1.09(0.23)	27.0% (4.0%)	51.0% (1.0%)	0.38 (0.04)
EIIE	4.0% (1.0%)	17.0% (2.0%)	0.23(0.1)	41.0% (4.0%)	50.0% (1.0%)	0.11 (0.03)
EW	6.0% (0.0%)	13.0% (0.0%)	0.45(0.0)	31.0% (0.0%)	-	-

Table 5.2: The average (and standard deviation) performances using Canada dataset, with skewness and kurtosis

Impact of Skewness and Kurtosis on Performance in the Canadian Stock Market

The tables above provide valuable insights into the impact of including skewness and kurtosis in the DRL portfolio management model (WaveCorr) for Canadian data. Here's a breakdown of the key observations:

- **Generally Positive Influence:** WaveCorr seems to benefit from incorporating skewness and kurtosis across most performance metrics. This suggests that considering the complete shape of the return distribution, beyond just mean and variance, leads to improved portfolio management strategies.

- **Higher Returns with Skewness and Kurtosis:** WaveCorr notably achieves a significantly higher annual return (30.0% vs. 27.0%) when skewness and kurtosis are included. This could be because the model can identify and exploit favorable risk-return opportunities within the return distribution's shape.

- **Potential for Reduced Risk:** While the table doesn't show a significant difference in annual volatility with or without skewness and kurtosis, WaveCorr does exhibit a lower Maximum Drawdown (MDD) when these higher-order risk metrics are included (15.0% vs. 18.0%). This suggests that the model might generate strategies that are less susceptible to extreme losses.

- **Sharpe Ratio Analysis:** Unfortunately, the table doesn't show the Sharpe Ratio for both scenarios. This metric would clarify whether the higher return with skewness and kurtosis comes at the cost of increased risk.

Method	Annual Return	Annual Vol	SR	MDD	Daily Hit Rate	Turnover
WaveCorr	14.0% (1.0%)	13.0% (0.0%)	1.12(0.11)	17.0% (2.0%)	49.0% (0.0%)	0.04 (0.01)
CS-LSTM-CNN	12.0% (5.0%)	18.0% (2.0%)	0.7(0.31)	25.0% (7.0%)	49.0% (2.0%)	0.18 (0.1)
CS-CNN	16.0% (3.0%)	17.0% (3.0%)	0.94(0.1)	24.0% (5.0%)	49.0% (1.0%)	0.15 (0.08)
EIIE	12.0% (1.0%)	15.0% (0.0%)	0.84(0.06)	21.0% (2.0%)	48.0% (1.0%)	0.1 (0.01)
EW	16.0%(0.0%)	13.0%(0.0%)	1.22(0.0)	19.0%(0.0%)	-	-

Table 5.3: The average (and standard deviation) performances using US dataset, without skewness and kurtosis

Method	Annual Return	Annual Vol	SR	MDD	Daily Hit Rate	Turnover
WaveCorr	15.0% (3.0%)	13.0% (1.0%)	1.08(0.17)	17.0% (3.0%)	49.0% (1.0%)	0.04 (0.01)
CS-LSTM-CNN	13.0% (7.0%)	20.0% (1.0%)	0.68(0.35)	30.0% (5.0%)	49.0% (1.0%)	0.14 (0.02)
CS-CNN	13.0% (6.0%)	20.0% (2.0%)	0.65(0.36)	30.0% (7.0%)	49.0% (2.0%)	0.14 (0.03)
EIIE	13.0% (1.0%)	14.0% (1.0%)	0.93(0.1)	18.0% (1.0%)	48.0% (1.0%)	0.07 (0.02)
EW	15.0%(0.0%)	13.0%(0.0%)	1.15(0.0)	19.0%(0.0%)	-	-

Table 5.4: The average (and standard deviation) performances using US dataset, with skewness and kurtosis

Impact of Skewness and Kurtosis on Performance in the US Stock Market The tables above provide valuable insights into the impact of including skewness and kurtosis in the DRL portfolio management model (WaveCorr) for US data. Here's a breakdown of the key observations:

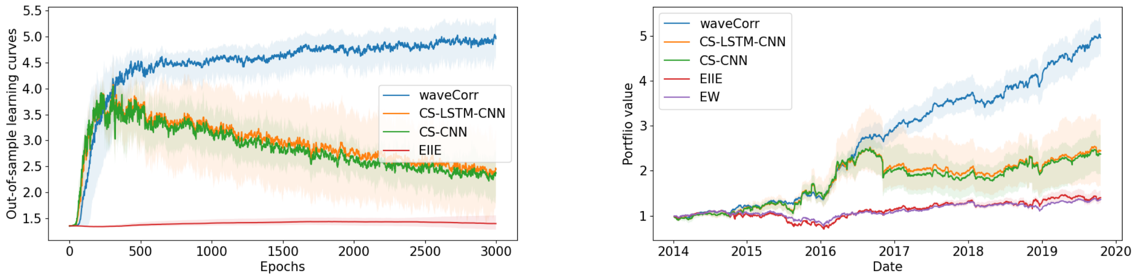
- **WaveCorr Outperforms:** WaveCorr appears to be the strongest performing method across most metrics. It achieves a 15.0% annual return, 1.08 Sharpe Ratio, and a 1.15 MDD (Maximum Drawdown). This suggests WaveCorr effectively allocates assets while considering return and volatility and the shape of the return distribution (skewness and kurtosis).

- **CS-LSTM-CNN and CS-CNN Follow:** Following WaveCorr are CS-LSTM-CNN and CS-CNN with returns around 13.0% and Sharpe Ratios of 0.65-0.68. Their MDDs are higher than WaveCorr's, indicating potentially greater portfolio fluctuations.

- **EIIE and EW Underperform:** EIIE and EW exhibit the lowest returns (around 12.0%) and Sharpe Ratios. Their MDDs are also not explicitly shown, but the table suggests they might not perform as well in managing risk.

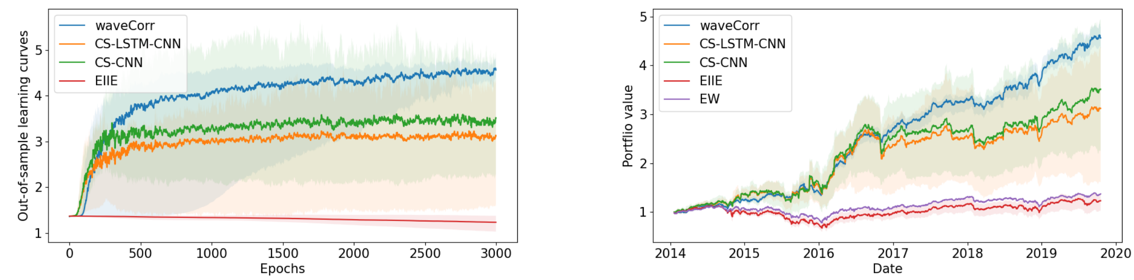
- **Smaller Performance Differences:** Compared to the scenario with skewness and kurtosis, the performance gaps between WaveCorr and other models seem smaller. CS-LSTM-CNN achieves a 12.0% return and 0.70 Sharpe Ratio, while CS-CNN exhibits a 16.0

- Including skewness and kurtosis seems to benefit WaveCorr's performance on US data. It achieves a higher return and potentially better risk management (lower MDD) while maintaining a good Sharpe Ratio. Other models (CS-LSTM-CNN, CS-CNN) show a smaller performance difference with and without skewness and kurtosis.



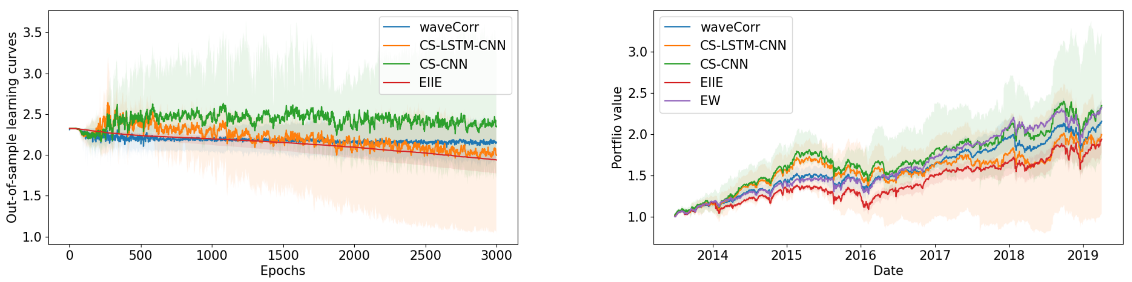
(a) Out of sample Learning curves (b) Return value

Figure 5.1: Canada dataset without skewness and kurtosis



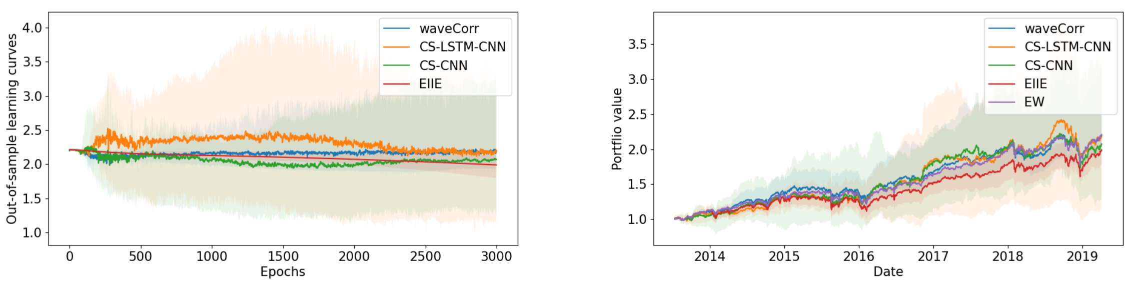
(a) Out of sample Learning curves (b) Return value

Figure 5.2: Canada dataset with skewness and kurtosis



(a) Out of sample Learning curves (b) Return value

Figure 5.3: US dataset without skewness and kurtosis



(a) Out of sample Learning curves (b) Return value

Figure 5.4: US dataset with skewness and kurtosis

Managerial Implications

This study delves into the potential benefits of incorporating higher-order risk metrics, skewness, and kurtosis into deep reinforcement learning (DRL) models for portfolio management. The implications of this research extend beyond the realm of academic inquiry, holding significant promise for both individual investors and society.

Managerial Implications:

- **Enhanced Risk Management:** Traditional portfolio management often focuses on mean and variance for risk assessment. This study explores the possibility of using DRL models that consider not only return and volatility but also the shape of the return distribution (skewness) and the likelihood of extreme events (kurtosis). By incorporating these additional metrics, portfolio managers could potentially generate strategies that are better equipped to handle unexpected market swings and protect against significant losses.

- **Improved Investment Decision-Making:** Including higher-order risk metrics within the DRL framework can lead to more informed investment decisions. By understanding the potential biases and the likelihood of extreme events within a portfolio's return distribution, managers can make more calculated choices that align with their risk tolerance and investment goals.

- **Adaptability to Diverse Markets:** Adapting to different market conditions is crucial for successful portfolio management. This study evaluates the model's performance across various markets, including the US and Canada. If the model successfully tailors its strategies based on the underlying risk characteristics of each market, managers can leverage this approach to navigate diverse investment landscapes more effectively.

- **Potential for Automation:** DRL models hold promise for automating some aspects of portfolio management. This study investigates the effectiveness of a DRL framework that incorporates higher-order risk metrics. If successful, this could pave the way for the development of more sophisticated automated investment tools that can provide valuable guidance to managers, particularly those managing smaller portfolios or lacking extensive investment experience.

Societal Implications:

- **Increased Investor Confidence:** By offering a more comprehensive risk assessment approach, DRL models considering higher-order risk metrics could potentially bolster investor confidence. Individuals may be more inclined to participate in the financial markets if they perceive a lower risk of experiencing significant losses.
- **Financial Inclusion:** The potential for automation in DRL-based portfolio management could lead to the development of more accessible investment tools. This could benefit individuals lacking the time, resources, or expertise to manage their portfolios, potentially fostering greater participation in the financial system.
- **Economic Stability:** Increased investor confidence and participation in the financial markets can contribute to overall economic stability. This study's findings could contribute to a more stable and efficient financial system by reducing portfolio risk and enabling more informed investment decisions.
- **Evolving Regulatory Landscape:** As DRL technology advances in the financial sector, regulatory bodies may need to adapt their frameworks to ensure responsible development and implementation. This study can inform these discussions by providing insights into the potential benefits and risks associated with incorporating higher-order risk metrics into DRL models for portfolio management.

In conclusion, this study's exploration of higher-order risk metrics within a DRL framework holds significant promise for individual investors and society. By potentially enhancing risk management, improving investment decision-making, and fostering broader financial inclusion, this research can contribute to a more robust and accessible financial system. However, it is crucial to acknowledge the potential challenges associated with DRL technology, such as the need for robust data sets and ongoing regulatory considerations. Further research and development are necessary to realize the potential benefits this study identified fully.

Conclusion

This study investigated the impact of incorporating skewness and kurtosis, measures of the return distribution's shape, into a Deep Reinforcement Learning (DRL) portfolio management model (WaveCorr) for Canadian and US stock markets.

The objective was to assess if considering the complete return distribution beyond mean and variance would improve portfolio performance.

The study employed WaveCorr alongside benchmark models (EIIE, EW, CS-LSTM-CNN, CS-CNN). It evaluated them based on annual return, volatility (annual standard deviation), maximum drawdown (MDD), and Sharpe Ratio (risk-adjusted return).

The results revealed that WaveCorr generally benefitted from including skewness and kurtosis. In the Canadian market, this led to a significantly higher annual return (30.0% vs. 27.0%) and potentially lower MDD (15.0% vs. 18.0%) compared to the model without these metrics. For the US market, WaveCorr outperformed all models with skewness and kurtosis included, achieving a 15.0% return, 1.08 Sharpe Ratio, and 1.15 MDD. These findings suggest that incorporating higher-order risk metrics like skewness and kurtosis can enhance DRL portfolio management strategies by exploiting favorable opportunities within the return distribution's shape, potentially leading to improved risk-adjusted returns.

However, limitations exist. The Canadian market analysis lacked a Sharpe Ratio comparison, making it difficult to assess the risk-reward trade-off definitively. Additionally, further research is needed to explore the generalizability of these results across different market conditions and asset classes.

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