Comparative Analysis of Deep Quantile Regression and Traditional Regression Models in Stock Price Prediction

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Abstract

Stock price prediction is very important in financial decision-making, assisting investors and institutions in managing risk and optimizing returns. Traditional regression models including Linear Regression, Polynomial Regression, and Random Forest Regression are widely used but are limited on predicting the conditional mean of stock returns. This approach fails to capture the uncertainty and asymmetry inherent in financial markets. This capstone project explores the application of Deep Quantile Regression (DQR) for stock return prediction and evaluates its effectiveness relative to traditional regression models. DQR utilizes deep neural networks to estimate multiple conditional quantiles, allowing for a wider range of prediction intervals. The study compares DQR and traditional models in terms of predictive accuracy, robustness, and their ability to capture the market uncertainty, using evaluation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Quantile Loss, and Prediction Interval Coverage Probability (PICP). Results show that Polynomial and Random Forest Regression have a reasonable accuracy, it only provides the mean of stock price predictions where the Deep Quantile Regression provides the full distribution and performs very well at the tail end of the distribution.

Introduction

Stock price prediction is a widely adopted practice in the finance industry for many years, offering valuable insights to investors and financial institutions. Accurate prediction supports informed decision-making, enhances risk management, and contributes to the development of more effective investment strategies. By anticipating future stock returns, financial professionals can allocate limited resources more efficiently, hedge against potential losses, and capitalize on emerging opportunities that might otherwise be overlooked. Because of these benefits, it can be both a challenging and essential task due to the complexity and volatility of financial markets. To address this, various regression models have been applied to predict expected stock returns based on historical data. These models include Multivariate Linear Regression, Multivariate Polynomial Regression, and Random Forest Regression.

Multivariate Linear Regression

Multivariate Linear Regression is the most basic and commonly used model for stock price prediction. It primarily focuses on identifying the linear relationship or trend between the stock price and multiple explanatory variables such as time, market indicators, or economic factors. By using the Ordinary Least Squares method, the model estimates

the coefficients that define the best-fitting line that minimizes the difference between predicted and actual values. Because of its simplicity, transparency, and interpretability, Multivariate Linear Regression is the common baseline model for forecasting and trend analysis.

Multivariate Polynomial Regression

Multivariate Polynomial Regression is an extension of Multivariate Linear Regression that incorporates higher-degree or polynomial terms to capture non-linear relationships often observed in financial markets. Stock prices are influenced by multiple interacting variables including market indices, interest rates, and economic indicators whose relationships are rarely purely linear. By introducing these additional terms, the model gains greater flexibility in fitting more complex trends compared to the linear model. Instead of fitting a straight line or hyperplane, it constructs a curved surface that better reflects nonlinear trends in the data. This often leads to improved performance in scenarios where the underlying data exhibits non-linear patterns.

Random Forest Regression

Random Forest Regression is a supervised learning algorithm that utilizes an ensemble learning approach by constructing a forest of multiple decision trees and aggregating their outputs. It uses the bootstrapping technique to create multiple random subsets of the historical stock data and introduces feature randomness when splitting nodes, ensuring that decision trees are not highly correlated. This method enables the model to capture complex and non-linear relationships between financial variables effectively. As a result, it often produces highly accurate predictions and shows a lower risk of overfitting compared to individual decision trees. Additionally, Random Forest is highly versatile, as it can be applied to both regression tasks by averaging the aggregated output and classification tasks through majority voting of the aggregated output.

Traditonal Regression Models Strength and Weakness

Each of these models offers distinct advantages in handling data complexity and capturing certain non-linear relationships or trends, making them important tools for stock price prediction. One of main strengths of traditional regression models is the simplicity and interpretability. These models provide a clear understanding on how explanatory variables influence the stock price. Another notable strength is the ease of implementation and validation. These models are supported by well-established statistical methodology, and they can be efficiently trained and validated with standard performance

metric such as R-squared, Root Mean Square Error, and Mean Absolute Error. Because of that, these models often serve as the baseline for evaluating more complex machine learning models.

Despite their advantages, traditional regression models have significant disadvantages that make them less suitable for stock price prediction. One of the disadvantages is that these models typically output only the conditional mean of the target variable. This fails to capture the full distribution of possible outcomes which is crucial in a highly volatile and non-linear financial markets. Another disadvantage is the assumption of stable statistical properties over time, even though financial markets are inherently dynamic and non-stationary since the market fluctuate due to external factors. Another disadvantage is the limited interpretability on non-linear relationships. Some models oversimplify the relationships while other nonlinear models like Random Forest Regression provide predictions that can be hard to explain in simple terms. These issues significantly reduce the effectiveness of traditional regression models in capturing the complexities of real-world market behavior. As a result, relying on these models can lead to unreliable or even misleading predictions, posing risks and consequences for investors and financial institutions.

Deep Quantile Regression

To address these limitations, recent advancements in machine learning have introduced modern regression models based on deep learning techniques, such as Deep Quantile Regression. Deep Quantile Regression is the extension of Quantile Regression that predict multiple conditional quantiles including the median of the target variable. It leverages deep neural networks to capture complex and non-linear relationships between the target and response variable.

In this research paper, the purpose is to explore the application of Deep Quantile Regression for stock price prediction. By leveraging the quantile loss function within a deep learning framework, the regression model would provide the entire conditional distribution of stock price returns, rather than a single expected return. This approach predicts point estimates as well as construct prediction intervals, which can offer valuable insights into the uncertainty and potential risk of price forecasts. The performance of Deep Quantile Regression on historical stock price data will be then evaluated and compare to the performance of traditional regression. In addition, the predicted values will be assessed against actual stock prices over the 30-day forecasting horizon. This comparison aims to determine whether Deep Quantile Regression provides a meaningful improvement in predictive accuracy and uncertainty quantification, and whether its application to stock price prediction is a worthwhile advancement over conventional approaches.

Literature Review

There are numerous studies that explore the stock prices prediction using various regression models. In fact, the regression models mentioned earlier have been evaluated and compared across studies in terms of their predictive performance and practical effectiveness.

Multiple Regression on Short-Term Stock Price Prediction

According to Rusu, Ștefan, Boloș, M. I., & Leordeanu, M. (2024) paper, the team conducted a comparative analysis of multiple regression models to investigate the performance for short-term stock price prediction. They examined Linear Regression, Support Vector Regression, Polynomial Regression and LASSO Regression for its respective strengths in handling linearity, nonlinearity, or feature selection. The dataset was obtained from Yahoo Finance and consisted of two years of historical stock data for Apple Inc., selected due to the company's large market capitalization and market influence. They later evaluated and compared the performance of each model with standard metrics including Mean Absolute Error, R-Squared, and Mean Squared Error. While the team performed a comparative analysis on regression models, they did not include and more complex models, such as Deep Quantile Regression and compared it. Not only that, but the analysis was also based solely on data from a single company which limits the generalizability. This limitation was noted and acknowledged by the team as well.

Random Forest Regression with Artifical Intelligence Techniques

Per Zheng, J., Duan Xin, Cheng, Q., Tian, M., & Yang, L. (2024) paper, the team explored the regression techniques with the application of artificial intelligences techniques in the context of smart finance. They selected Random Forest Regression as the base model because of the capability and integrated it with artificial intelligence techniques to enhance predictive performance. The modified regression was applied to predict the stock trends of three major companies (Apple, Samsung, and GE) for future time horizons of 30, 60, and 90 days based on a dataset comprising approximately 7,000 trading days. The team evaluated the performance of the model through the measurement of the Area Under the Curve (AUC) metric to assess its accuracy. Its result was compared with the performance with other regression models including Support Vector Regression, Logistic Regression, Gaussian Discriminant Analysis (GDA) and Quadratic Discriminant Analysis (QDA).

This study differs from the proposed research is that Random Forest Regression was modified using artificial intelligence techniques to enhance its predictive capability. Another key difference is that the comparison did not include the Deep Quantile Regression model, which serves as a central focus of the proposed research. Finally, the last difference is the approach of learning task. The regression models in the study were used for classification tasks like the stock trend while for the proposed research, the traditional models will be used for regression tasks and predicting the stock prices.

Deep Neural Networks on Stock Price Forecasting

With advancements in machine learning, the application of deep neural network techniques for stock price prediction have been studied and evaluated in recent years. Per Omar, A. B., Huang, S., Salameh, A. A., Khurram, H., & Fareed, M. (2022) paper, the team explored the deep neural network framework and its application on stock price forecasting. They integrated the framework to three models (Autoregressive Integrated Moving Average Model, Autoregressive NN Model, and Autoaggressive Random Forest Model). Autoregressive Integrated Moving Average Model is a statical method commonly used for forecasting time series data, combining three key components of autoregression, differencing, and moving averages. Autoregressive NN Model is a forecasting approach that combines the principles of autoregression with the learning capabilities of neural networks. The model uses historical time series values as input features to the network. With that methodology, it captures both linear and non-linear temporal dependencies in the data. With those models, the team forecasted stock index prices in three different time frames: the whole period, the pre-Covid-19 period, and the Covid-19 period. For the dataset, they used the daily close price of the KSE-100 index, and it comprised a total of 5,077 observations starting from January 1, 2001, to August 20, 2021. The dataset was later divided to two subsets: pre-Covid-19 period (January 1, 2001, to February 25, 2020) and Covid-19 period (February 26, 2020, to August 20, 2021). To examine and compare the performance and effectiveness of proposed models, the team used multiple evaluation metrics including the Mean Absolute Error, Root Mean Absolute Error, Mean Absolute Percentage Error, and Correlation coefficient.

While the team applied the deep learning framework to three models, they did not explore the Deep Quantile Regression model. Another difference is that the models used for the study are specifically designed for time series forecasting where past observations influence future values. This is different from the tradition regression models since they are built for general predictive modeling where observations are assumed to be independent of each other.

Per Abe, M., & Nakayama, H. (2018) paper, the team evaluated the application of deep neural networks and applied it to perform one-month ahead stock price prediction

with 25 financial and market factors over a 10-year rolling timeframe. Their dataset was based on MSCI Japan Index constituents, comprised of 319 constituents of the free float-adjusted market capitalization in Japan. For the preprocessing, they ranked each financial factors across the stock at each time point and normalized it. From there, the team designed multiple Deep Neural Networks architecture starting with the model containing three hidden layers and increasing the depth to five and eight hidden layers. Its predictive performance was later compared with other regression models: Support Vector Regression and Random Forest Regression. The models were assessed based on rank correlation, directional accuracy, and long-short portfolio returns.

While the team evaluated the deep learning framework on stock price prediction, their framework was designed to generate point forecasts of expected returns using lagged financial factors. This is different from the proposal research since it focuses on applying the framework to a Quantile Regression and estimates conditional quantiles, which allows for a full distribution of stock price prediction.

Deep Quantile Regression in Power and Energy Sector

While there is a growing body of research applying deep neural network techniques to stock price prediction, there remain relatively few studies utilizing Deep Quantile Regression in this context. In contrast, there are more studies that has been conducted within the power and energy sectors instead, where the model is experimented with various optimizations and evaluated for probabilistic forecasting. This highlights how Deep Quantile Regression can be adapted to different forecasting domains.

Per Yu, Y., Yang, M., Han, X., Zhang, Y., & Ye, P. (2021) paper, the team proposed a Deep Quantile Regression model designed for regional wind power forecasting purposes. The team used a combination of power historical data and numerical weather prediction data. To evaluate the performance of the proposed model, they compared it with other models as benchmarks including the Quantile Regression Neural Network model, sparse Bayesian learning model, and individual forecast power accumulation method. There are various key differences between this study and the proposed research. One of the differences is that the study focused on regional wind power forecasting using historical energy data, while the proposed research explores the application of Deep Quantile Regression in stock price prediction, where the input features are financial indicators and lag returns instead. Another key difference is the approach on comparative analysis. The team in the study compared their Deep Quantile Regression model against other probabilistic forecasting models, while the proposed research aims to compare the Deep Quantile Regression with traditional regression models to assess their relative forecasting performance.

Per Zhu, J., He, Y., Yang, X., & Yang, S. (2024) paper, the team examined the application of Deep Quantile Regression on ultra-short-term wind power probabilistic forecasting. They developed a non-crossing multi-output quantile regression deep neural network, optimized through chaotic particle swarm optimization. This modified model leveraged a multi-output deep neural network to output all quantile estimations simultaneously through a single training process. Various datasets were used for this study as they were derived from two case studies in wind power. The team utilized datasets derived from two case studies in wind power forecasting: the first consisting of wind power data from Ontario with a one-hour resolution, and the second using numerical weather prediction data from the Global Energy Forecasting Competition 2014. All datasets were split into 70% for model training, 15% for validation, and the remaining 15% for testing. Given the model's complexity, the continuous ranked probability score was used to assess the performance because it can effectively measure the compatibility of the predicted distribution with the observation.

While the study demonstrated the performance of the model on wind power prediction and provided detailed insights that can be shared with other fields like stock price prediction, the model is more complex from the model used in the proposed research. The Deep Quantile Regression used in the proposed research has a more straightforward structure and is not optimized. This simplification is intentional because the purpose is to balance model interpretability and predictive accuracy within the context of financial forecasting.

Per Lu, S., Xu, Q., Jiang, C., Liu, Y., & Kusiak, A. (2022) paper, the team explored the performance of a Deep Quantile Regression model integrated with non-crossing constraints and sparse-group lasso regularization for probabilistic electric load forecasting. The non-crossing constraint was implemented to ensure that the predicted quantiles remained properly ordered, preventing unrealistic quantile crossing that can occur when each quantile is estimated independently. The sparse-group lasso regularization was introduced to enhance model simplicity by eliminating unimportant signals and emphasizing the most relevant features. The dataset used in the study consisted of daily power usage data from four million households collected between 2016 and 2018 from China's power supply system database. To evaluate the model's performance, the team used various metrics including Continuous Ranked Probability Score, Average Quantile Loss, and the Monotonicity of quantile outputs.

The approach on Deep Quantile Regression from this study is different from the proposed research in many key aspects. For starters, the model in their study is more complex, integrating non-crossing constraints and sparse-group lasso regularization, while the proposed research utilizes a more straightforward Deep Quantile Regression model. Not only that, the objective of evaluation is also very different.

Research Question and Hypotheses

Research Question: what extent Deep Quantile Regression outperforms traditional regression models (Multivariate Linear, Multivariate Polynomial, and Random Forest Regression) in modeling the distribution of stock returns over the 30-day forecasting horizon?

- ***H1 Hypotheses:*** Deep Quantile Regression provides more accurate and informative predictions of stock return distributions than traditional regression models.
- ***Null Hypotheses:*** Deep Quantile Regression does not perform significantly better than traditional regression models in predicting stock return distributions.

Data Sources and Variables

For this research paper, the primary data source is the historical daily stock price data for a selected group of publicly traded companies and will be obtained from Yahoo Finance. Yahoo Finance is selected to ensure consistent, reliable, and reproducible data collection. Since the platform maintains continuous historical data, the dataset contains the fundamental stock information with minimal missing or unknown data. The selected companies are the top 25 companies of the S&P 500 index, based on the market capitalization. This approach captures a diverse representation of different industries and company types. There are eight variables in the dataset and six of them are numeric. They are defined as below:

- ***Date:*** the timeframe of the stock
- ***Ticker:*** the stock symbol
- ***Open:*** the opening price of the stock
- ***High:*** the highest price of the stock during the period
- ***Low:*** the lowest price of the stock during the period
- ***Close:*** the closing price of the stock during the period
- ***Adjusted Close:*** the adjusted closing price of the stock after corporate action during the period
- ***Volume:*** the total number of shares traded during the period

Statistical Methods

For statistical methodology, the approach was a comparative analysis between traditional regression models and Deep Quantile Regression. Unlike traditional regression

models where it output a single conditional mean prediction, Deep Quantile Regression applies the quantile loss or pinball function to directly estimate specific quantiles. Because of that, this allows the model to provide a better understanding of the full distribution of the target variable, which is useful in stock price prediction. By applying both traditional regression models and Deep Quantile Regression to the same dataset, this research examines and evaluates the strengths and limitations of each approach on stock price prediction.

Exploratory Data Analysis

Once the data was successfully obtained, an exploratory data analysis was performed to assess data qualities and gain data insights before facilitating the model development and evaluation. The dataset covers the period from March 2015 to April 2025, and it comprises of 62,014 observations. The data size provides a robust size for Deep Quantile Regression and traditional regression model comparisons. In addition, the dataset has no missing or null values.

The descriptive statistic was applied on the numerical variables to understand their distributional properties. The results below show that the mean values are relatively high, which can be attributed to the presence of companies with large market capitalizations such as, Apple and Amazon, in the dataset. The statistics also reveal a wide range across all variables. This indicates that there is a heteroscedasticity since the data appears to be highly volatile and non-stationary. This would impact the precision of traditional regression models, especially for multivariate linear and polynomial regression since the assumption of constant variance is violated.

	Open	High	Low	Close	Adj Close	Volume
count	62014.0	62014.0	62014.0	62014.0	62014.0	62014.0
mean	141.56086584108724	143.07424772773797	140.0350164344138	141.6015763823585	133.43708748962885	48511844.81407424
std	138.92891335612862	140.40273619548796	137.4154369340322	138.95783461008043	136.79064431815377	109755149.04670437
min	0.481249988079071	0.4882499873638153	0.4772500097751617	0.4827499985694885	0.4672988057136535	491000.0
25%	47.380001068115234	47.85825157165527	46.85350036621094	47.380001068115234	43.527337074279785	5798100.0
50%	103.8000030517578	104.875	102.6349983215332	103.81999969482422	93.24971008300781	14996150.0
75%	175.20750427246094	177.07500076293945	173.33337783813477	175.19000244140625	168.2579689025879	42448625.0
max	1076.47998046875	1078.22998046875	1068.010009765625	1076.8599853515625	1072.45361328125	3692928000.0

Figure 1: Descriptive Statistic

In addition, the mean is larger than the median for all variables, which indicates each distribution may be right-skewed and have a long tail on the high end, especially `Volume` variable. This interpretation is further supported by the standard deviation being larger compared to the mean, showing that the data is very spread out. The histogram below reinforces the finding as it shows each distribution is indeed right skewed.
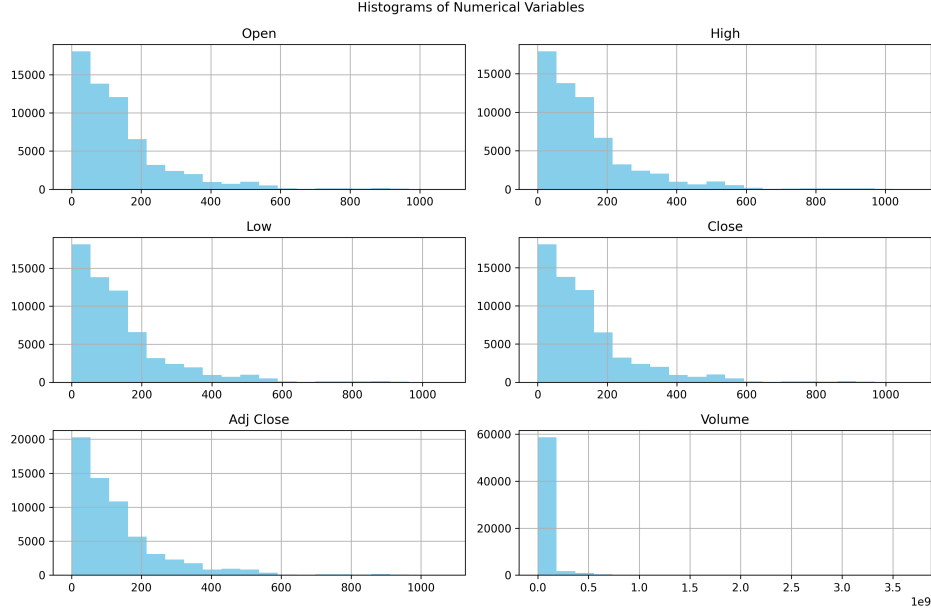
Figure 2: Histogram

Pre-processing

Due to the findings identified during the exploratory data analysis, the original variables were not suitable as features for both traditional and Deep Quantile Regression models. Because of that, the dataset was preprocessed for model development and evaluation. Multiple features were engineered to address problems such as the skewness observed in original variables. In addition, they also capture trend behaviors and predict short-term directional movement that may influence future stock prices. This enables the models to be trained on various aspects of market complexity. The following engineered features and formulas are defined as below: - **Lagged Returns:** the percentage change in the adjusted closing price of a stock from the prior day

$$R_{t-1} = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100 \tag{1}$$

- **1-Day Forward Returns:** the percentage change in value from the previous day's closing price to the current day's closing price

$$R_t^{1f} = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100 \tag{2}$$

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- **5-Days Forward Returns:** the percentage change in value from the closing price from 5 days ago to the current day's closing price

$$R_t^{5f} = \frac{P_t - P_{t-5}}{P_{t-5}} \times 100 \tag{3}$$

- **5-Days Rolling Standard Deviation:** the measure of the stock's volatility over the past 5 days period

$$\sigma_t^5 = \sqrt{\frac{1}{5} \sum_{i=0}^{4} \left(R_{t-i} - \bar{R}_t^5\right)^2}, \quad \bar{R}_t^5 = \frac{1}{5} \sum_{i=0}^{4} R_{t-i} \tag{4}$$

- **21-Days Rolling Standard Deviation:** the measure of the stock's volatility over the past 21 days period

$$\sigma_t^{21} = \sqrt{\frac{1}{21} \sum_{i=0}^{20} \left(R_{t-i} - \bar{R}_t^{21}\right)^2}, \quad \bar{R}_t^{21} = \frac{1}{21} \sum_{i=0}^{20} R_{t-i} \tag{5}$$

- **Relative Strength Index (RSI):** the momentum indicator that measure the rate and volatility of the stock's price

$$RSI_t = 100 - \frac{100}{1 + RS_t}, \quad RS_t = \frac{\text{Average Gain over } n \text{ days}}{\text{Average Loss over } n \text{ days}} \tag{6}$$

- **Simple Moving Average:** the average closing price over the timeframe of 20 days

$$SMA_t^{20} = \frac{1}{20} \sum_{i=0}^{19} P_{t-i} \tag{7}$$

- **Moving Average Convergence Divergence (MACD):** the momentum indicator that identifies a difference between two moving averages

$$MACD_t = EMA_t^{12} - EMA_t^{26} \tag{8}$$

- **Simple Moving Average Ratio:** the ratio of the current price to the 20-day Simple Moving Average

$$SMA\_Ratio_t = \frac{P_t}{SMA_t^{20}} \tag{9}$$

- *Natural logarithm of Trading Volume* the logarithm of trading volume

$$\text{LogVolume}_t = \ln(V_t) \tag{10}$$

There are missing data for some of the features because they depend on prior observations that fall outside the available dataset. This resulted in incomplete sequences at the beginning or end of the dataset. To address this, missing values were imputed using a combination of forward-fill and backward-fill methods. Furthermore, all features were scaled to ensure that they contributed equally during the model training.

The heatmap below shows the relationship among the engineered features. The original variables except for `Volume` variable are perfectly correlated as they are dependent to each other. For engineered features, there are few correlations identified. For instance, `Relative Strength Index` and `Simple Moving Average Ratio` show a positive correlation with key return indicators such as `Lagged Return` and `5-Days Forward Returns`. This correlation may indicate a multicollinearity and can impact the simpler models such Multivariate Linear and Polynomial Regression. To mitigate this issue, the Ridge (L2) Regularization was applied to Linear and Polynomial Regression. This approach introduced a penalty term to the model's loss function to avoid overfitting and improve the predictive performance.
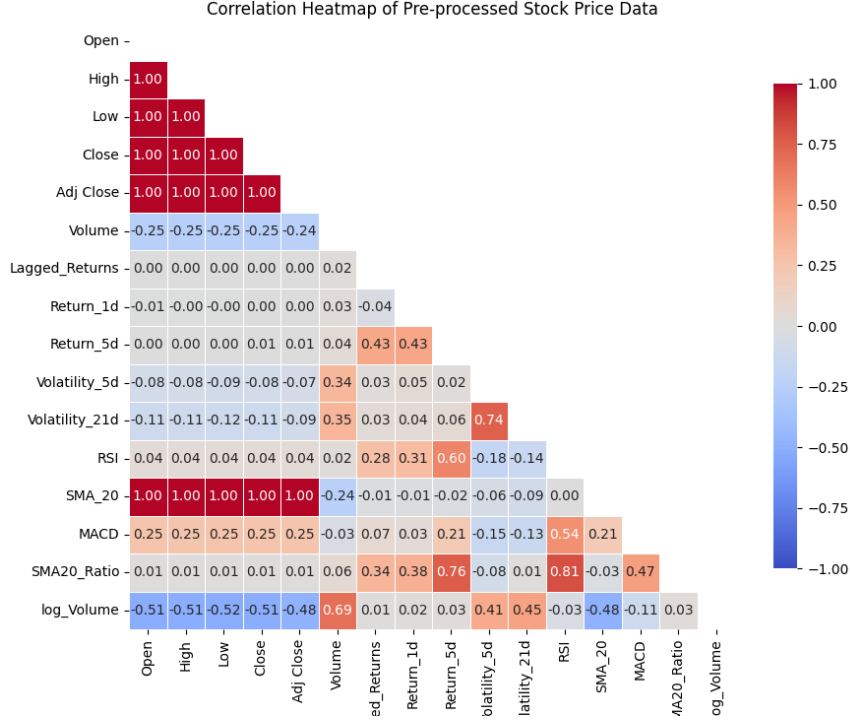
Figure 3: Feature Correlation Heatmap

Model Training

The dataset was later divided into three subsets: 70% for training, 15% for hyperparameter tuning, and the remaining 15% for final performance evaluation. This approach was to provide a robust and unbiased assessment for each models' predictive performance. The predictive performance of Deep Quantile Regression was evaluated and compared against traditional regression models. All models used the engineered features as input variables, and the target variable was the adjusted closing price for future time horizons of 30 days. For Deep Quantile Regression, the input variables were fed into the feed-forward neural network with 2 hidden layers. In addition, the model was applied with monotonicity constraints to avoid the quantile crossing and ensure that the estimated quantiles are ordered properly.

Each model was trained independently to ensure consistency and enables a direct comparison of each model's learning ability on historical stock price and predictive capability on forecasting stock prices. To assess and evaluate the predictive performance for all regression models, various metrics were used. This approach provided a comprehensive

evaluation of both point prediction accuracy and uncertainty estimation. The following metrics for traditional regressions are defined below:

- **Root Mean Squared Error:** the average of absolute difference between the predicted and actual value. It is used to measure how far the predicted values are from the observed actual values.
- **Mean Absolute Error:** the square root of averaged squared error. It measures the average magnitude of the prediction errors from both underfitting and overfitting direction

For Deep Quantile Regression, the model was evaluated based on multiples quantiles (0.1, 0.5, 0.9, 0.99) with the following metrics:

- **Pinball Loss or Quantile Loss:** the evaluation metric that is specifically designed for Deep Quantile Regression. It measures how well the predicted quantiles align with the actual outcomes
- **Prediction Interval Coverage Probability:** the evaluation metric that measures the reliability of prediction intervals for Deep Quantile Regression

Discussion of Results

Model Evaluation

All traditional regression models were trained and evaluated and here are the results from the evaluation metrics:

	Model	Root Mean Squared Error	Mean Absolute Error
0	Random Forest Regression	1.3359656291030595	0.3486533982141817
1	Multivariate Polynomial Regression with Ridge Regularization	0.8068523179706838	0.4100554099955666
2	Multivariate Linear Regression with Ridge Regularization	4.6197687184226615	2.441011046421716

Figure 4: Evaluation of Traditional Regression

Based on the result, it clearly shows that Multivariate Linear Regression with Ridge Regularization is the weakest model. The Multivariate Polynomial Regression with Ridge Regularization have the best accuracy out of all models, but its predictive performance is lower than Random Forest Regression. The Random Forest Regression have a best predictive performance, but its accuracy is slightly lower compared to the Polynomial Regression.

For Deep Quantile Regression, the model was trained and evaluated on all quantiles (0.1, 0.5, 0.9, 0.99). Here is the result from the evaluation metric:

	Quantile	Quantile Loss	PICP
0	0.1	0.163034	0.1521
1	0.5	0.306365	0.3849
2	0.9	0.137693	0.7512
3	0.99	0.01956	0.9669

Figure 5: Evaluation of Deep Quantile Regression

The values from Quantile Loss show that the model has high accuracy precision at the extremes of the distribution (0.1, 0.99). However, the accuracy is lower in the central quantiles (0.5, 0.9), indicating that the model may underestimated the variability. This is further evidenced by the PICP values, where the tail end quantiles have coverages close to their expected values. In addition, the model predicts values that are too low or too narrow in the middle of the distribution.

Models Comparsion

By comparing the results from all models, it shows that Deep Quantile Regression provides more accurate and informative predictions of stock return distributions than traditional regression models by providing the full distribution of stock price forecasting. The Multivariate Polynomial Regression with Ridge Regularization have the best accuracy, followed by the Random Forest Regression, based on the values from RSME. However, this only shows the conditional mean of stock price forecasting. The Deep Quantile Regression captures the shape, spread, and asymmetry of future stock price returns. The Quantile Loss and PICP values show how well the model performs on the tail end of the distribution which is an insight that cannot be provided by Multivariate Polynomial and Random Forest Regression.

Conclusion

In conclusion, the project shows that Deep Quantile Regression provides many significant advantages over traditional regression models. While models like Polynomial

Regression and Random Forest Regression effectively estimate the conditional mean, they fail to capture the uncertainty and asymmetry inherent in financial markets. The Deep Quantile Regression addresses that by predicting multiple quantiles. This provides a comprehensive view of the full distribution of future stock returns. In additon, the evaluation metrics show that the model not only delivers competitive accuracy compared to traditional model but also excels at modeling tail risks. These advantages makes the Deep Quantile Regression a vialable alternatives in stock price forcasting.

Code Appendix

https://github.com/eddiexunyc/capstone_work_project/tree/main

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