Digital Object Identifier

Applying Predictive Analytics to Financial Markets

COREA KITTII[1], ARON SAMAYOA[2], AND DANIEL CASCO.[3]

ABSTRACT Within this paper we present a price prediction application that utilizes tick-level price data from financial markets in order to perform predictive analytics by way of machine learning models. The application includes a data importation tool written Python that makes use of both the PyArrow and Pandas libraries in order to import data from both CSV files and Parquet files, which is then both stored in and managed by a MySQL database. Two types of machine learning models are implemented: Long-Short-Term Memory models and transformer models. These models can be trained on specific securities in order to perform predictive analysis. Instances of fully trained models can be saved for each security in the database, where they can be retrieved for future use. This application provides two interfaces: a user interface and an administrator interface. Users are capable of viewing candlestick charts that are formed out of the tick-level price data, and can view the results of the predictive analysis performed by the machine learning models. Administrators can do the same, while also having the ability to initiate training sessions for the models, as well as any required maintainance of the database. With this application prediction future price movements of financial markets can be done simply, quickly, and accurately.

INDEX TERMS Algorithmic Trading, Financial Markets, LSTM, Machine Learning, MySQL Database, Pandas, Price Prediction, PyArrow, Python, Tick-level Data, Transformer Models, React Native

I. INTRODUCTION

IT is generally understood that accurately predicting the future is extraordinarily difficult, if not impossible; however, that hasn't stopped people from trying, especially in regards to financial markets. Of all the research that has been performed on these markets, predicting future price movements has proven to be one of the most challenging problems due to the variables involved, such as market volatility, investor sentiment, and factors external to the financial market, which include the economy, climate, politics, and more. Where simpler models often fall short due to the complexities of financial time series data, machine learning techniques, particularly deep learning, have shown promise. Of the many different types of deep learning models, Gated Recurrent Units (GRU), Long-Short-Term Memory (LSTM), and Transformer models have displayed promising performance, with our application utilizing the latter two. Extensive research has been performed on this subject, which has explored a wide variety of machine learning techniques in order to find those suitable for price prediction. These range from the more classic support vector machines (SVM) all the way to the more advanced neural networks. Studies have proven that using deep learning models for price prediction is effective, while determining which models are the most effective is an ongoing process [1]. Precision price prediction has had it's importance proven via advancements made in algorithmic trading, especially in high-frequency trading, where decisions must be made based on real-time analysis of the market [2]. Further refining the accuracy of price predictions can be done by utilizing tick-level price data, which can capture even the smallest market movements due to it's granularity [3].

Past research has performed comparisons on the performance of GRU, LSTM, and Transformer models in regards to price prediction, with the dataset consisting of Tesla (TLSA) price data ranging from 2015 to 2024. The dataset underwent preprocessing in order to correct for missing values and to normalize price fluctuations, along with other adjustments that allowed for the optimization of training each model. The results of the experiments that were performed showed that LSTM models performed better than both GRU and Transformer models, while Transformers performed the worst out of the three [1].

II. PROJECT OVERVIEW

Our application will utilize historical tick-level price data from the financial market in order to perform predictive analytics using machine learning models, with the application also providing a tool to import said data. Users will be provided an interface that allows them to view the price data in the form of candlestick charts, as well as view the results of the predictive analysis produced by the machine learning models. Administrators are capable of doing that on top of having the ability to both initiate model training and perform necessary maintainance.

A. SYSTEM DESIGN

The system is designed in a modular fashion, and features the data importation tool, the database, the two types of machine learning models, an interface for administrators, and an interface for normal users. A more detailed description is as follows:

1) Data Importation Tool

The data importation tool is implemented using the Python programming language, which allows us to take advantage of it's excellent third-party library support. We utilize both the PyArrow and Pandas libraries in order to process both CSV files and Parquet files.

2) MySQL Database

Once imported, data is stored within a MySQL database for easier access. Candlestick charts are generated using this data, and it is also fed into machine learning models during their training. Each instance of a fully trained model is also stored within the database, allowing for easy retrieval. The database also stores the results of predictive analysis so that they can be viewed by users.

Data within the database is stored according to the following schema:

a: Tick-Level Data

Price data for each security is stored in a table whose name is in the format TICK_DATA-[security].

- trade_id: A unique ID is assigned to each trade
- trade_time: Unix-timestamp of when the trade took place
- price: The value of the security at the time of the trade
- volume: How much of the security was traded
- side: Whether the trade was a buy or sell order

b: Candlestick Charts

Candlestick charts for each security is stored in a table whose name is in the format CANDLE_[timeframe]-[security].

- trade_id: A unique ID is assigned to each trade
- open_time: Unix-timestamp of the first trade during the time frame
- close_time: Unix-timestamp of the last trade during the time frame
- open_price: Value of the security at the start of the time frame
- high_price: Highest value the security reached during the time frame
- low_price: Lowest value the security reached during the time frame
- close_price: Value of the security at the end of the time frame
- volume: How much of the security was traded during the time frame

c: Model Instances

All trained models instances are saved in the database in the MODEL_INSTANCES table.

- security: The security the model was trained on
- model_id: A unique ID assigned to each model saved in the database
- model_type: Whether the model is an LSTM or a Transformer
- date_trained: Timestamp of when the model was trained

d: User Information

User information is saved in the USER_INFO table.

- user_id: A unique ID is assigned to each user; no duplicate ID's are allowed, and this field cannot be null.
- first_name: The user's first name; this field cannot be null, but duplicate values are acceptable.
- last_name: The user's last name; this field cannot be null, but duplicate values are acceptable.
- username: Each username must be unique; this field cannot be null.
- password: Contains the password hash. Each password must be at least a minimum length, and feature a mix of alphanumeric and special characters. This field cannot be null.
- admin_status: Set to true or false depending on whether the user has been granted administrator rights.

3) Machine Learning Models

Within our application we implement two types of machine learning models:

- Long-Short-Term Memory (LSTM) models, which excel at performing predictive analysis on time-series data that spans a long period of time.
- Transformer models, which perform better at predictive analysis on time-series data that spans a shorter period of time, and are generally faster to train than LSTM's.

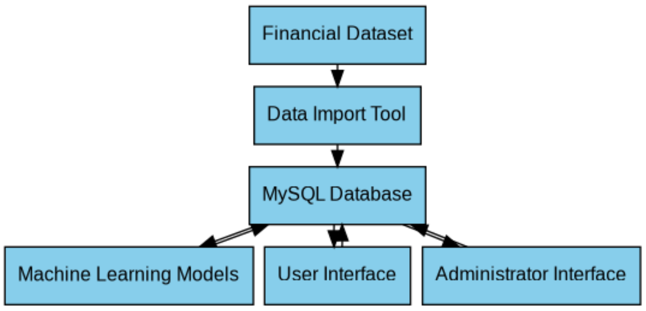
Models are trained on specific securities to improve the accuracy of their predictions; in other words, each instance of a fully trained model is a specialist in the security it was trained on.

4) User Interface

We use React Native for the user interface, which is a Javascript framework that allows for the development of cross-platform mobile applications, as well as React Native for Web, which allows for the porting of React Native applications to web browsers and greatly expands the number of platforms users can use to access our application. In regards to the UI itself, it has the following functionalities, with differences existing between normal users and administrators:

- View candlestick charts generated from imported tick-level price data.
- View the results of predictive analysis performed by trained machine learning models.
- Initiate model training sessions (Administrator Only).
- Data importation (Administrator Only).
- Database management and maintainance (Administrator Only).
- User account creation, modification, and deletion (Administrator Only).

5) Design Diagram



B. DATASET

Our choice of datasets to use for testing was limited by two main factors: time and cost. While tick-level price data can be obtained from stock exchanges, it is often at a significant cost. The stock exchange IEX does offer historical tick data for free, but it requires spending a significant amount of time parsing out unneeded data, as the files they provide contain everything that happens on their network. We ultimately decided to source our data from the crypto exchange Binance, who provides their tick data in compressed CSV files that can be readily imported into our database. From their historical data repository at data.binance.vision, we selected five currency pairs with volume levels ranging from high to moderate from their spot trading data:

- BTC/USDT (Bitcoin & Tether)
- ETH/USDT (Ethereum & Tether)
- ETH/BTC (Ethereum & Bitcoin)
- BTC/USDC (Bitcoin & USD Coin)
- ETH/USDC (Ethereum & USD Coin)

C. DISCUSSION

In this section, we shall discuss in depth the potential advantages of our application, as well it's limitations. We'll also discuss how it fares against similar applications and services.

1) Advantages and Limitations

The primary advantage our application has when compared to other price prediction solutions is the use of tick-level price data. Training our machine learning models on data with a greater level of granularity allows for them to gain greater insight on how the financial market functions, as opposed to using OHLC price data. The creation of an OHLC candlestick involves throwing out most of the information that was generated during the time period the candlestick represents, with that discarded data potentially representing hundreds or thousands of individual trades. That does mean, however, that the storage requirements for tick data are drastically higher than OHLC data. Additionally, acquiring tick data can be prohibitively expensive, especially when it concerns the stock market (IEX is an exception, though it has it's own issues, as mentioned earlier). For business with deep pockets or existing subscriptions to providers of tick data, however, this may be a non-issue.

As it currently stands, our application does have some limitations that should be kept in mind. Our use of machine learning gives us an edge when it comes to predictive analytics, but it does require significant computing resources in order to both train and run them. Additionally, training these models takes time, and insufficient computing resources can extend the time required. As mentioned earlier, our use of tick-level price data means that storage requirements are significantly higher compared to OHLC data, even when utilizing compression. As an example, in our dataset one CSV file decompresses from 1.2 MiB to 5.5 MiB, increasing 4.5x in size. The entirety of the BTC/USDT portion of our dataset takes up approximately 60 GiB; assuming a 4.5x increase after decompression, it would then take up 270 GiB, and our entire dataset would take up 450 GiB. MySQL's default storage engine, InnoDB, does feature compression features, though we have yet to implement them.

2) Comparison to Competitors

Our application is, or at least is largely, unique, though precise comparison with other price prediction solutions is difficult, as details on their inner workings are sparse and obscured by marketing. To date we have not found an application that allows for the level of control over the process of performing predictive analysis, from data importation to model training to data visualization. Users are not using some machine learning model that was pre-trained by another company, are instead involved in the process of training and fine-tuning a model that can suit their specific requirements.

D. CONCLUSION

The development of this price prediction application has and continues to be a challenging endeavor, but it nevertheless has potential. Machine learning techniques are proven to be effective in performing predictive analysis, and the use of tick-level data allows our models to gain a more granular insight into price movements than is otherwise possible with OHLC data. The availability of two different model types also allows users to find the one that works best in their specific situation. That being said, their are potentially steep resource requirements, both in compute and storage.

In the future, additional features could be added, such as import and analysis of real-time data and adding support for sentiment analysis, potentially via the implementation of Large Language Models such as Google's Gemini, Anthropic's Claude, or smaller, more efficient models that can be run locally, such as Alibaba's Qwen, Microsoft's Phi, and others. There is room for optimizations as well; the model training process could be made more efficient, and MySQL could be replaced with a more flexible database system, such as PostgreSQL. All these additions and improvements would significantly improve our application's capabilities while reducing resource requirements, all the while making it a more compelling option for business's in need of it's feature-set.

In conclusion, this application serves as a showcase of the effectiveness of machine learning in predictive analysis on financial data, and the importance of a larger and more granular dataset. It can be used in a practical fashion in order to extract value from financial markets, and it can be used academically in order to further the study and development of machine learning in the realm of finance.

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