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PROJECT RESULTS PRESENTATION

Link to Repository: <https://github.com/aghersisayan/MachineLearningIIT>

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INTRODUCTION

For this Fall 23 Term project, we have chosen to develop a machine learning model based on Logistic Regressions, to forecast the movement of the stock value of a top 5 company in the world by market cap: Amazon Inc. (AMZN) (1.5 trillion USD, November 2023).

Why Amazon?

- Publicly traded since 1997. 25 years of data.
- Some ups and downs. Diverse data.
- Part of Nasdaq 100 and S&P 100.

Scope

- Forecasting the stock movement based on historical data: We are not trying to predict the exact value of the stock, as that would introduce too much error and requires more information.
- Preprocessing of data: We are normalizing the data as it is a requirement when working with time series.
- Comparing with a more simple regression that doesn't include data from previous periods: To illustrate cons and pros, we are implementing a logistic regression model to compare with. This will help visualize differences between more simple and more complex models.
- Statistical tests and measurements: For comparison, we are using Accuracy, Precision, Recall, F1 score, Confusion matrix.
- We are Not forecasting the exact value of stock, only the ups and downs
- This is a comparison: We want to highlight the usage of historical data.

OBJECTIVES

We are going to define the objectives of this project and the expected results for each one:

Objective 1: Define the dataset.

- Including the dates to be included in the analysis

- Result 1 for Objective1: Constraints for the data

- Result 2 for Objective 1: Analysis of correlation between variables

Objective 2: Split the data and format it

- Format the data for the time series analysis (preprocessing) and split

- Result 3 for Objective 2: Python code for data preprocessing

Objective 3: Design a Recurrent Neural Network for the data and train it

- Result 4 for Objective 3: Python code for model, data split and train

Objective 4: Implement a state of the art benchmark for comparison

- Result 5 for Objective 4: Python model, data split and train

Objective 5: Compare both models using accuracy estimators

- Result 6 for Objective 5: Metrics for both models and comparison.

Objectives 1 and 2, and their Results will be ready for midterm presentation

Objectives 3 to 5, and their results will be ready for Final presentation

METHODS AND TOOLS

The programming language is Python, and the ML model will be generated with TensorFlow.

For measuring accuracy, loss and MSE

For compute resources, we'll upload the data set and ipython notebook to GoogleColab, which provides enough compute-time and resources for this project

THEORY AND CONCEPTS

How does a RNN differ from a Linear Regression or a Logistic Regression?

RNNs are a special type of machine learning model that allows capturing information from previous states. While a Linear regression or Logistic regression predict values or classes based on the current input, a RNN also considers previous values. This is useful for situations in which temporal dependencies are present (like stock market movements). For this project we will include this advantage into our logistic regression by using the Moving Average to capture previous values.

What are stock market movements?

When trying to forecast the value of a stock in the stock market, we can take the previous values and input them into a linear regression model. This would allow us to predict the future value based on historical data. But for stock movements, we are not trying to forecast the exact value of the stock. We only want to know if the next value will be high or lower than the current. So, we call that a stock market movement.

Which dataset are we using? and how does the data look in the dataset?

We are using the dataset available at [Kaggle - Amazon stock 1999-2022](#) . It presents the daily values from 1999 to 2022, with details of Open value, Close value, High, Low and Volume of transactions.

What is the difference between Time Series Forecasting and Time Series Analysis?

Time series analysis is the study of the data to gain insights like seasonality and trends. Time series forecasting predicts values in the future.

Will there be feature augmentation?

A common indicator used in stock market valuation is the Moving Average (MA). This is a line generated by calculating the average of the values from a specific point in time to the present. Some typical values are MA-200, which is

the moving average of the last 200 periods or the MA-50 for 50 periods. We will be creating two new features with MA-200 and MA-50.

What is the vanishing gradient problem and how to solve it with RNN?

When we update weights in a RNN, old values end up vanishing due to a constant multiplication that reduces their impact on the output. This is the vanishing gradient problem. Long memory models losing their old memories. To solve this, a special type of RNN is created: Long Short Term Memory or LSTM RNN. These models have characteristics to maintain old values fresh in the time flow. This is not included in this project, but is worth noting.

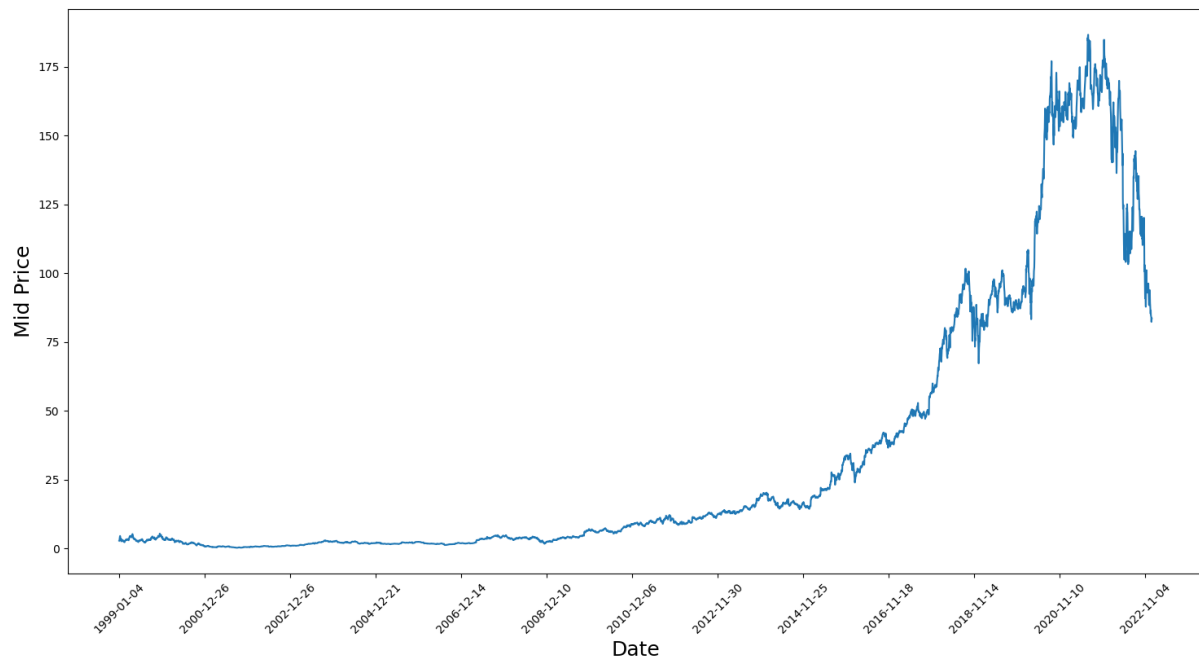
What are some improvements that are not included in this solution?

Anomaly detection and seasonal changes will not be covered on this work this time. They are kept as proposed improvements for future work.

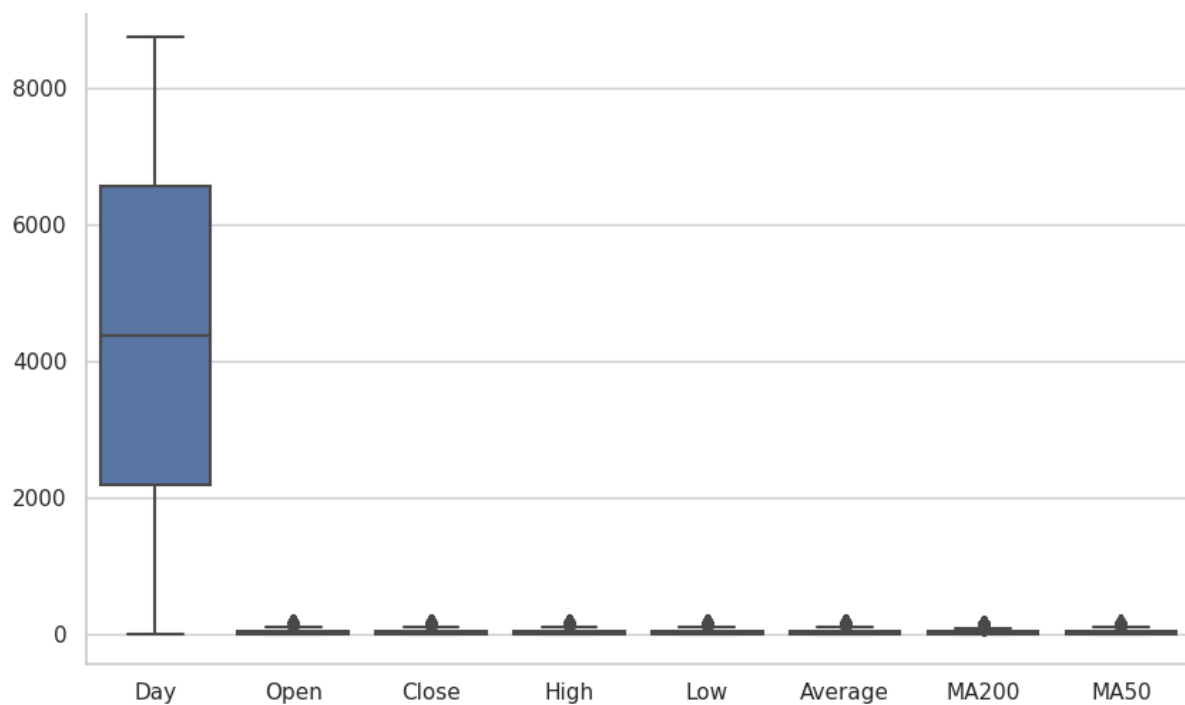
RESULTS

Result 1: Data constraining

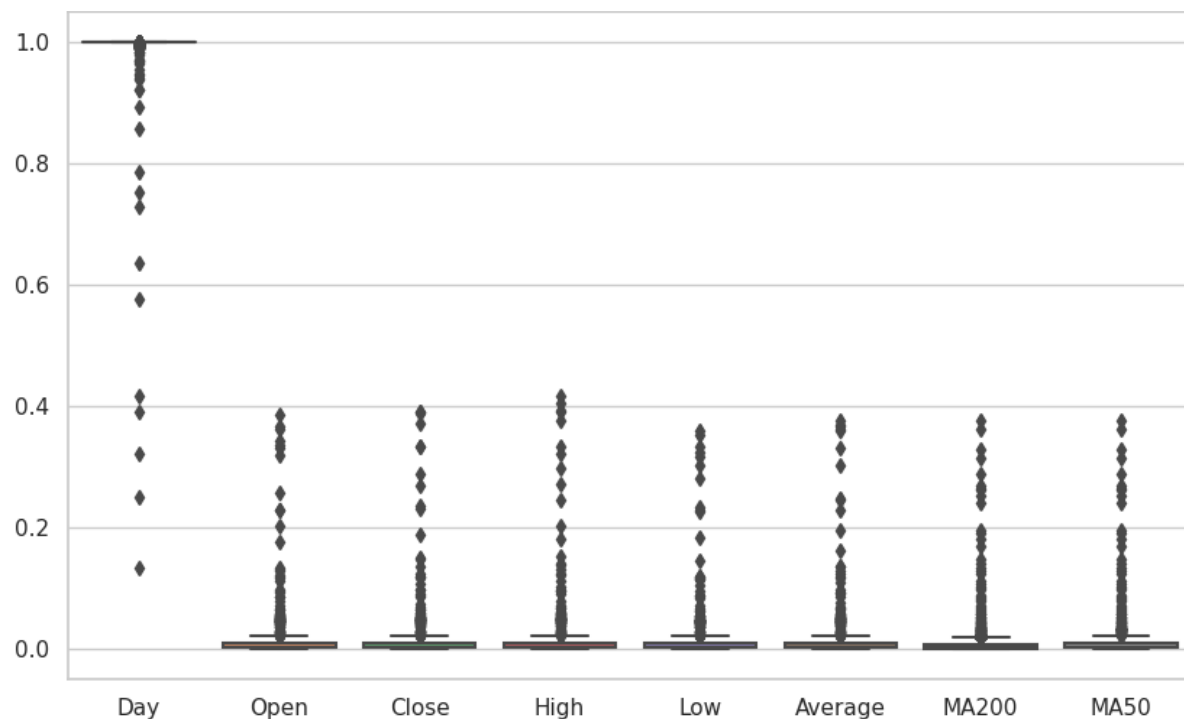
We will only use data from 1999 (year in which Amazon.com went public) and 2022 (last date from the dataset).



Result 2: Data analysis (original data)



Result 3: Normalized data and table visualization



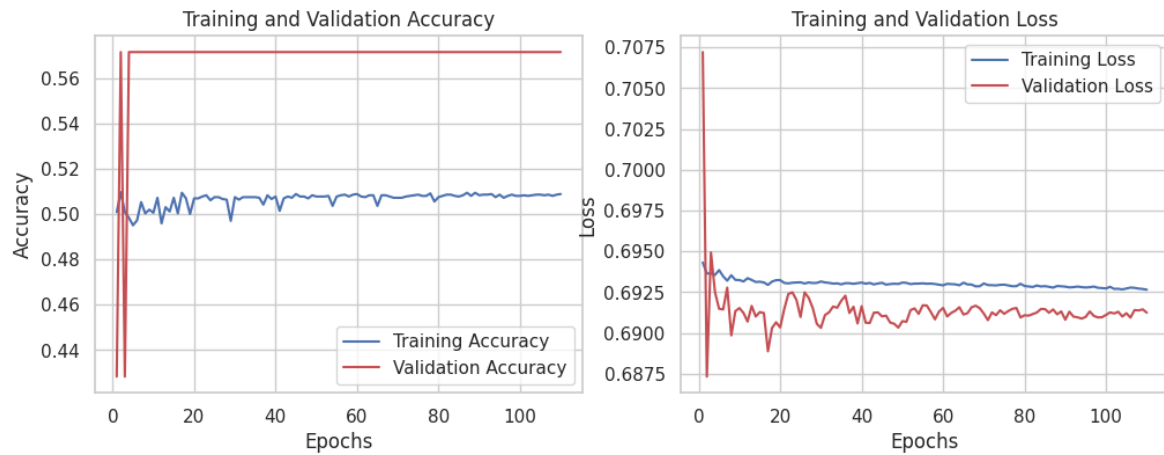
	Open	High	Low	Close	Average	MA200	MA50
0	0.360488	0.391635	0.351894	0.390466	0.375477	0.375477	0.375477
1	0.342362	0.405444	0.332792	0.389039	0.365700	0.360606	0.360606
2	0.366292	0.377036	0.359913	0.370657	0.368475	0.329463	0.329463
3	0.334354	0.390739	0.324295	0.387387	0.360870	0.314536	0.314536
4	0.384232	0.415252	0.316979	0.334183	0.359208	0.287049	0.287049

Result 4 and 5: Logistic regression and LSTM model from literature

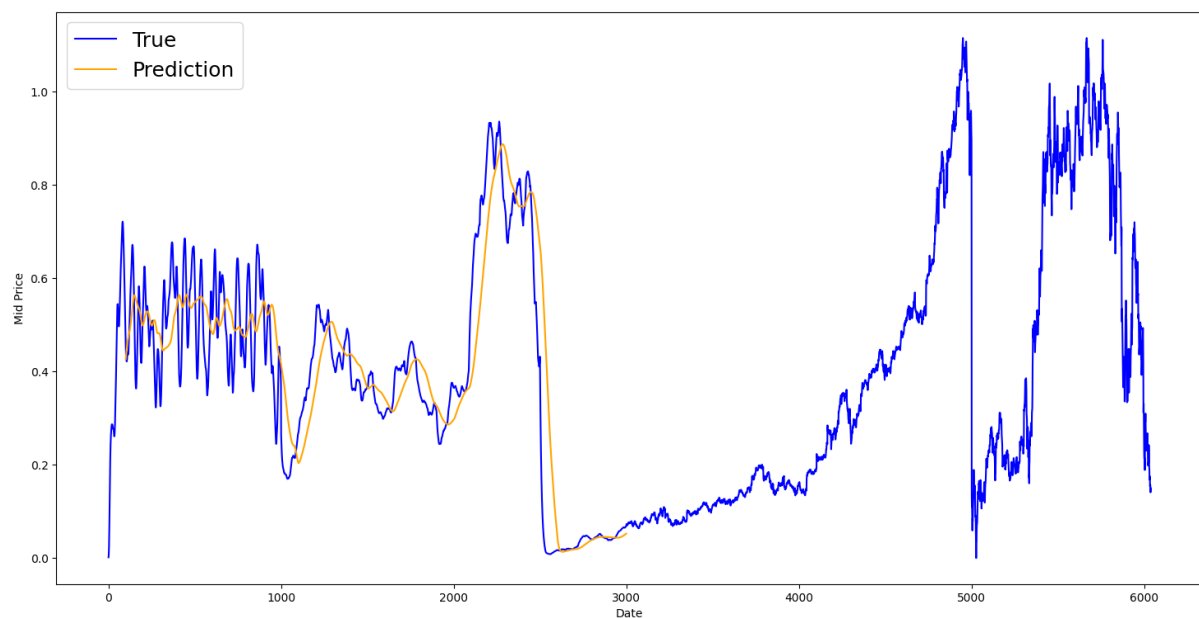
```
model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(train_data.shape[1],)),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])
```

Result 6: Comparison of metrics

- Logistic Regression metrics



- Logistic Regression test accuracy: 0.5078577399253845
- LSTM metrics



- LSTM MSE error for EMA averaging: 0.00010

CONCLUSIONS

- LSTM behaves better, with a MSE of less than 0.01
- Logistic regression achieves an accuracy of 50%
- While a more complex model is better at predicting movement, simple models can also be used.
- Datasets are the most important part of ML models

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