

# Amazon Stock Price Forecasting

## 1. Project Objective

Forecasting the next 5 business-day closing prices (one trading week) of Amazon stock, using time-series modeling techniques, and identify the most effective predictive approach.

## 2. Project Summary

This project explores multiple forecasting models including ARIMA, Facebook Prophet, LSTM, and XGBoost to predict Amazon's next-week closing stock prices. The dataset is enriched with time-series features such as lag values, rolling statistics, and technical indicators (RSI, MACD, CMF). Among the evaluated models, XGBoost delivered the most accurate results, with a forecasting error of no more than 1.08%, and was therefore selected for deployment in the final web application.

## 3. Dataset Overview

Based on historical Amazon stock data (1997-2021)

## 4. Tools and Techniques Used

- Languages: Python
- Libraries: pandas, NumPy, scikit-learn, XGBoost, matplotlib, seaborn, statsmodels, prophet, keras, joblib
- Environment: Jupyter Notebook
- Deployment: Flask API for real-time customer input and forecasting

## 5. Feature Engineering

- Lag features (lag\_1 to lag\_7)
- Rolling statistics (mean, std, min, max)
- Technical indicators: RSI, MACD, CMF

## 6. Models Compared

- ARIMA
- Facebook Prophet
- XGBoost
- LSTM

## 7. Evaluation Metrics

| Model   | Mean Absolute Error | Root Mean Squared Error |
|---------|---------------------|-------------------------|
| -----   | -----               | -----                   |
| ARIMA   | 3.85%               | 4.46%                   |
| Prophet | 2.07%               | 2.39%                   |
| XGBoost | 1.08%               | 1.44%                   |
| LSTM    | 1.44%               | 1.77%                   |

LSTM and XGBoost performed best overall. ARIMA and Prophet were useful as a baseline models but had lower performance.

## 8. Key Takeaways

- XGBoost outperforms deep learning and classical models significantly because it leverages: rich technical indicators, engineered lag/rolling features, simpler training and less data-requirement compared to LSTM
- LSTM Underperformed, but with careful tuning and more improvement could come closer to XGBoost
- Flask app successfully deployed for real-time customer input and forecasting

## 9. Resources

[GitHub Repo](#)

[Kaggle Notebook](#)

[Flask App Demo](#)