A Comparative Study of Forecasting Performance for Daily Closing Prices of the Top 10 S&P 500 Stocks Using Statistical and Deep Learning Methods

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ABSTRACT

This study evaluates the long term forecasting performance of the top 10 S&P 500 stocks using an 80/20 data split with a 286 day testing horizon. Results show that Double Exponential Smoothing (DES) is more accurate for stocks with clear trends, while deep learning models perform better for series with complex, non-linear patterns. The findings indicate that forecasting performance depends more on the structural characteristics of the time series than on model complexity.

INTRODUCTION

Forecasting highly volatile S&P 500 stock prices presents a significant challenge for extended periods. While statistical methods perform well with linear patterns, they often struggle with long term volatility and non-linearity. To address these limitations, deep learning models like Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM) have emerged as powerful tools for analyzing complex sequences. Consequently, this study compares the long term forecasting performance of the top 10 S&P 500 stocks between statistical methods and deep learning techniques, utilizing an 80/20 data split to predict 286 consecutive future values.

OBJECTIVES

To compare the long-term forecasting performance of models for the daily closing prices of the top 10 stocks in the S&P 500 index over a 286 day horizon.

MODELS

Statistical Methods

- Forecast Sheet
- Classical Decomposition with Trend
- Double Exponential Smoothing (DES)
- Box and Jenkins

Deep Learning Methods

- Recurrent Neural Network (RNN)
- Long Short-Term Memory (LSTM)

Double Exponential Smoothing (DES)

Level $L_t = \alpha y_t + (1+\alpha)(L_{t-1} + T_{t-}1)$

Trend $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$

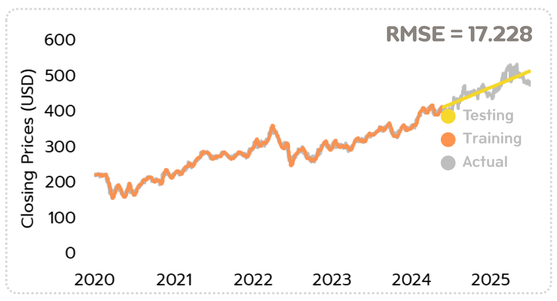
Forecast (p periods ahead) $\hat{y}_{t+p} = L_t + pT_t$

EVALUATION CRITERIA

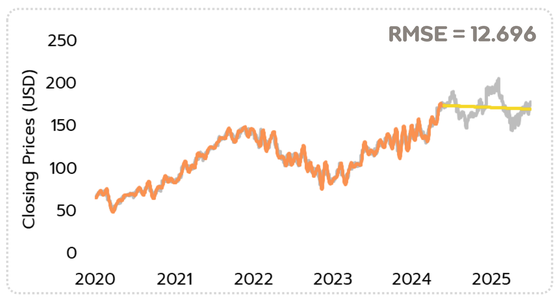
$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

**The model's robustness was tested against a 20% out of sample period, covering 286 future values to simulate a real world long term investment horizon.

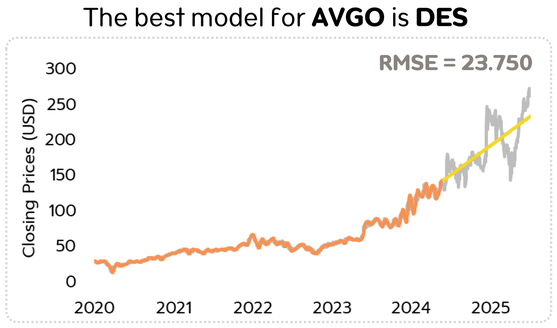
The best model for **BRK.B** is **DES**



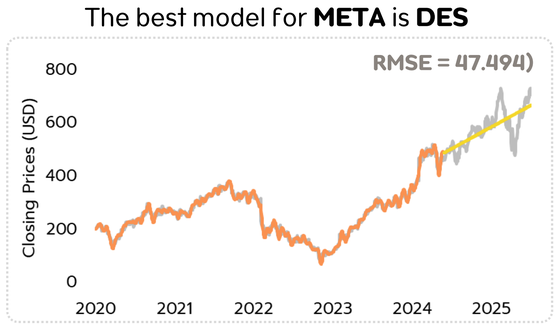
The best model for **GOOG** is **DES**



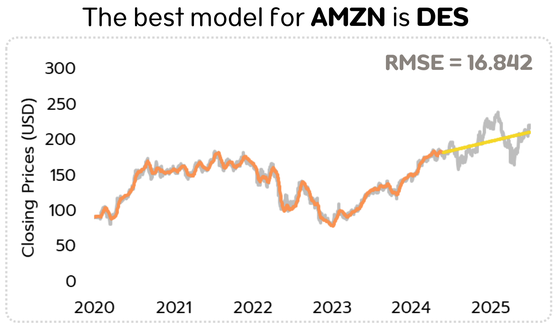
The best model for **AVGO** is **DES**



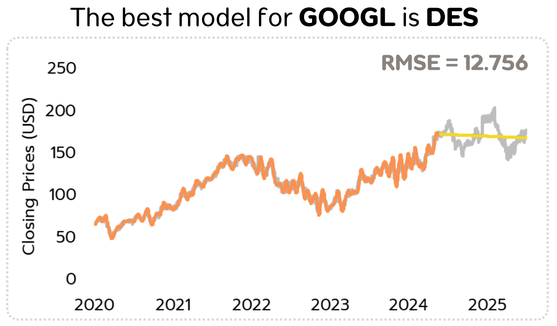
The best model for **META** is **DES**



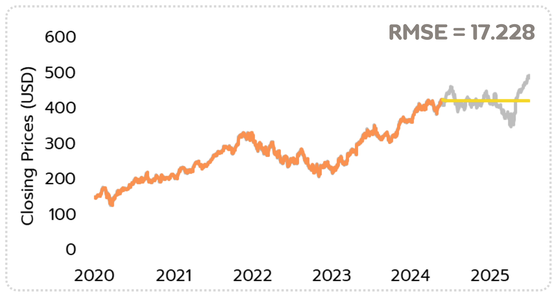
The best model for **AMZN** is **DES**



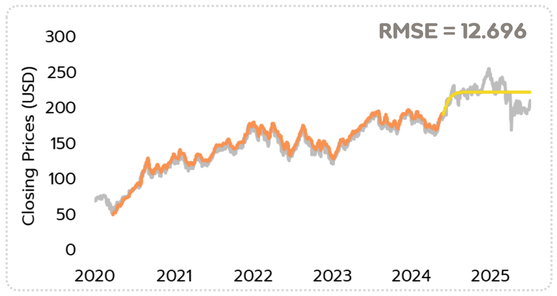
The best model for **GOOGL** is **DES**



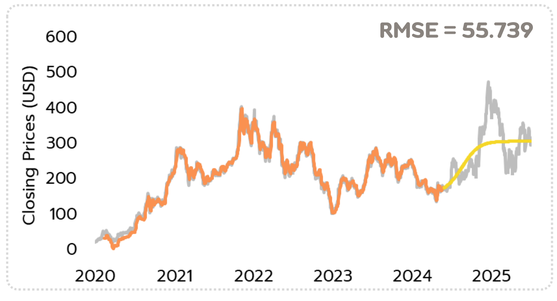
The best model for **MSFT** is **BOX-JENKINS**



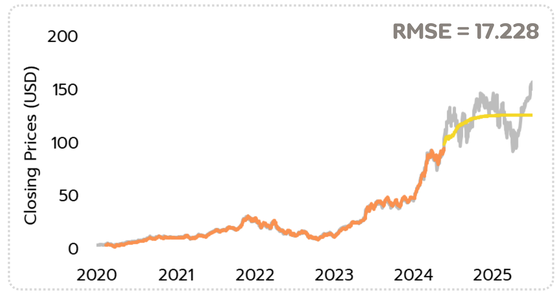
The best model for **AAPL** is **LSTM**



The best model for **TSLA** is **LSTM**



The best model for **NVDA** is **RNN**



CONCLUSION & DISCUSSION

Comparative results over a 286 day testing horizon (20% of the dataset) reveal that Double Exponential Smoothing provides the most accurate long-term forecasts for BRK.B, GOOG, AVGO, META, GOOGL, and AMZN, particularly for series with sustained trend components. In contrast, deep learning models outperform statistical methods for stocks with higher long term volatility and less distinct patterns, such as TSLA, AAPL, and NVDA. These findings suggest that long term predictive performance depends on the structural characteristics of the time series rather than model complexity alone.

Double Exponential Smoothing yielded the best results for the majority of stocks **exhibiting clear trends**, providing stability and mitigating overfitting during the extended 286 day period. Conversely, for highly volatile stocks, **deep learning** techniques demonstrated superior capability in **capturing complex**, **non-linear** relationships over the long term.

References

[1] Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. Journal of Applied Mathematics, 2014.

[2] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. Statistical and Machine Learning forecasting methods: Concerns and ways forward. PLOS ONE Year 2018. Page No. e0194889.