A comparison between LSTM and Facebook Prophet models: a financial forecasting case study

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Presentation structure

- Introduction
- LSTM model
- Facebook Prophet model
- Trading simulator
- Conclusions and future work

Introduction

- Machine Learning as a technical analysis tool
- LSTMs have been tested in time series and forecasting problems
- Facebook Prophet has less literature about it

Objectives

- Implementation and testing of an LSTM and a Facebook Prophet forecasters for S&P500 index
- Implementation of a trading simulator as backtesting system
- Performance comparison between models

LSTM model

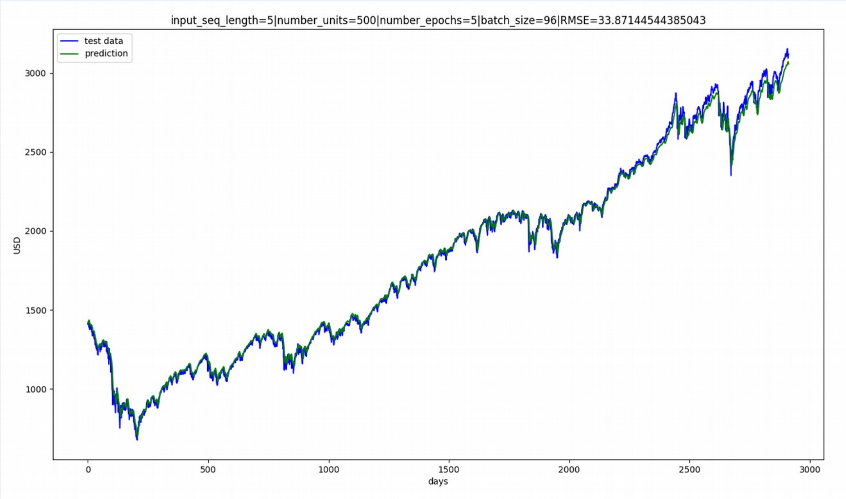
- Evolution of RNN cell that allows long and short term memory
- Hyperparameters tuned:
  - Architecture (layers)
  - Number of units
  - Batch size
  - Number of epochs
  - Input sequence length or timesteps
- Other hyperparameters: loss function, optimizer, dropout...

LSTM model

- Measure of the fitness of the model: RMSE
- MinMax normalization
- Grid search

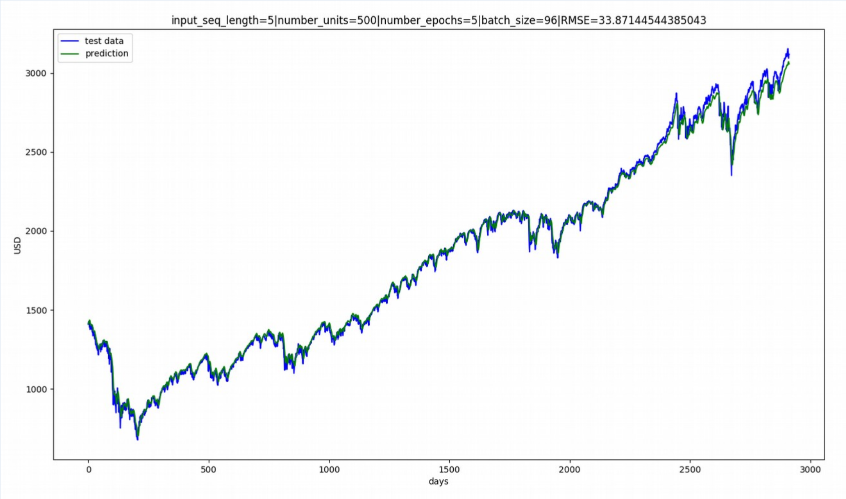
LSTM model

- Selected model:
  - Timesteps: 5
  - Number of hidden layers: 2
  - Number of units: 500
  - Number of epochs: 5
  - Batch size: 96
- RMSE = 33.87



LSTM model

- LSTM conclusions:
  - There is shift of ~5 observations which minimizes RMSE quite well and it's hard to avoid
  - Models with short and long windows into the past perform similarly
  - It benefits from limited training



Prophet model

- Based on the additive model
- Analyst in the loop
- Decomposable time series model: trend, seasonality and holidays

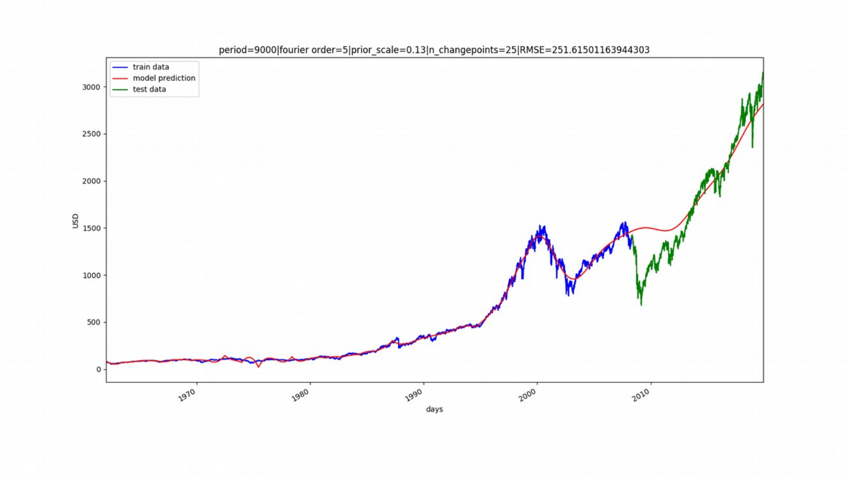
$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

Prophet model

- Hyperparameters tuned:
  - Period
  - Fourier order
  - Changepoints

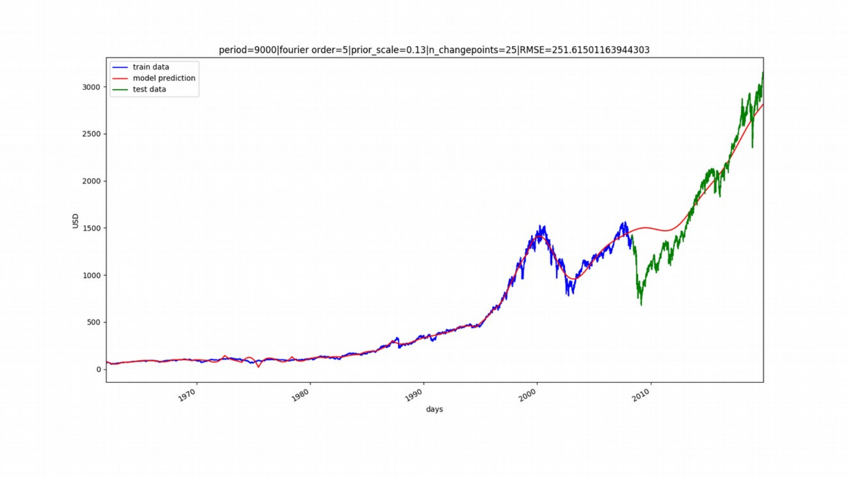
Prophet model

Original data

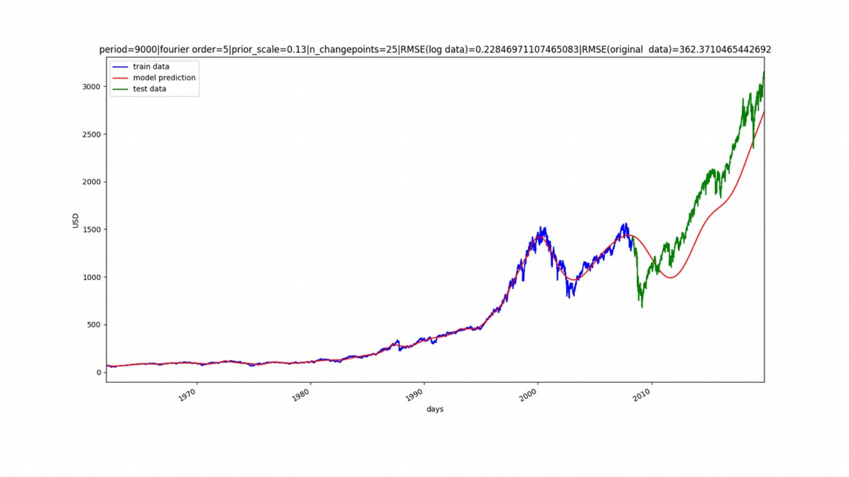


Prophet model

Original data



Logarithmic transformation



Prophet model

- Prophet conclusions:
  - Logarithmic transformation generates less robust models
  - Period affects the most to the final accuracy of the model
  - Low period seasonalities do not work well, neither alone nor combined
  - Fourier order is also determinant and a small change generates totally different models.

Trading simulator

- Backtesting platform: LSTM – Prophet comparison in a trade situation
- Performance analysis: RMSE – ROI

Trading simulator

- Auxiliary investing strategies implemented as benchmarks:
- ROI performances (2008-2019)

Model	ROI	Final capital
LSTM	1.11	21,061$
Facebook Prophet	0.73	17,308$
SMA (20 days)	0.69	16,930$
SMA (60 days)	0.36	13,643$
Buy and hold	1.19	21,961$
Random	-0.15	8,500$
N-last value (5 days)	1.29	22,900$

Conclusions

- LSTM model is quite robust and performs similarly to buy and hold strategy (better in some models)
- Prophet model has positive returns but it is not a solid forecaster:
  - Seasonalities poorly defined (period of 9000 days)
  - Lack of market knowledge to take full advantage of analyst in the loop approach
- Backtesting platform proved essential

Future work

- Better understanding of S&P500 index and its cyclic behaviour
- Deeper exploration of Prophet configurable hyperparameters
- Trading simulator improvements: live data and more sophisticated inversion mechanisms.

Gràcies per la vostra atenció