FOREX Time Series Prediction

Combining AI, Advanced Analytics, and Trading Strategies to Track Global Market Sentiment

IE 7860 Final Project

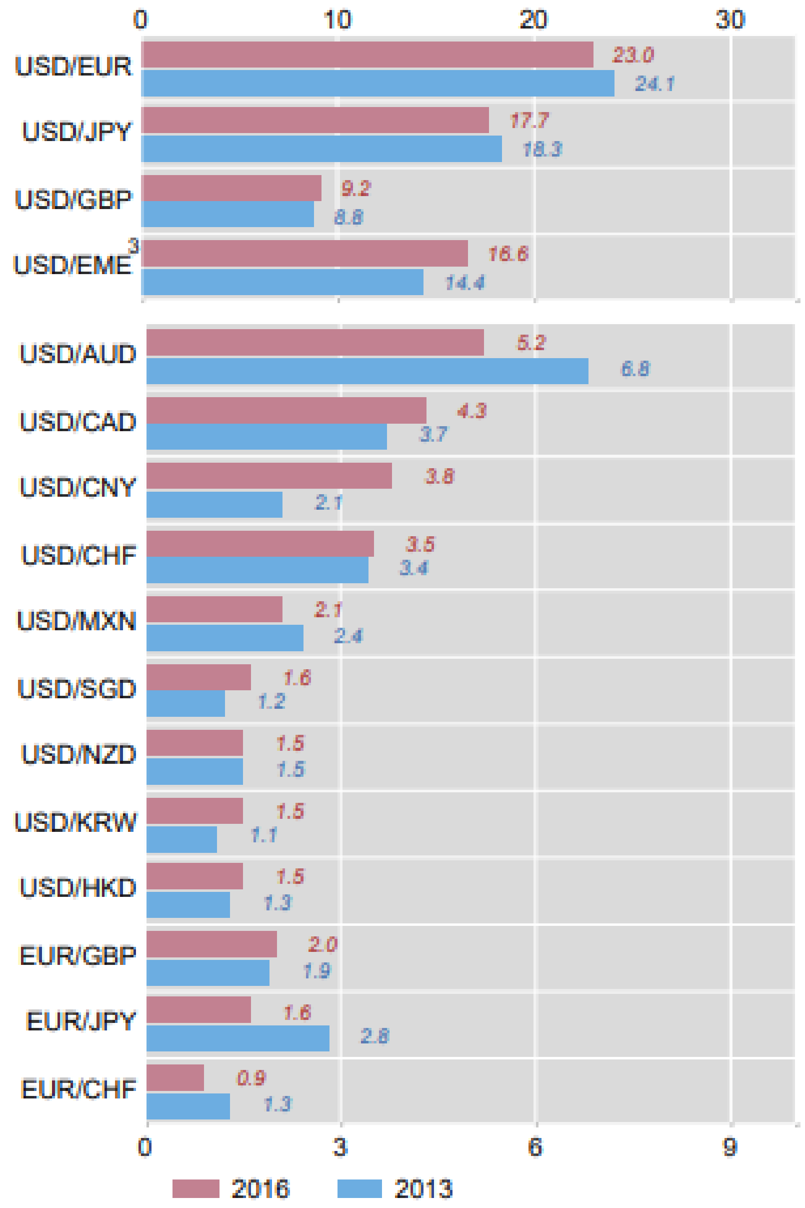
Alex Neuman and Joel Woznicki

Background

- Foreign Exchange trade volume exceeds $995B daily
  - Monthly volume ~$23T

- Top six currencies by volume,
  one “mid-major”,
  and one emerging:

1) Great Britain Pound Sterling
2) Euro
3) Japanese Yen
4) Canadian Dollar
5) Australian Dollar
6) Swiss Franc
7) South African Rand



Goal

For this project, we will Predict the price of currencies with respect to US Dollar over time using:

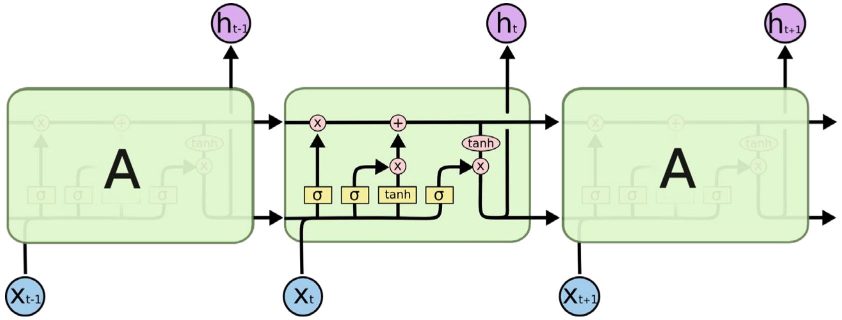
- Time Series Technical Analysis
- Key Indicator Fundamental Analysis

To model the optimal portfolio over a span of time, managing risk.

$$\text{Alpha} = r - R_f - \text{beta} * (R_m - R_f)$$

Methods

- LSTM (long short term memory) for each currency



Compare performance to:

- Naïve Model (price today = price at start of time period)
- Simple Windowed MLP (multi-layer perceptron)
- NARX (nonlinear autoregressive exogenous model)
- GARCH (generalized autoregressive conditional heteroscedastic)

Data

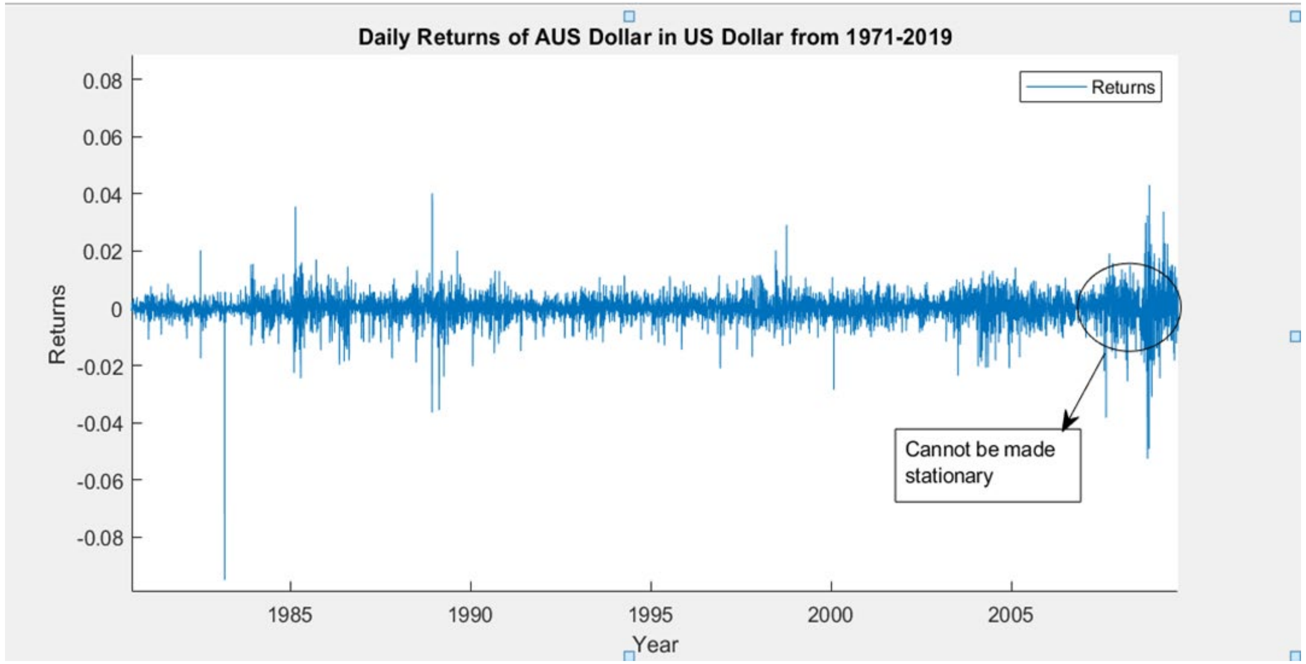
- FRED Exchange Rate
- World Bank Economic Data
- S&P 500 index daily close, gold, oil, and other commodities

All via Quandl

Benchmark Performance

GARCH(1,1) model was used to benchmark.

Predicting 7 periods (i.e. one week) lead to an MSE of .04.

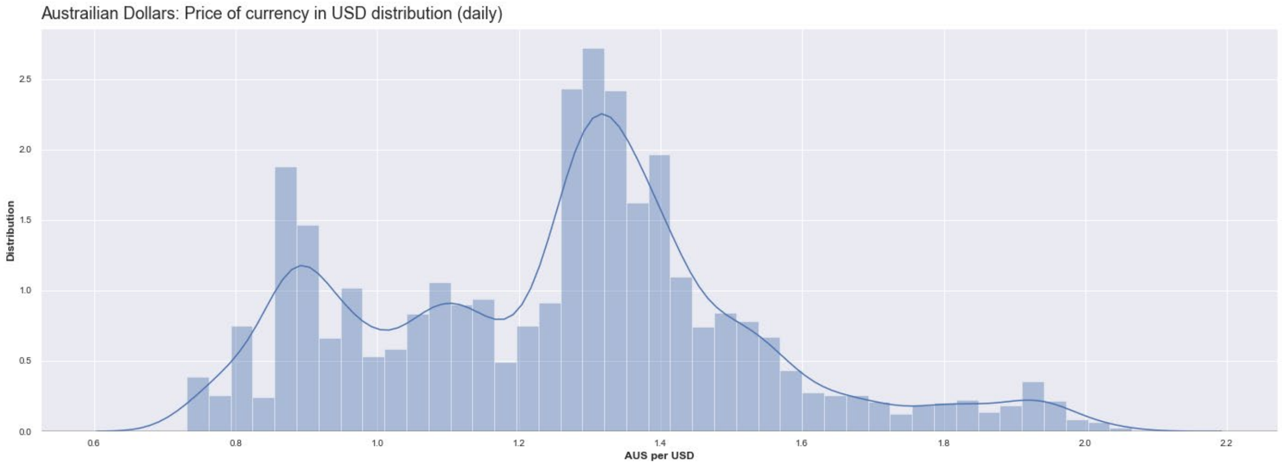


Note: Data could not be made stationary, requiring the use of a GARCH.

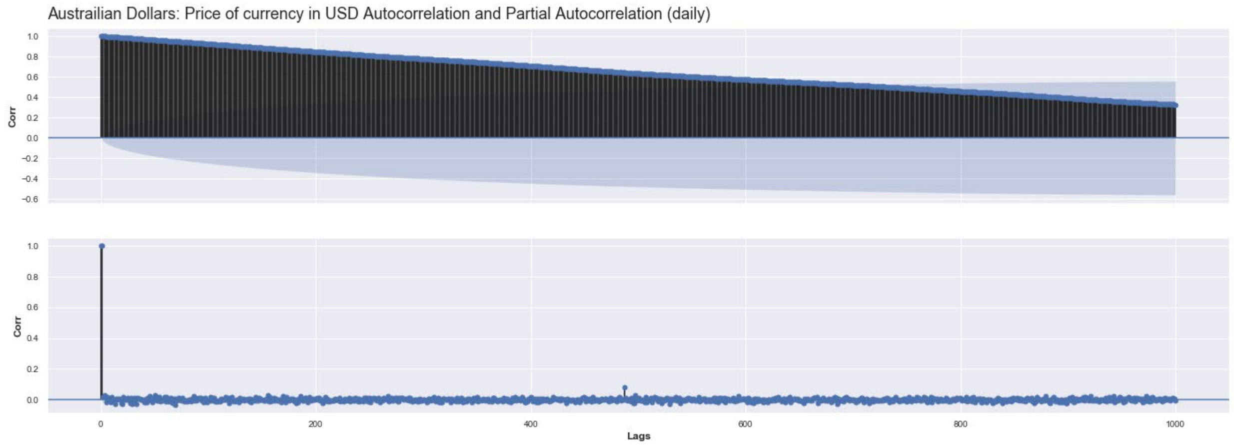
Technical Indicators

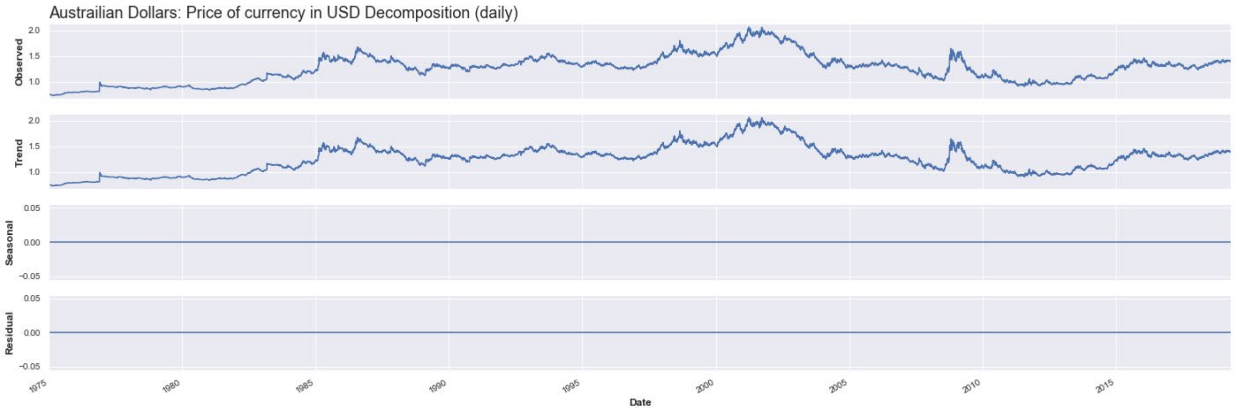
- Two classes of technical indicators were used; mean reverting and trend chasing.
- 8 were chosen and incorporated in the LSTM.
- Examples include Relative Strength Index, Exponential Moving Average, and Bollinger bands.

EDA (Australian Dollars)

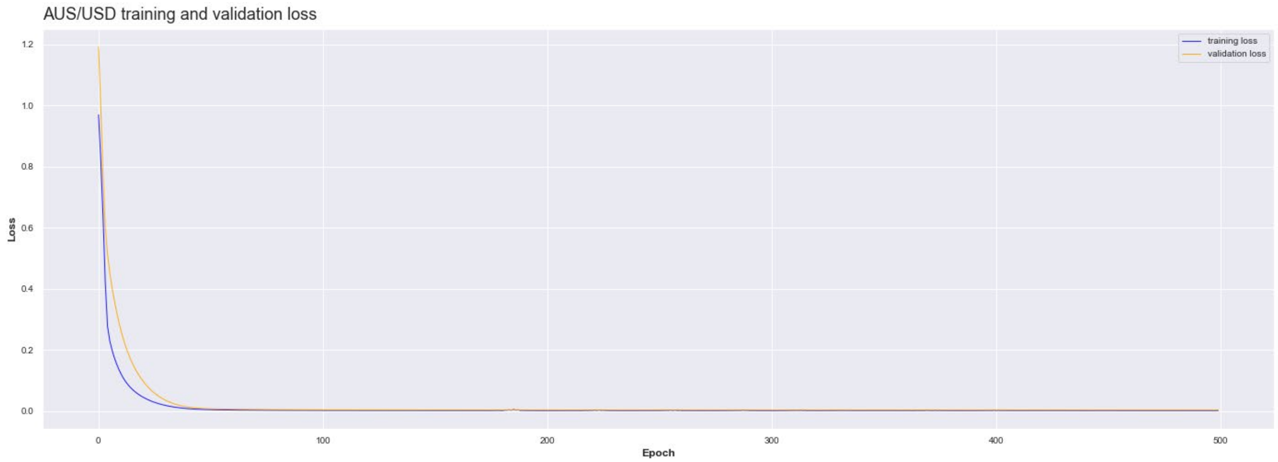


EDA (Australian Dollars)





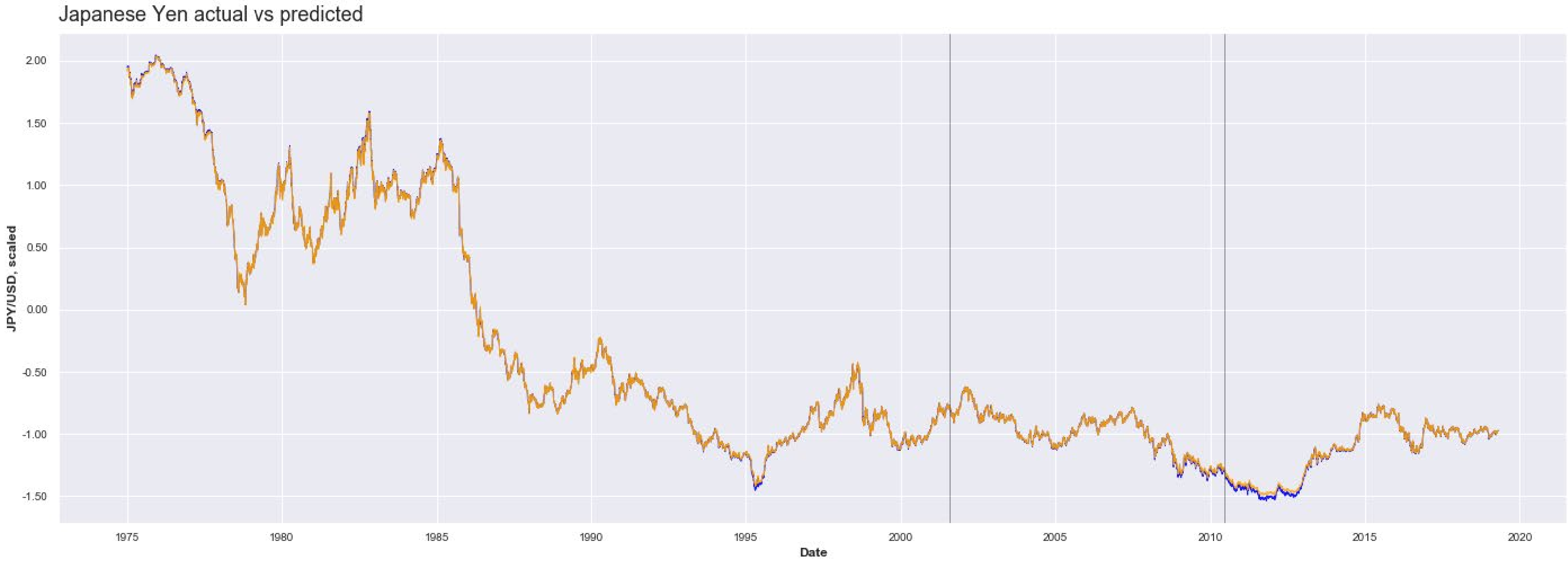
Results (Australian Dollars)




```
Predicting AUS, daily


Data prepared:
    Number of Features: 1
    Number of Outputs: 1
    Lookback 365 time steps

Model:
    1-layer LSTM with feed-forward linear output from 5 hidden nodes.

Training Model for 500 epochs - start time: 2019-04-26 11:53:40.902413
    Optimized using Adam, learning rate: 0.001
    Loss calculated with MSE

Epoch 0, Train Loss: 0.9699176546924237, Validation Loss: 1.1912934347055852
Epoch 100, Train Loss: 0.05352278394430841, Validation Loss: 0.08739411983279384
Epoch 200, Train Loss: 0.02763625380925638, Validation Loss: 0.0453128700862033
Epoch 300, Train Loss: 0.018880179861221334, Validation Loss: 0.031064881308909022
Epoch 400, Train Loss: 0.014479847070219935, Validation Loss: 0.023925228256734134
Epoch 499, Train Loss: 0.01182898135133669, Validation Loss: 0.01966585660901425
Training completed at 2019-04-26 12:04:23.823834, taking: 642.921421 seconds. Test error: 0.0009672340755868289 (vs baseline:
```

Results (Australian Dollars)

Results (Japanese Yen)



Next Steps

- Bayesian hyperparameter optimization
  - To beat the naïve model with LSTM
- Multi-step LSTM
- Portfolio optimization