Classical Machine Learning vs. Deep Learning Second Elizabethan Age Financial Portraiture Post-Europe: Forecasting the GBP/USD Exchange Rate in the Era of Brexit

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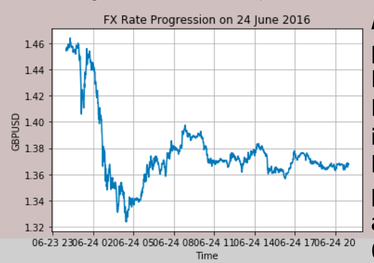
"Famous have been the reigns of our queens. Some of the greatest periods in our history unfolded under their spectre". (Winston Churchill, 1952)

Introduction and Data:

The British Pound (ISO Code: GBP) is the world's oldest currency still in use. It has featured its longest serving monarch, **Queen Elizabeth II** in its banknotes for decades. Taking inspiration from the monarch it features on the currency, **the British Pound is an acclaimed symbol of financial stability**. Representing the challenges Britain has faced, the value of the Pound and its volatility has been **a reliable barometer of Britain's political and economic state.** Of all the political and economic issues that impacted the British Pound, **Britain's relationship with Europe** stands alone as the most significant. In the past three decades, biggest moves in the GBPUSD exchange rate occurred over Europe. On June 24th 2016, **the GBPUSD exchange rate moved as much as 10% intraday following the Brexit vote to leave the European Union,** declining 8% on the day.

The British Pound is in the news as a barometer for the impact of the **Brexit** process for the United Kingdom. Here is the intraday data for the GBPUSD exchange rate data from that day:



As Britain heads to its 5th public vote, 3rd General Election with its 3rd Prime Minister in 5 years, we identify the machine learning model that can provide the best one-step ahead forecast of the GBP/USD exchange rate in high-frequency space

Keep Calm: Alternative High Frequency Data

For this project, we are **NOT using daily time series.** Instead, we are using exciting **alternative financial data,** namely GBP/USD tick data available in milliseconds from Dukascopy, a Swiss broker. We use the intraday data from the volatile day following the Brexit referendum. **Our data has 254,111 observations**

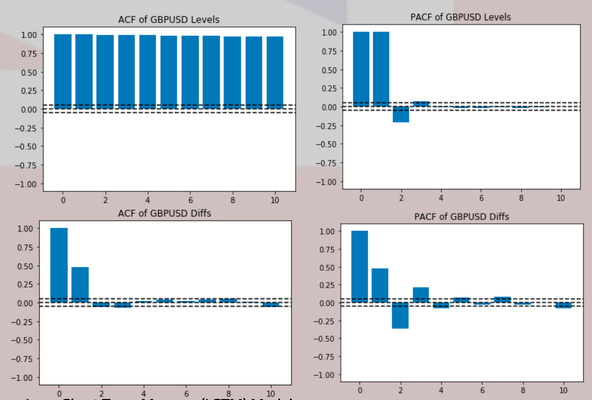
And Carry On: Data Preprocessing

Not every millisecond has a GBP/USD quote necessarily and time intervals do not have the same amount of quotes. To allow for representative time intervals with sufficient number of quotes, we sample **the Open, High, Low and Close (OHLC) of 30 second intervals** and take their average, In our project, we fit machine learning and deep learning models to GBP/USD exchange rate data in 30 second intervals to predict the one-step ahead forecast of the next 30 second interval 's GBP/USD exchange rate.

Methodology: ARIMA, LSTMs, CNN, and Hybrid Models

Autoregressive Integrated Moving Average (ARIMA) Models:.

- ARIMA(p,d,q) models estimate the relationship between a variable Y_t, its lags, eg. Y_{t-1}, Y_{t-2}, and the lags of the forecast errors, eg. $\varepsilon_{t-1}, \varepsilon_{t-2}$
- The ARIMA **hyperparameters** (p,d,q) are determined by the significant lags in the **Autocorrelation (ACF)** and **Partial Autocorrelation (PACF) functions** of the variable Y_t and, where there are clear trends, the difference of Y_t, i.e. diff(Y_t), provided below.
- We choose ARIMA (1,1,1) model to predict the one-step ahead forecast of the GBPUSD exchange rate in 30 second intervals. ARIMA (1,1,1) model is written as: $Y_t - Y_{t-1} = \varphi_1 (Y_{t-1} - Y_{t-2}) + \varepsilon_t + \theta_1 (\varepsilon_{t-1})$



Long Short Term Memory (LSTM) Models:
We apply:

- **Vanilla LSTMs:** Single Layer LSTMs, 5-50 Neurons, ReLU activations
- **Stacked LSTMs** : Multi-Layer LSTMs, 50 Neurons, ReLU activations
- **Bidirectional LSTMs:**

Convolutional Neural Networks:

- Mapping a sequence of inputs (lags) to outputs to find patterns
- eg [1.3099. 1.3087. 1.3095] mapped to the 4th
- value in the sequence [1.3091]

Multi-layer Perceptrons (MLPs):

- Standard feed-forward neural networks

Hybrid Long Short Term Memory (LSTM) – Convolutional LSTM Models

- CNN-LSTMs
- Conv LSTMs

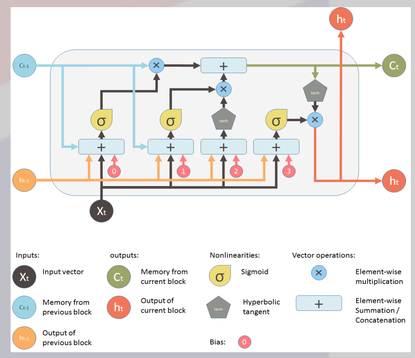
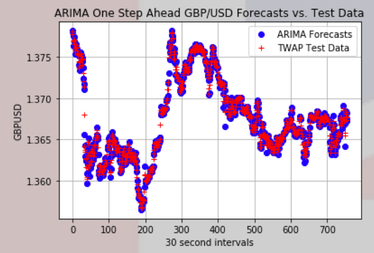
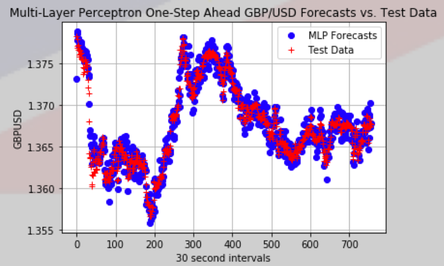


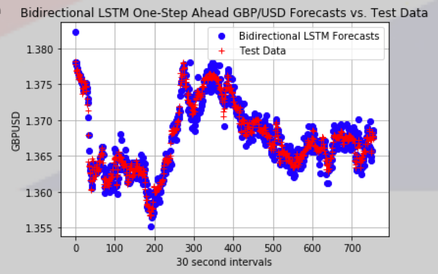
Diagram source: https://medium.com/ mlreview/understanding-lstm-and-its-diagrams-37e2f46f1714

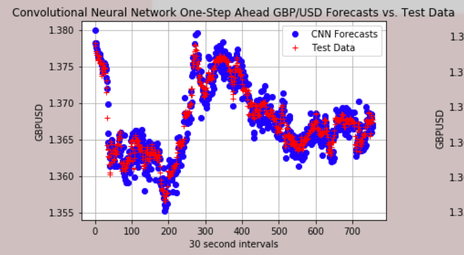
Results: Clear Outperformance by ARIMA, MLP outperforms DL models, Hybrids Are Greater than the Sum of their Parts

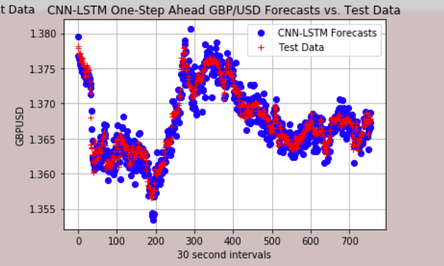
Looking at the performance on the test set, we observe that **ARIMA outperforms DL methods. MLP outperforms other DL methods**. We used **walk-forward validation** for our testing as we are interested in the one-step ahead forecasts and time series forecasts far out into the future leveraging other time series forecasts are not reliable. The sequential nature of the time series has to be preserved, and was in our testing.

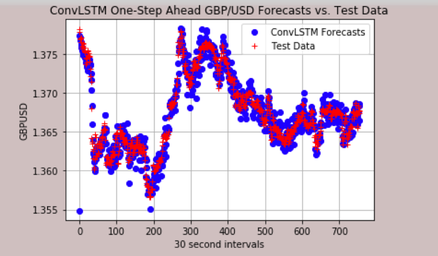


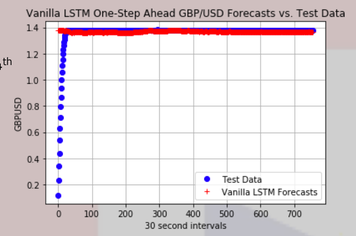












Results: RMSE and MAPE Tables

Model	RMSE ($)	MAPE (%)
ARIMA (1,1,1)	0.0004627	0.0226326
MLP	0.0011496	0.0639537
CNN	0.0015240	0.0870874
CNN LSTM	0.0016940	0.0970920
Conv LSTM	0.0015676	0.0771198
Bidirectional LSTM	0.0013143	0.0742361

God Save the Queen (and Her Prime Ministers): Next Steps

- Perhaps in the world's oldest democracy, it is an interesting coincidence that the **models that outperform on the most volatile day the British Pound** has seen in more than a decade, are a) a **classical** machine learning ARIMA model, **and** later followed by b) and **bidirectional LSTM** model **hybrid** Conv-LSTM . It provides an inescapable allegory, underlining the importance of democratic and pragmatic tradition as well as agreement on both sides of the British political spectrum to resolve Brexit. It was not lack of crises that made Britain a steady, stable democracy, but it was how it has overcame the crises it faced that has given rise to its stability.
- For new research, we would like to explore
- For next steps, we will explore:
  - Rolling window walk forward validation, keeping the number of training samples same
  - ARIMA models with the AR lags greater than 1 to draw a link between the number of steps in the deep learning models and
  - A hybrid ConvLSTM-ARIMA model to explore room for reduction in the residuals
  - Running these algorithms on a week of data, to learn more patterns in the preceding days' intraday activity. Overnight gap risks/discontinuity in data would be a challenge.

Last but not least: Introduce variables that take into account the political leadership/analyses of the time. Margaret Thatcher successfully forecasted the problems with the Euro as well as the political union and overreach at the supranational level of Europe in the 1980s. In the stories our machine learning models tell, we search for these clues that have shaped Britain, its currency and the wider world.