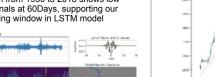


Exploration of predicting power of ARIMA, Facebook Prophet and LSTM on time series

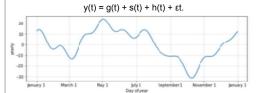
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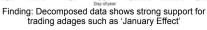
Data Revisit

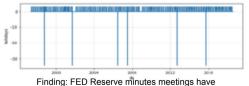
Wavelet heat spectrum from 1950 to 2018 shows low frequency cyclical signals at 60Days, supporting our choice of 60D sliding window in LSTM model



Facebook Prophet







significant impact on market movements



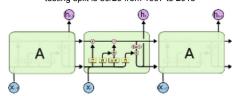
De-noised Data

-CS230 2018 Presentation Link: https://youtu.be/CmsFhF9ROns



LSTM

Log return of de-noised price data was fed into LSTM. The frame includes two hidden layers, whose dimensions are 256*128. A moving 60D window is used to predict the next 5D price trend. Dropout rate is 0.1. Epoch 200. Training and testing split is 80/20 from 1997 to 2018



Results - LSTM comparisons



	Training Error	Testing Error	Testing Period Performance
FbProphet	NAN	7.49E-06	-2.29%
LSTM w/o Filter	9.62E-08	7.76E-06	-10.98%
LSTM w/ Wavelet Filter	1.58E-04	8.46E-06	10.55%
LSTM w/ Kalman Filter	1.62E-04	7.74E-06	25.93%

Data Description

Goal and Models

We obtained SP500 historical daily market prices from Yahoo Finance ranging from 1950 to present, and FED Reserve minutes schedule from Bloomberg terminal from 1997 to 2020. We applied Daubechies wavelet and Kalman filter to de-noise the daily adjusted closing prices and derived daily log returns as stationary inputs to feed LSTM.

The goal of our project is to predict the future price movement using historical information. We used daily SPY data and Fed Reserve minutes schedule to test three models including **ARIMA**, **Facebook Prophet**, and **LSTM**. Based on errors and trading performance, we found LSTM superior.

Future

Expand data scope - More securities Expand dimension - Multi features

Reference

[1] Colah's Blog, "Understanding LSTM Networks", 2015 [2] S.Taylor, B.Letham, "Forecasting at Scale", 2017 [3] R.Nau, Introduction to ARIMA: Nonseasonal Models, Available: https://people.duke.edu/~rnau/411arim.htm

ARIMA (p,d,q)

$$\hat{y}_t \ = \ \mu + \varphi_1 \ y_{t\text{--}1} + \ldots + \varphi_p \ y_{t\text{--}p} - \theta_1 e_{t\text{--}1} - \ldots - \theta_q e_{t\text{--}q}$$

We tried different parameters to achieve stationarity of input and accuracy in prediction, however the results were not satisfying. Possible reason could be the changing trend in price data.

