MACHINE LEARNING FOR FOREX FORECASTING

Kevin Jeswani WCD Bootcamp, 2022 (Part-Time)

Overview

- ML in quantitative finance
- Data gathering, cleaning
- EDA
- Classical forecasting
- Boosted Trees
- RNN LSTM

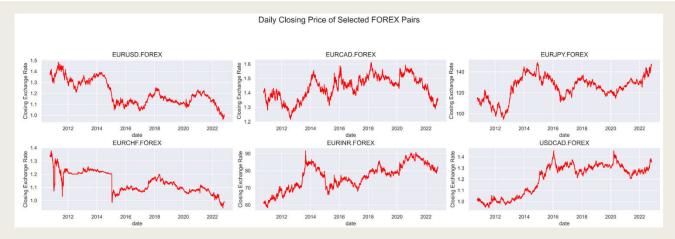
Background/Motivation

- Technical analysis (moving averages, momentum indicators, etc.) and classical indicators
- Evolving into applied ML, and deep learning (DL) as a bare minimum
- Stock price prediction a common problem, akin to demand forecasting
- DL / Reinforcement learning (RL) "game-ification"
- "Side-hustle-ification" now enabled by many new cheap platforms (ex. Alpaca, QuantConnect)
- FOREX: interest in economic/geopolitics (implement geopolitical news trading?)
 - Less susceptible to speculation, more stable, cyclical
 - Goal: find a way to anchor forecasting to the best technical indicators i.e.,
 mimic the best practices of a professional trader

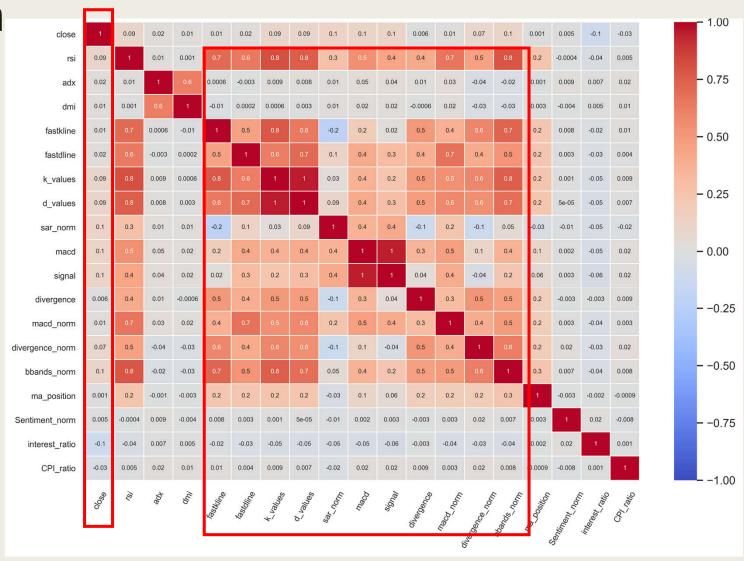
Workflow

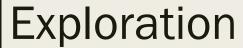


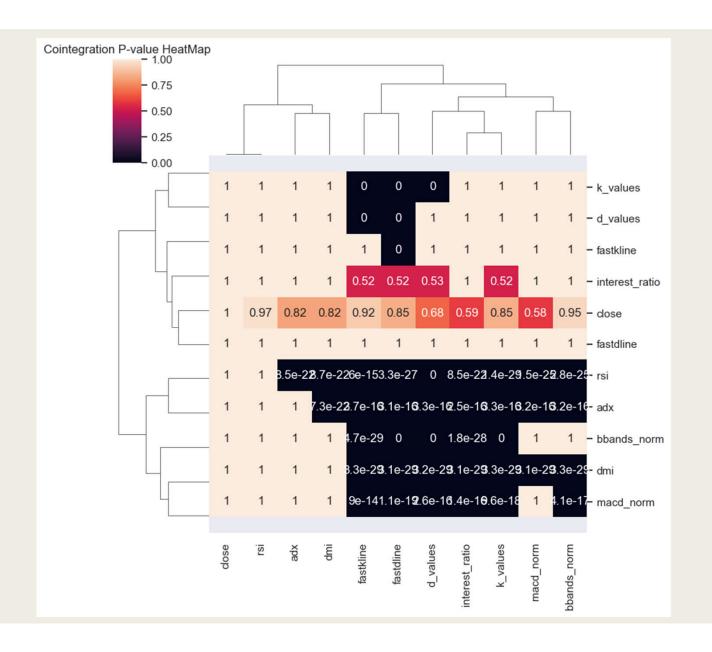
Data Gathering

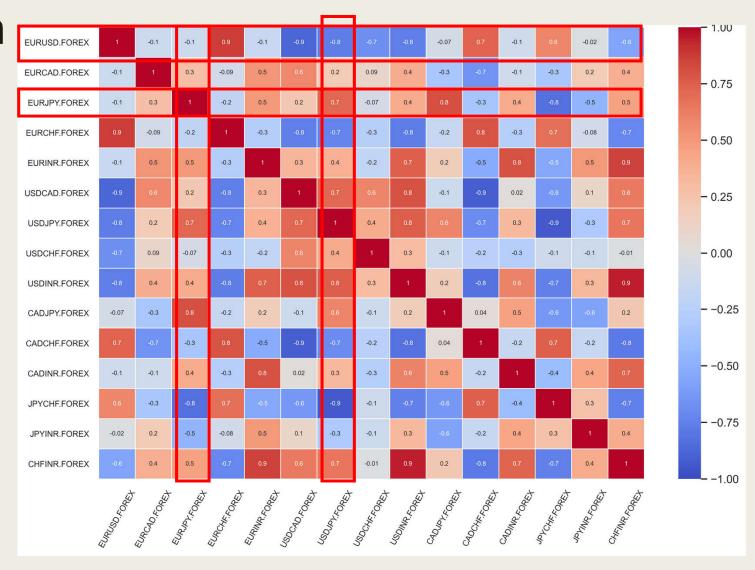


- EOD HD API
- Initially: stocks options data
- 15 FOREX pairs 1min for 12 years: EUR USD JPY INR CAD CHF
 - resampled daily + 15min
- EOD Technical Indicators (RSI, moving avgs., MACD, ADX, DMI,...etc = 11)
- News Sentiment Indicator
- Interest & CPI
- Standard light cleaning and processing
 - Normalization of 5 TS
 - 9 Moving average TS into one moving average buy/sell signal TS
 - Interest & CPI ratio





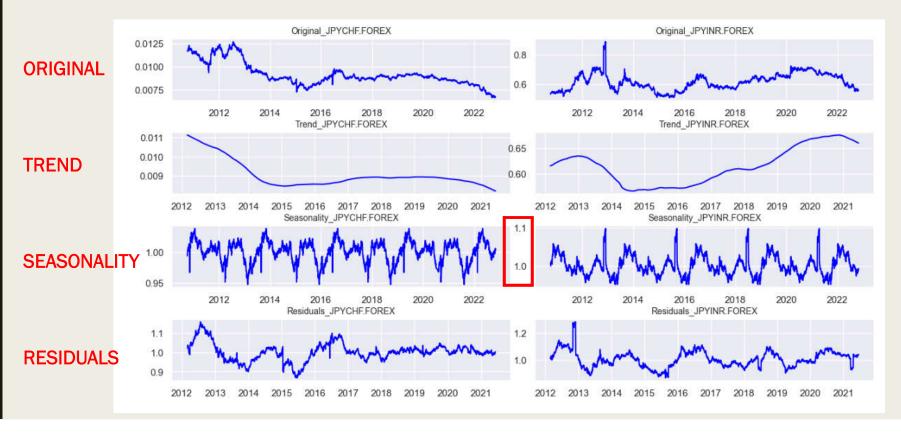




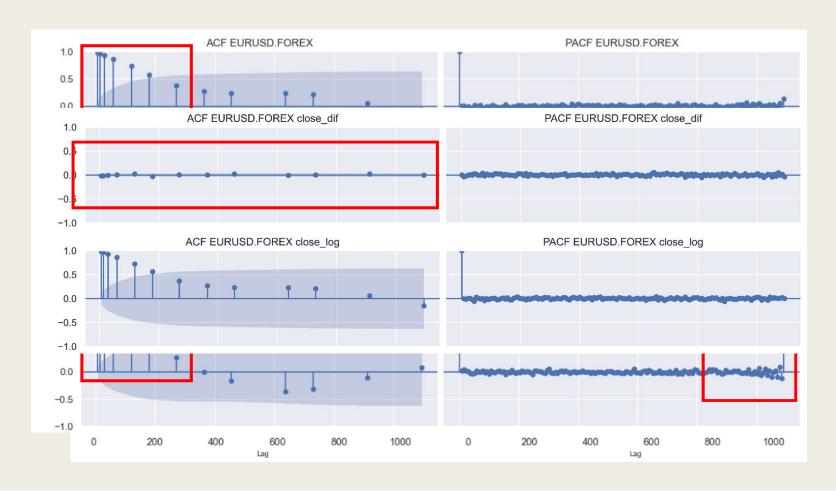
- Stationary vs. non-stationary
- KPSS statistic & AD Fuller test recursive testing of lags for each time series
 - Lags = 7 365 days (smaller discretization)+ 1-3 years (larger disc.) vs. default suggested lag values in range of n=30
 - Mostly = stochastic trend only
 - = difference-stationary

		Stationary?		
	min p-val ADF	lag ADF	max p-val KPSS	lag KPSS
EURUSD.FOREX	0.101	180	0.095	638
EURCAD.FOREX	0.363	180	0.049	730
EURJPY.FOREX	0.085	270	0.100	270
EURCHF.FOREX	0.004	14	0.100	180

- Long periods 1-3 years
- Multiplicative vs. additive
- +/-5-12% seasonal effect using 1-3 year periods



■ ACF/PCF



ML: VARMAX

- Multivariate + exogenous variables vectorized analysis classical model
- Requires stationarity* but tested both differenced and undifferenced (poor performance)
- Endogenous: (close, close differenced +7d)
- Exogenous: (rsi, dmi, macd_norm, ...3 to 7 total indicators) little affect on model
- \blacksquare p and q = (0,3); & trend (none,constant, linear, polynomial)
- No exog var weights removing completely had little effect

For all models generally used:

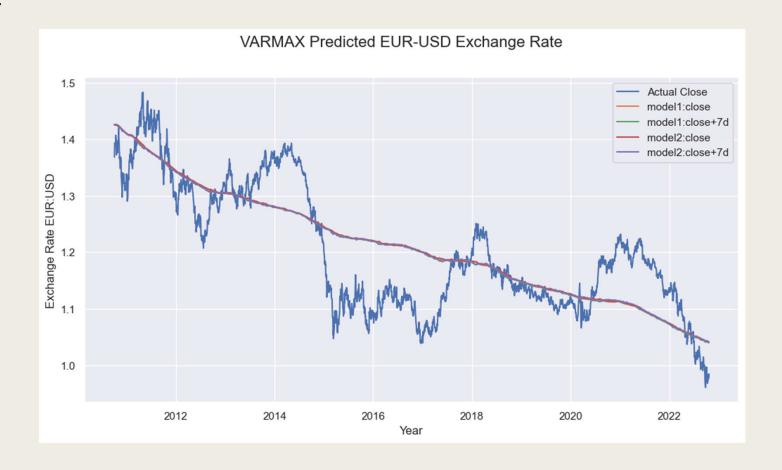
■ Training: 2010-Oct to 2022-May

■ Testing: 2022-May to 2022-Nov

ML: VARMAX

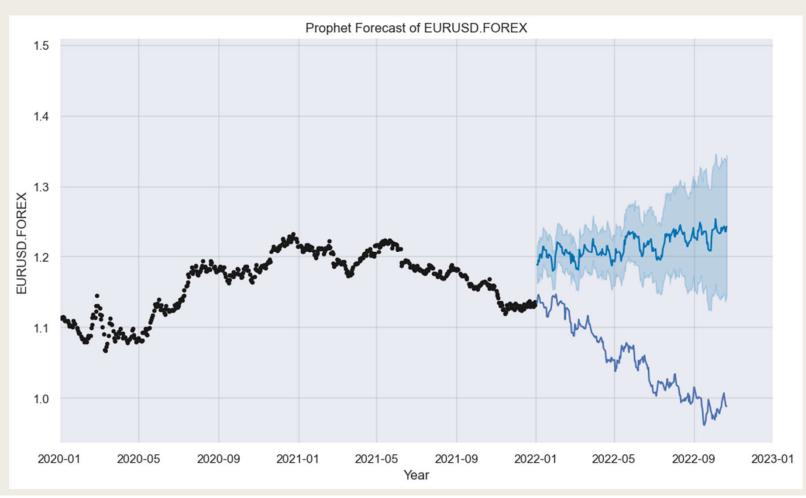
■ MAE: 0.057

R2: 0.6

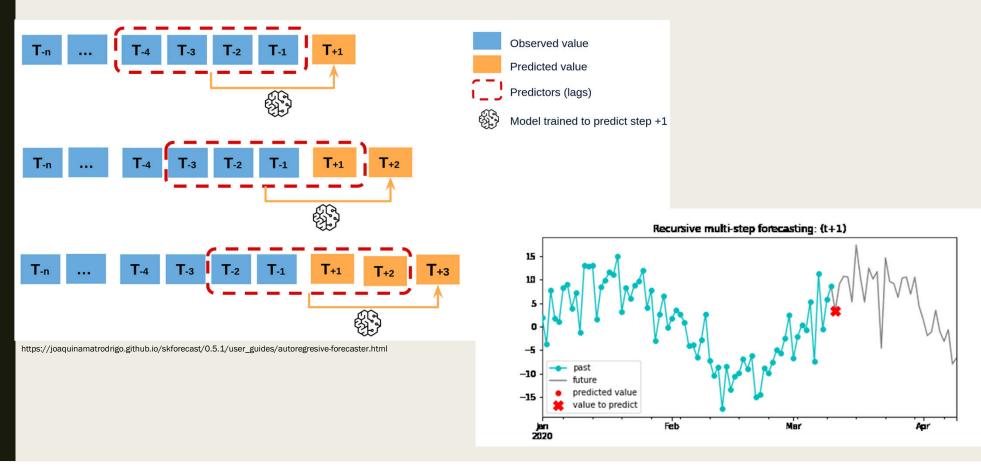


FB Prophet

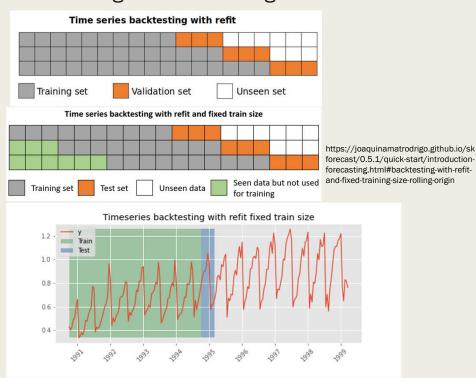
■ Made for business time series (demand forecasting) – strongly relies on seasonal effects

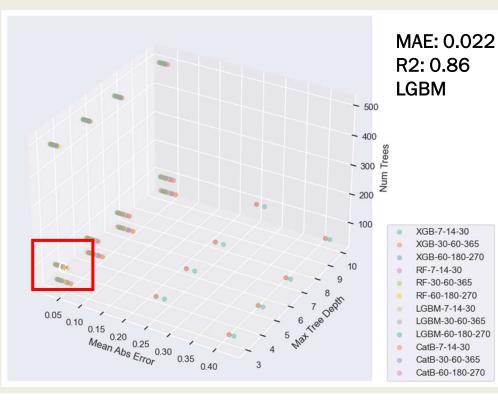


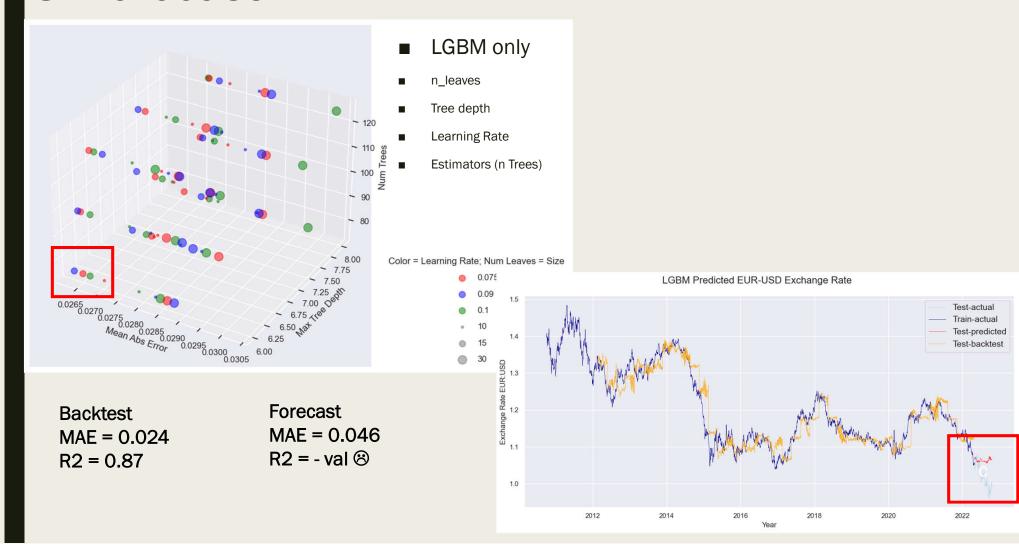
- Recursive multi-step forecasting keeps relationship of lags to current step in tact
- Creates matrix for us with sklearn

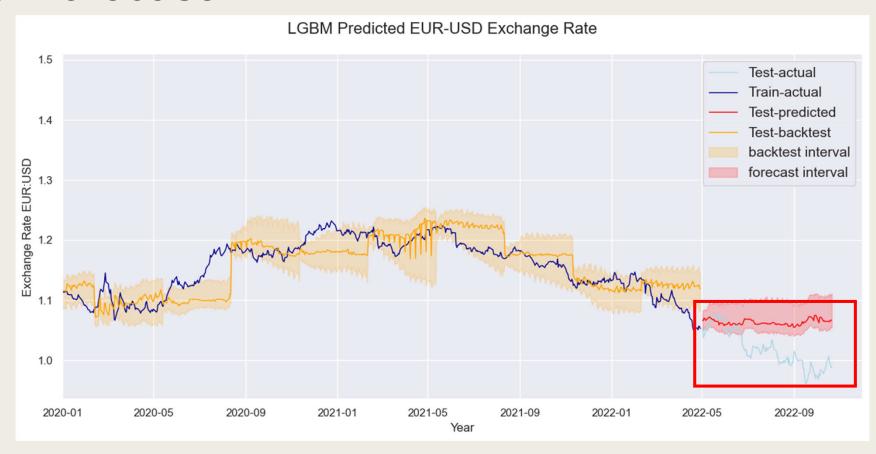


- Embedded Cross-validation for forecaster
- GridSearch CV hyperparameter tuning for each sklearn model
- XGBoost vs. RandomForest vs. CatBoost vs. LGBoost
- Exogenous: including all available indicators









Lags in model = 95% of feature importance

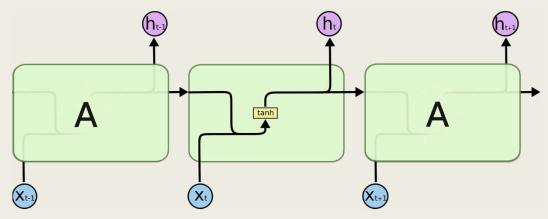
LSTM - Keras

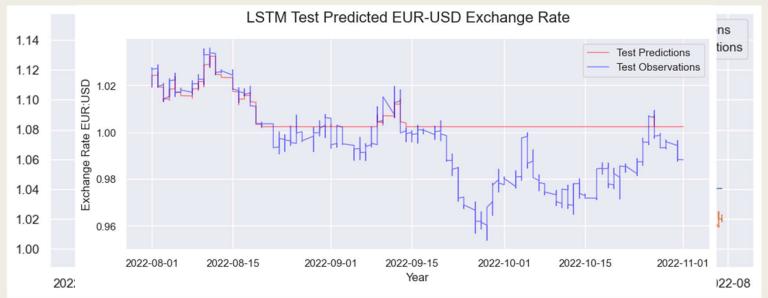
- RNN
- Exog = [7,14,30]d lags

Exponential Moving Averages [50, 100,200]d lags

MAE: 0.012

R2: 0.14





Conclusion

- Tested wide array of forecasting models'
- Technical indicators not absorbed by models
- Combination of LSTM: short term price prediction
- Try to refine boosted trees: Run several exchange pairs exog. and multi-var endog.
- LSTM + other models
- Voting
- Deep Reinforcement Learning