Time Series Forecasting for Metaverse Stocks

Group 3:
Charlene Yu, Kaicheng Zhang,
Sherry Zha, Wanxuan Zhang

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Why Metaverse

Business Case and Problem Statement

Business Case

Metaverse has become a hot topic in daily conversations in the last decade. After Neal Stephenson created the term in his fiction Snow Crash back in 1992, the development of metaverse has undergone several important milestones. Giant tech companies like Meta, Google, Microsoft were either developing their own AR/VR/XR products or procuring specialized companies doing relevant business all aiming to secure their seats in the metaverse ecosystem.

Problem Statement

Stock price indicates a company's market value and reflects investor perception of the company's ability to grow its profits in the future. Our goals are to understand and interpret the association between large Metaverse companies' stock movements and major events in the industry. We will develop time series models using historical data to capture Meta's stock movement.

We have included a series of events: 30 events related to Meta(i. e., Facebook Connect, shareholder/earning meetings), 9 industry events related to Metaverse. We hope to see if the events, along with trading volume and interest rate as exogenous variables, can better capture meta's stock price movement in the past 5 years.

Key Events of Metaverse from 2017 until now

2017
- Fortnite was released
- CryptoKitties becomes first widely recognized blockchain game

2018
- Animoca Brands acquires Sandbox
- Axie Infinity released (blockchain based war game)
- Interactive episode Bandersnatch (from Netflix)

2019
- Google AR function released

2020
- Covid-19 leads to remote routine

2021
- Microsoft unveils Mesh
- Facebook changes name to Meta

2022
- Facebook reported a rare decline in its fourth quarter profit

Hypothesis

We can predict Meta's future stock price given historical data using time series models.

Assumptions

- We include events/holidays, interest rate and trading volume as regressors because they may have an impact on stock price.
- If events have an impact on stock prices, it will be effective on the same day.
- Each model's assumptions will be covered in later slides.

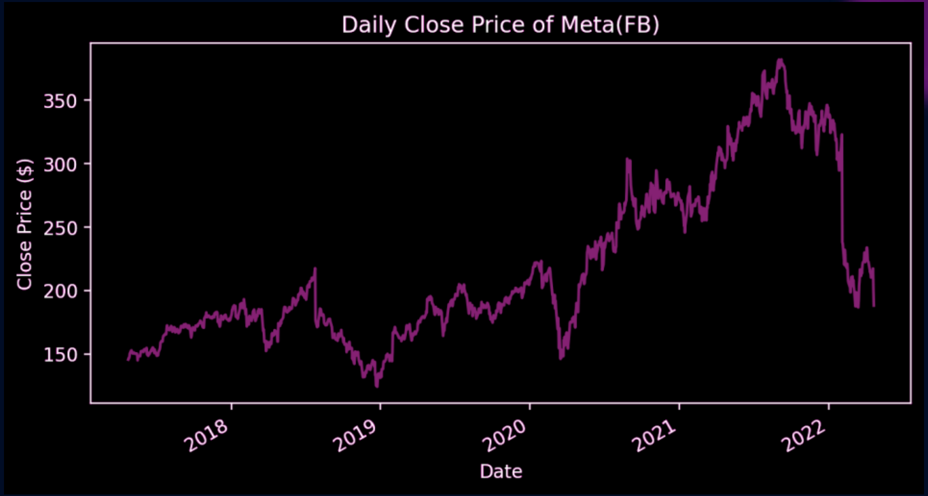
02
Data Description

Processing and Exploratory Data Analysis

Our Focus: Meta (FB)

Response variable: daily close prices of Meta
Timespan: 2017/4/24 - 2022/4/21
No data on weekends or NYSE holidays

	Close Price	Volume (million)
count	1259	1259
mean	219.7453	21.4627
std	64.3306	14.0008
min	124.0600	6.0463
max	382.1800	188.1199



Stationary Tests

Meta (FB) daily close price

Difference period: 1

alpha = 0.05

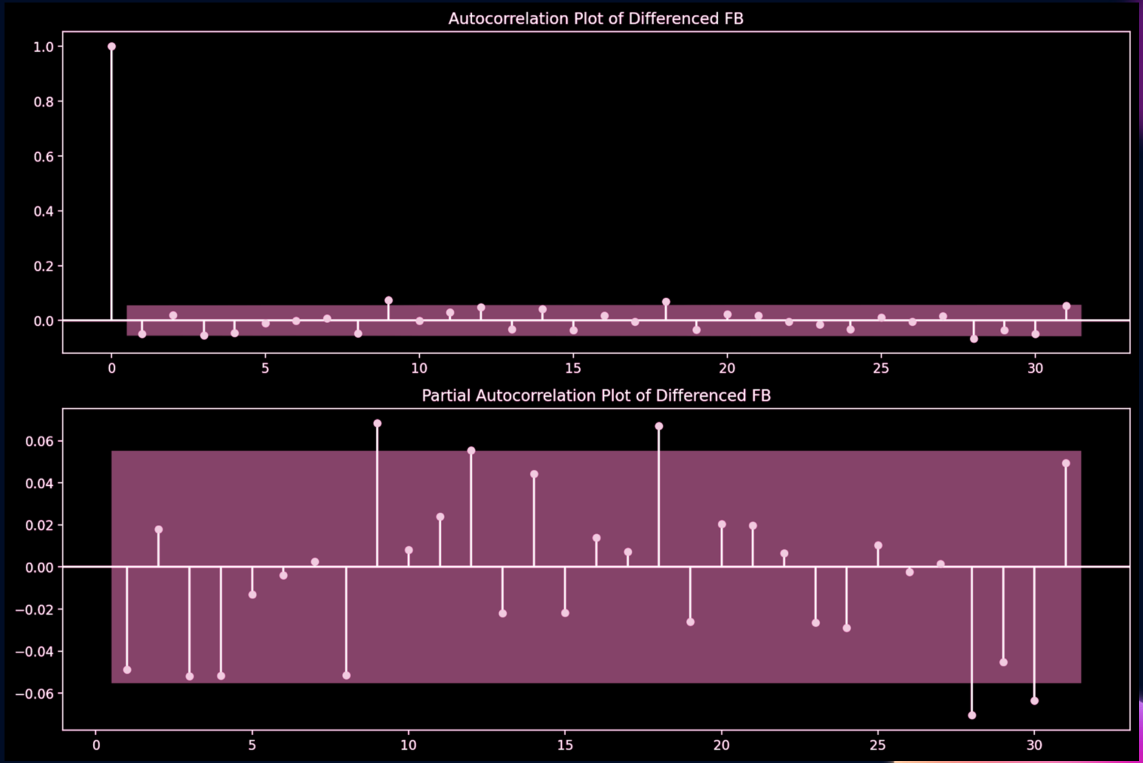
ADF test:

- P-value = 0
- stationarity: True

KPSS test:

- P-value = 0.1
- stationarity: True

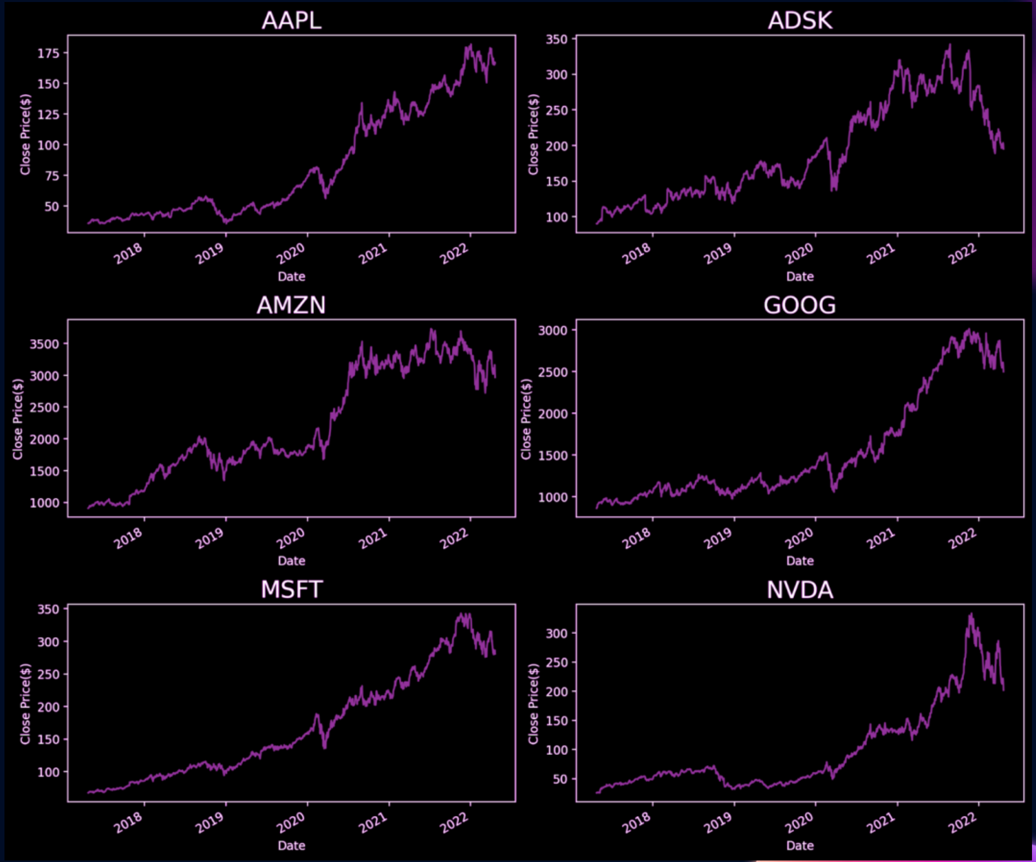
Assumption for: ARIMA



Other Stocks

Timespan: 2017/4/24 - 2022/4/21

Company	Stock	DTW with FB
Autodesk	ADSK	665.94
Microsoft	MSFT	1357.01
NVIDIA	NVDA	2720.09
Apple	AAPL	3769.14
Google	GOOG	51704.99
Amazon	AMZN	75546.48



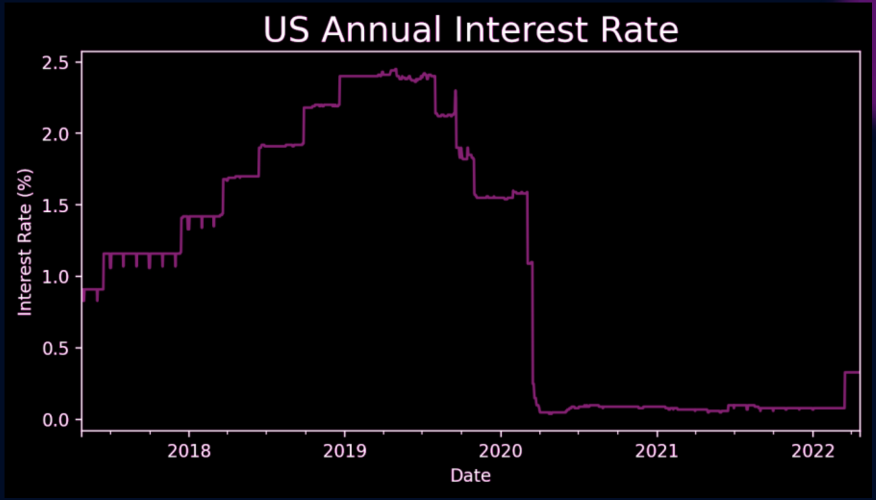
Other Regressors

Annual Interest Rate in the US

- Frequency: Daily
- 2017/4/24 - 2022/4/21

List Of Events

- 30 events related to Meta, 9 Metaverse industry events, i. e., Facebook Connect event, shareholder meeting, earning calls
- Feature Engineering: Treated as dummies



03
Modeling

Approaches and Results

Exponential Smoothing

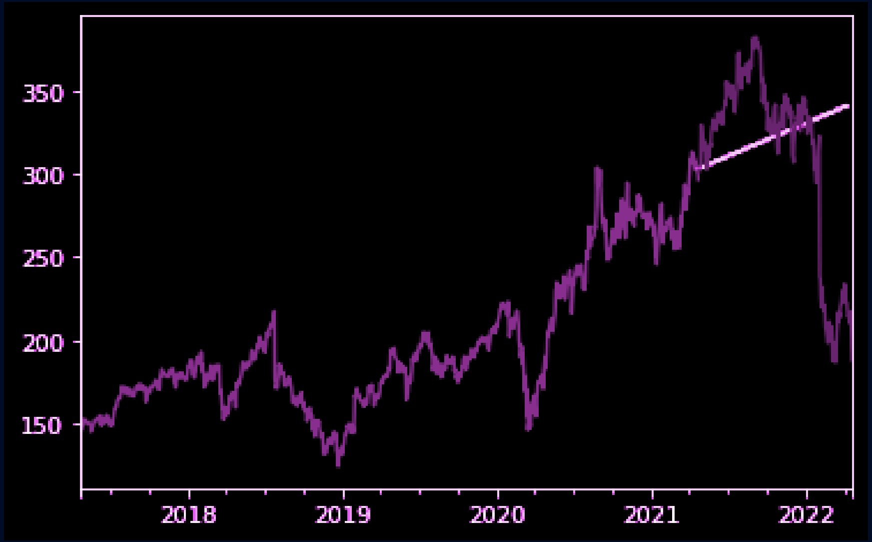
Model Operation

Holt Winter's a series of smoothing approaches that extended from SES by considering trend and seasonality effect

Trend and Seasonality tried different combinations of 'Additive'/'Multiplicative' trend and seasonality, case without seasonality, damped trend

Tradeoff

PROS simple to implement, higher weight on recent observations, can capture trend and seasonality
CONS produces lagged forecast, cannot handle irregular pattern, cannot deal with non-stationary data



Holt Winters Smoothing with additive trend and additive monthly seasonality

Vector Autoregression (VAR)

Model Operation

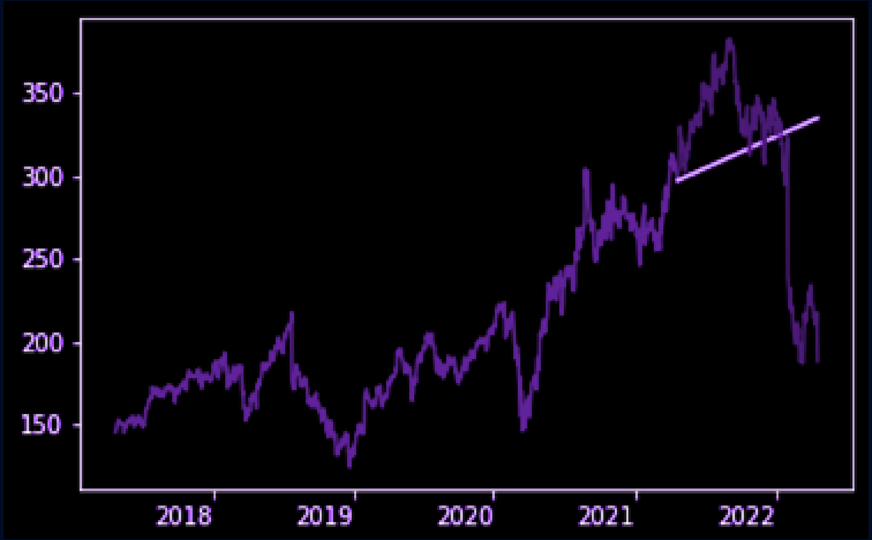
Correlation and DTW extracted metaverse stocks that has the highest correlation/closest distances with FB

Causality verified the Granger Causal relationship between stocks

VAR Order using BIC as the criteria to obtain the best fitted order

Tradeoff

PROS consider cross-correlated time series, modeling multiple time series simultaneously
CONS need test for causality before implementation, intertwined errors, stationarity check needed, all series need consistency in differencing



VAR model with order of 1;
ADSK, AMZN, GOOG, MSFT stock prices included alongside with FB as cross-correlated variables

Prophet

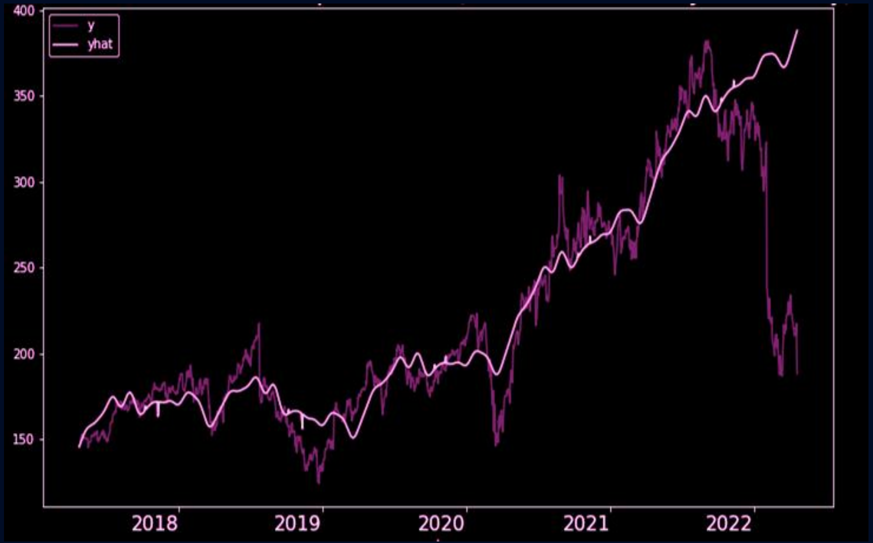
Model Operation

Hyperparameter Selection attempted different values of wide range of hyperparameters, as well as considered holiday effect

Potential External Regressors Interest Rate and Trade Volume as regressors

Tradeoff

PROS no stationarity assumption, easy integrates holiday, robust to missings
CONS inflexible input format, need precise fine-tuning



changepoint_prior_scale=0.01, n_changepoints=100, seasonality_prior_scale=0.1, seasonality_mode='additive', daily_seasonality=True
model.add_country_holidays(country_name='US')

ARIMA

Model Operation

Stationary Assumption take the first difference to make it stationary

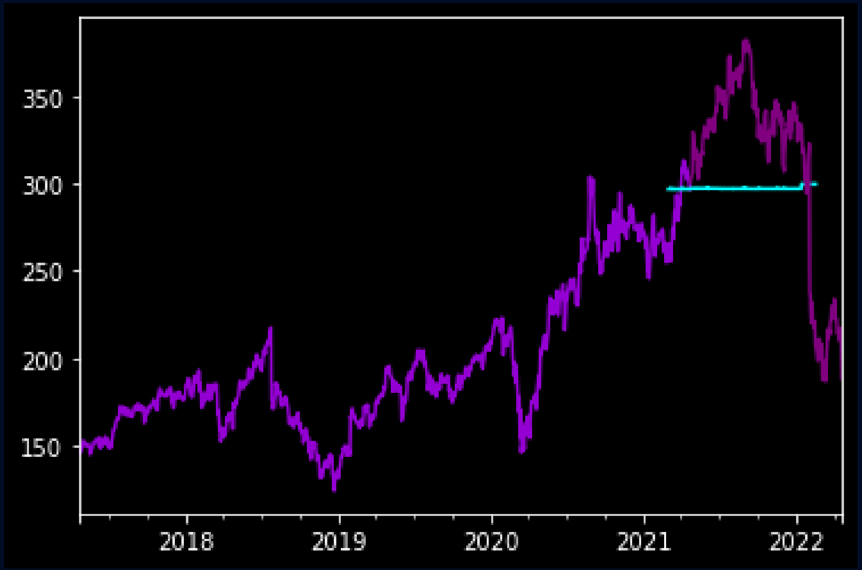
AR and MA orders use Auto ARIMA to find the best orders, with AR order = 4, MA order = 2

External Variables interest rate and events

Ljung-box test shows no autocorrelation of residuals

Tradeoff

PROS performs well on short-term forecast, easy to interpret
CONS difficult to predict turning points, need to determine (p,d,q) order first



ARIMA (4, 1, 2)

LSTM

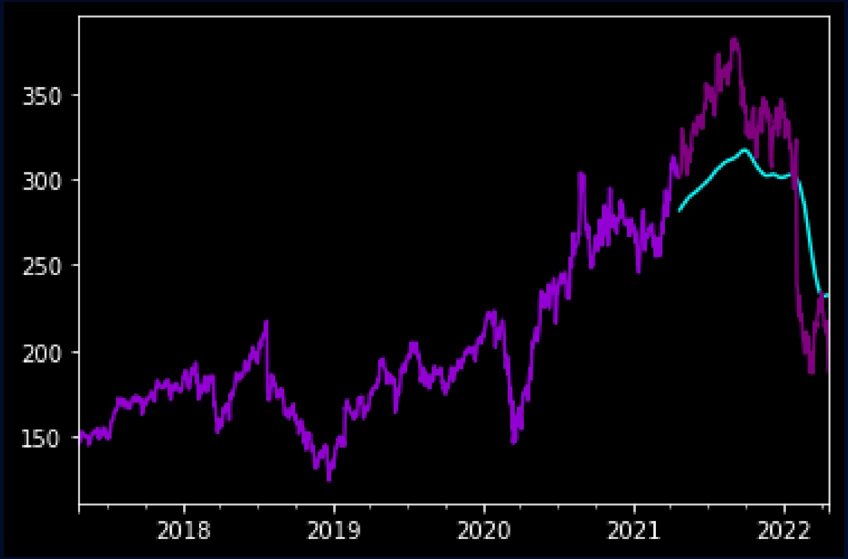
Model Operation

Long Short-Term Memory a type of recurrent neural network that learns long-term dependencies

Time Window use the data from previous 60 days for forecasting

Tradeoff

PROS do not need to calculate parameters based on the data, can apply to multivariate time series, store previous time step information well
CONS limit explainability, long training time, large memory required (71k total parameters)



3-Layer LSTM with unit = 50, dropout = 0.25,
window size = 60, optimizer = SGD,
batch size = 64, epoch = 200

Model Comparison

	Smoothing	VAR	Prophet	ARIMA	LSTM
MSE	4048.785	3946.655	6111.669	3219.271	**1361.455**
sMAPE	0.153	0.161	0.166	0.172	**0.106**

Best Model: LSTM

04
Insights

Summary and Future Work

Insights

- Among all models,
  - sMAPE works best with our data which is devoid of zeros and extreme values.
  - LSTM performs the best because of its long-term memory architecture.
- How do external regressors impact Meta's stock price?
  - Interest Rate/Trading Volume: adding these regressors have no performance boost on our predictions; their influences on stock price are limited
- How and where can we use those models?
  - In a business setting, we can implement LSTM to predict Meta stocks.
  - The predictions from LSTM will guide investment decisions.
  - From companies' standpoint, better stock price forecast can reflect market confidence toward their business, thus serve as a basis for determining business strategy

Future Work

Going forward, what can we do to better predict?

- More external regressors: P/E ratio, events on Meta policies & regulations.
- Extend the impact of events to a longer period.
- Use recursive multi-step forecast for better results.
- We can predict other Metaverse stock prices using similar methodologies.

Thanks!

Q & A