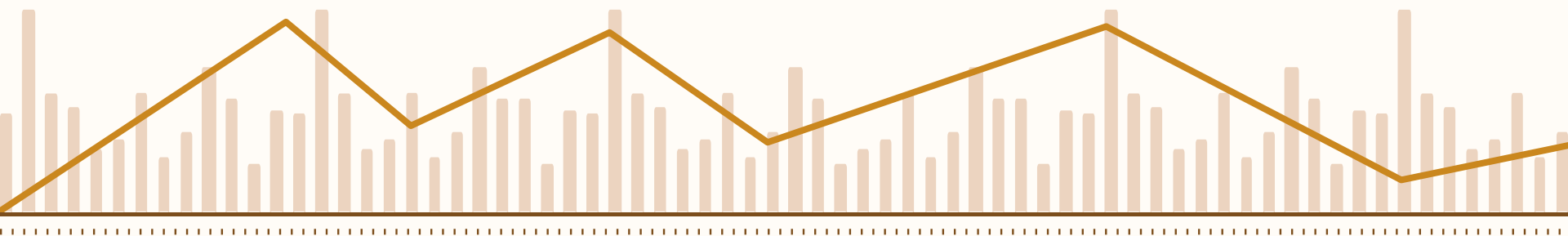


Stock Price Anomaly Detection & Forecasting

Cynthia Du

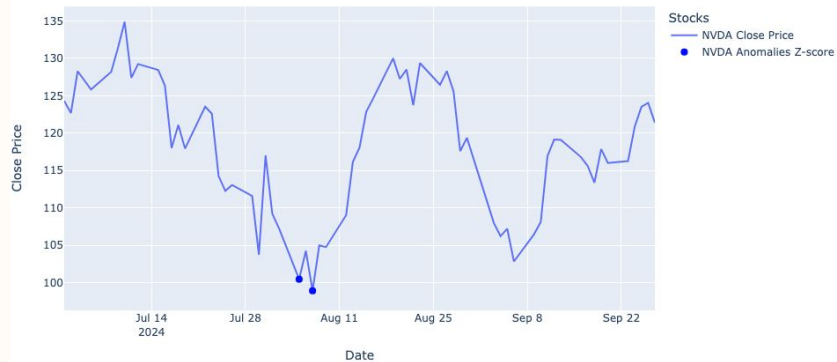


1

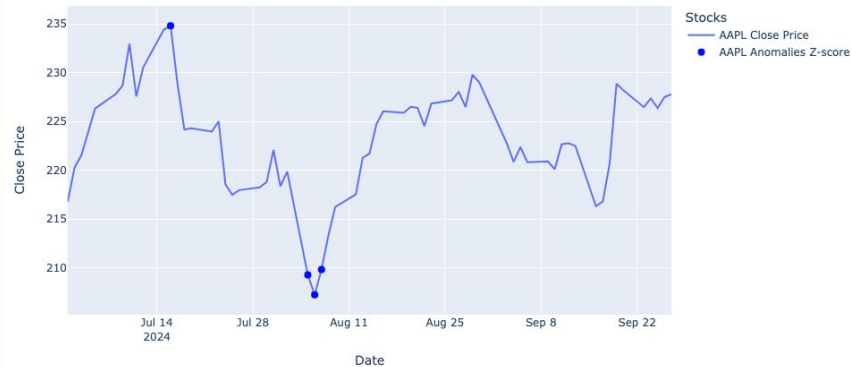
Statistical Deviations



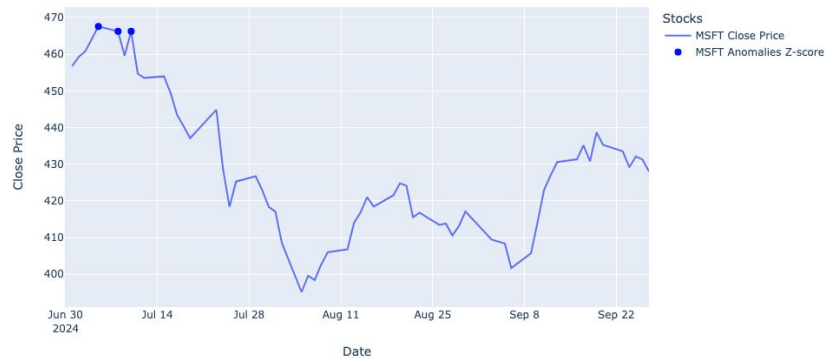
NVDA Stock Prices with Anomalies (Z-score > 2)



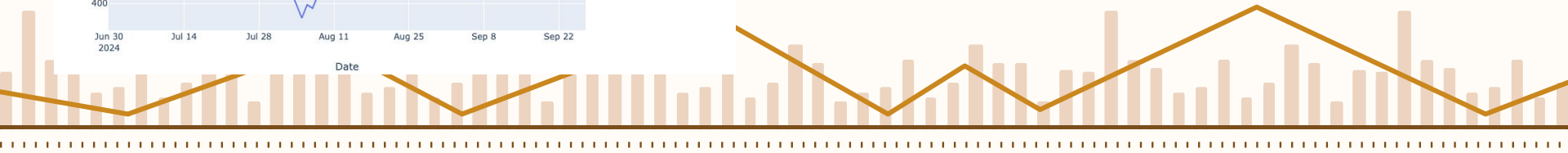
AAPL Stock Prices with Anomalies (Z-score > 2)

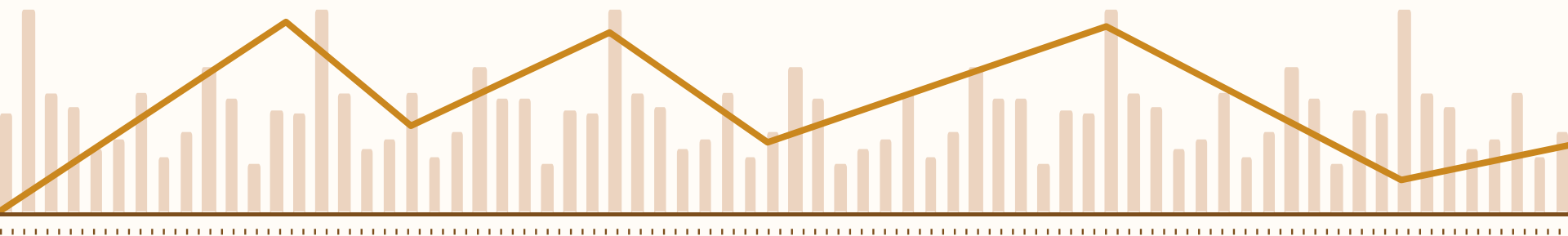


MSFT Stock Prices with Anomalies (Z-score > 2)



**Statistically an
anomaly.... but is it
actually?**





2

Analyzing Stock Volatility

Hidden Markov Model

Used to identify market regimes + trends, good in detecting shifts in market behavior

State 0

Periods of low volatility and stable returns

Represents calm market / minimal price fluctuations

State 1

Periods of high returns or increased volatility

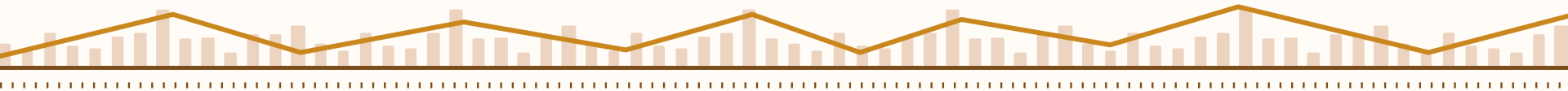
Indicates bullish trends or recovery phases with larger upward price movements.

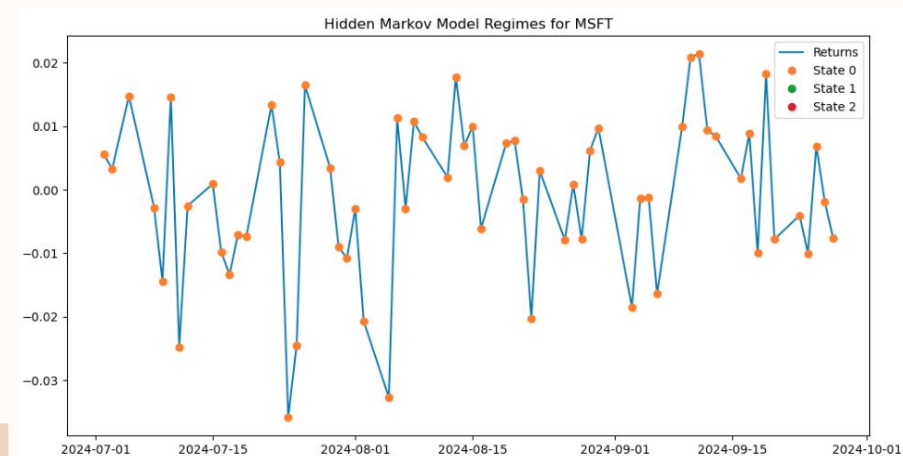
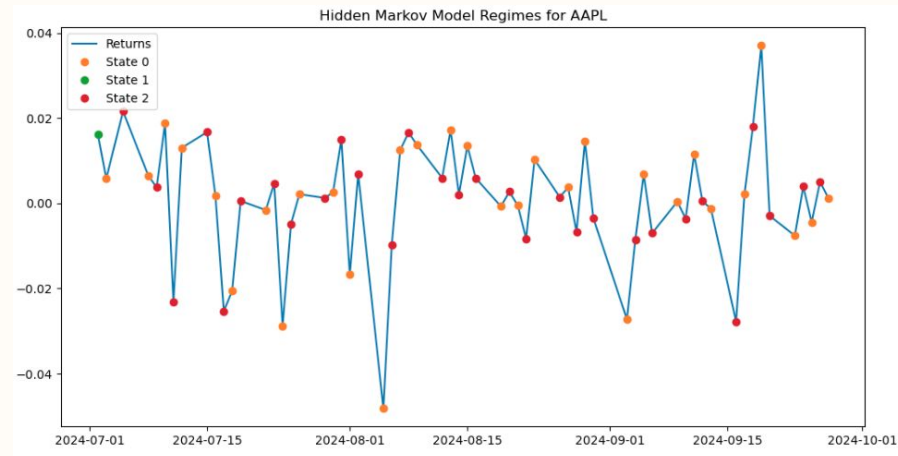
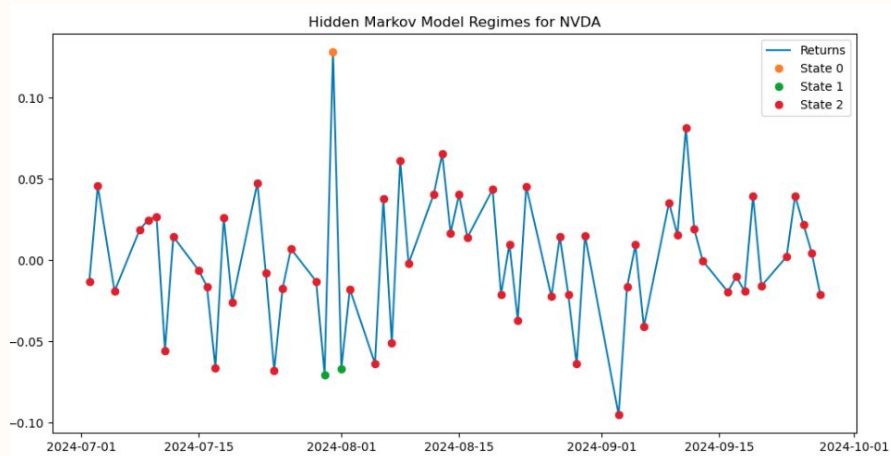
State 2

Periods of high volatility or bearish activity / negative returns

Associated with sharp declines, corrections, or market uncertainty.

Volatility: degree of variation in a stock's price over certain period. High volatility indicates that the stock's price changes significantly over a shorter period

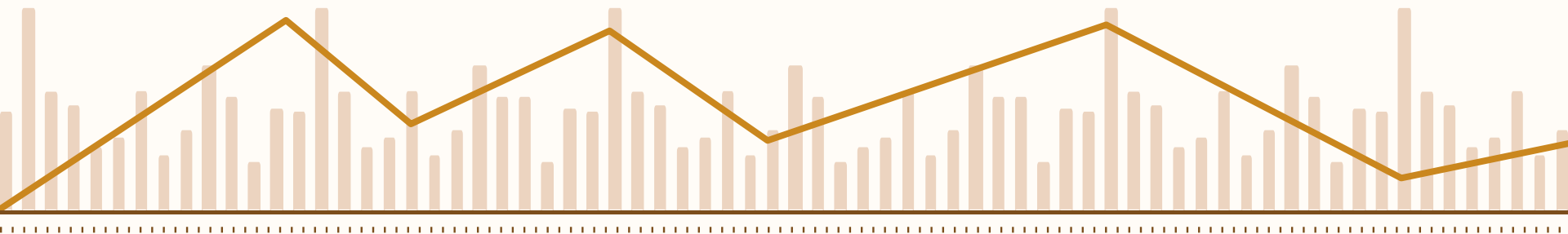




NVDA: Showcases distinct volatility patterns with most periods in high-return states (State 1) and bearish states (State 2). Risky but potential for high returns :)

AAPL: Reflects relatively stable transitions with brief shifts to bearish states.

MSFT: Demonstrates consistency in low volatility states, with limited bearish activity. Most stable :0



3

STL Decomposition + ARIMA Forecasting

STL Decomposition

(Seasonal and Trend decomposition using Loess)

Decompose the time series into its components (seasonal, trend, and residual) and use the residuals to detect anomalies

Trend: Reflects the underlying movement over time, which is typically smooth.

Seasonal: Reflects short-term fluctuations that repeat over a fixed period (e.g., yearly, monthly, etc.).

Residual: Represents randomness or noise that cannot be explained by trend or seasonality.

ARIMA Forecasting

(Auto-Regressive Integrated Moving Average)

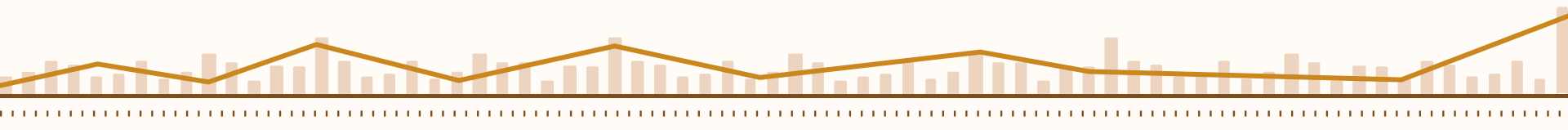
Used for time series forecasting

Captures three key components:

Auto-Regression (AR): Incorporates dependence between an observation and a specified number of lagged observations.

Integration (I): Makes the time series stationary by differencing it (removing trends).

Moving Average (MA): Models the error of the time series as a linear combination of error terms from past observations.



STL Decomposition

ARIMA Forecasting

(Seasonal and Trend decomposition using

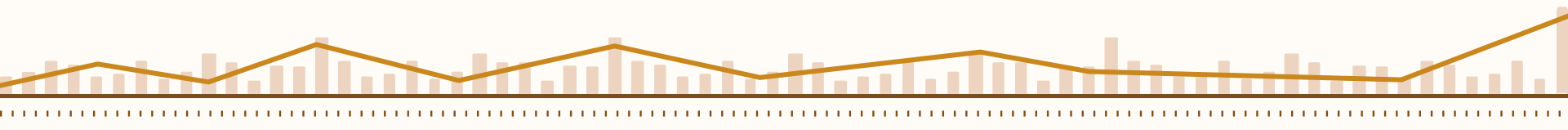
(Auto-Regressive Integrated Moving

```
1 # Forecasting with ARIMA (on the trend component)
2 trend = result.trend.dropna()
3 arima_model = ARIMA(trend, order=(1, 1, 1))
4 arima_fit = arima_model.fit()
5
6 # Forecasting future values
7 forecast_steps = pd.date_range(start=forecast_start_date, end=forecast_end_date, freq='B')
8 forecast = arima_fit.get_forecast(len(forecast_steps)).predicted_mean
9 forecast = pd.Series(forecast.values, index=forecast_steps)
```

```
1 # Combine forecasted trend with the seasonal pattern (from the last cycle)
2 seasonal_cycle = result.seasonal[-len(forecast):]
3 forecast_with_seasonality = forecast + seasonal_cycle.values
4 forecast_with_seasonality = forecast_with_seasonality.loc[aapl_test.index]
```

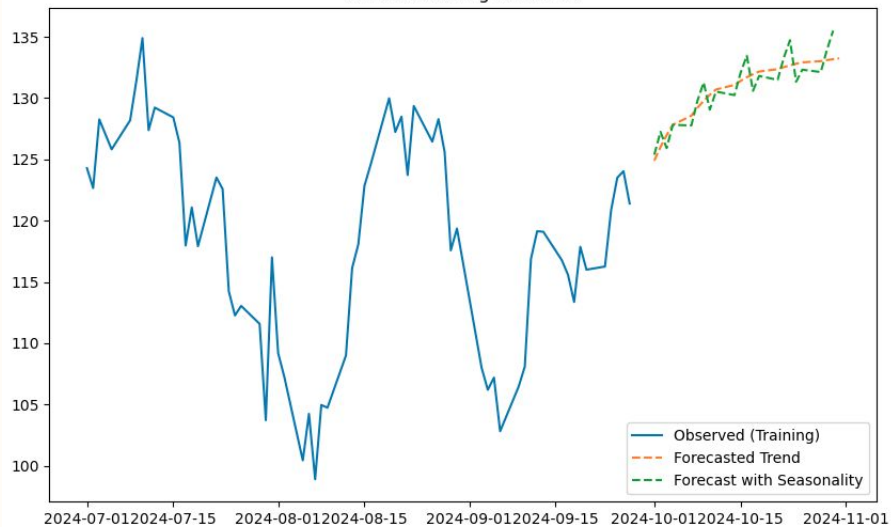
seasonality.

error terms from past observations.

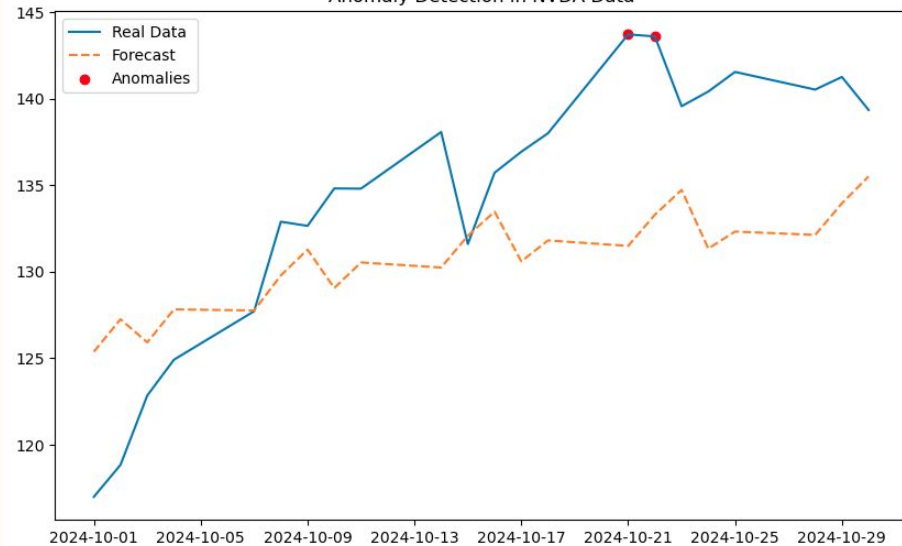


NVDA

STL Forecasting for NVDA

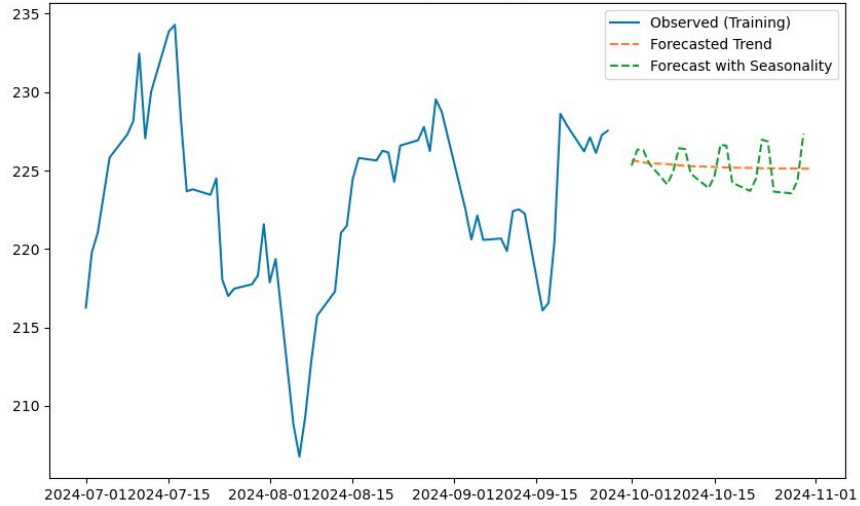


Anomaly Detection in NVDA Data

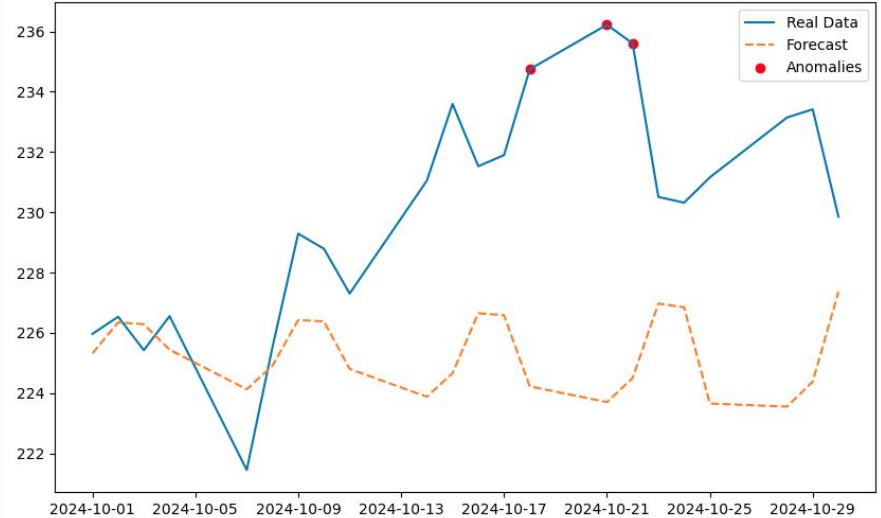


AAPL

STL Forecasting for AAPL

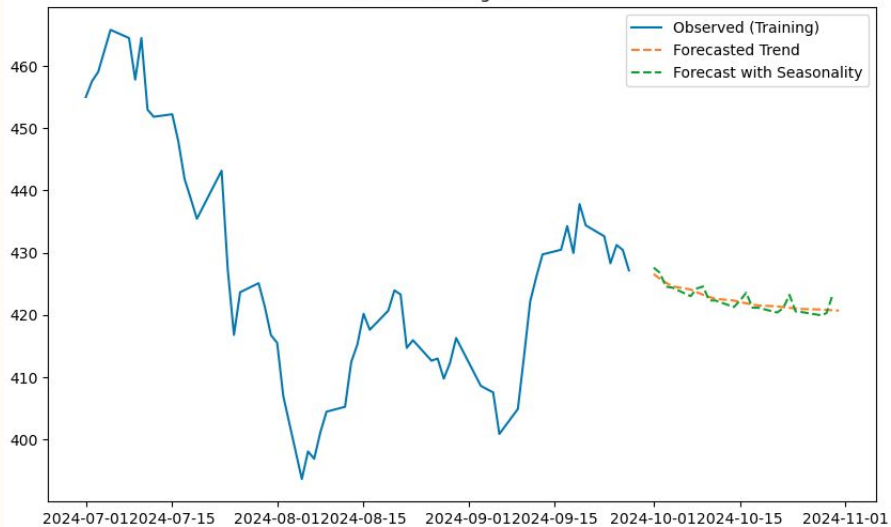


Anomaly Detection in AAPL Data

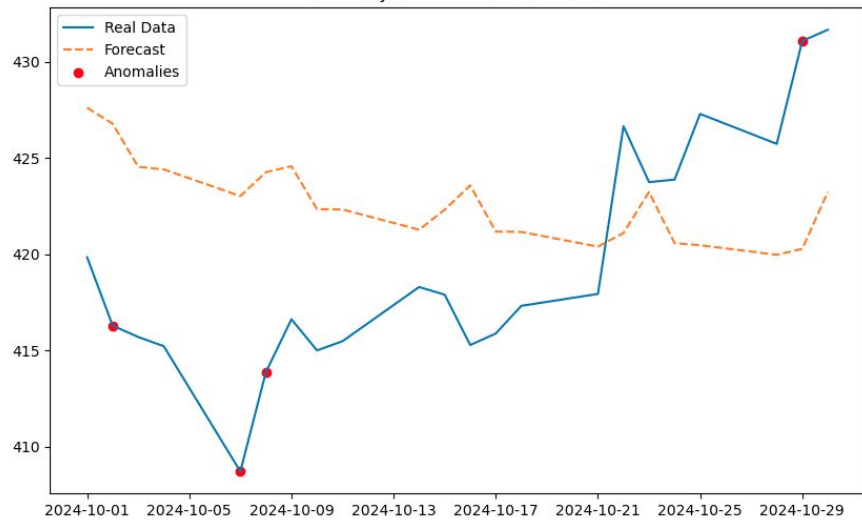


MSFT

STL Forecasting for MSFT



Anomaly Detection in MSFT Data



Thank you!

Shoutout to the best mentor Justin and Bree for their help !!!

