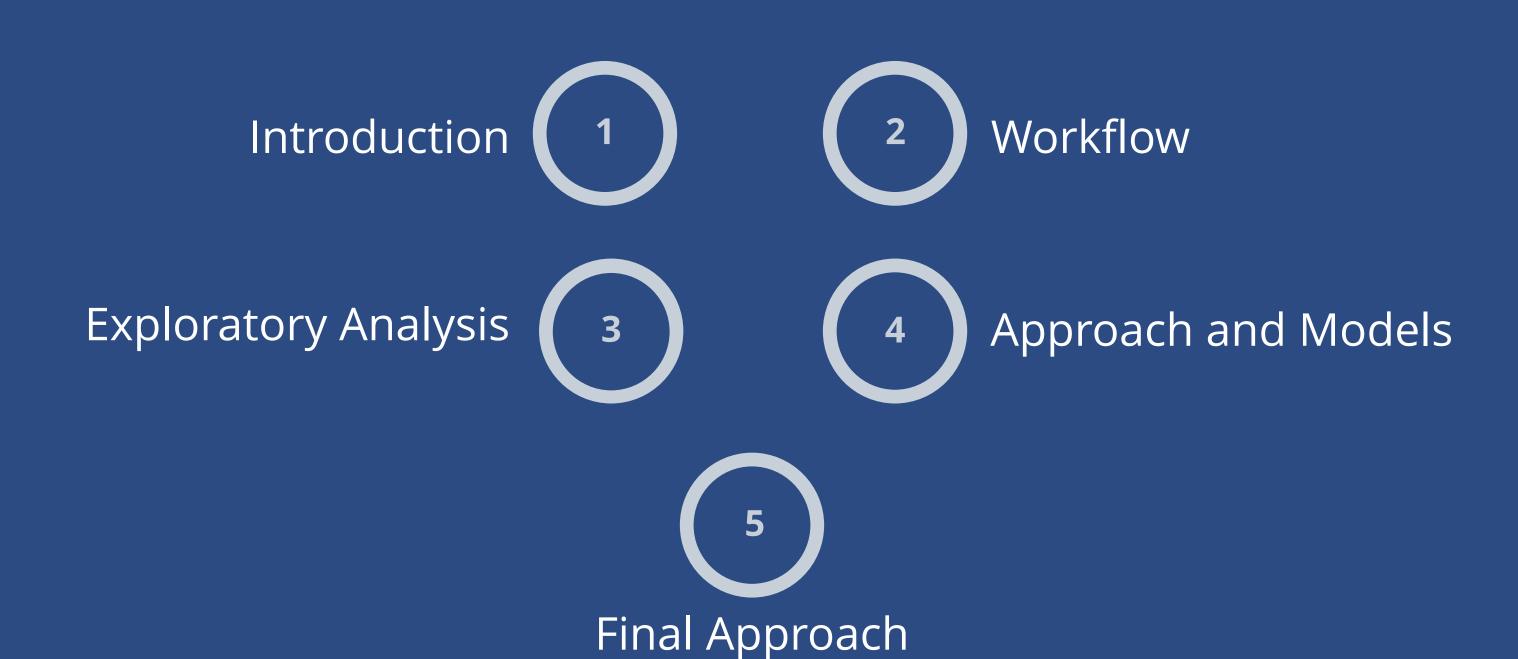


### Sales Forecasting

**Team-278** 

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### INTRODUCTION



#### Introduction



- Company manufactures electric fans and sells them to consumers in various regions.
- Due to poor forecasting, the demand and supply ratio is poor.
- The task is to improve forecasting using advanced time series and machine learning algorithms.
- We have used data visualization tools and developed various time series, forecasting models.

(2) WORKFLOW

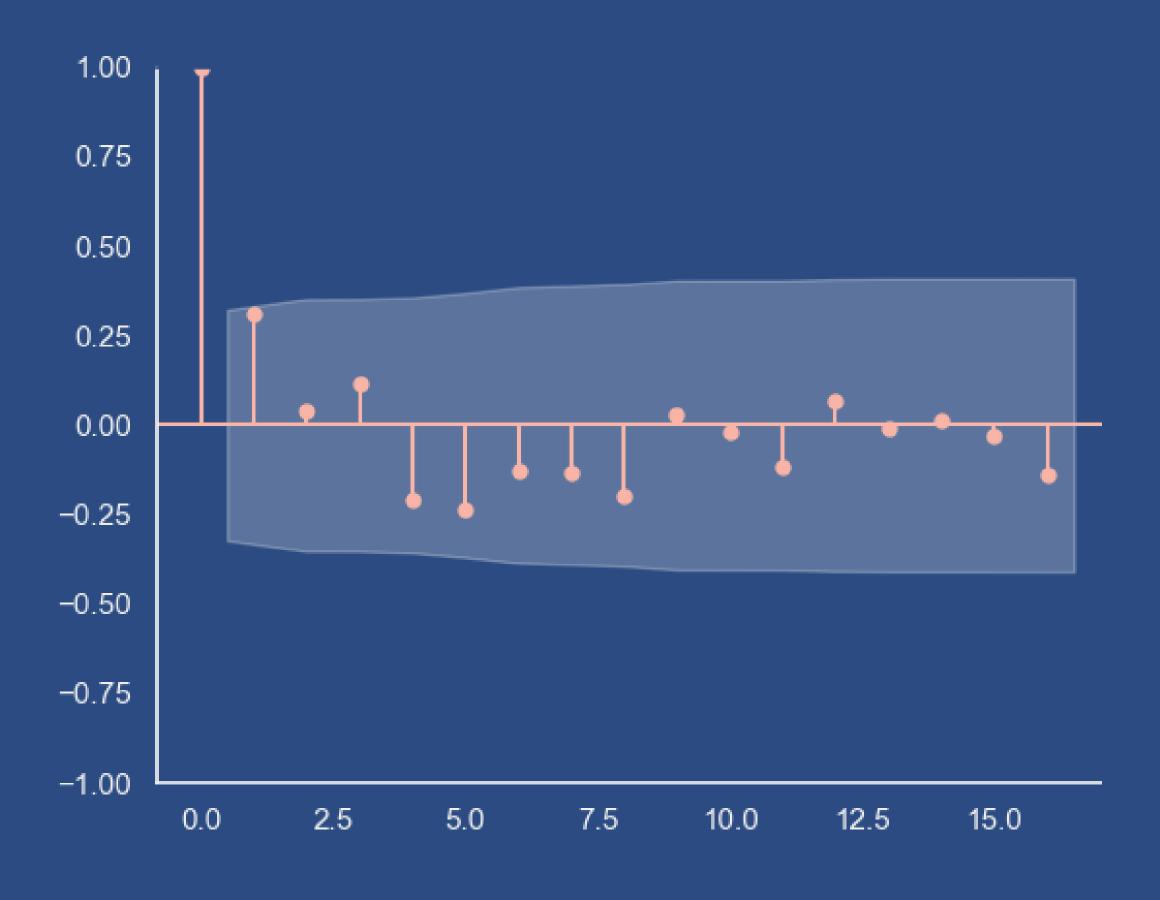
#### WorkFlow



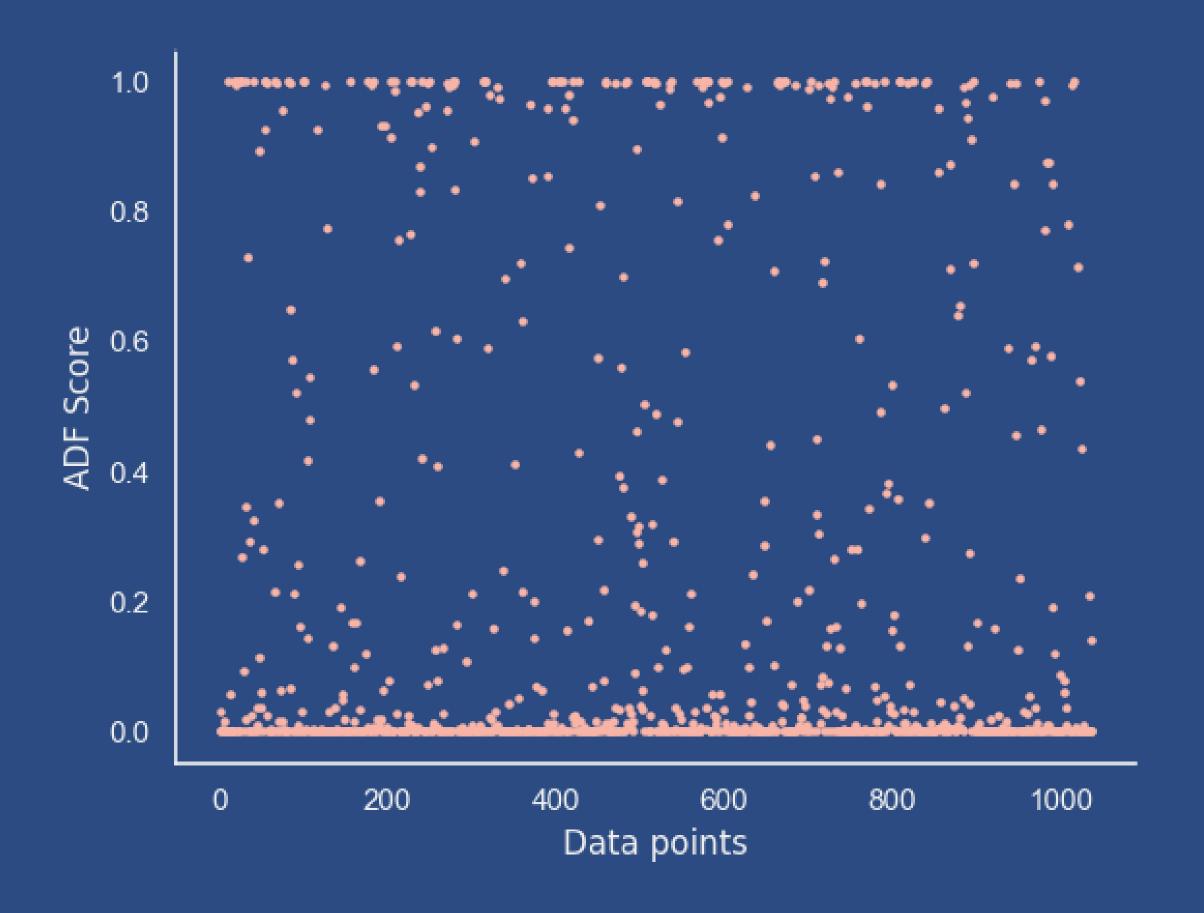
## 3

# EXPLORATORY ANALYSIS

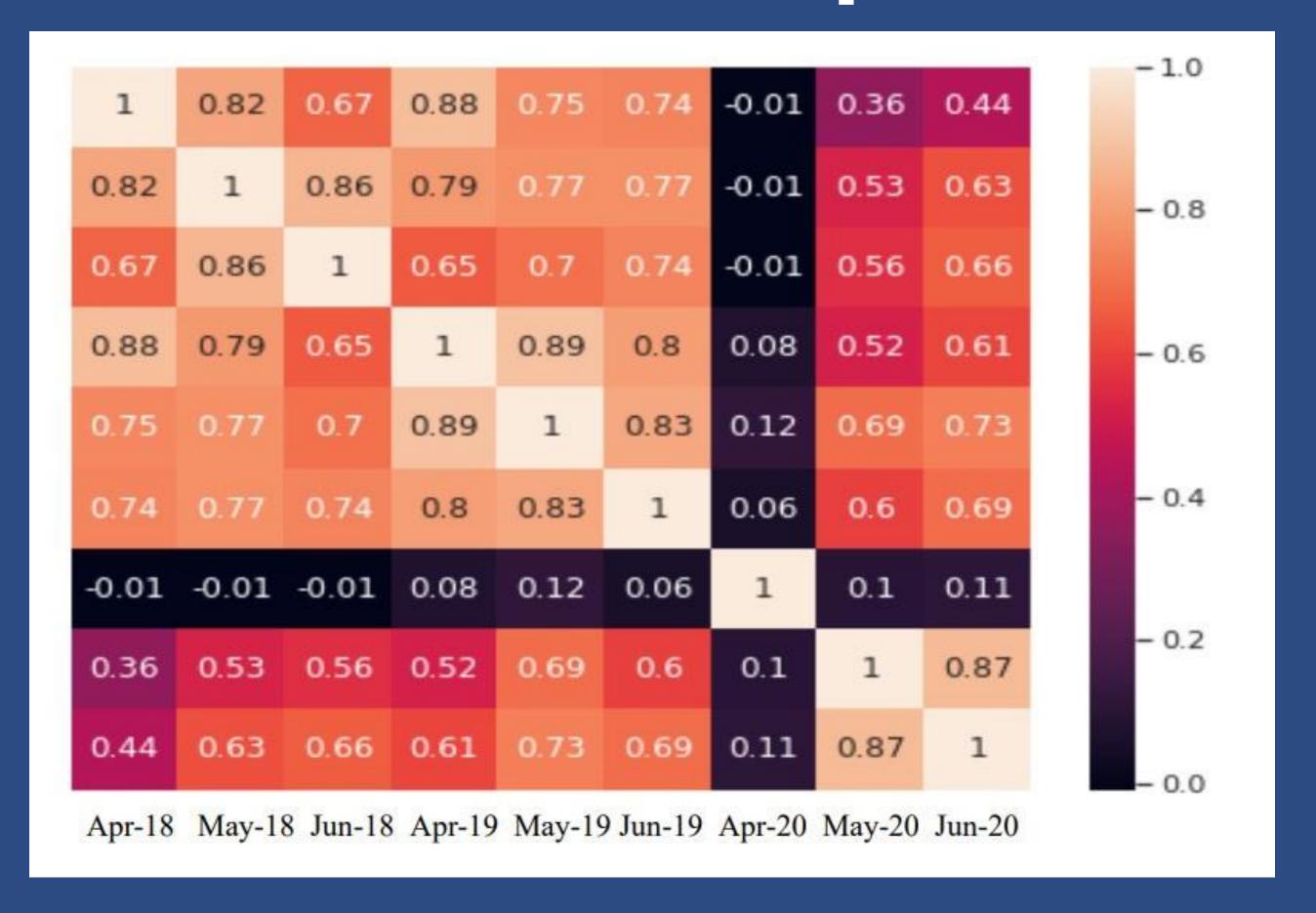
#### Autocorrelation Plot



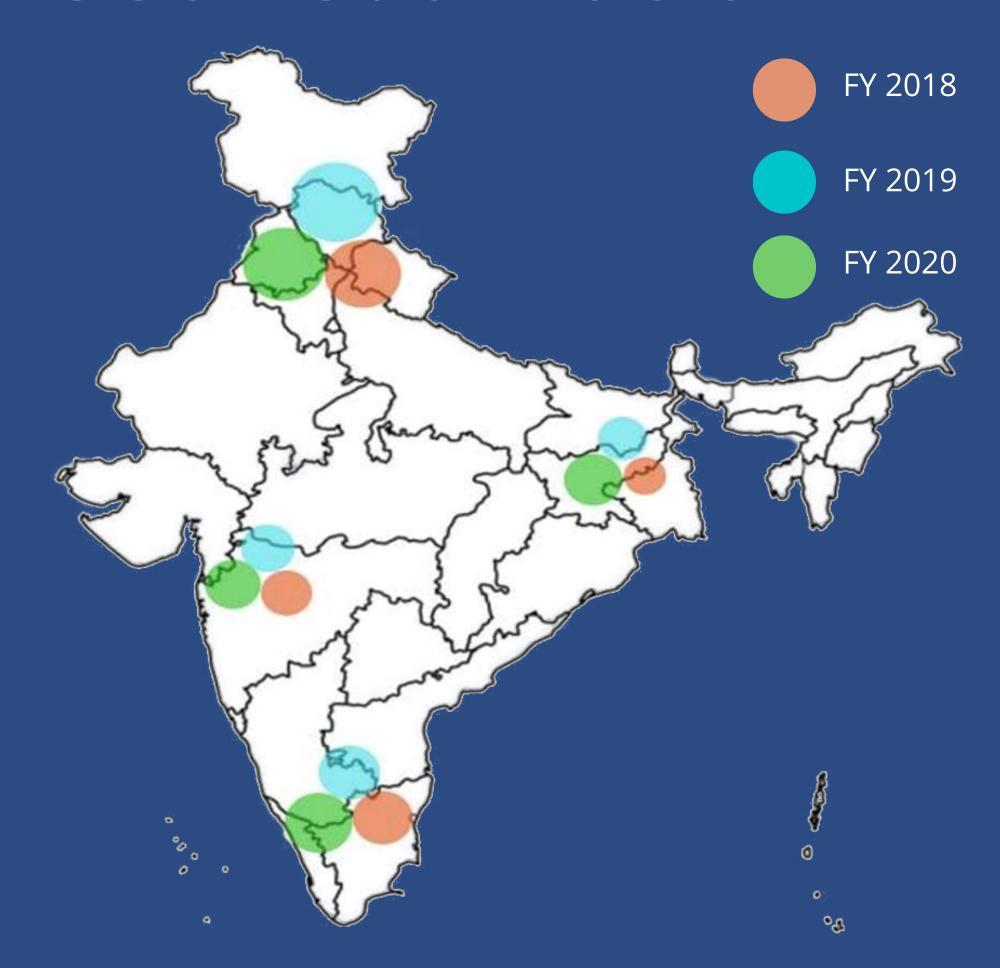
#### Augmented Dickey-Fuller (ADF) Test



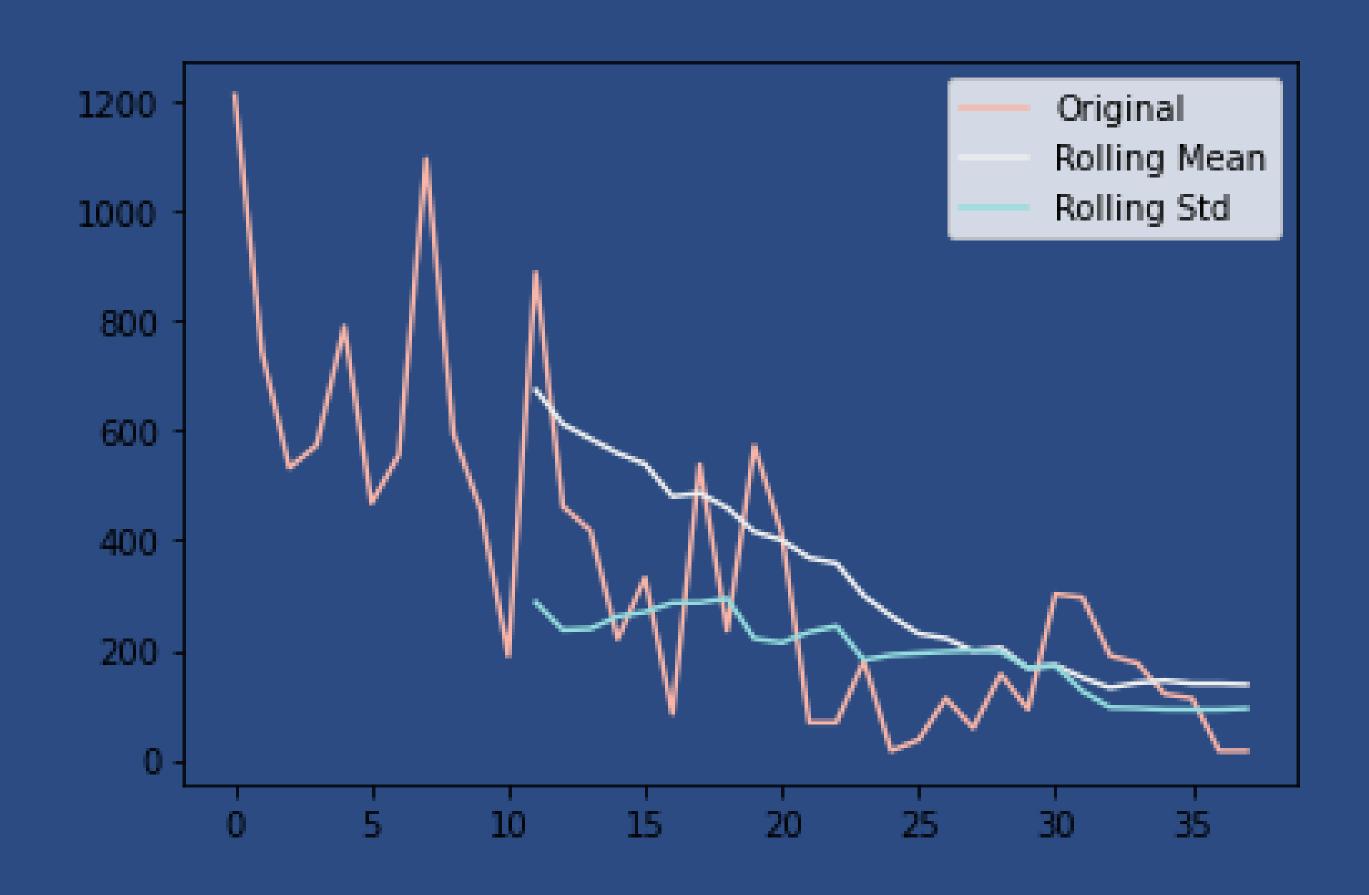
#### Heat Map



#### Geovisualization



#### Rolling Mean and Rolling Standard Deviation



## APPROACH & MODEL

#### Approach and Models

Models	MAPE	Root Mean Square Error
Random Forest	85%	355
XG Boost	93%	404
ARIMA	102%	473
SARIMA	215%	556
Holt Linear Trend	298%	621
Holt's Winter	365%	745
FB Prophet	655%	934
LSTM	94%	412
Temporal Fusion Transformer	544%	898

## APPROACH



#### Problem



- In our initial approach, we made use of Random Forest, XG boost regressor, LSTM,TFT, ARIMA, SES, SARIMA, SARIMAX, HOLT'S linear trend, HOLT'S winter and FB prophet models.
- They turned out to be much more complex and resulted into a large MAPE.

  Moreover, the data provided wasn't showing similar trends over a larger time span.

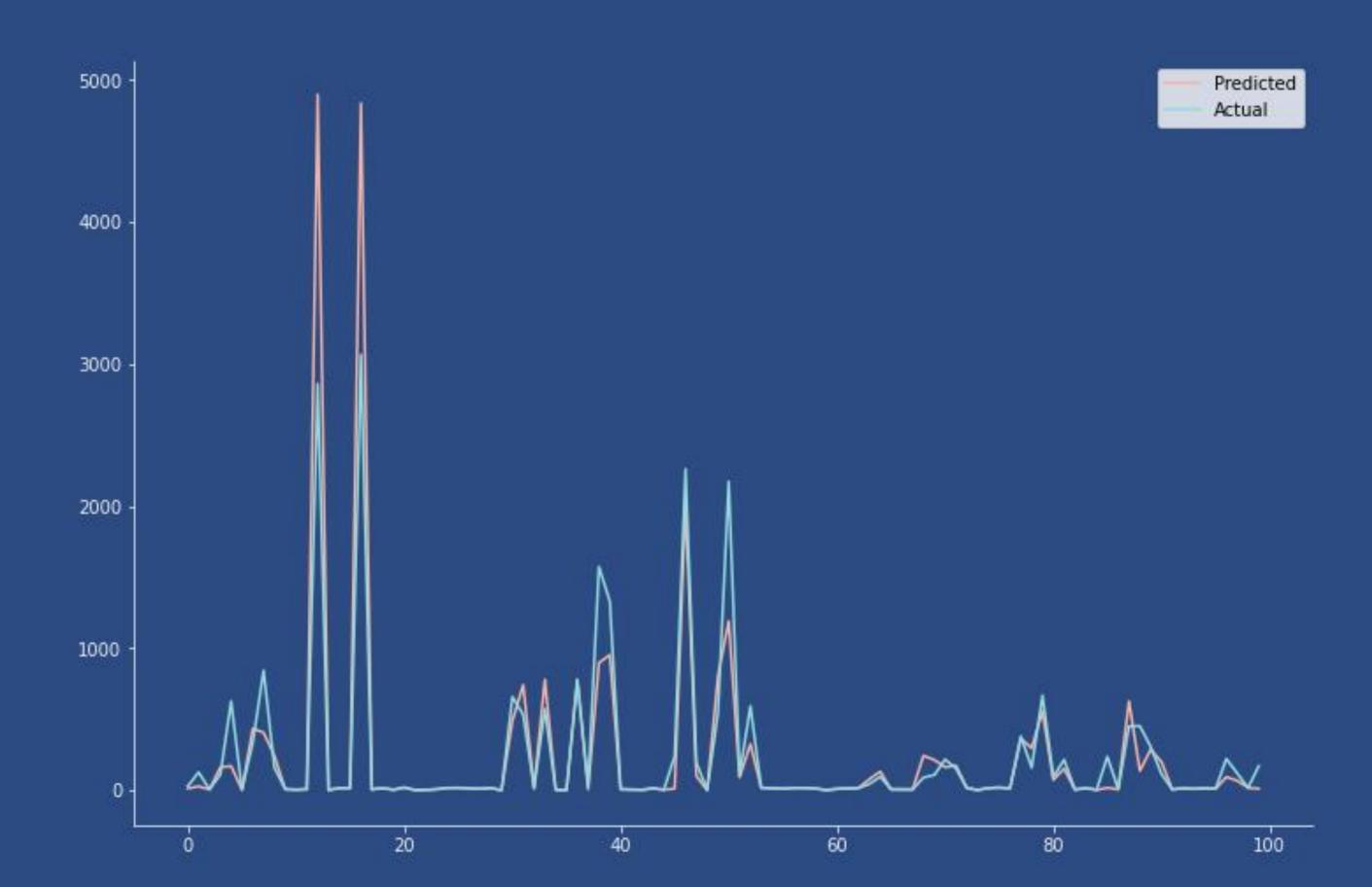


#### Solution

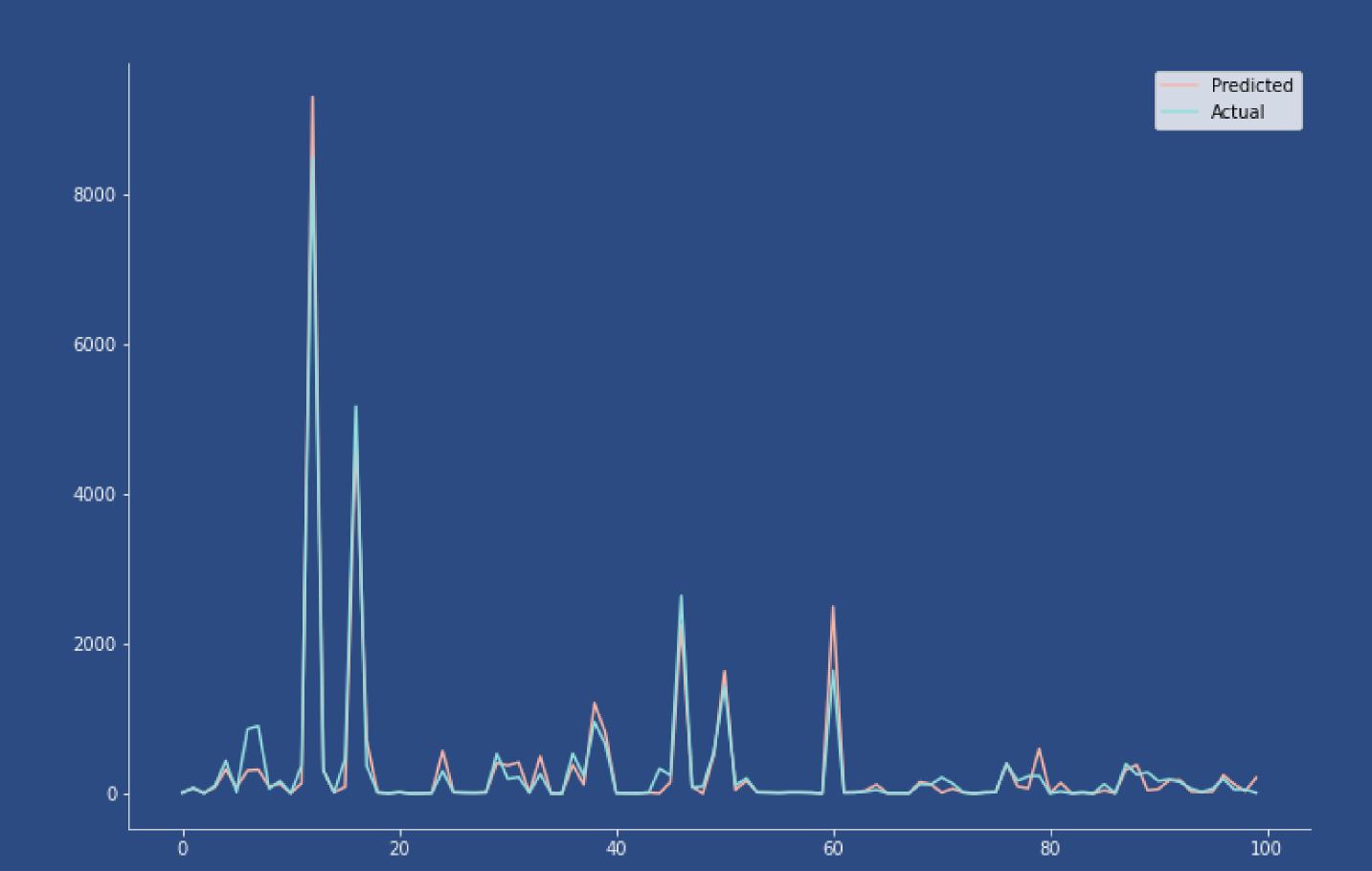


- Comparing sales of consecutive months shows a strong correlation between them. MAPE reduced significantly when month's sales were predicted by taking the previous month's sales.
- MAPE favors under-forecasting because the percentage error can't exceed 100% for relatively lower forecasts, while there is no upper limit for forecasts that are too high.
- So our final approach was as follows: Predicted June's sales is the minimum of April and May sales.

#### Predicted vs Actual June-18



#### Predicted vs Actual June-19



### Thank You.