

July 4, 2020

# Demand Forecasting and Budget Optimization using Python

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Rising AI 2020

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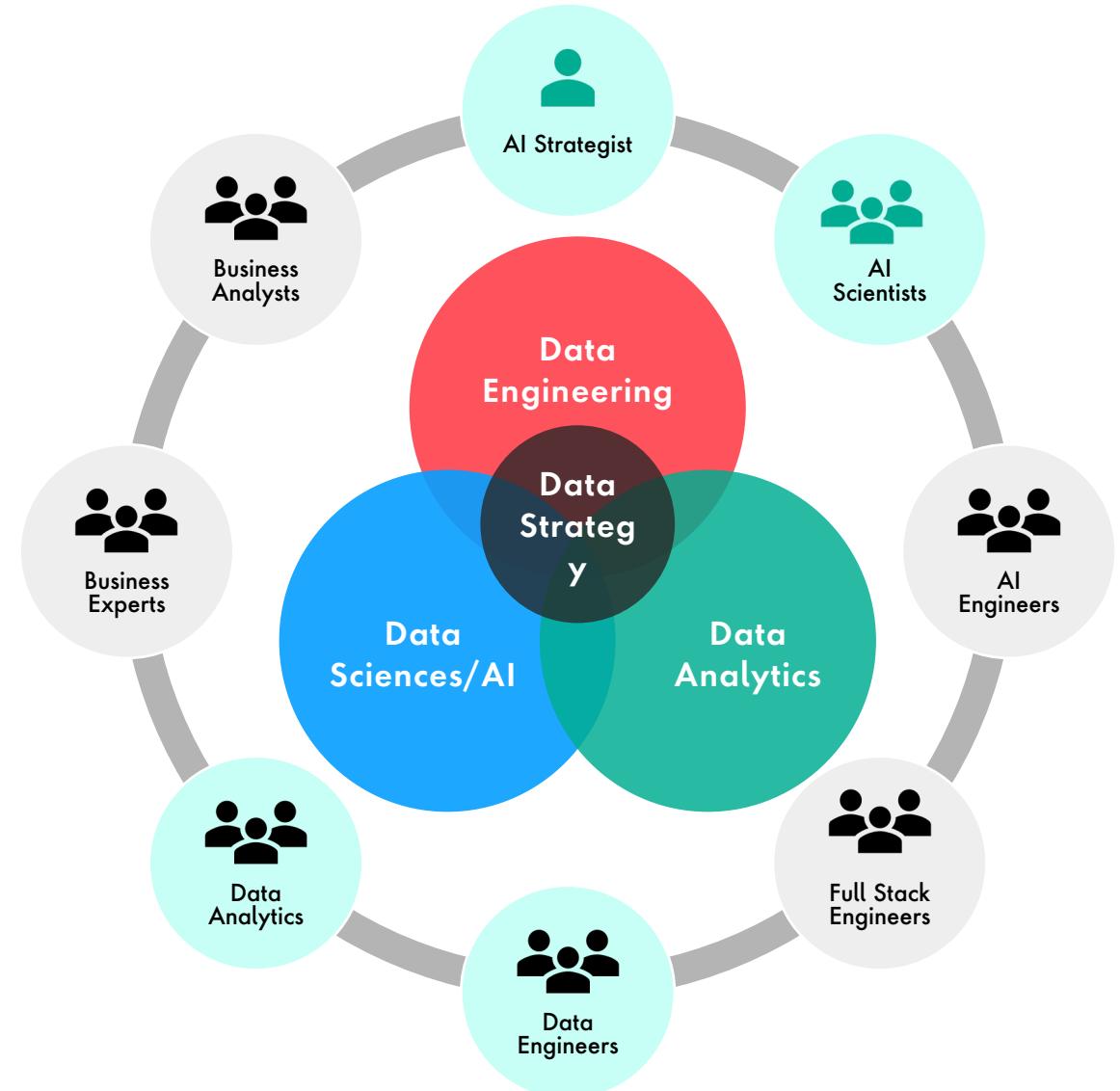


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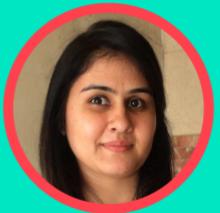
We work with organizations  
to bring Data to life **now**  
while establishing a path to **next**



# Celebrating women in Data

## Demand Forecasting and Budget Optimization Using Python

4th July | Online Workshop | 11:20 am - 1:20 pm



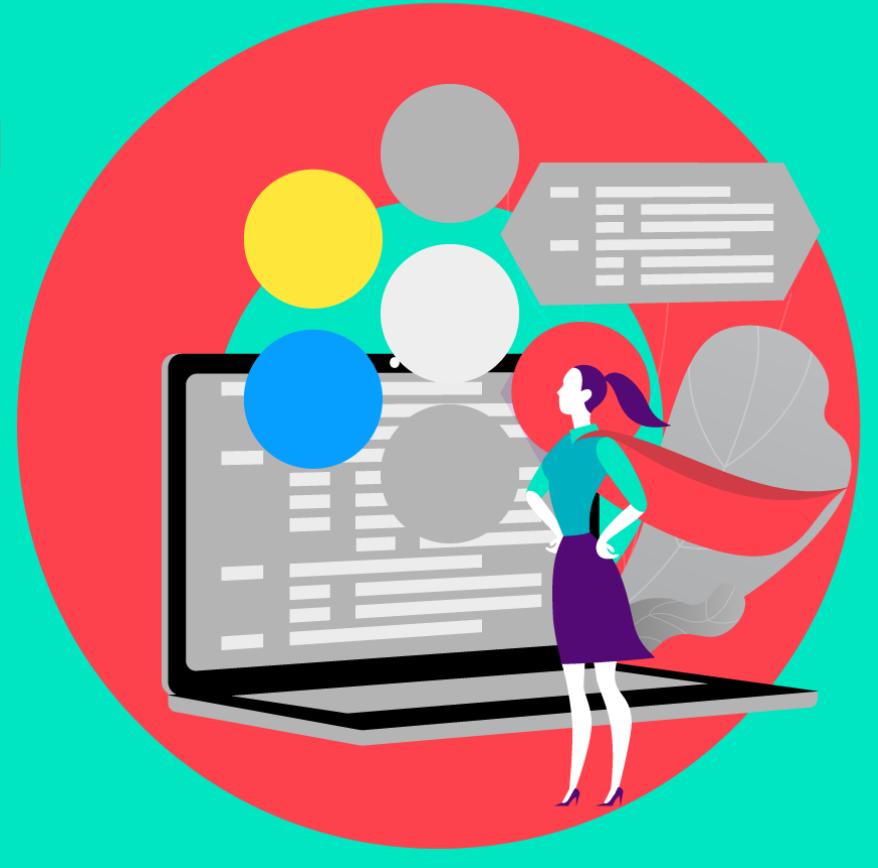
**Priyamvada Joshi**  
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**Sharmistha Chatterjee**  
Senior Manager,  
Data Science





Let's Get Started

- Demand Forecasting
  - Introduction
  - Techniques and Comparison
  - Use Case
  - Demo
- Budget Optimization
  - Introduction
  - Impact on forecasting
  - Use Case

# Key Takeaways

- Spectrum of Forecasting techniques
- Architect Forecasting methods for Scale
- Understanding Business problem  
(Automotive Industry)
- Hands on implementation of ARIMAX  
and Causal impact.
- Leveraging Forecasting output for Budget  
Optimization





What is one word that you can associate with demand forecasting?

Go to [www.menti.com](http://www.menti.com) and use the code 493694

<https://www.menti.com/prz9womap6>

# Demand Forecasting

A photograph of a person's hands holding a circular frame, like a camera lens or a magnifying glass, over a scenic landscape of a river and mountains at sunset. The sky is a gradient from blue to orange.

## Why demand forecasting ?

### What businesses look for ?

- Can I **optimize** my inventory to minimize costs as well as manage demand.
- Can I create custom campaigns and **increase** my customer base using past behavior
- How can I optimize my **costs** on marketing spend

# Techniques and Comparison

In this section, we like to present the various techniques used for forecasting as well as the uniqueness of each of them

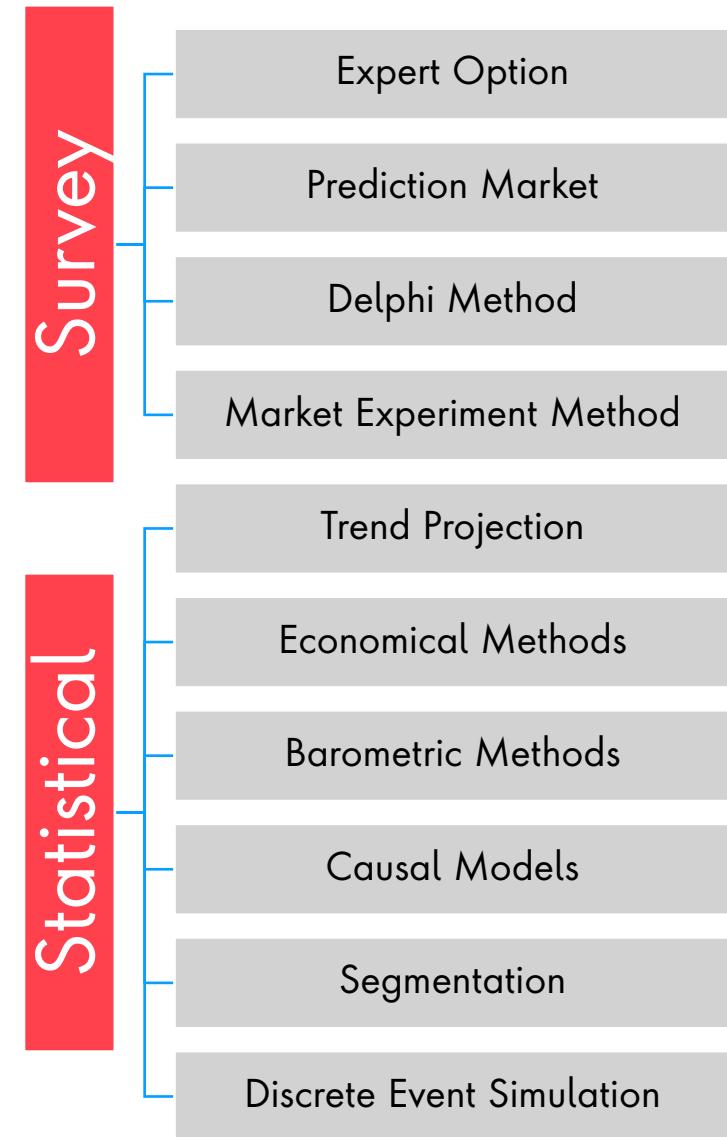
## Conventional demand forecasting techniques

### Survey methods

- Simple & Direct Method
- Good for short term
- Decisions dependent on volume of survey
- People oriented

### Statistical methods

- Complex
- Good for long term forecasting
- Require good volume of historical data



# Expert Opinion



# Delphi Method



# Prediction Market



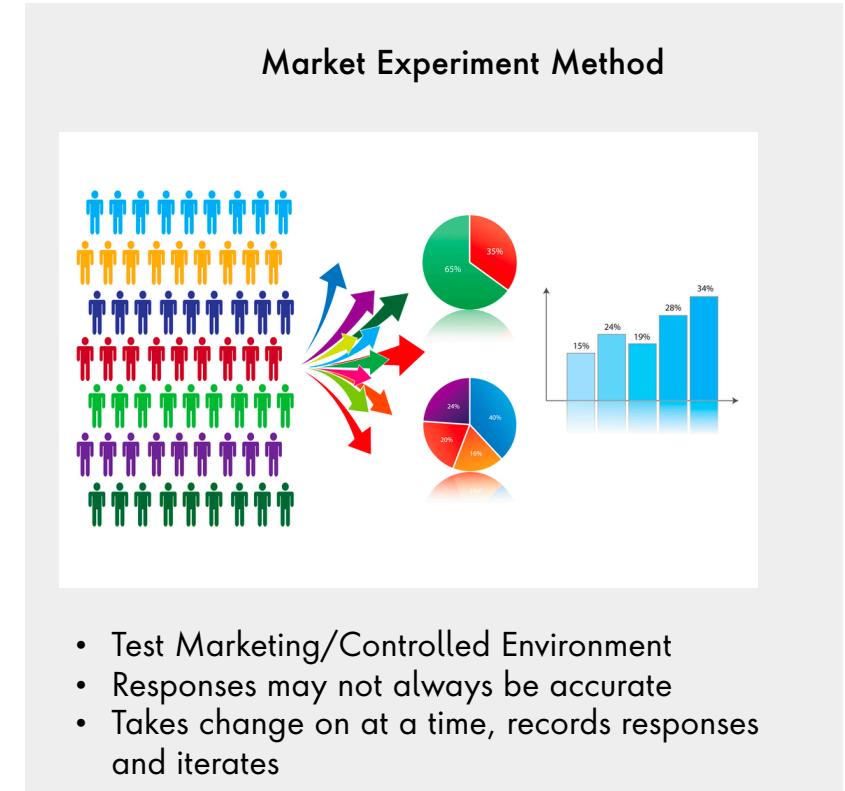
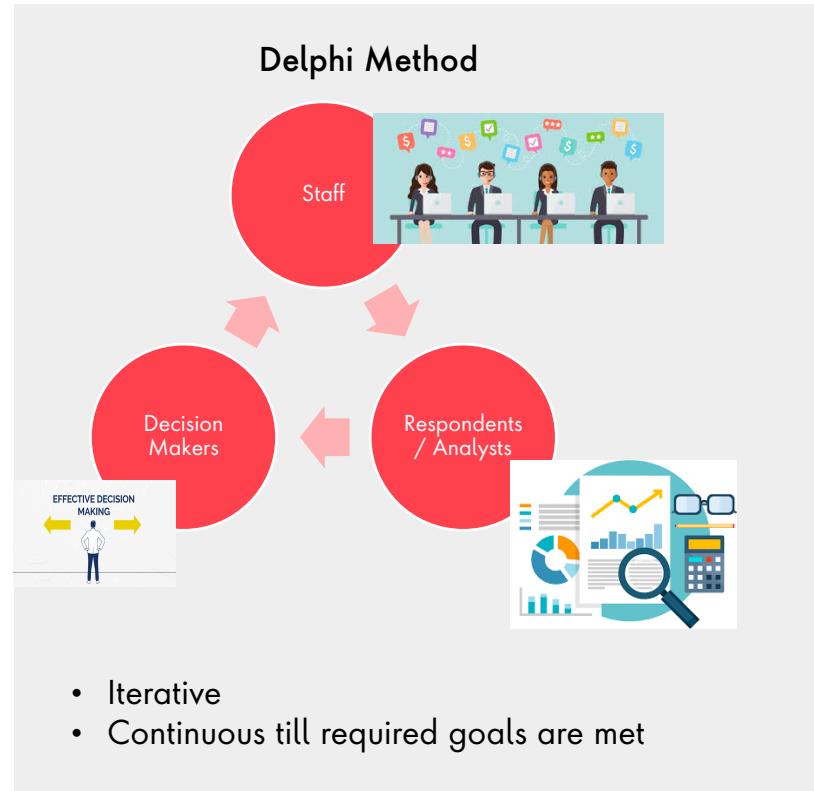
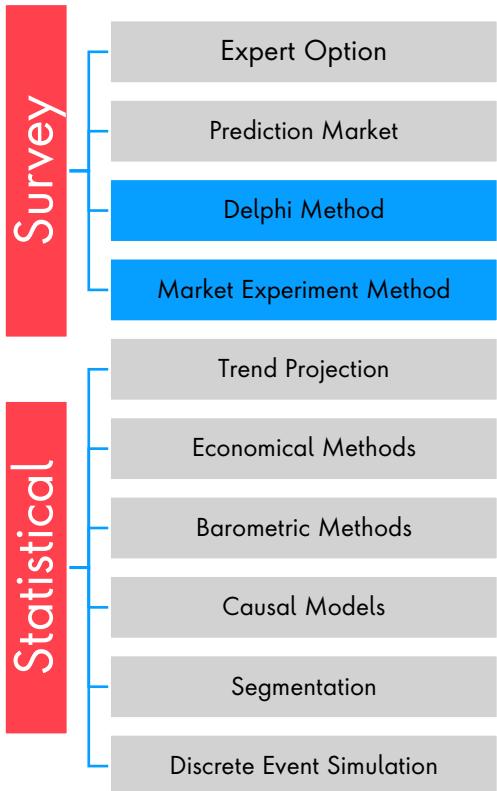
# Market Experiment Method



# Survey Methods

In this section, we like to present the various techniques used for forecasting as well as the uniqueness of each of them

**In this method, consumers or experts are directly contacted and asked for feedback of product and future purchase plans**



# Statistical Methods

In this section, we like to present the various techniques used for forecasting as well as the uniqueness of each of them

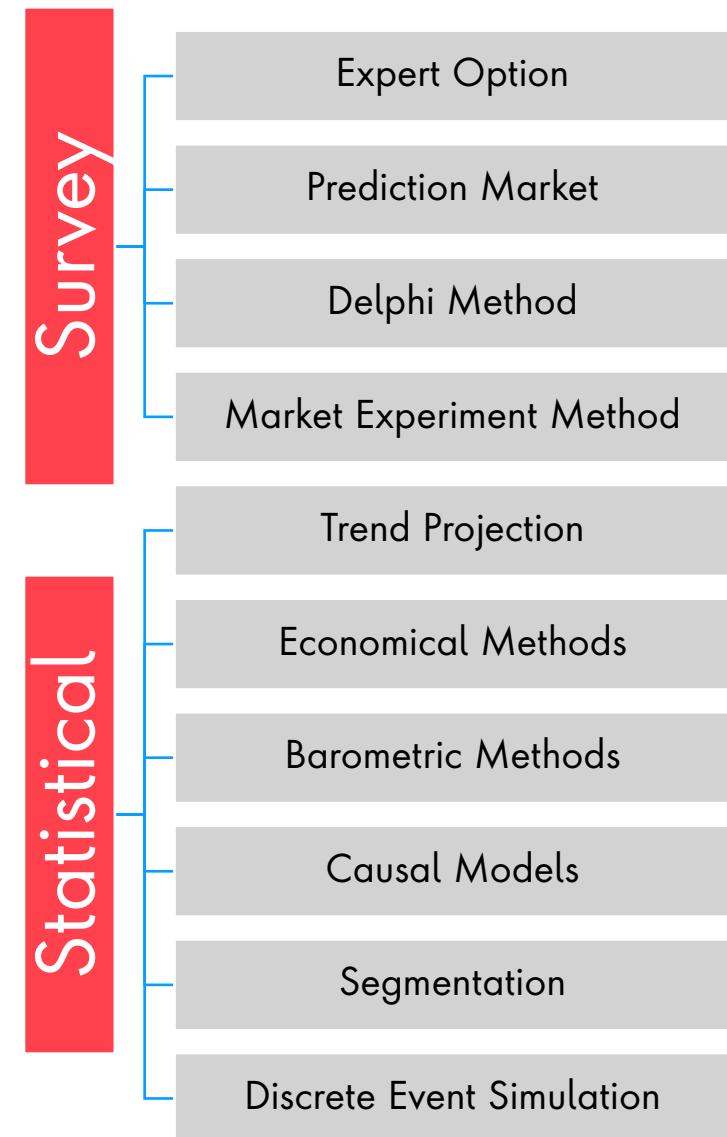
**Another perspective of looking at forecasting can be also**

## Time series forecasting

- moving average method
- exponential smoothing method
- trend projection methods

## Causal methods

- chain-ratio method
- consumption level method
- end use method
- leading indicator method



# Trend Projection



# Economical Methods



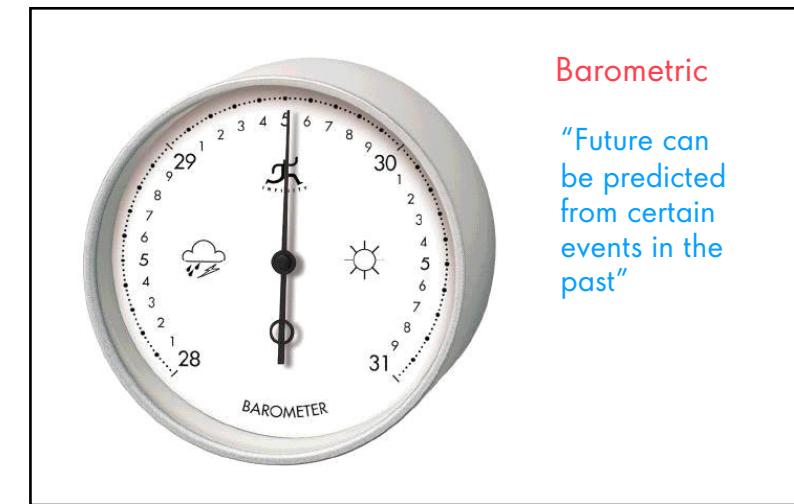
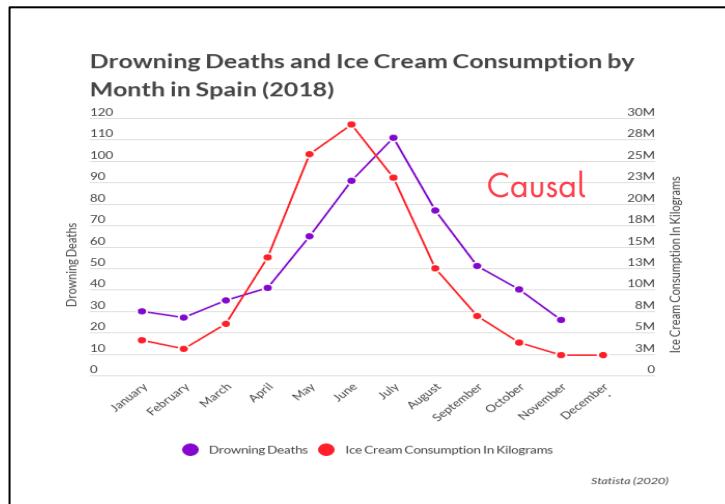
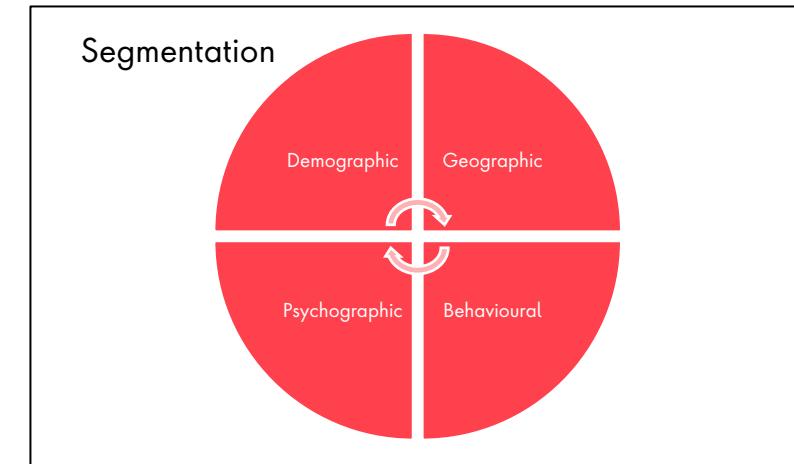
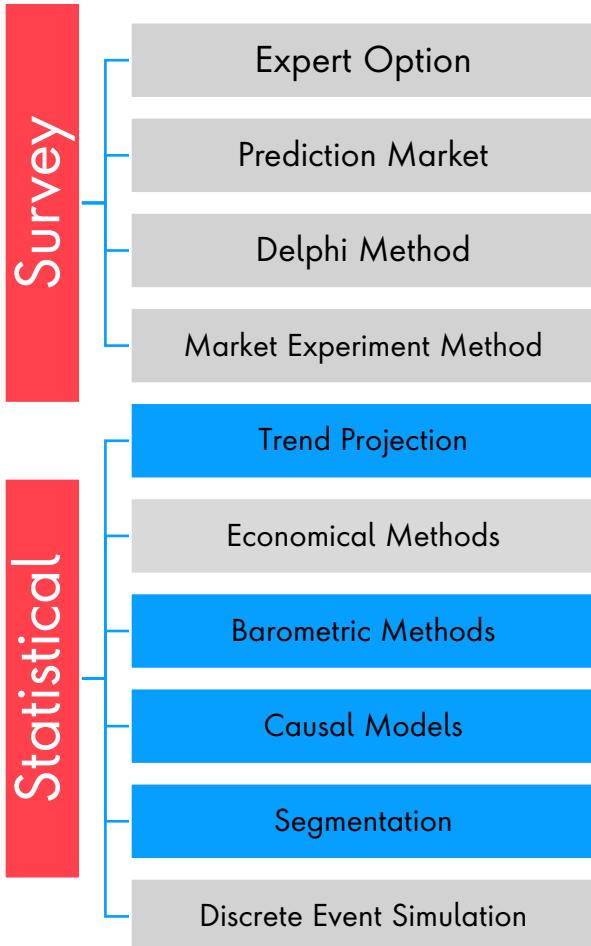
# Segmentation



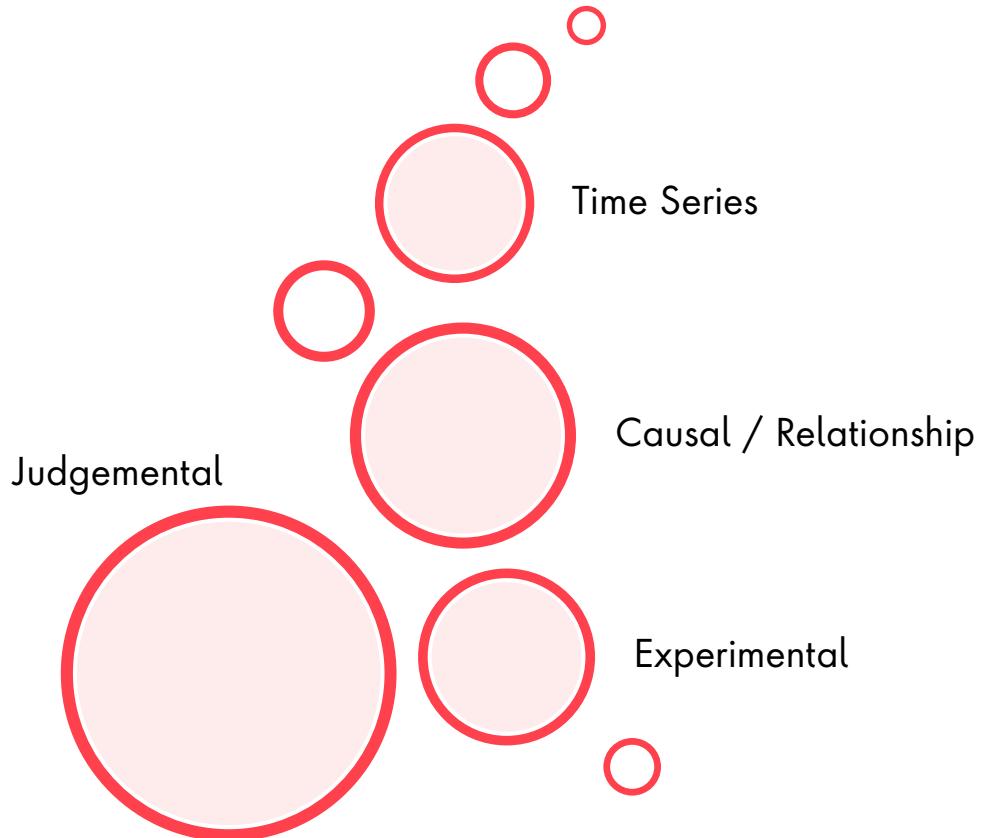
# Discrete Event Simulation

# Statistical Methods

In this section, we like to present the various techniques used for forecasting as well as the uniqueness of each of them



# How do I pick the right technique ?



| Subjective   | Objective   |
|--|---|
| <b>Judgmental</b><br>"Some expert knows the answer" <ul style="list-style-type: none"><li>• Salesforce Surveys</li><li>• Jury of Experts</li><li>• Delphi Sessions</li></ul>   | <b>Causal / Relationship</b><br>"There is an underlying relationship" <ul style="list-style-type: none"><li>• Econometric Models</li><li>• Leading Indicators</li><li>• Input-Output Models</li></ul> |
| <b>Experimental</b><br>"Sampling local, then extrapolating" <ul style="list-style-type: none"><li>• Customer Surveys</li><li>• Focus Groups</li><li>• Test Marketing</li></ul> | <b>Time Series</b><br>"Look for patterns in historical data" <ul style="list-style-type: none"><li>• Black Box Approach</li><li>• Moving Averages</li><li>• Exponential Smoothing</li></ul>           |



# Which techniques have you applied ?

Go to [www.menti.com](http://www.menti.com) and use the code 493694

<https://www.menti.com/prz9womap6>



Let's deep dive

## Traditional Time series Vs Deep learning

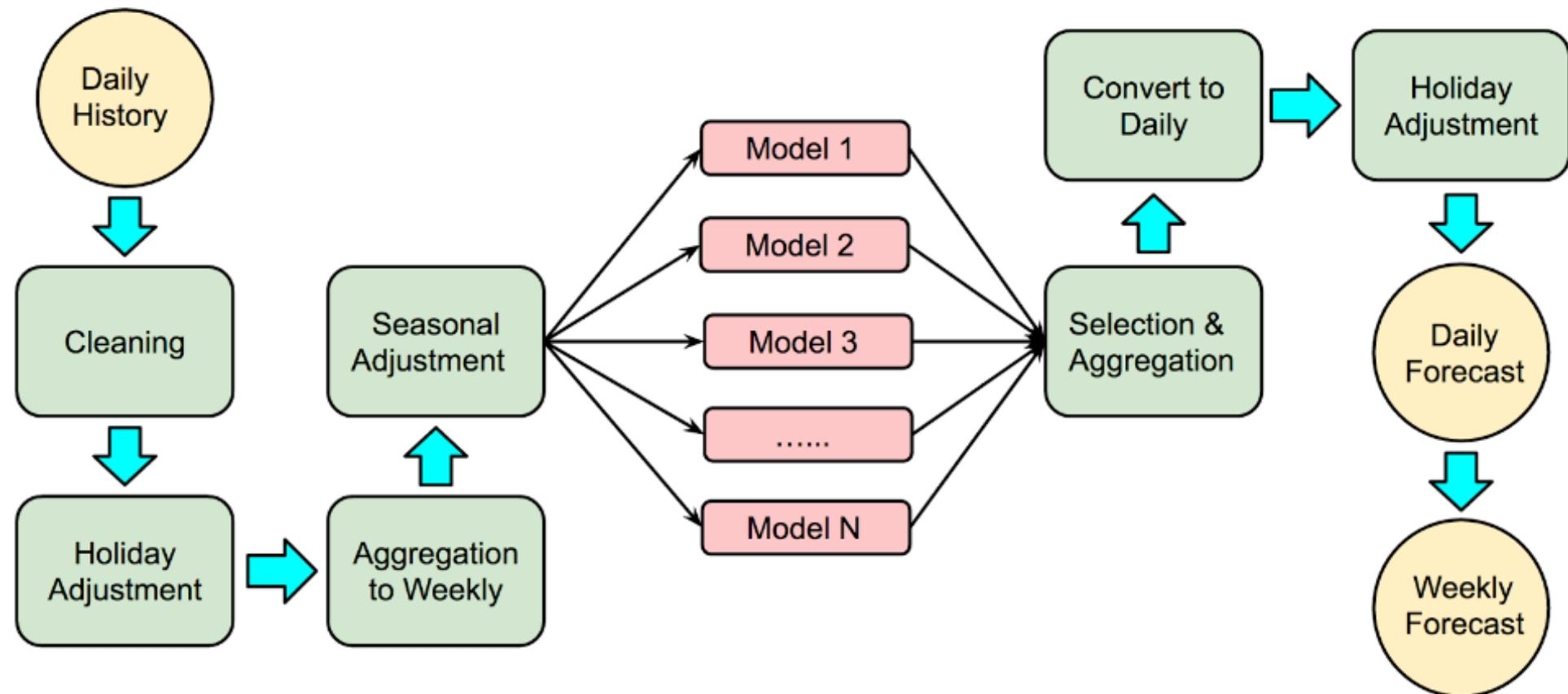
### Traditional Time Series

- Mostly Univariate
- Seasonality
- Not suitable for long term
- Require complete data
- Easy to interpret

### Deep Learning

- Multivariate
- Suitable for high volume of data
- Blackbox with complex relations
- Lack of interpretability
- Requires high computational resources

# System design for Conventional Time Series Seasonal Prediction



## Additional Factors for consideration

Now that we understand the techniques of forecasting and the client impact, let's think about some of the other factors that needs to be considered while designing such system

ARIMAX model extends the univariate ARIMA model through inclusion of exogenous variables  $X$ , whose effect on forecasted values is calculated through regression.

$$\Delta^D y_t = \underbrace{\sum_{i=1}^p \phi_i \Delta^D y_{t-i}}_{\text{ARIMA}} + \underbrace{\sum_{j=1}^q \theta_j \epsilon_{t-j}}_{\text{Exogenous Variables}} + \underbrace{\sum_{m=1}^M \beta_m X_m t}_{\text{Exogenous Variables}} + \epsilon_t$$

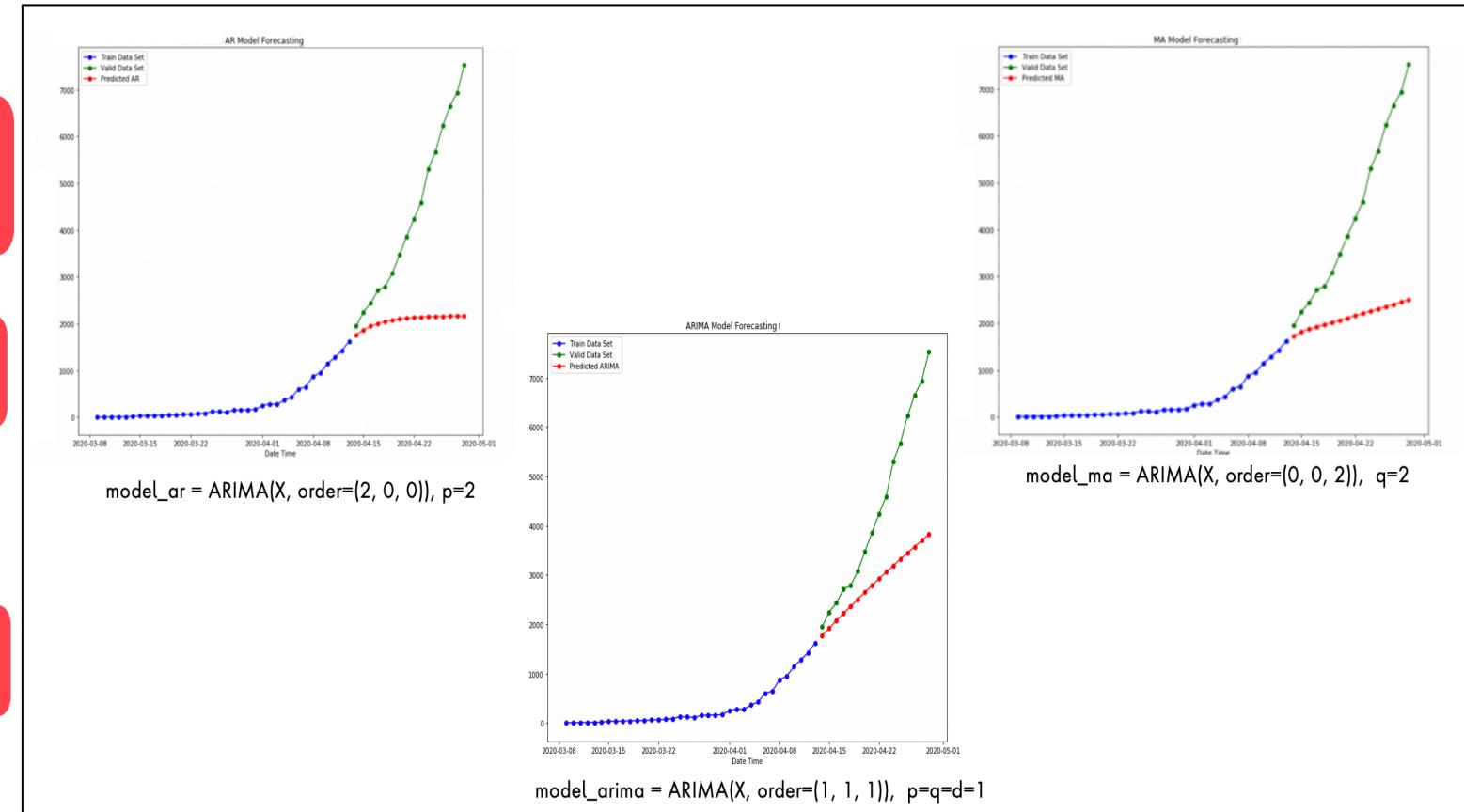
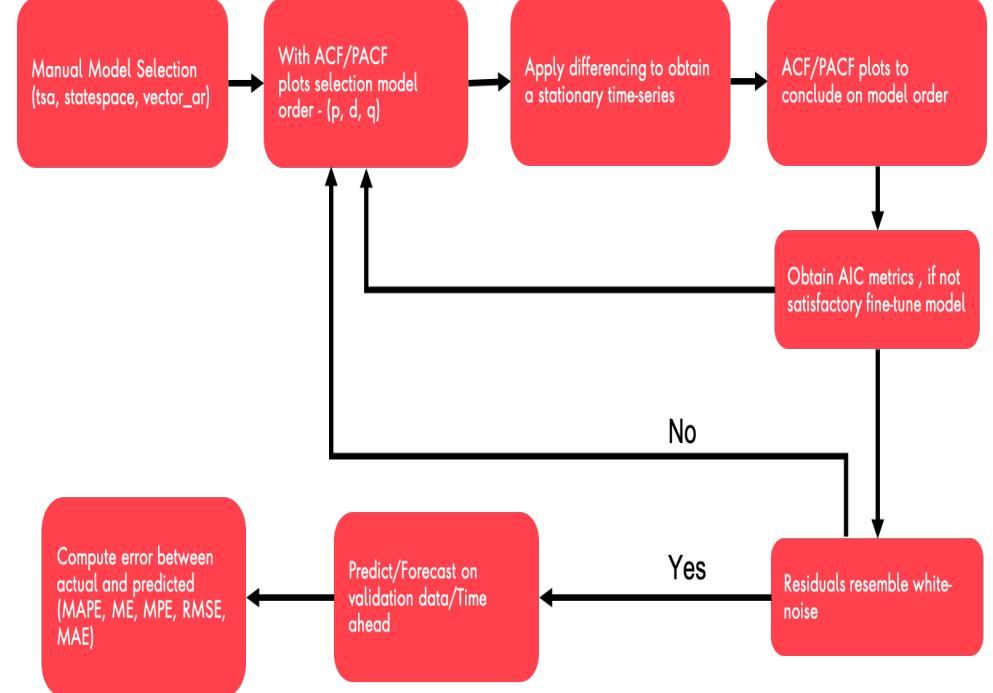
ARIMA

Univariate Time Series Forecasting

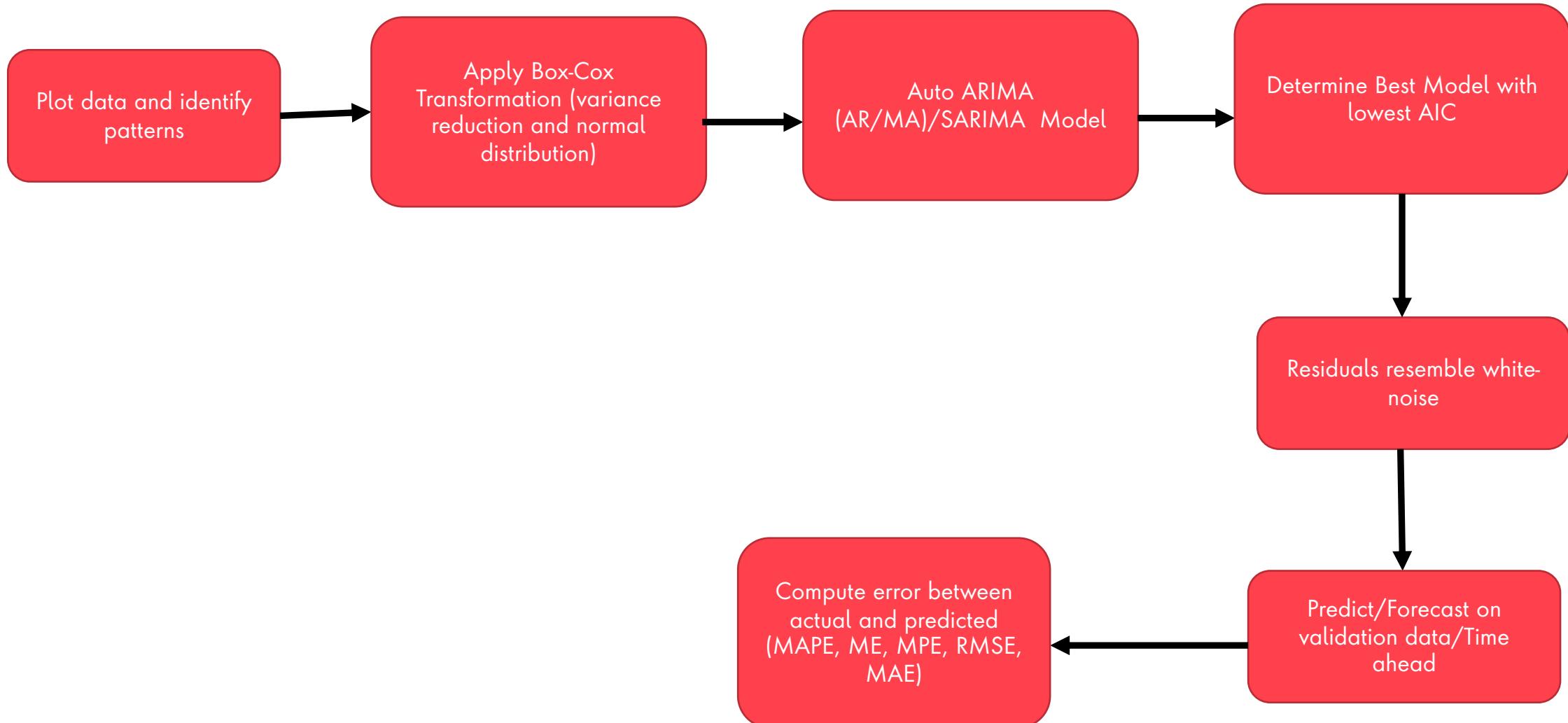
Exogenous Variables

Independent Variables influencing forecasted values

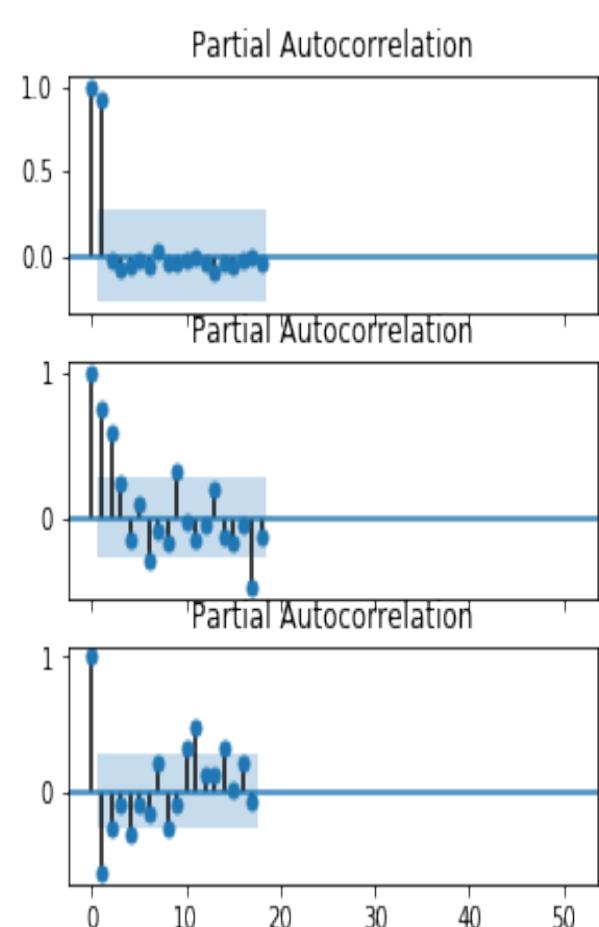
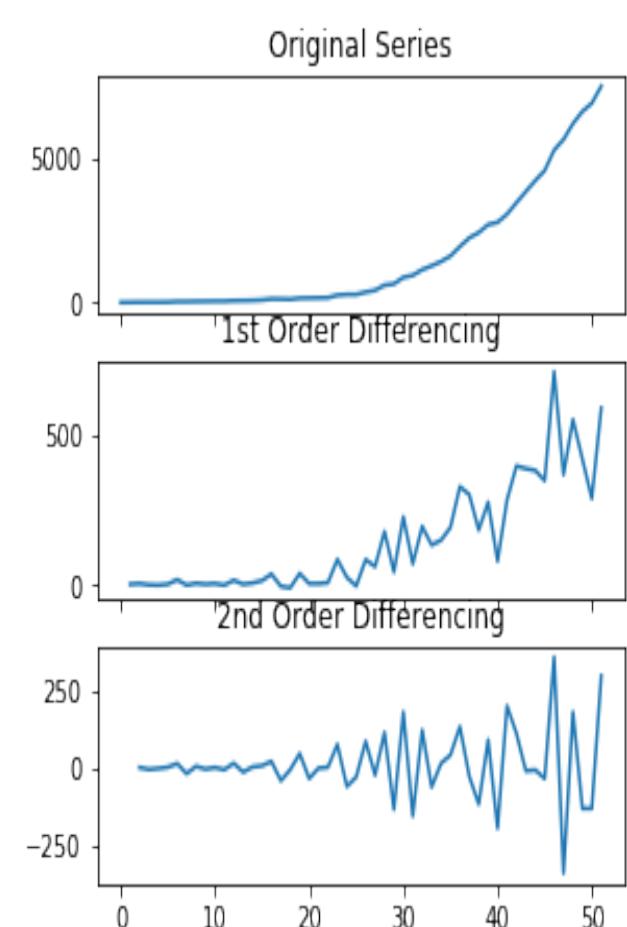
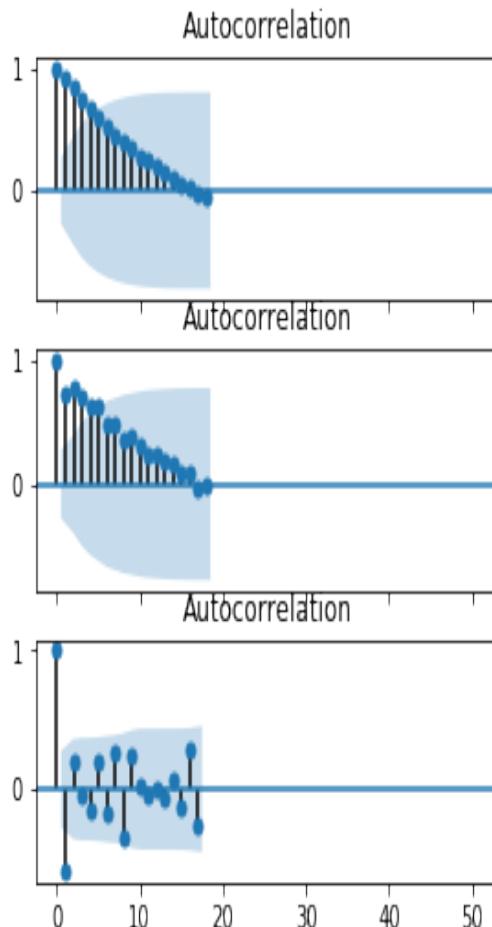
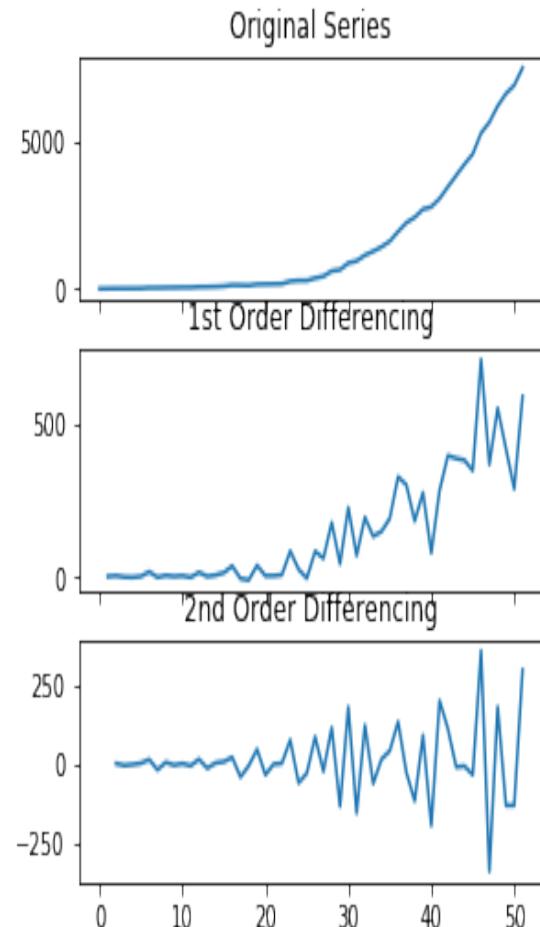
# Selection of best model -ARIMA



## Selection of best model –Auto ARIMA



# Auto and Partial Autocorrelation





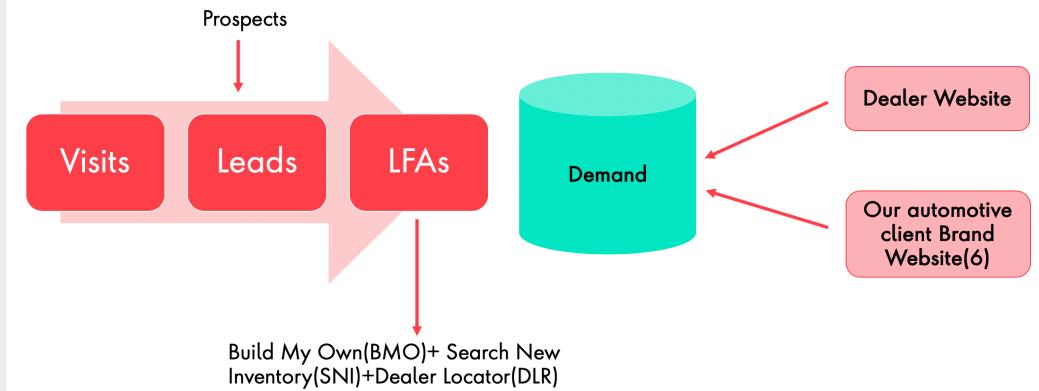
HOW ?  
we did it in action

# Use Case – Automotive Client

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

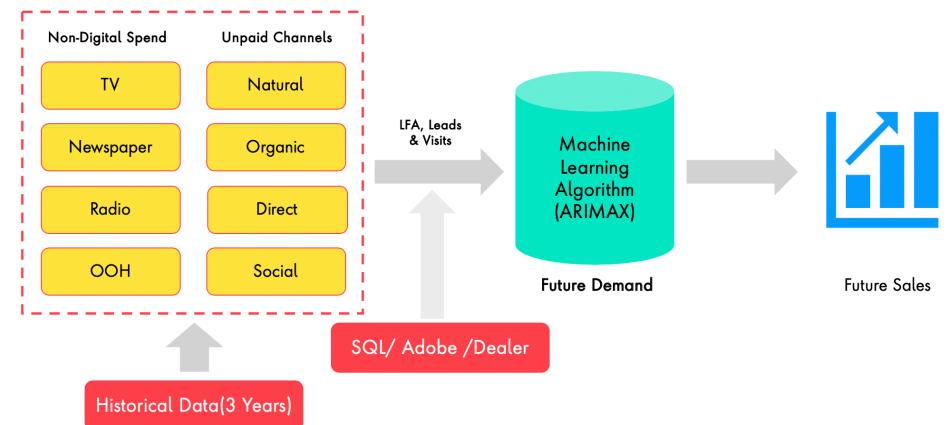
- The objective was to understand and predictions of demand drivers(Visits, **Lower Funnel Activities**(LFAs) and Leads) by brand and model by keeping media spends in consideration.
- Client wanted to see the impact of advertisements they run on TV and Radio at prime time on there website performance and which can help to allot the budgets in future.

## What is Demand?



## Projection - Process

To understand and prediction of demand drivers by Brand and Model by keeping the Media spends in Consideration.



# Use Case – Automotive Client

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

In order to see the impact of media spend , we thought of opting ARIMAX, as there are additional explanatory variables (multivariate) in numeric format. Also we chose ARIMA as my future values are dependent on my past three years of data.

## Our Impact: With AI & Machine Learning We Can Now...

### Identify KPIs

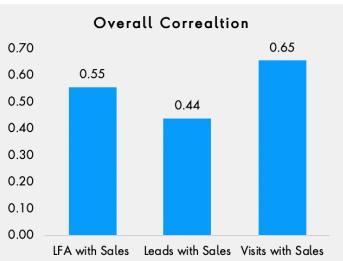
Identify the top KPIs responsible for sale and their prediction.

### Forecast Test Drive Bookings

Forecast test drive bookings for upcoming months with **86%** accuracy.

### Predict LFA

Predict Lower funnel activities done by customer with **85%** accuracy.



### Predict Visitors

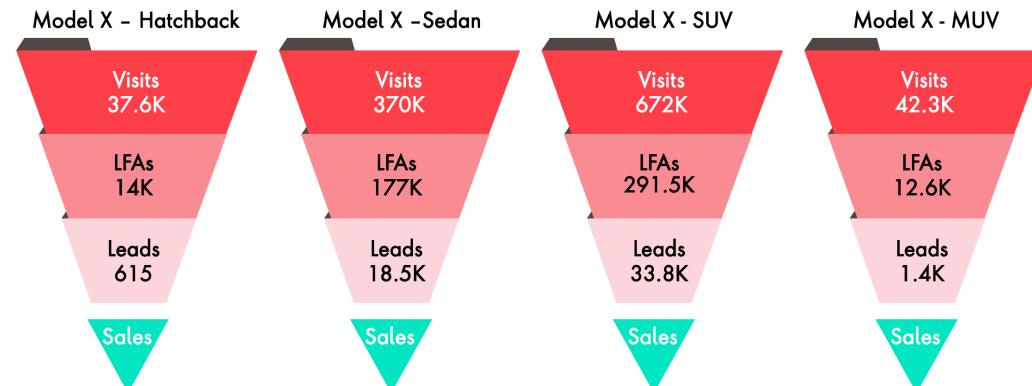
Predict Visitors coming to website with **80%** accuracy.

### Forecast Car Model Demands

Forecast the KPIs at model level with **80%** accuracy.

## Projections - Result

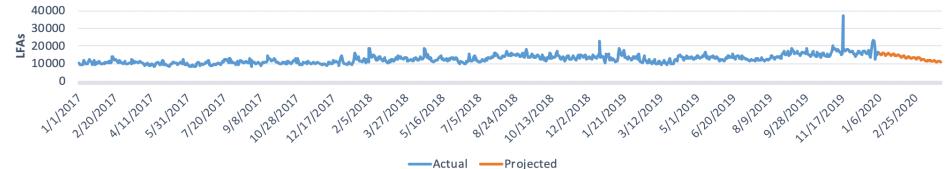
Model X – Projection Funnel



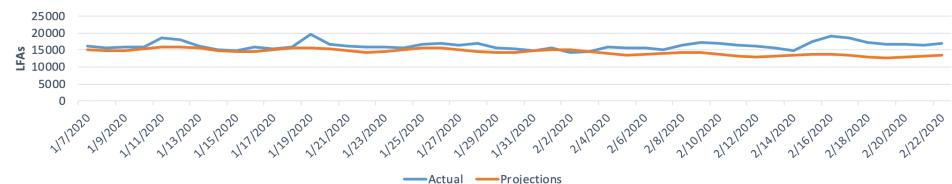
## Projections - Result

Model X – Projections

Brand X - Forecast



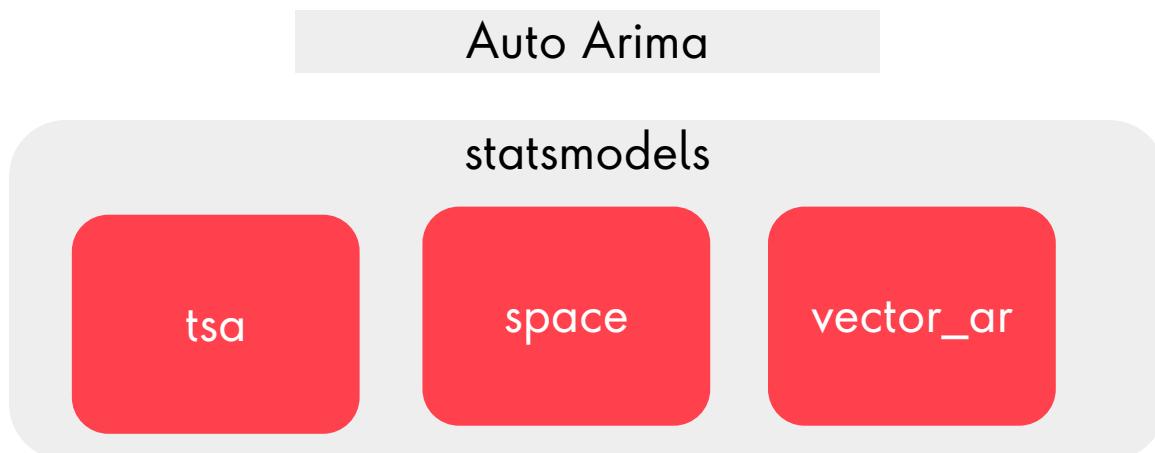
Brand X - Actual vs Projected



# Use Case Walk through

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

## Packages



## Package Used

```
import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

Let's see it action

# Use Case Walk through

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

RMSE/MAPE

$$MAPE = \frac{\sum \frac{|A-F|}{A} \times 100}{N}$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}}$$

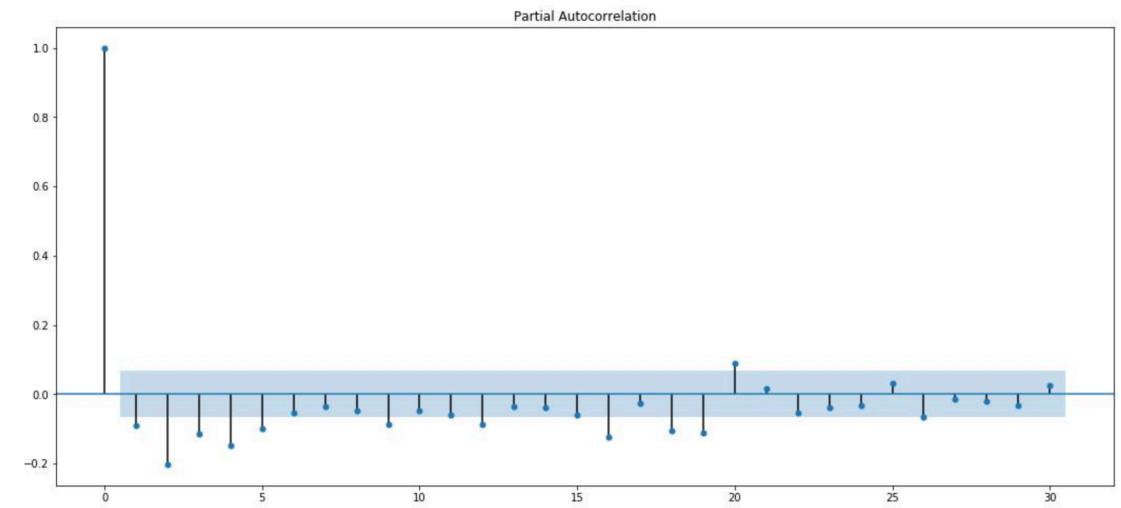
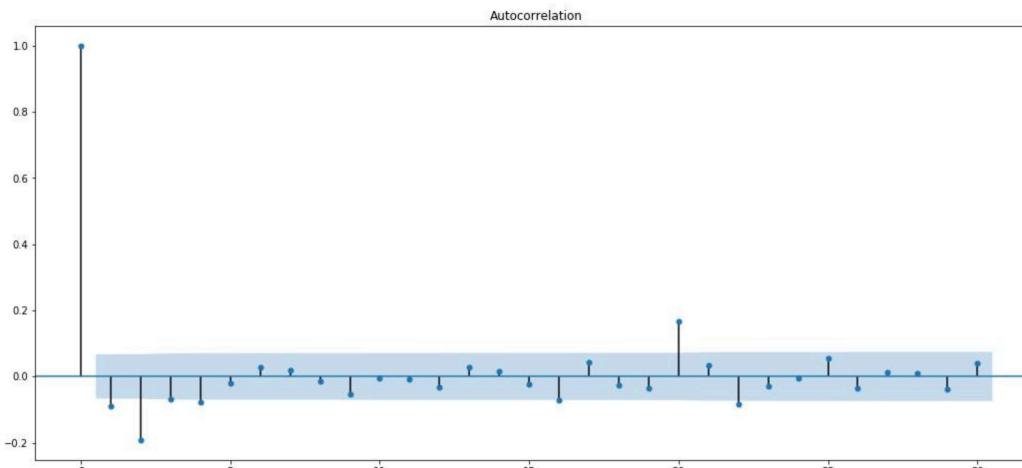
RMSE/MAPE

```
#####
rmse = round(np.sqrt(mean_squared_error(test_last60[var], pred_test_last60[0])), 0)
mape = round(mean_absolute_percentage_error(df_mape_inf[var], df_mape_inf['preds']), 2)
####
```

# Use Case Walk through

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

## Setting pdq



```
plot_acf(ts_visits_diff)
plt.savefig('visits_acf_'+nameplate+'.png', bbox_inches='tight')

plot_pacf(ts_visits_diff)
plt.savefig('visits_pacf_'+nameplate+'.png', bbox_inches='tight')
```

# Use Case Walk through (Demo)

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

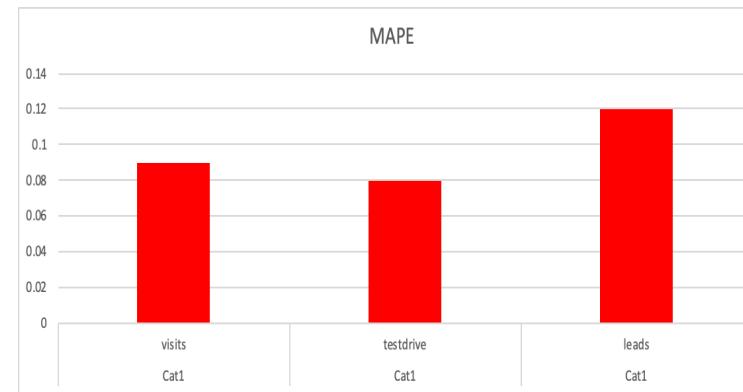
## Forecasting Values

```
ar = ARIMA(endog=train_all_known[var], exog=train_all_known[exog_var], order=(p,d,q))
# fit ARIMA model
model = ar.fit()
# predict test using ARIMA model
pred_unknown = model.forecast(steps=len(test_all_unknown), exog=test_all_unknown[exog_var])
```

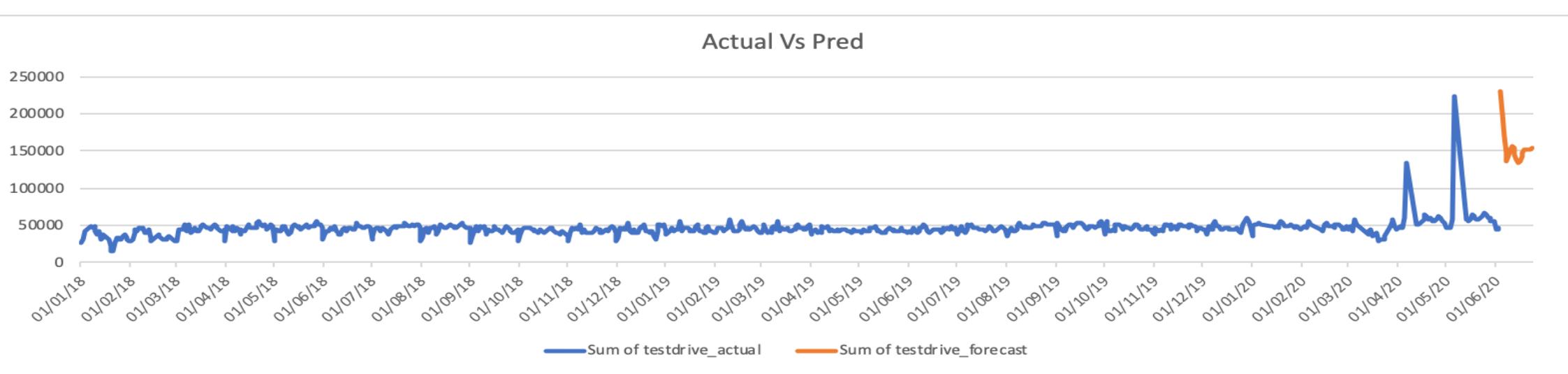
# Outputs - ARIMAX

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

RMSE / MAPE



Actual Vs Pred



# Causal Impact

# Causal Impact

In this section, we like to present the additional factors embedded with data

**Another perspective of looking at forecasting can be also**

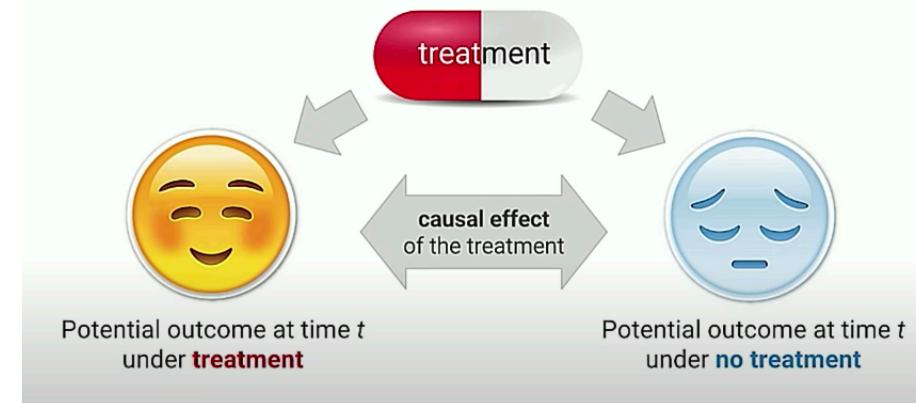
## Time series forecasting

- Moving average method
- Exponential smoothing method
- Trend projection methods

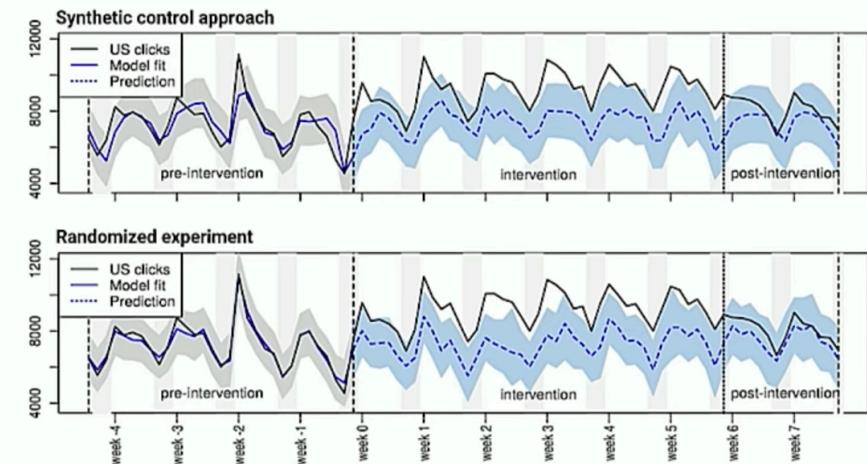
## Causal methods

- Chain-ratio method
- Consumption level method
- End use method
- Leading indicator method

## The problem of causal inference



## Causal effect of advertising on clicks



Source - Inferring the effect of an event using CausalImpact by Kay Brodersen  
(<https://www.youtube.com/watch?v=GTgZfCltMm8>)

# Use Case Walk through – Causal Impact (Demo)

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.

## Important Package

```
from causalimpact import CausalImpact  
import matplotlib
```

## Causal Impact

```
impact = CausalImpact(df1, pre_period, post_period)
```

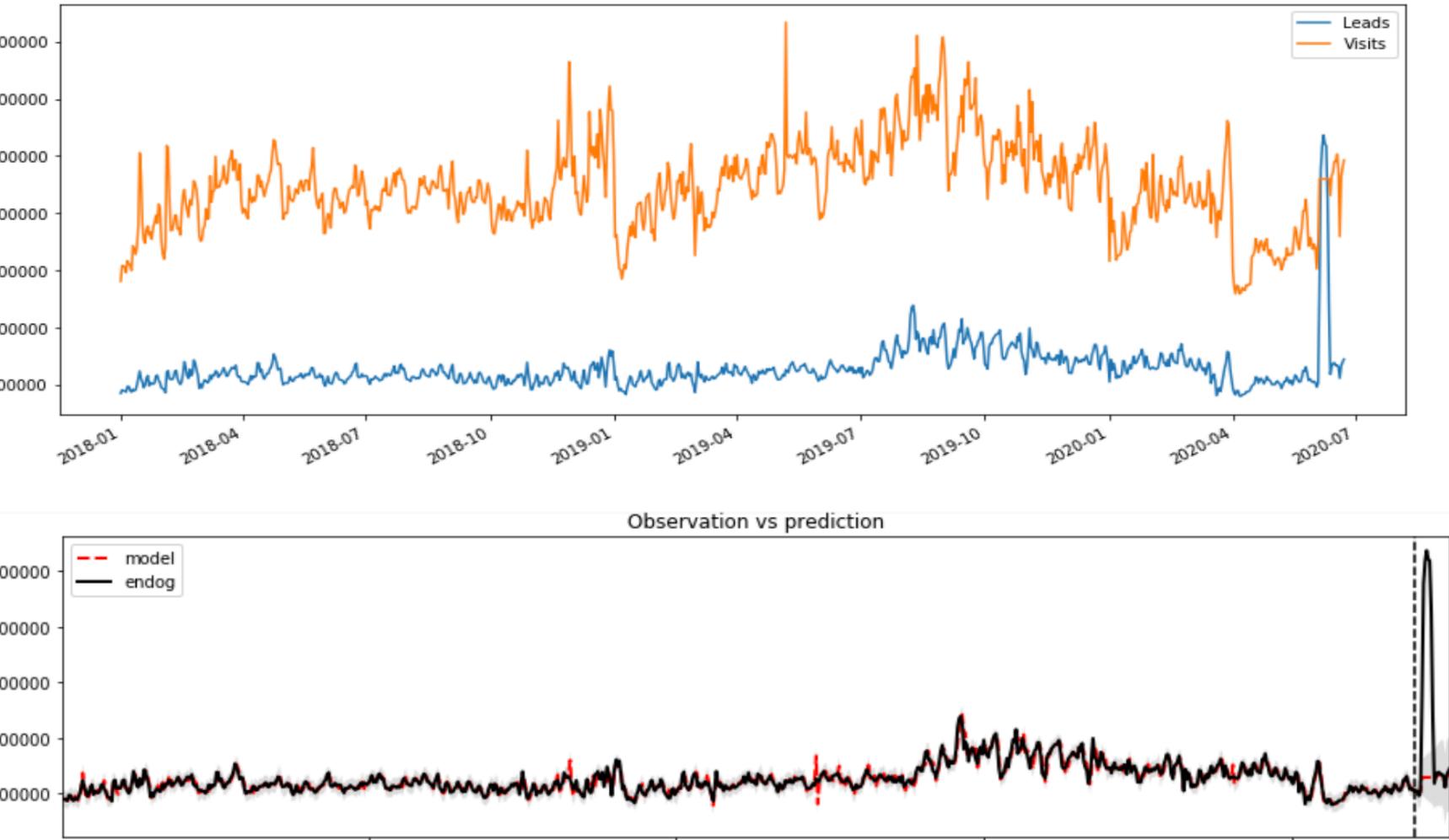
```
print(impact.summary())
```

|                        | Average           | Cumulative           |
|------------------------|-------------------|----------------------|
| Actual                 | 233427            | 5368826              |
| Predicted              | 125368            | 2883474              |
| 95% CI                 | [ 78838, 171898 ] | [ 1813279, 3953669 ] |
| Absolute Effect        | 108058            | 2485351              |
| 95% CI                 | [ 154588, 61528 ] | [ 3555546, 1415156 ] |
| Relative Effect        | 86.2%             | 86.2%                |
| 95% CI                 | [ 123.3%, 49.1% ] | [ 123.3%, 49.1% ]    |
| P-value                | 0.0%              |                      |
| Prob. of Causal Effect | 100.0%            |                      |
| ---                    |                   |                      |

Let's see it action

## Outputs - Causal

Let's look at how we applied these techniques to solve the business problem for one of our automotive client.



# Budget Optimization

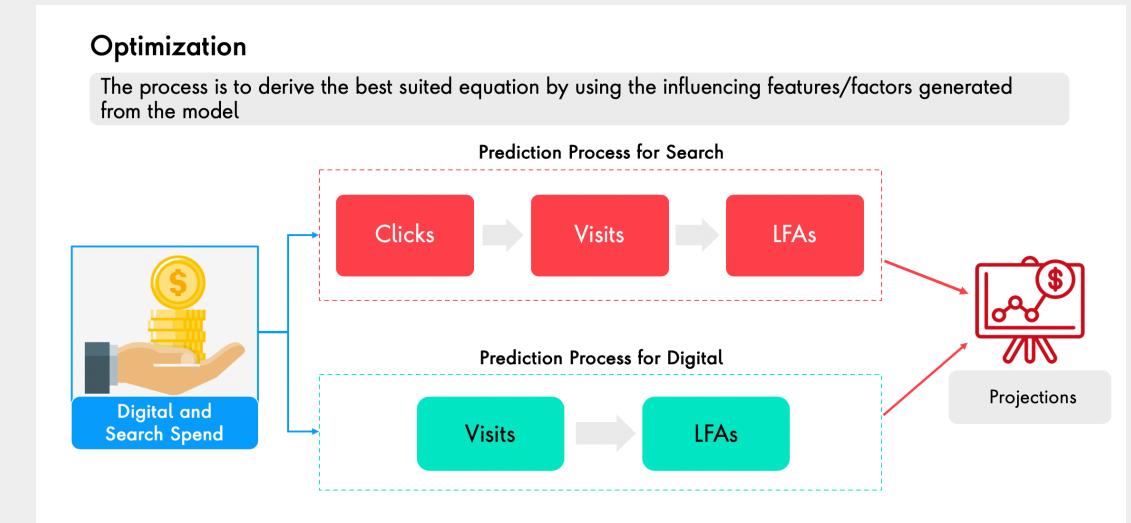
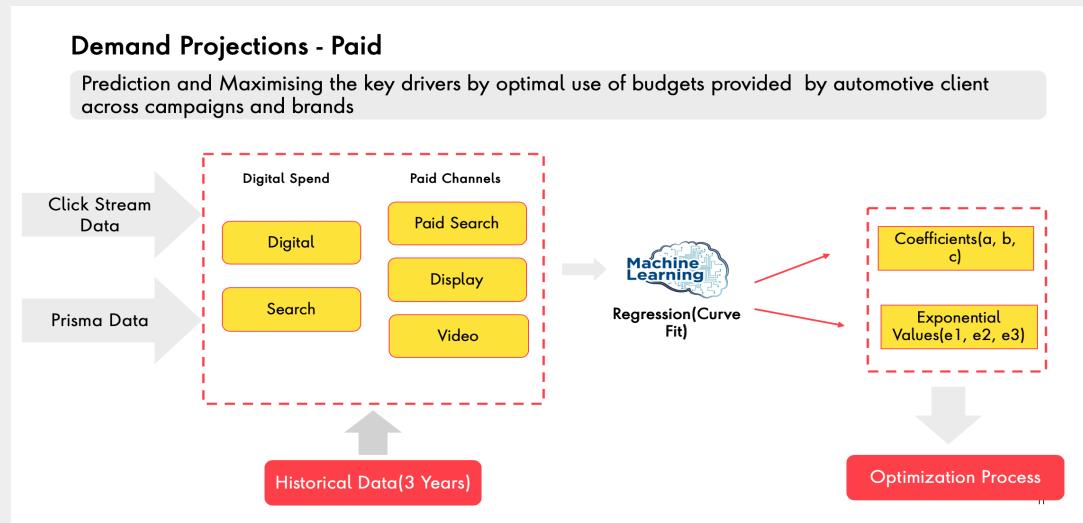
# Budget Optimization and its impact for forecasting

Let's understand about budget optimization and how it influences forecasting in the context of the automotive client use case that we briefly discussed earlier

## Addressing the Problem:

- We collated data from **disparate sources** to create a unified view to understand **how spend was affecting the demand drivers**.

## Factors which can influence the forecasting.

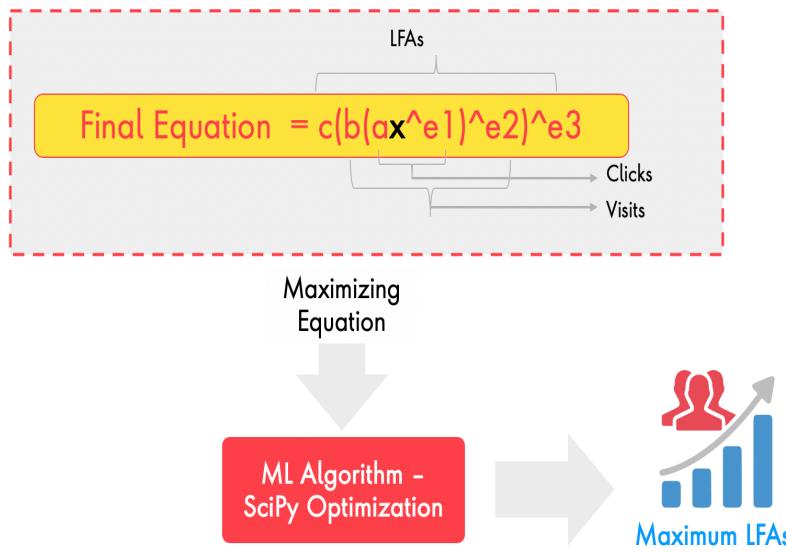


# Budget Optimization and its impact for forecasting

Let's understand about budget optimization and how it influences forecasting in the context of the automotive client use case that we briefly discussed earlier

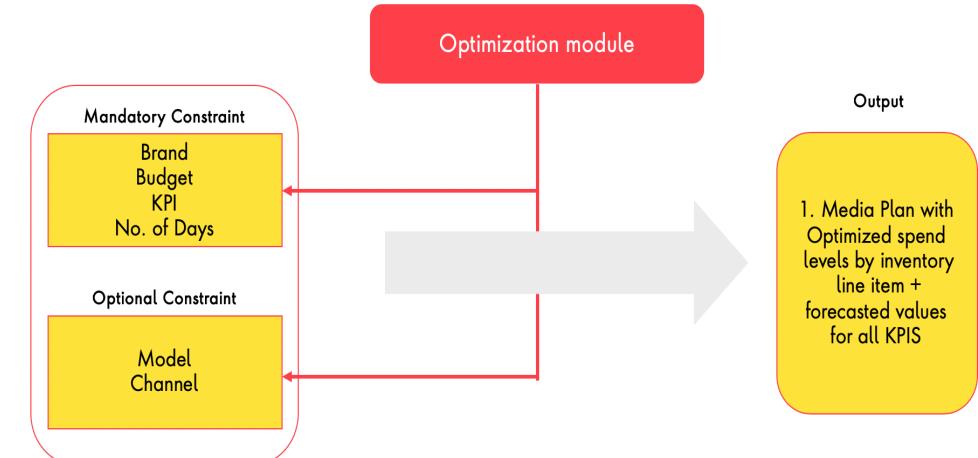
## Optimization Equation

Optimising the overall budget and maximising the equation to get maximum LFA with 99% utilisation of entire budget allocated to specific brand.



## Optimization Equation Constraints

After setting up the equation , we had set some constraints as per the business requirement.



# Budget Optimization and its impact for forecasting

Let's understand about budget optimization and how it influences forecasting in the context of the automotive client use case that we briefly discussed earlier

## Goal Setting - Result

| Total Target: 800K, Total Campaigns: 350, No of Days = 31 |          |             | Channel level Constraints<br>Digital = 450K, Search = 350K |          |             |
|---|----------|-------------|--|----------|-------------|
| Nameplate   | LFAs     | Budget      | Nameplate  | LFAs     | Budget      |
| Model A   | 20,175   | 5,06,515    | Digital  | 445,605  | 7,831,590   |
| Model B   | 2,668    | 42,564      | Search   | 354,417  | 5,109,602   |
| Model C   | 4,45,658 | 55,07,300   | Total  | 8,00,022 | 1,29,41,193 |
| Model D   | 98,601   | 19,41,071   |  |          |             |
| Model E   | 4,976    | 60,358      |  |          |             |
| Model DX  | 81,470   | 21,13,756   |  |          |             |
| Model CX  | 1,46,112 | 27,61,168   |  |          |             |
| Total   | 8,00,022 | 1,29,41,193 |  |          |             |

## Key Features

### Intelligence @ Scale

- Ability to maximize the LFAs with given budget in a single click by using Machine Learning Algorithms.
- Ability to achieve the LFAs by Optimizing the budget along with the business level constraints

### Extensibility

Currently used for our automotive client but can be used for other clients to achieve targets and Budget Optimization

#### Predict Targets

Predict Targets with 80% accuracy.

### Performance @ Scale

Reduced the processing time from 45 mins to under 3 mins thus enabling faster delivery and scalability across different brands

# Optimization – Scipy Package

## Obtaining Coefficients & Exponents – curve\_fit

```
def fit_curve(x,y):
    """
    power curve y = a*(x^b)
    """
    popt, pcov = curve_fit(lambda fx,a,b: a*fx**b, x, y, maxfev = 10000)

    pred_y = popt[0]*x**popt[1]

    r2 = r2_score(y,pred_y)
    rmse = round(np.sqrt(mean_squared_error(y, pred_y)), 0)

    df_mape_inf = pd.DataFrame()
    df_mape_inf['y'] = y
    df_mape_inf['pred_y'] = pred_y
    df_mape_inf = df_mape_inf[df_mape_inf['y'] != 0]
    mape = round(mean_absolute_percentage_error(df_mape_inf['y'], df_mape_inf['pred_y']), 2)

    # https://www.dummies.com/education/math/business-statistics/how-to-calculate-the-adjusted-coefficient-of-determination/
    #r2_adj = (1 - (1 - r2) * ((len(y) - 1)/(len(y) - (1 + 1 )))

    #confidence = np.sqrt(np.diag(pcov))

    return([popt,[r2,mape,rmse],pred_y])
```

# Optimization – Defining Objective function

## Defining Objective function

```
#Defining the objective function(For Search and Digital Campaigns together)
def objective(x):
    eq=(((((x[0]+spend_flr[0]+aar[0])**es[0])*cs[0])**ev[0])*cv[0])**el[0])*cl[0]
    eq2=0
    for i in range(1,len(cs)):
        if i<len(df_s):
            eq=eq+((((x[i]+spend_flr[i]+aar[i])**es[i])*cs[i])**ev[i])*cv[i])**el[i] #For Search campaigns
        else:
            eq2=eq2+(((x[i]+spend_flr[i]+aar[i])**evs[i])*cvs[i])**el[i])*cl[i] #For Digital campaigns
    return -(eq+eq2)
```

# Optimization

## Defining Objective function

### Available Methods

- SLSQP
- trust-ncg
- TNC
- COBYLA

## Optimization

```
start_time_c = time.time()
#Optimize
solution = minimize(objective,x0,method='SLSQP',bounds=bnds,constraints=cons)
xc = solution.x

# show final objective
print('Final Objective: ' + str(objective(xc)))

# print solution
print('Solution')
#for i in range(0,len(x)):
#    print(str(x[i]))
end_time_c = time.time()
print("Total Time Taken: {} seconds".format(end_time_c - start_time_c))
```



**Discussion Time !!!**

# thank you

"You can reach us with details on the github page"

<https://bit.ly/rising2020ps>

<https://datacoe-publicissapient.github.io/risingai2020>

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