July 4, 2020

Demand Forecasting and Budget Optimization using Python

publicis sapient

Rising AI 2020

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We work with organizations
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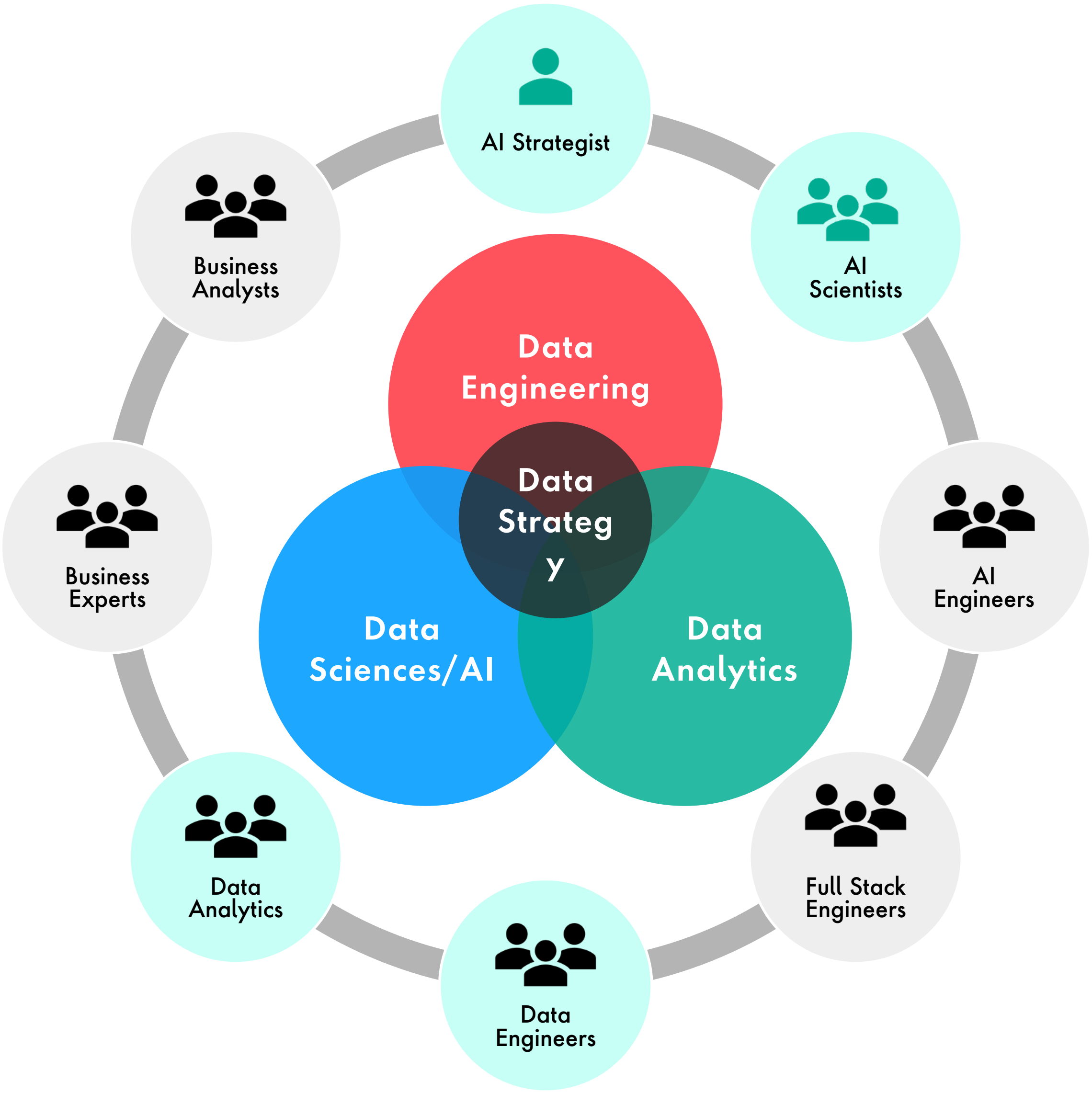


https://bit.ly/rising2020ps

Let's Get Started

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

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

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 and use the code 493694

https://www.menti.com/prz9womap6

Demand Forecasting

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

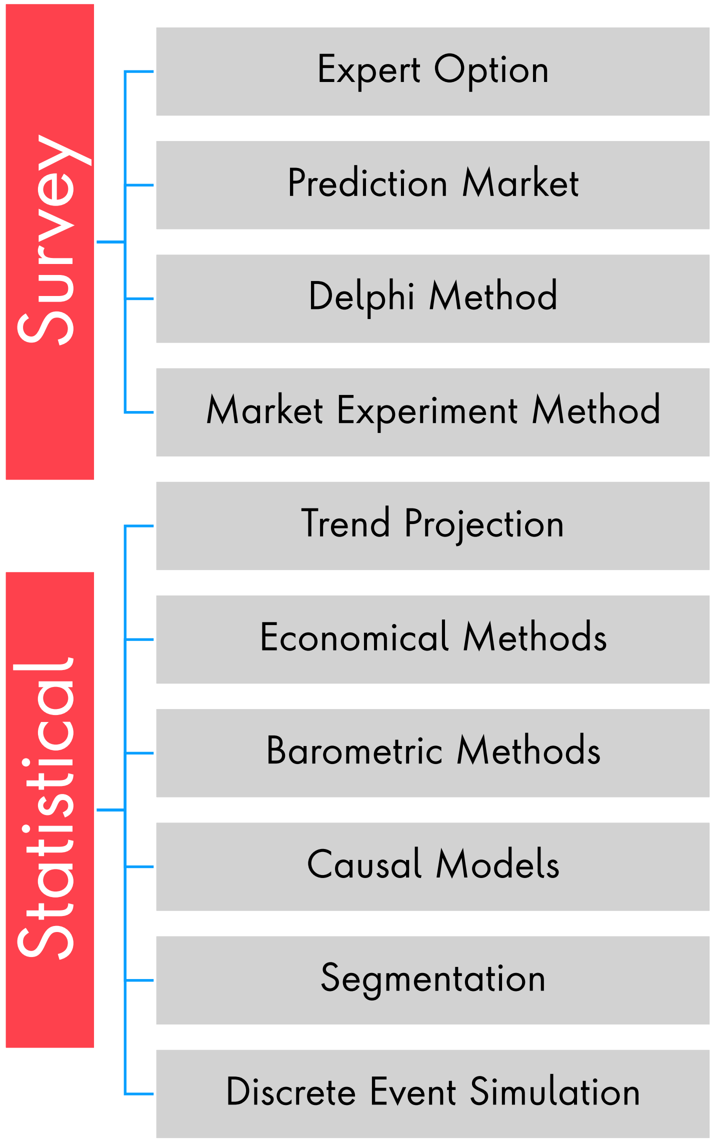
Conventional demand forecasting techniques

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

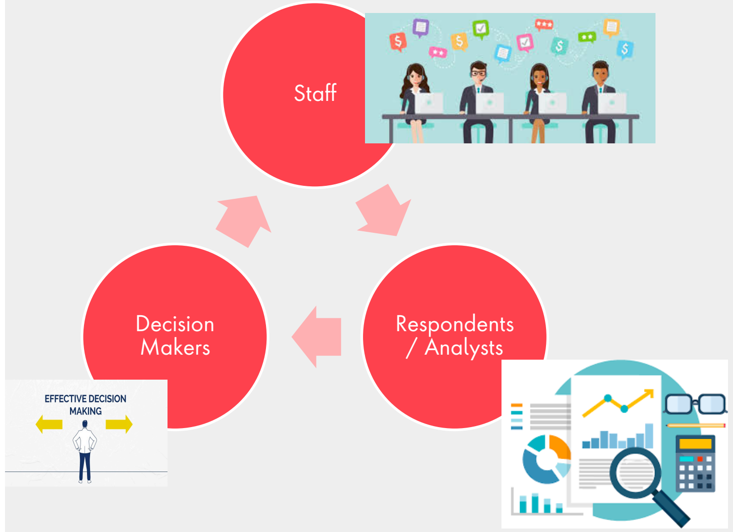
Survey

- Expert Option
- Prediction Market
- Delphi Method
- Market Experiment Method

Statistical

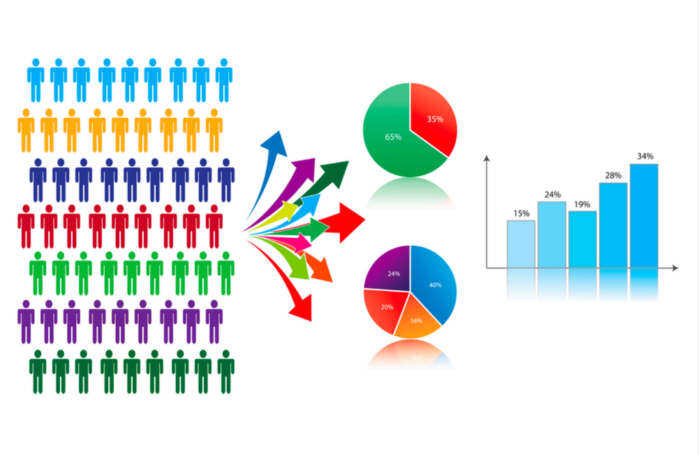
- Trend Projection
- Economical Methods
- Barometric Methods
- Causal Models
- Segmentation
- Discrete Event Simulation

Delphi Method



- Iterative
- Continuous till required goals are met

Market Experiment Method



- Test Marketing/Controlled Environment
- Responses may not always be accurate
- Takes change on at a time, records responses and iterates

Statistical Methods

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

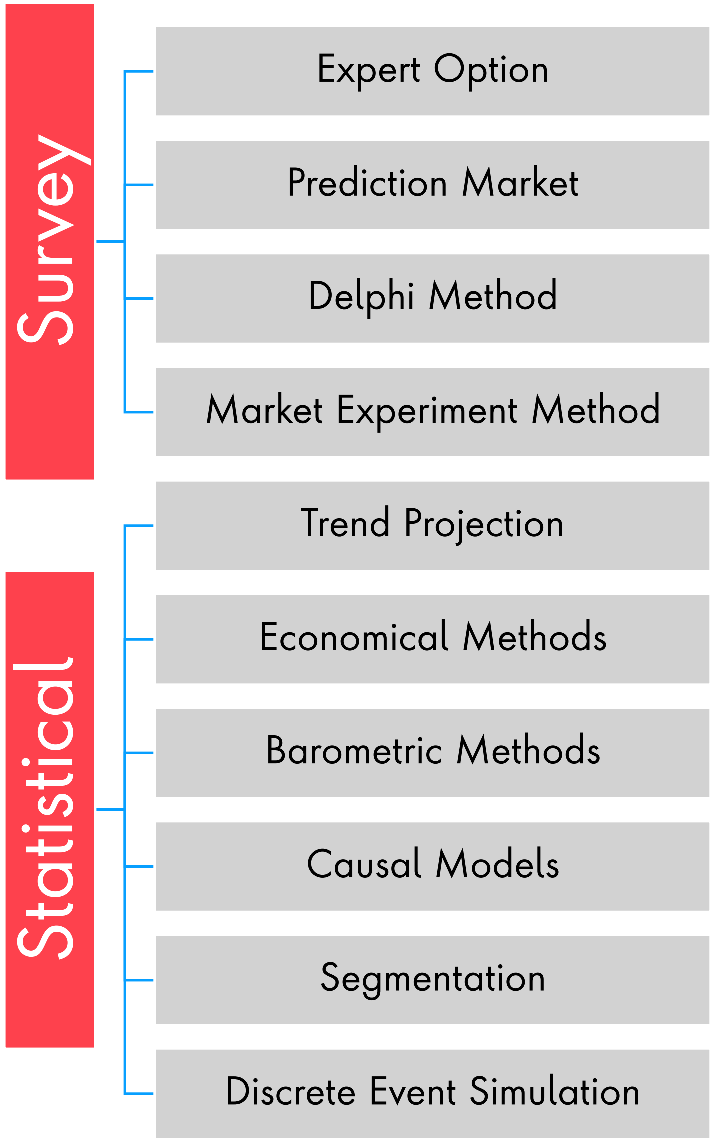
Another perspective of looking at forecasting can be also

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

Survey
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Statistical
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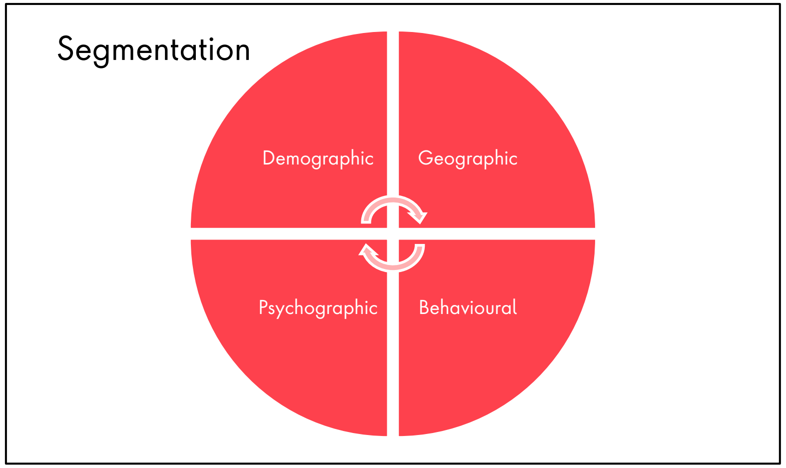
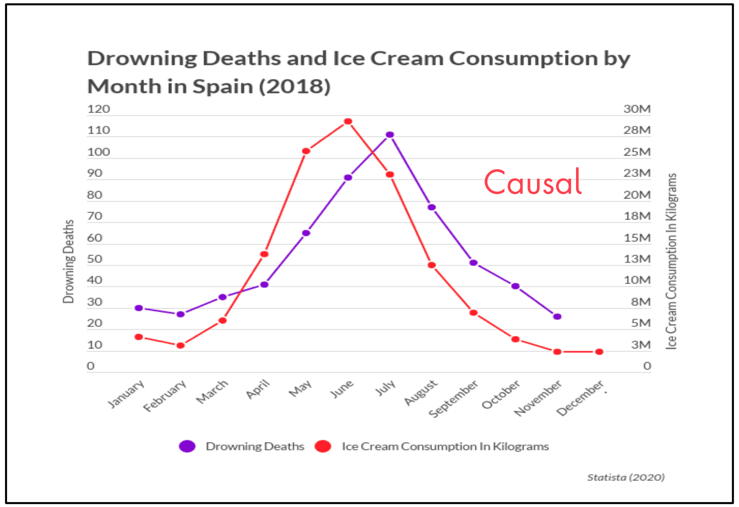
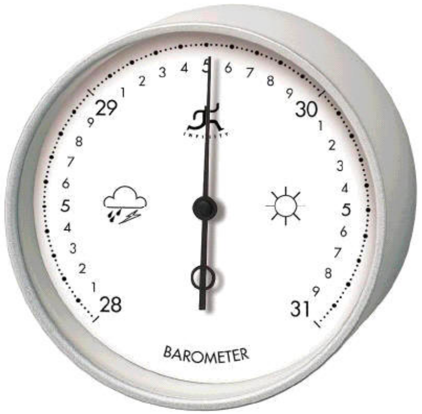
- Discrete Event Simulation





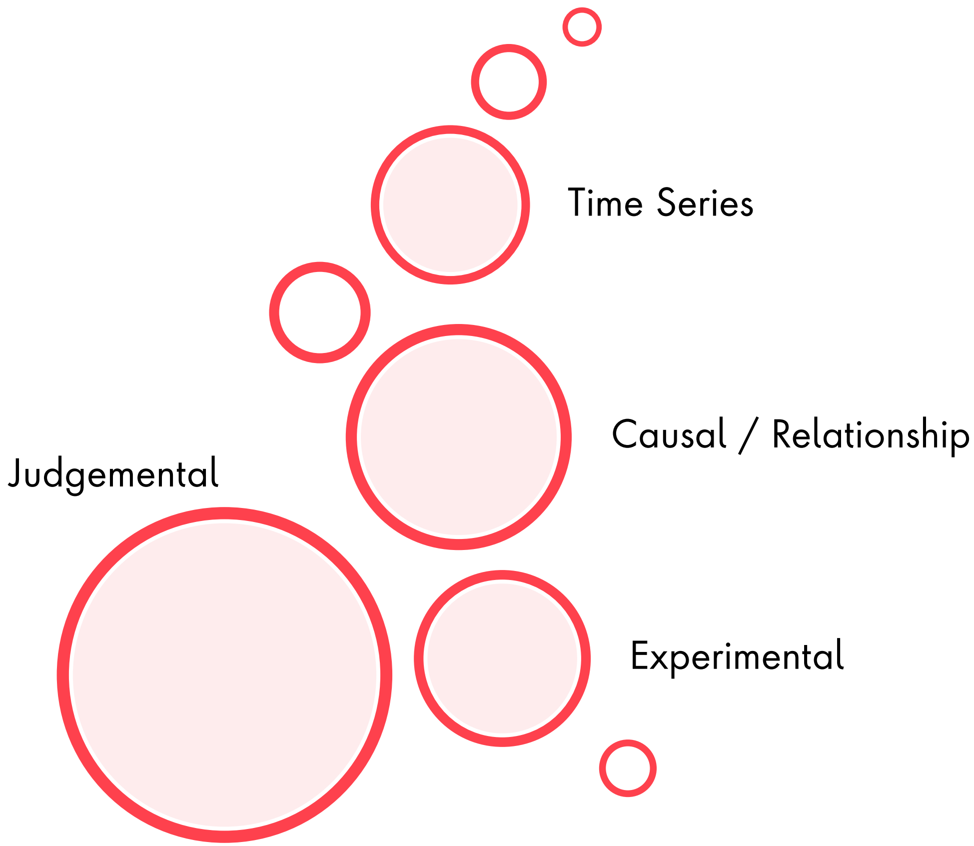


Barometric

"Future can be predicted from certain events in the past"

https://scm.ncsu.edu/scm-articles/article/demand-forecasting-a-cross-discipline-perspective-part-i-model-output-statistics-mos

How do I pick the right technique ?



Subjective	Objective
Judgmental "Some expert knows the answer" • Salesforce Surveys • Jury of Experts • Delphi Sessions	**Causal / Relationship** "There is an underlying relationship" • Econometric Models • Leading Indicators • Input-Output Models
Experimental "Sampling local, then extrapolating" • Customer Surveys • Focus Groups • Test Marketing	**Time Series** "Look for patterns in historical data" • Black Box Approach • Moving Averages • Exponential Smoothing

Which techniques have you applied ?

Go to www.menti.com and use the code 493694

https://www.menti.com/prz9womap6

Let’s deep dive

Traditional Time series Vs Deep learning

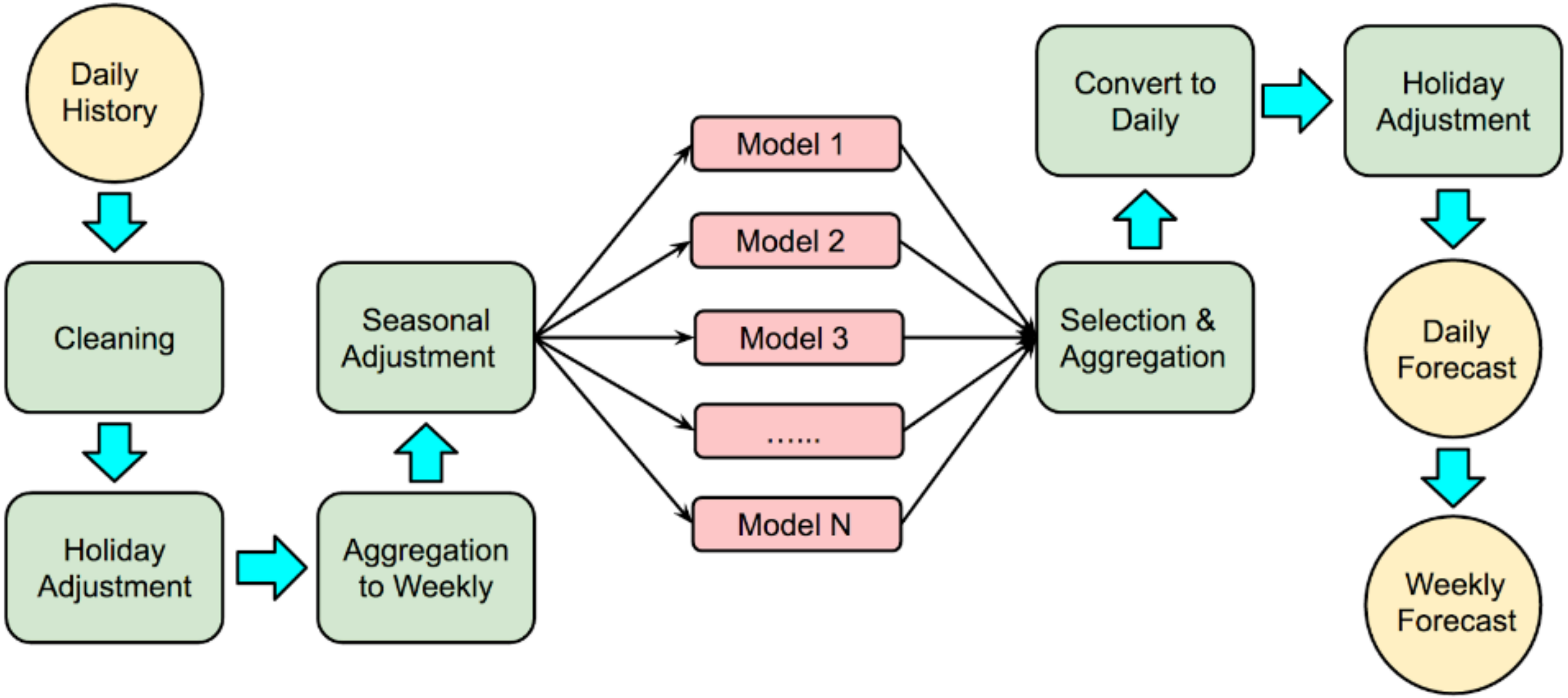
Traditional Time Series

- 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



Source: Our quest for robust time series forecasting at scale, Eric Tassone and Farzan Rohani, 2017, Forecast procedure in Google

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.

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

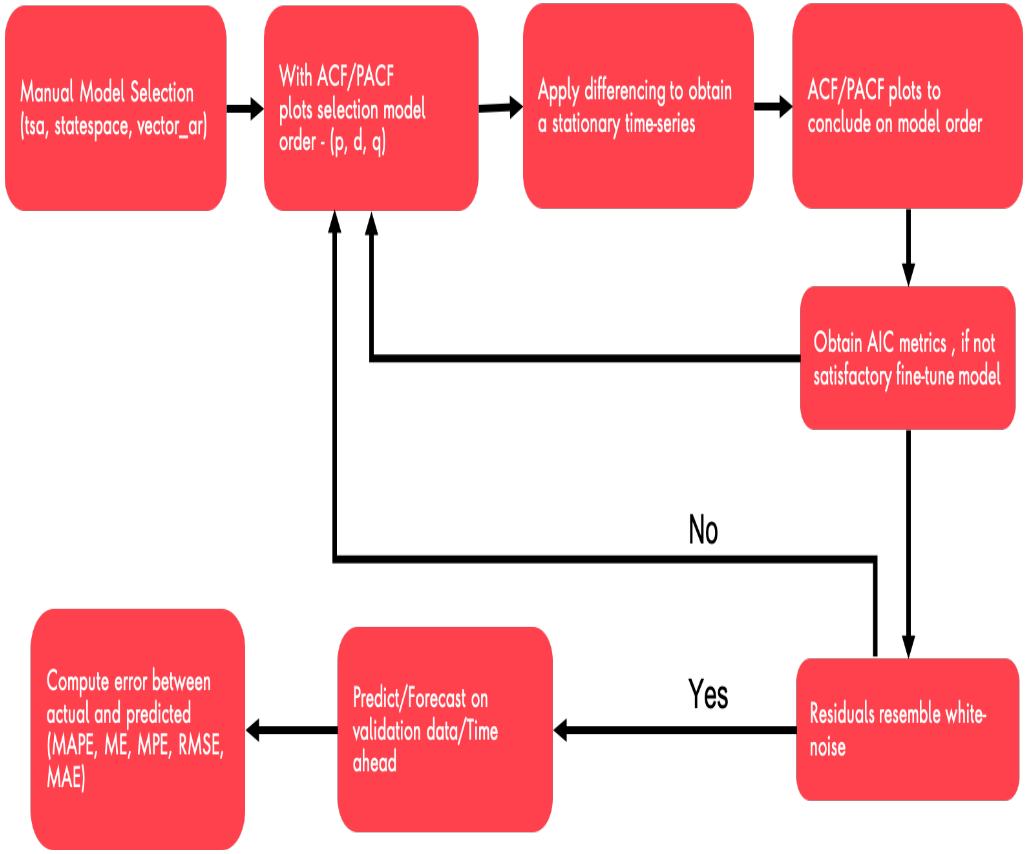
ARIMA

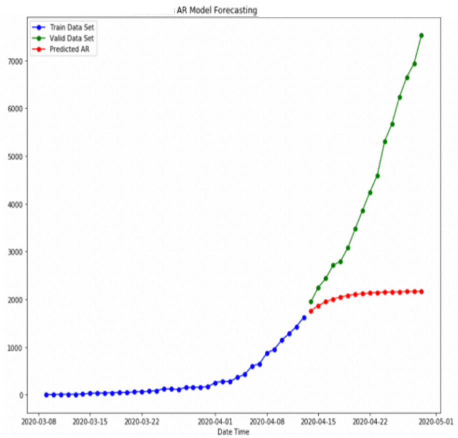
Univariate Time Series Forecasting

Exogenous Variables

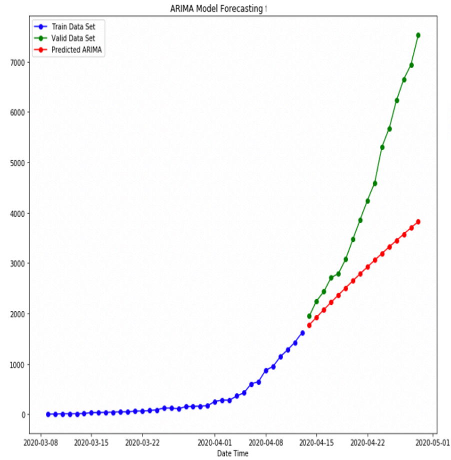
Independent Variables influencing forecasted values

Selection of best model –ARIMA

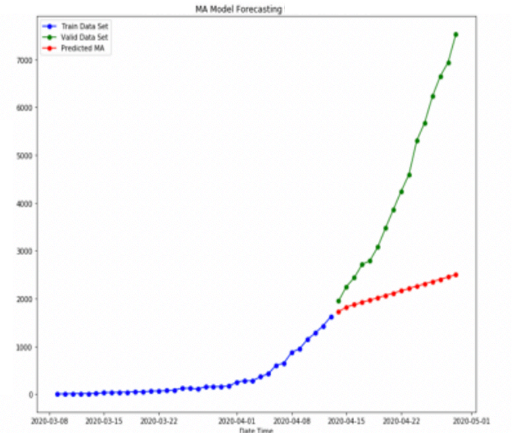




model_ar = ARIMA(X, order=(2, 0, 0)), p=2

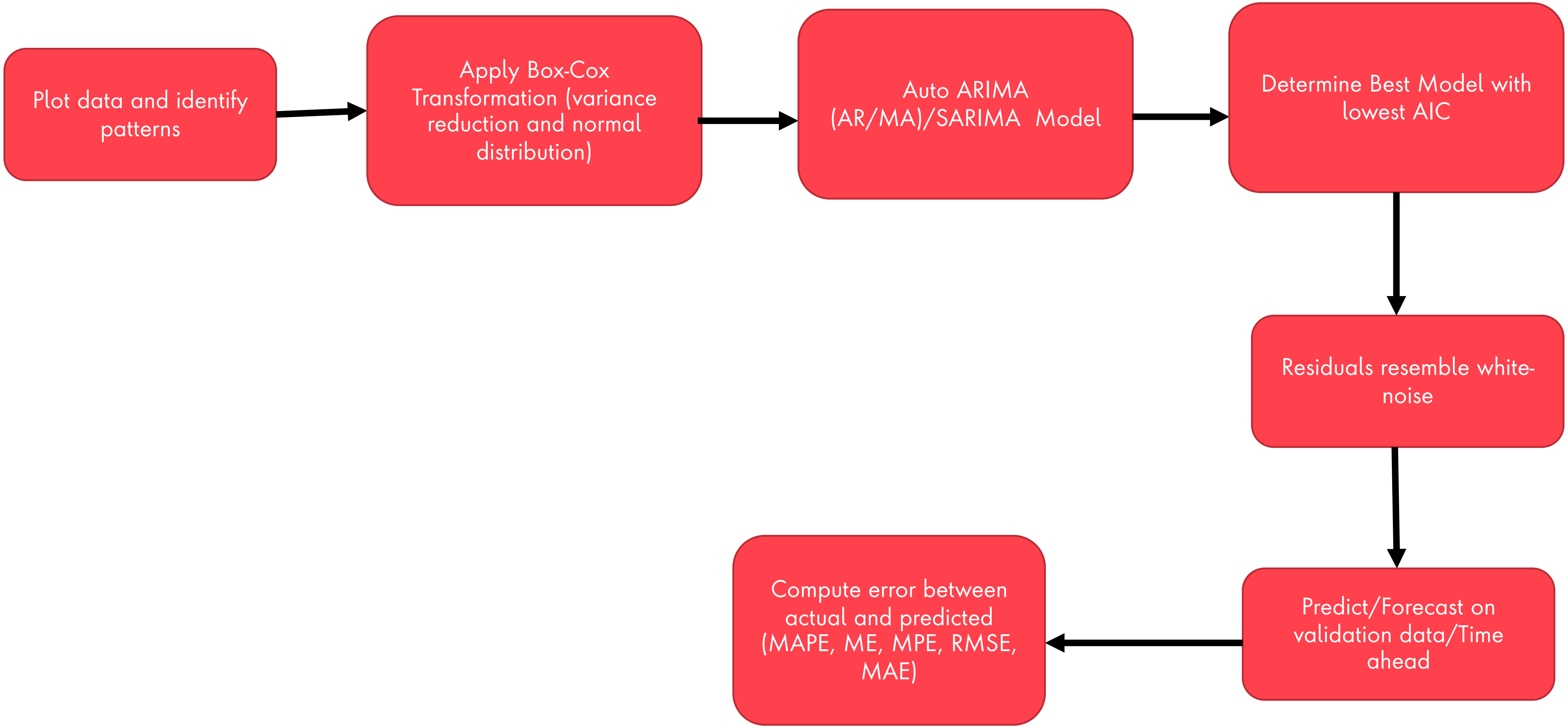


model_arima = ARIMA(X, order=(1, 1, 1)), p=q=d=1

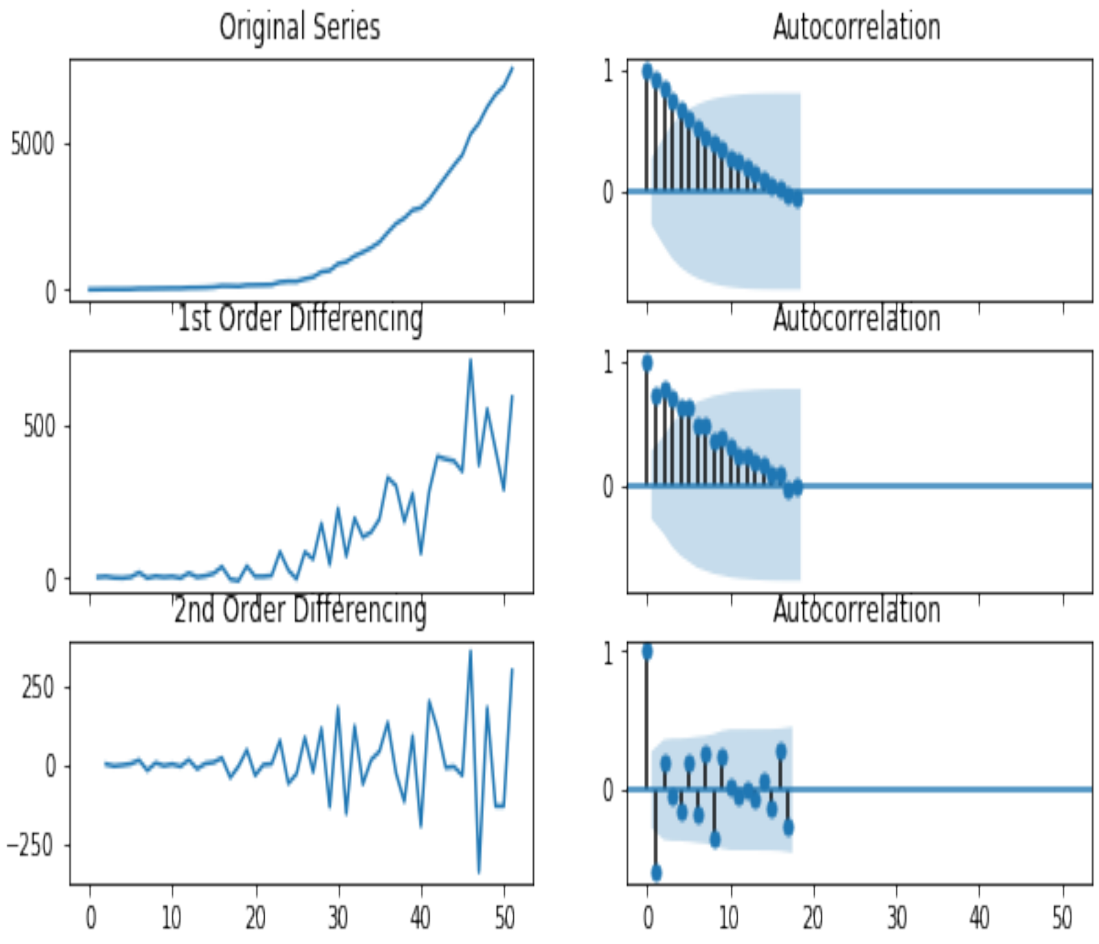


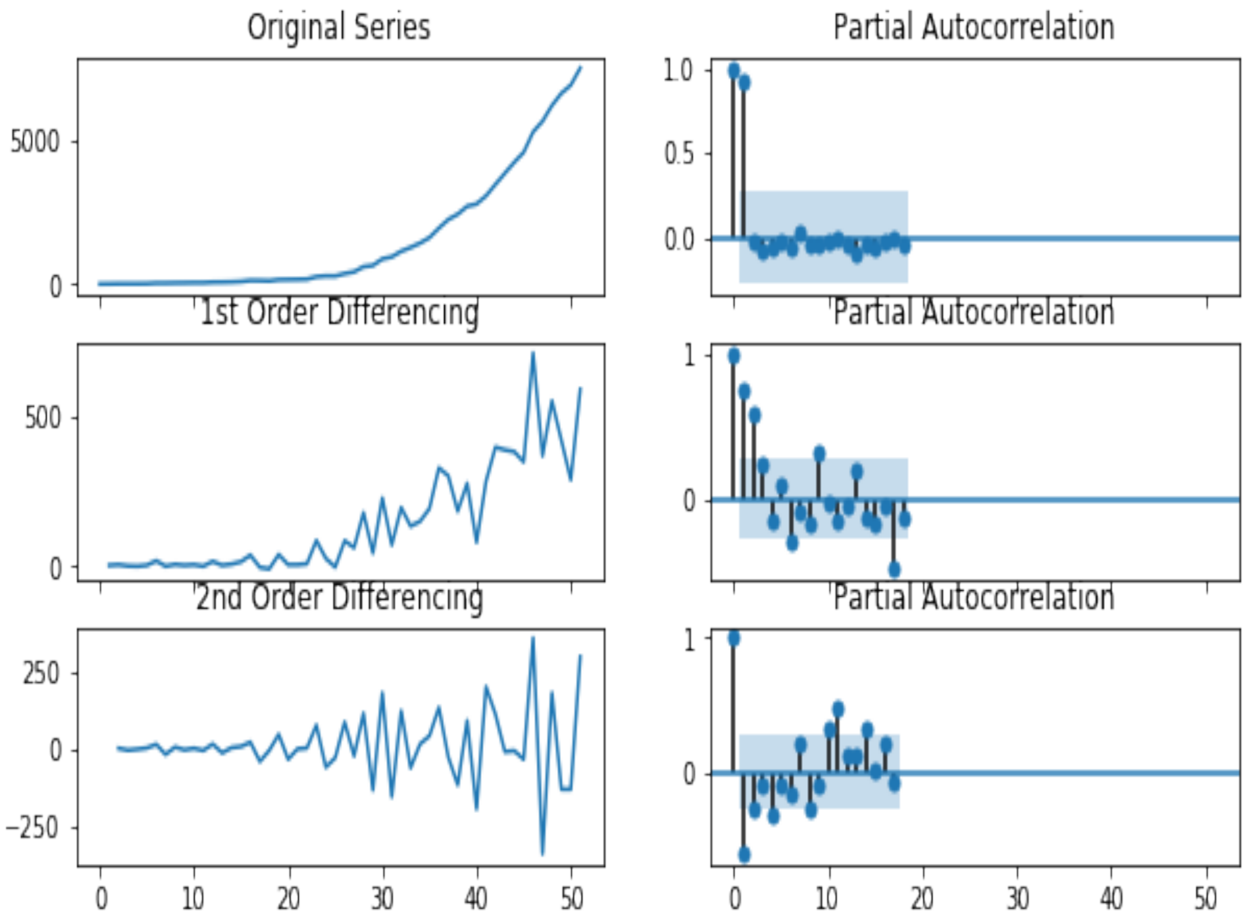
model_ma = ARIMA(X, order=(0, 0, 2)), q=2

Selection of best model –Auto ARIMA



Auto and Partial Autocorrelation





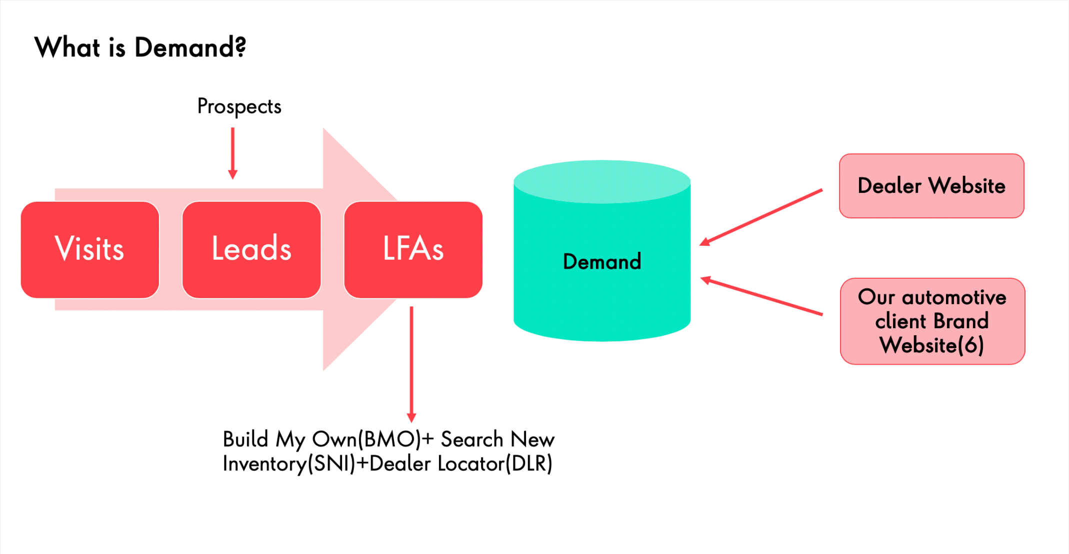
HOW ?
we did it in action

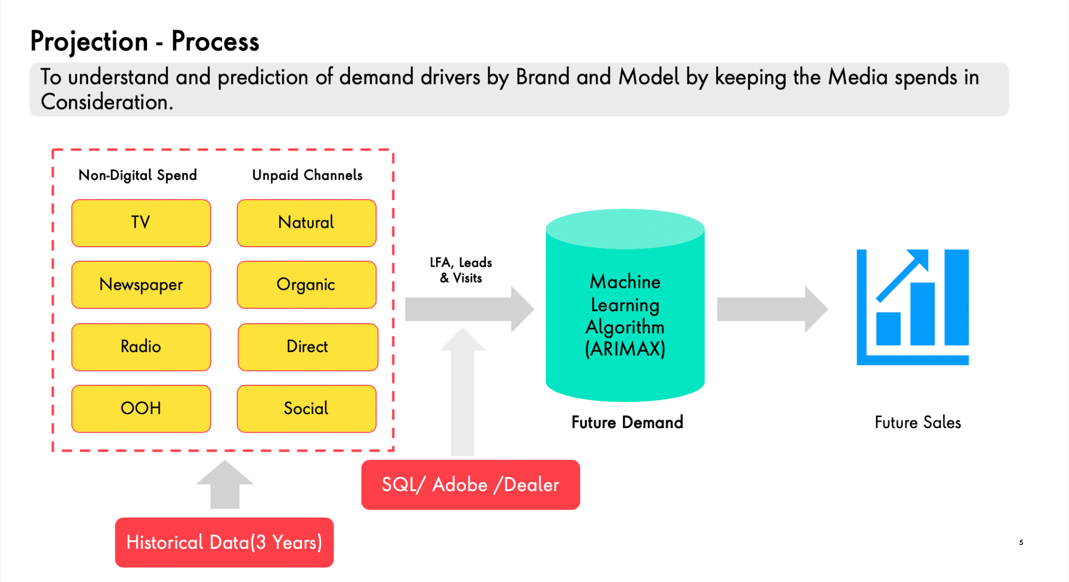
Use Case – Automotive Client

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.





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

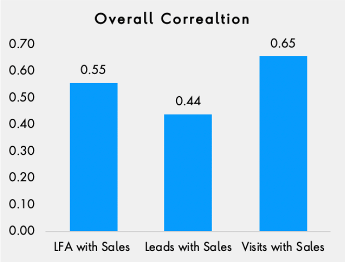
Identify the top KPIs responsible for sale and their prediction.

Forecast Test Drive Bookings

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

Predict LFAs

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



Predict Visitors

Predict Visitors coning to website with 80% accuracy.

Forecast Car Model Demands

Forecast the KPIs at model level with 80% accuracy.

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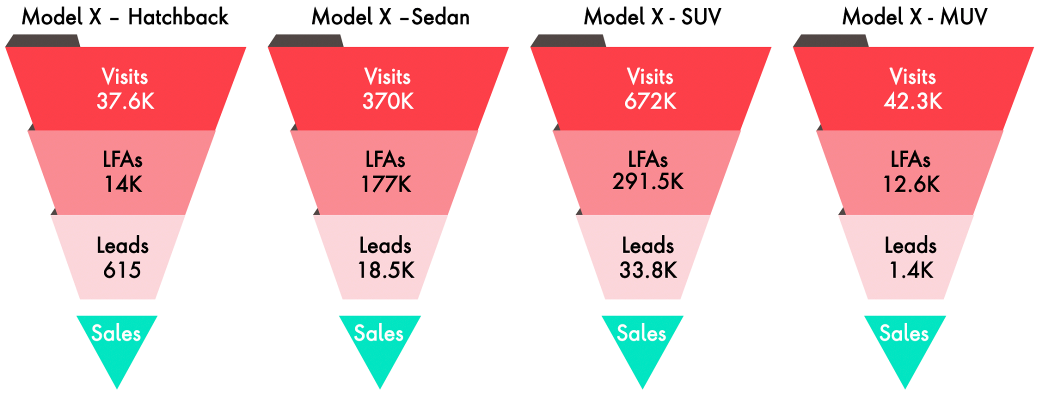
Projections - Result

Model X – Projection Funnel



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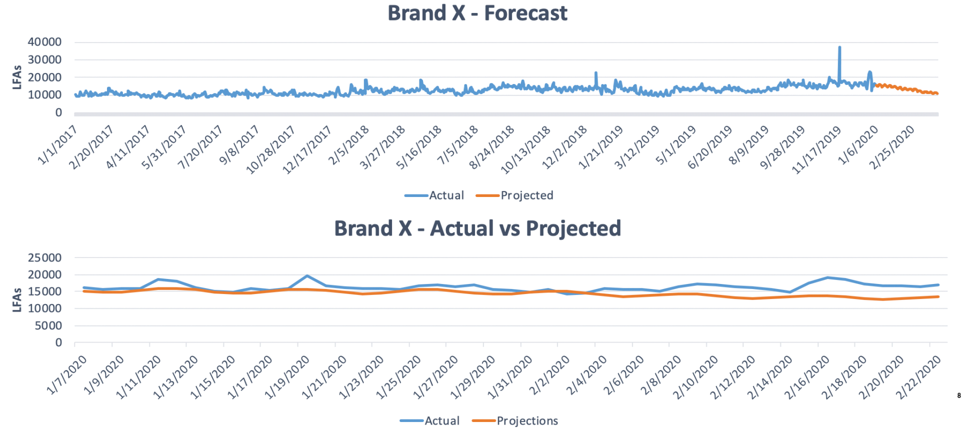
Projections - Result

Model X –Projections



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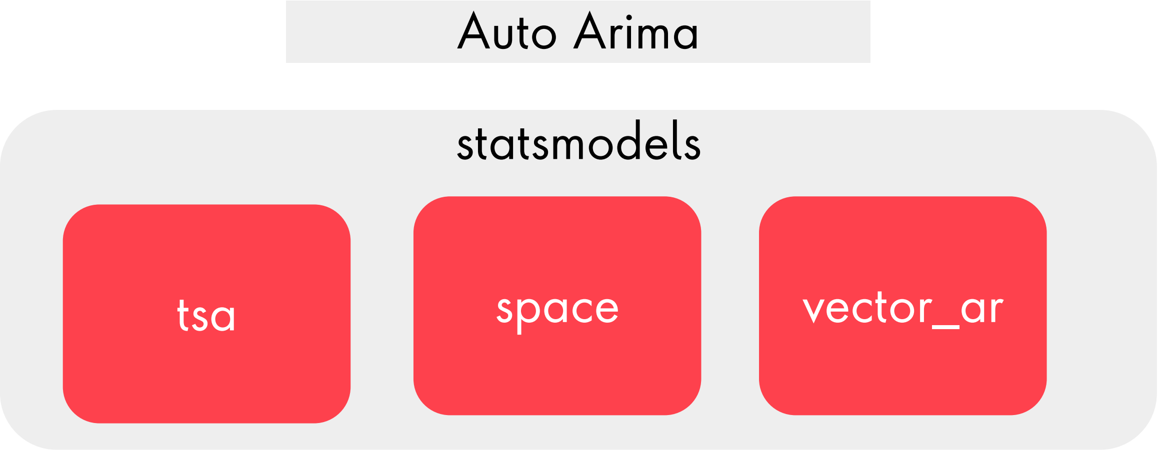
Use Case Walk through

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
```

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

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

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

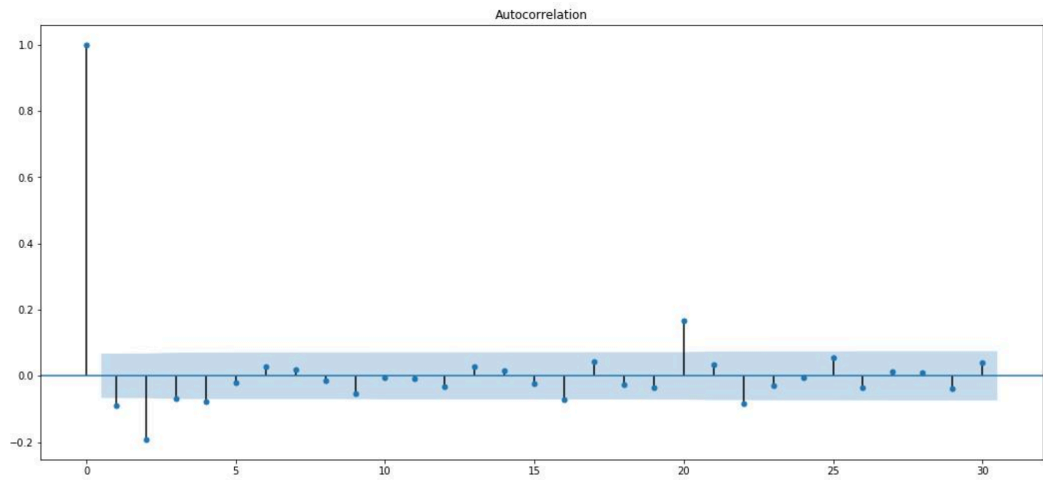
RMSE/MAPE

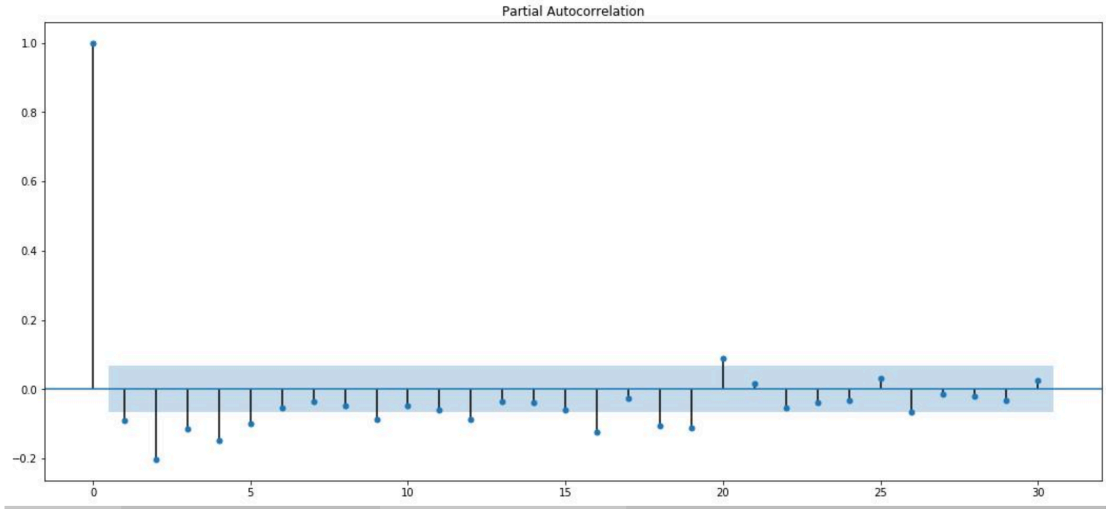
```
    ##############################################
  rmse = round(np.sqrt(mean_squared_error(test_last60[var], pred_test_last60[0])), 0)
  mape = round(mean_absolute_percentage_error(df_mape_inf[var], df_mape_inf['preds']), 2)
  #else:
```

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

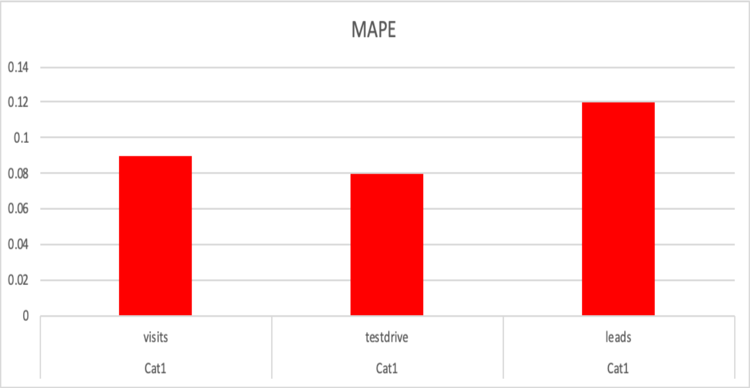
```
ar = ARIMA(endog=train_all_known[var], exog=train_all_known[exog_var], order=(p,d,q))
# fit ARIMA model
model = ar.fit()
# predict test using ARIMA model
pred_unknown = model.forecast(steps=len(test_all_unknown), exog=test_all_unknown[exog_var])
```

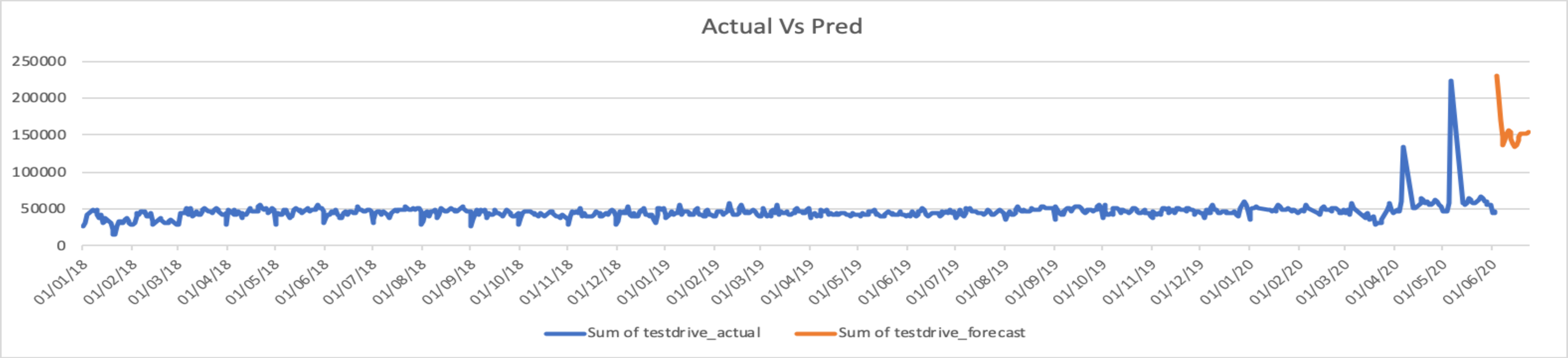
Let's see it action

Outputs - ARIMAX

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

RMSE /MAPE





Causal Impact

Causal Impact

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

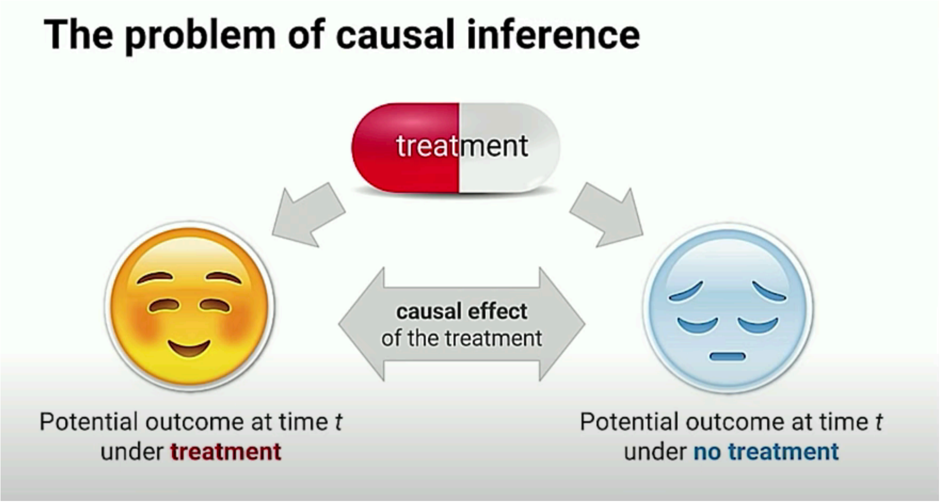
Another perspective of looking at forecasting can be also

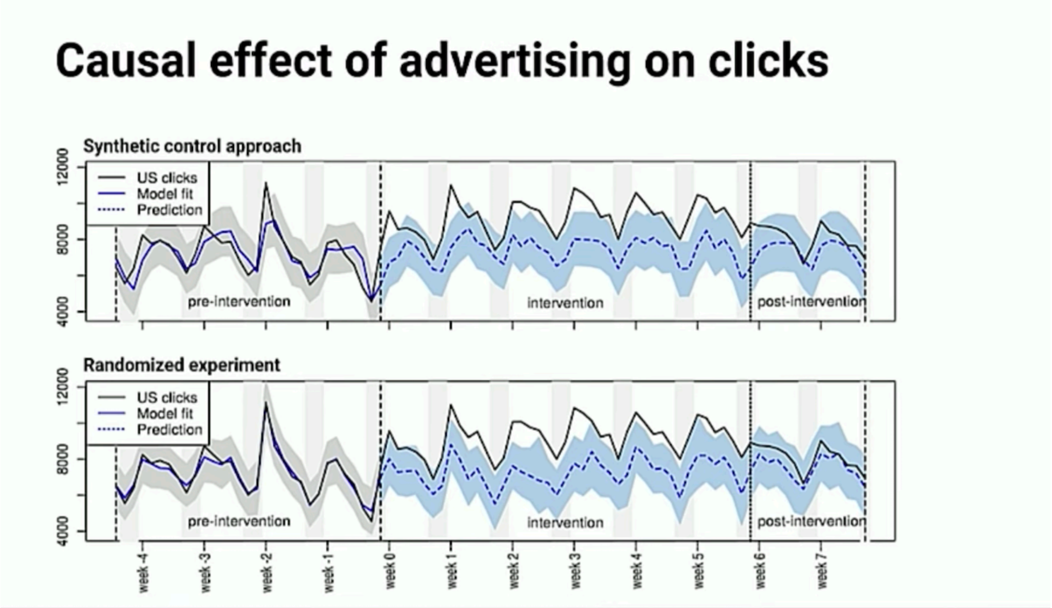
Time series forecasting

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

Causal methods

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





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

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)
```

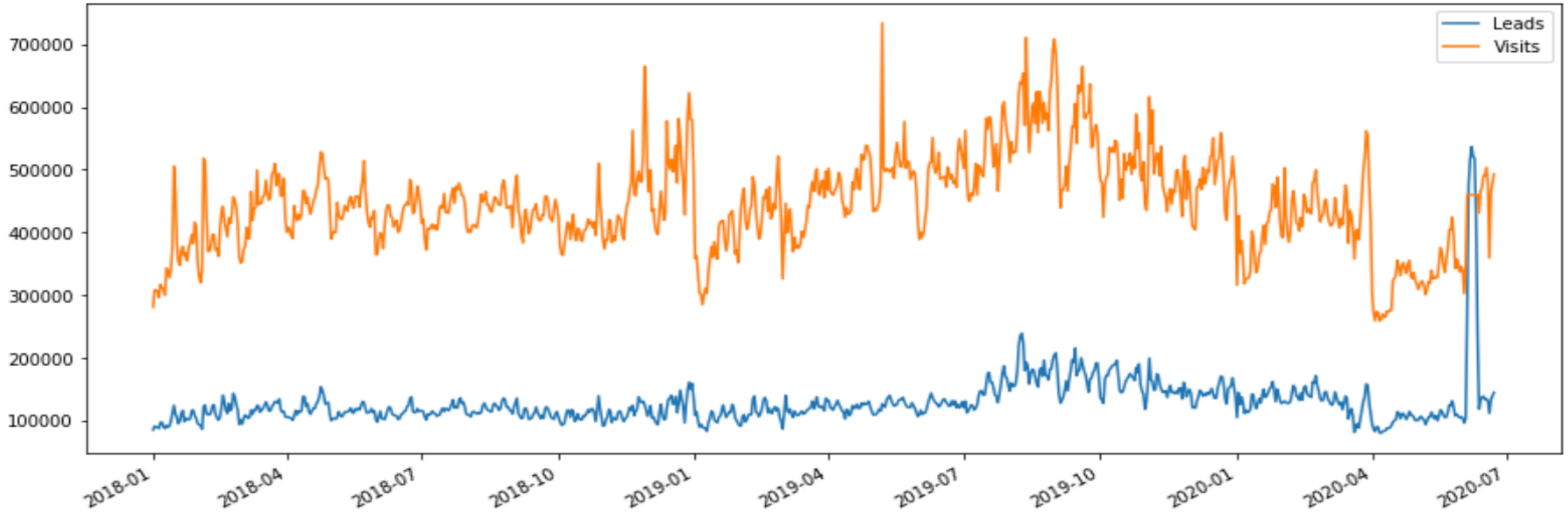
```
print(impact.summary())
```

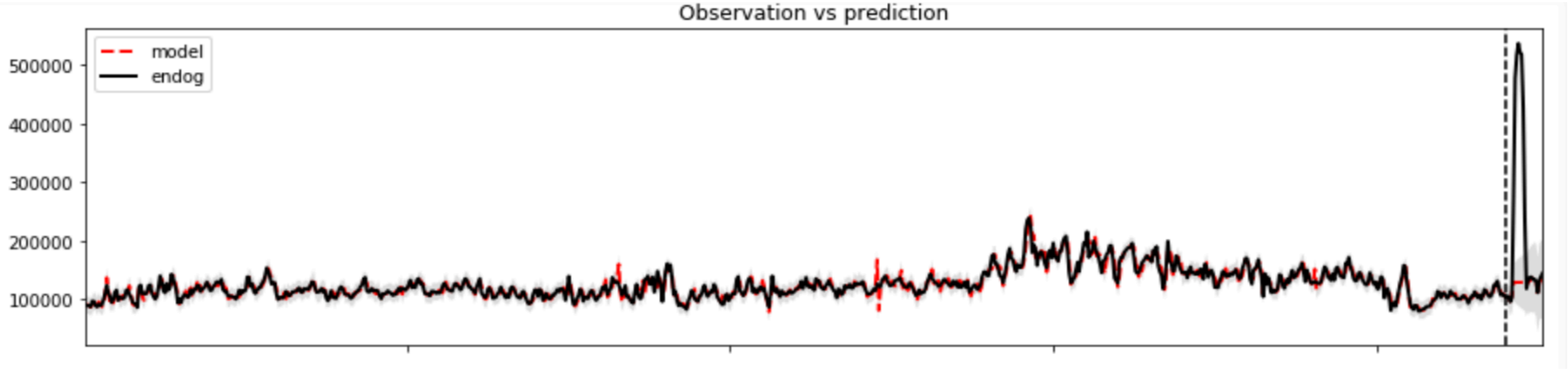
```
                              Average              Cumulative
Actual                        233427                 5368826
Predicted                     125368                 2883474
95% CI                 [78838, 171898]    [1813279, 3953669]

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%
None
```

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

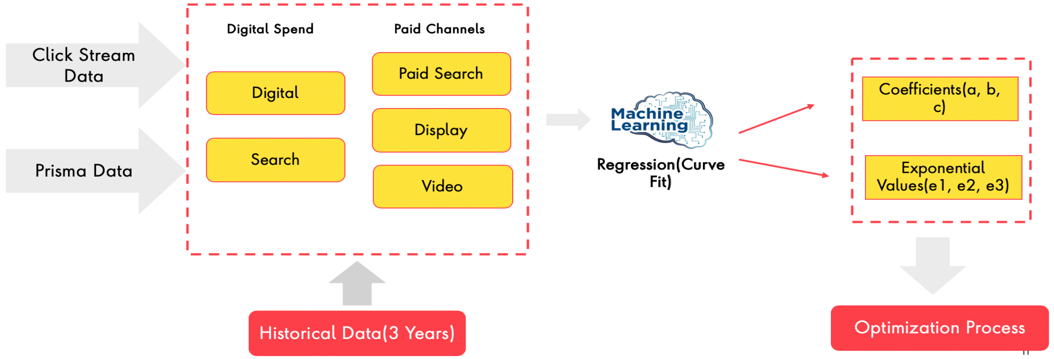
Addressing the Problem:

- 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.

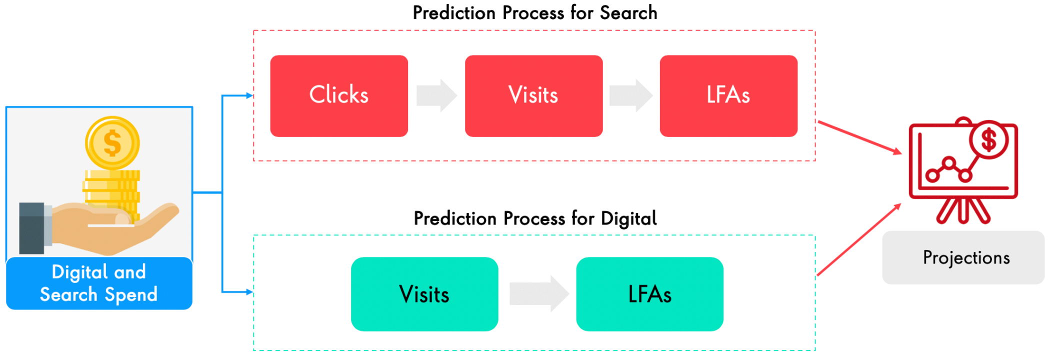
Demand Projections - Paid

Prediction and Maximising the key drivers by optimal use of budgets provided by automotive client across campaigns and brands



Optimization

The process is to derive the best suited equation by using the influencing features/factors generated from the model

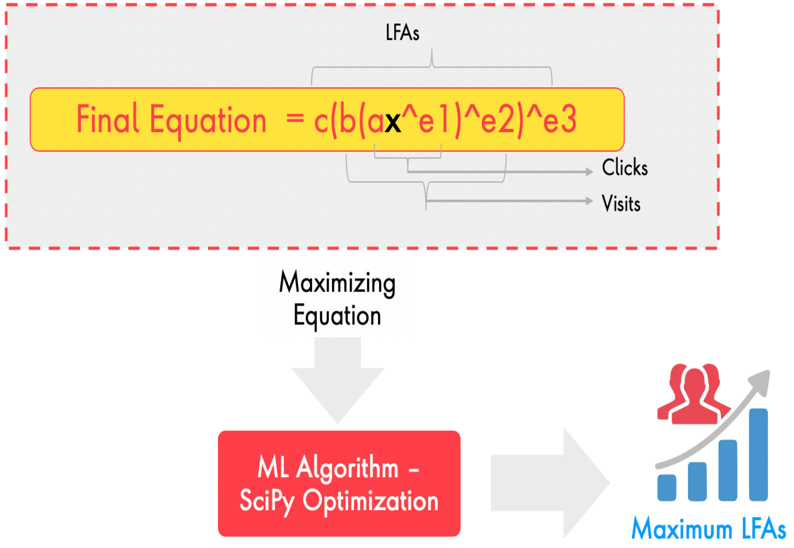


Budget Optimization and its impact for forecasting

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

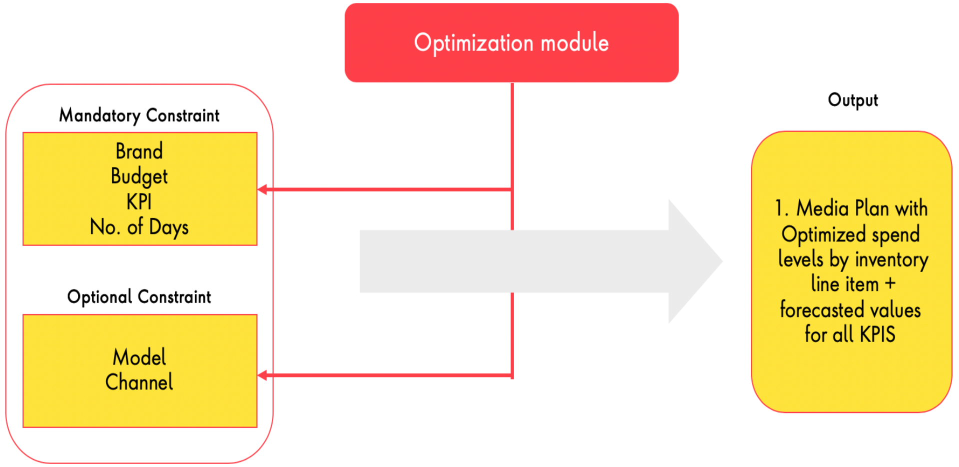
Optimising the overall budget and maximising the equation to get maximum LFAs with 99% utilisation of entire budget allocated to specific brand.



X = Total spend

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

Nameplate	LFAs	Budget
Model A	20,175	5,06,515
Model B	2,668	42,564
Model C	4,45,658	55,07,300
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

Channel level Constraints
Digital = 450K, Search = 350K

Nameplate	LFAs	Budget
Digital	445,605	7,831,590
Search	354,417	5,109,602
Total	8,00,022	1,29,41,193

Key Features

Intelligence @ Scale

1. Ability to maximize the LFAs with given budget in a single click by using Machine Learning Algorithms.
2. 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])*cl[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: {0} 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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