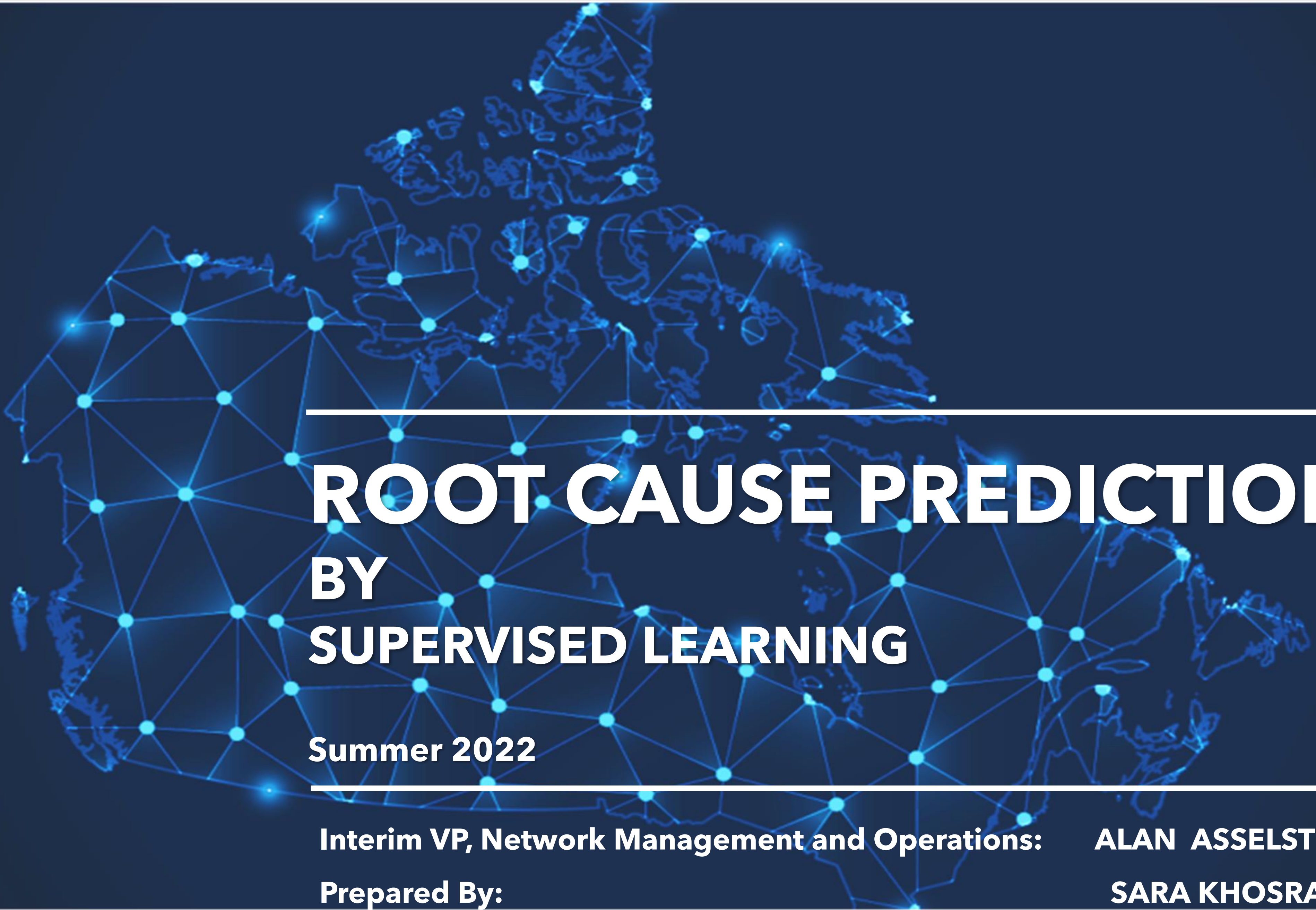


ROOT CAUSE PREDICTION

BY

SUPERVISED LEARNING

Summer 2022

Interim VP, Network Management and Operations: ALAN ASSELSTINE

Prepared By: SARA KHOSRAVI

CONTENTS

1 Project Overview

2 Hypothesis

3 Data Cleaning

4 EDA

5 Feature Engineering

6 Model Generation

7 Conclusion and Recommendation

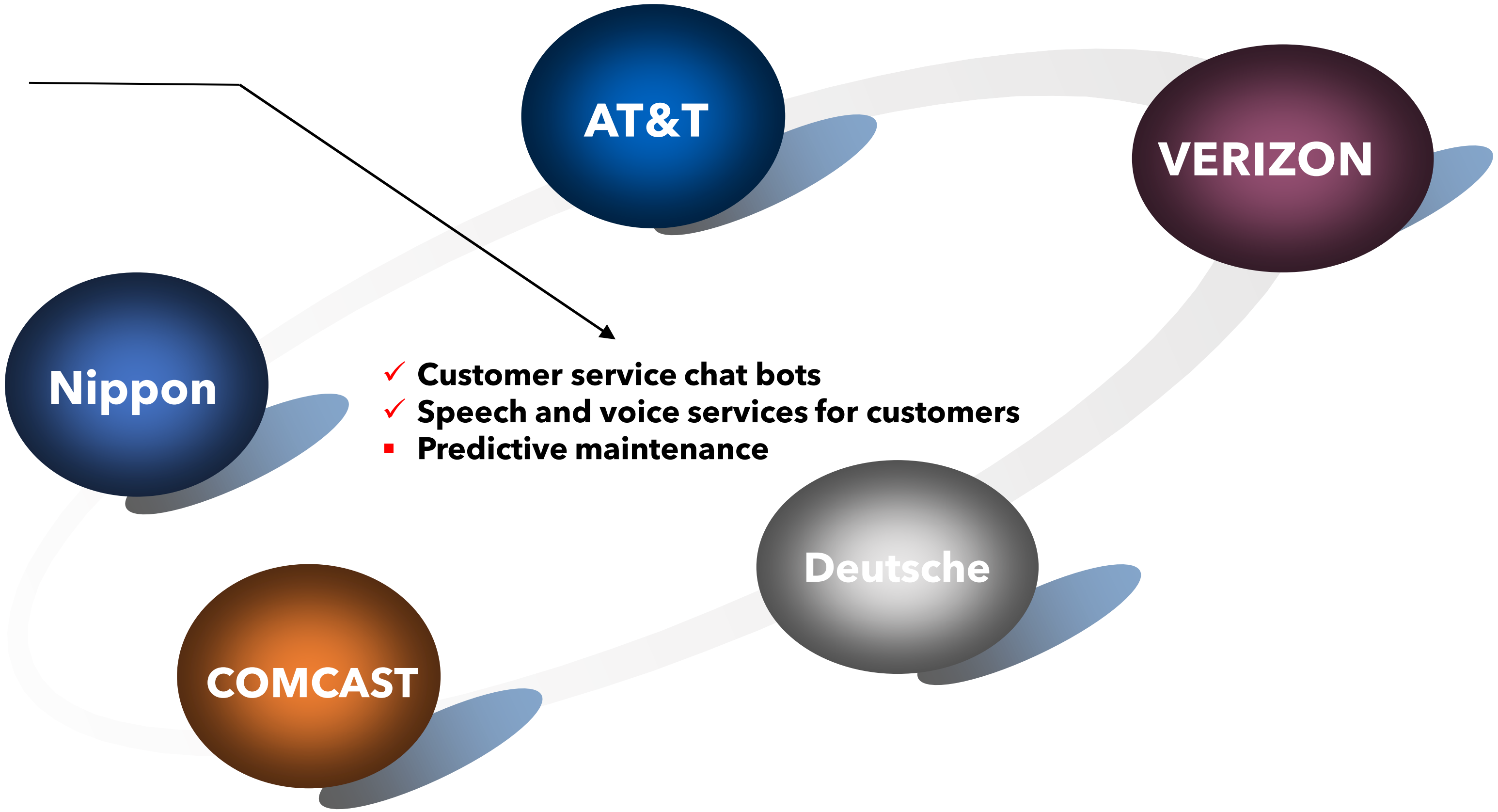
Project Overview

INTELLIGENCE **APPLICATIONS**

TOP NETWORK COMPANY

Telecommunications is one of the **fastest-growing industries** as well as one that uses artificial intelligence and machine learning in many aspects of their business from enhancing the customer experience to predictive maintenance to improving network reliability.

Predictive maintenance – The ability to fix problems with telecom hardware (such as cell towers, power lines, etc) before they happen, by detecting signals that usually lead to failure



- ✓ **Customer service chat bots**
- ✓ **Speech and voice services for customers**
- ▪ **Predictive maintenance**

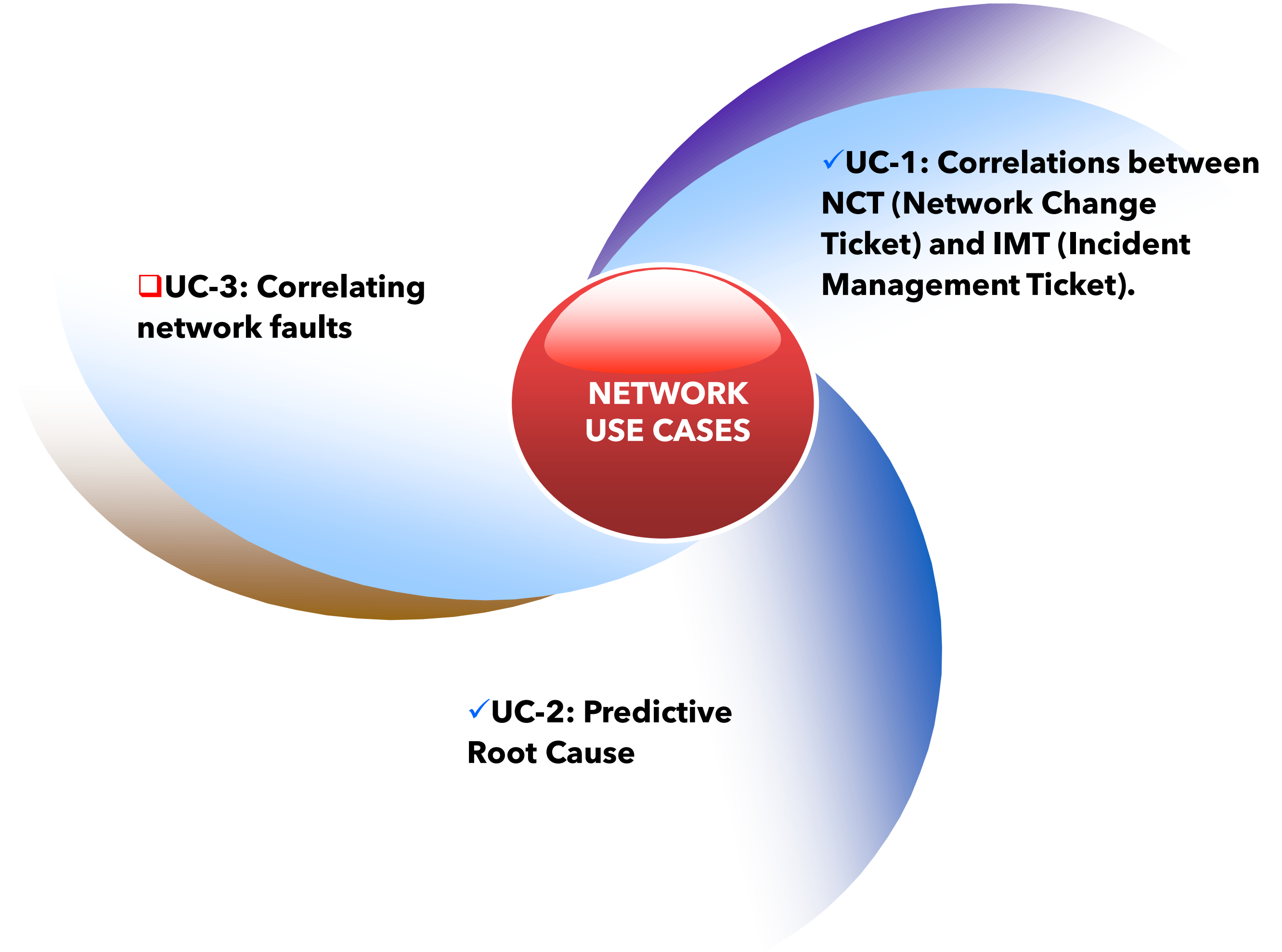
INTRODUCE **USE CASES AI/ML**

REVIEW

ACCORDING TO THE AI NERVE CENTRE , THEY HAVE ALREADY STARTED 10 PROJECTS.

SOURCE: Community of Practice - AI Nerve Centre: ANC – AI Nerve Centre community of practice JULY 2022

FURTHERMORE, TEAMS HAVE THEIR OWN ML/AI PROJECTS, LIKE OUR GROUP.



NETWORK USE CASES

✓UC-1: Correlations between NCT (Network Change Ticket) and IMT (Incident Management Ticket).

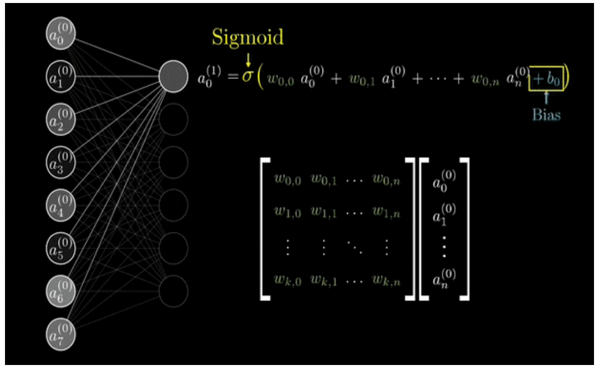
✓UC-2: Predictive Root Cause

□UC-3: Correlating network faults

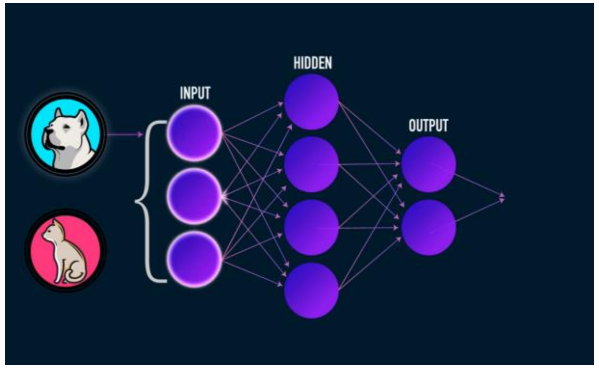
INTRODUCE **ML/AI**

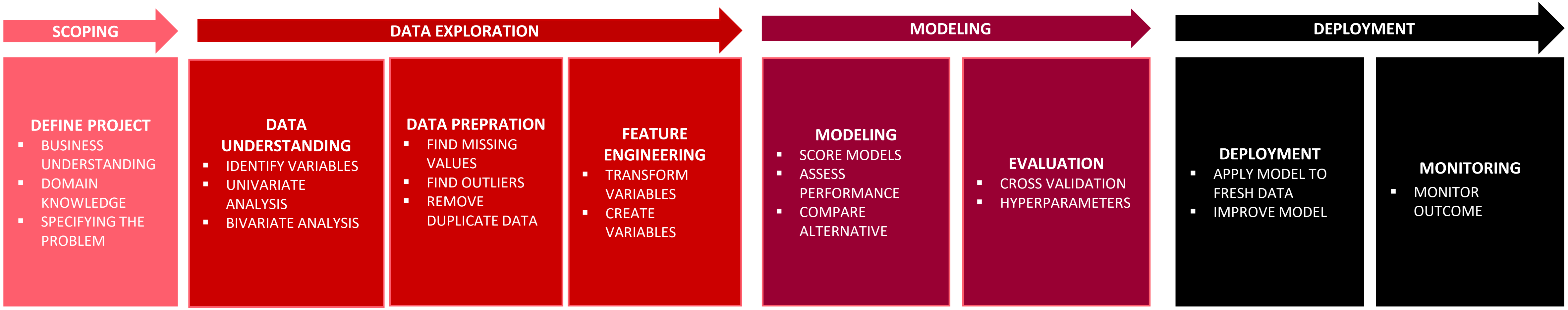
REVIEW

Machine learning algorithms use **computational** and **statistical** methods to directly use data instead of using predicted values that might act like a model. The efficiency of machine learning algorithms improves as the number of samples and data increases during the process. **Acceleration time** from analytics can help facilitate capacity planning for new services.



$a_0^{(0)}$ $a_1^{(0)}$ $a_2^{(0)}$ $a_3^{(0)}$ $a_4^{(0)}$ $a_5^{(0)}$ $a_6^{(0)}$ $a_7^{(0)}$
Sigmoid
$a_0^{(1)} = \sigma\left(w_{0,0}\, a_0^{(0)} + w_{0,1}\, a_1^{(0)} + \cdots + w_{0,n}\, a_n^{(0)} \boxed{+ b_0}\right)$
Bias
$\begin{bmatrix} w_{0,0} & w_{0,1} & \cdots & w_{0,n} \\ w_{1,0} & w_{1,1} & \cdots & w_{1,n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k,0} & w_{k,1} & \cdots & w_{k,n} \end{bmatrix} \begin{bmatrix} a_0^{(0)} \\ a_1^{(0)} \\ \vdots \\ a_n^{(0)} \end{bmatrix}$





SCOPING

DEFINE PROJECT
- BUSINESS UNDERSTANDING
- DOMAIN KNOWLEDGE
- SPECIFYING THE PROBLEM

DATA EXPLORATION

DATA UNDERSTANDING
- IDENTIFY VARIABLES
- UNIVARIATE ANALYSIS
- BIVARIATE ANALYSIS

DATA PREPRATION
- FIND MISSING VALUES
- FIND OUTLIERS
- REMOVE DUPLICATE DATA

FEATURE ENGINEERING
- TRANSFORM VARIABLES
- CREATE VARIABLES

MODELING

MODELING
- SCORE MODELS
- ASSESS PERFORMANCE
- COMPARE ALTERNATIVE

EVALUATION
- CROSS VALIDATION
- HYPERPARAMETERS

DEPLOYMENT

DEPLOYMENT
- APPLY MODEL TO FRESH DATA
- IMPROVE MODEL

MONITORING
- MONITOR OUTCOME

THE **PROBLEM**

REVIEW UC2 PREDICTIVE ROOT CAUSE

□ Rogers Company has collected a data for network and would like to analyze the dataset for Root Cause Prediction.

□ This report consists of a preliminary exploratory data analysis and a classification model among independent variable and target using Python and provide a best fit.

□ The **data contains** Network Automation attributes from **November 2021 to YTD**.

□ The **source** of data is provided by **Remedy** and **ESAP**.

□ The **aim** is to build a **predictive model** and find out the **Root Cause** of the Network.

□ Using this model will try to understand the Network and predict the root cause.

□ Using **supervised learning model** will try to understand the climate and predict the temperature. The models build in the project are as follows:

1. Logistic Regression
2. SVC Model
3. K-Nearest Neighbors
4. Decision Tree Model

5. Random Forest Model

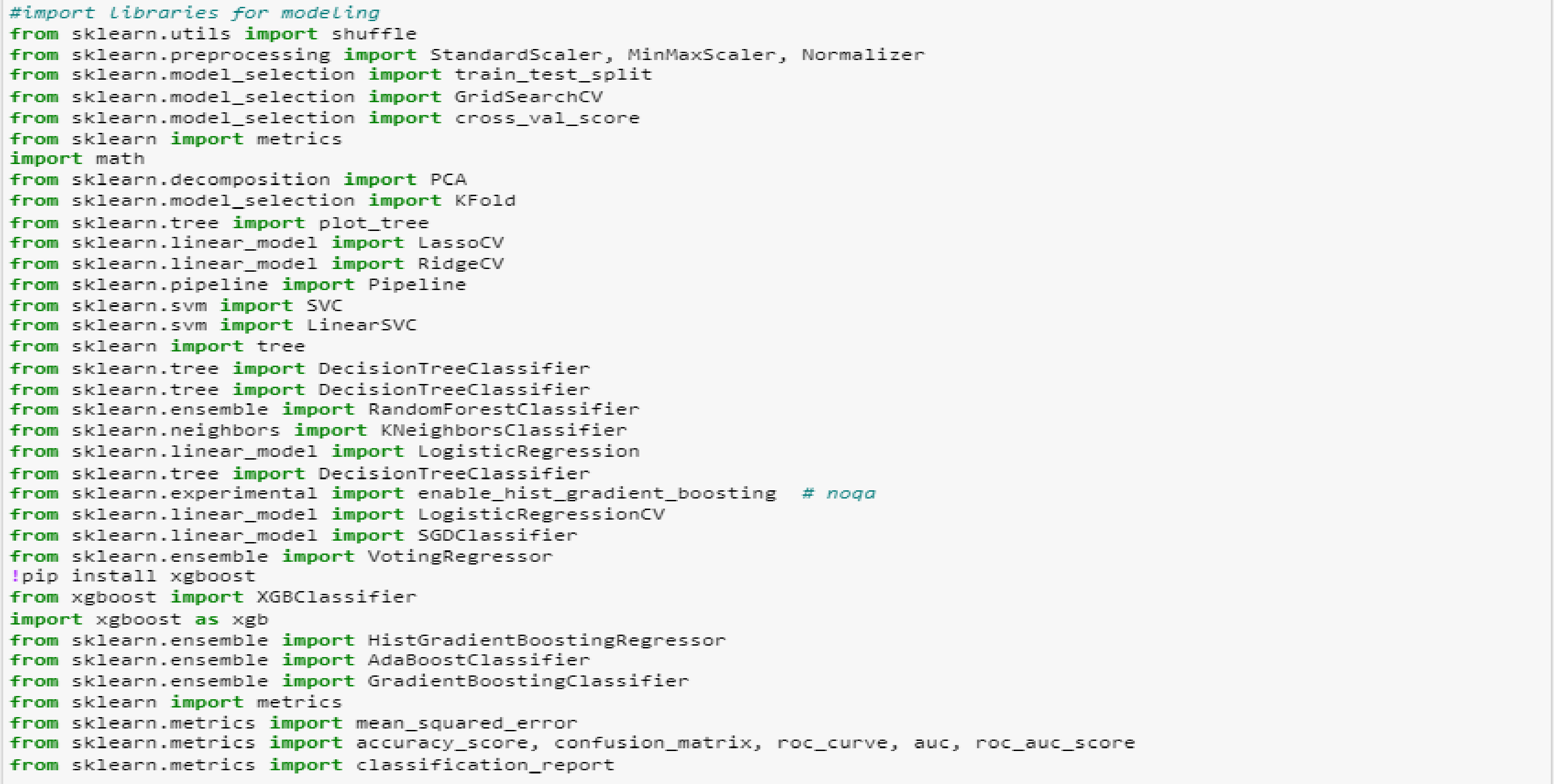
5. XGBoost Model

6. AdaBoost Model

THE **ENVIRONMENT**

INSTALLING PACKAGES AND LIBRARIES

USING SKLEARN FOR CLASSIFICATION

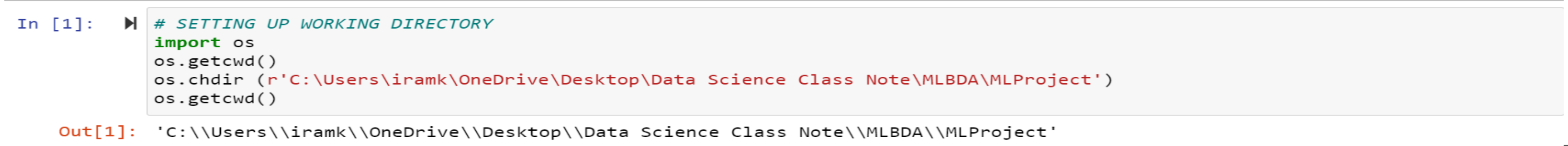


```
#import libraries for modeling
from sklearn.utils import shuffle
from sklearn.preprocessing import StandardScaler, MinMaxScaler, Normalizer
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn import metrics
import math
from sklearn.decomposition import PCA
from sklearn.model_selection import KFold
from sklearn.tree import plot_tree
from sklearn.linear_model import LassoCV
from sklearn.linear_model import RidgeCV
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.experimental import enable_hist_gradient_boosting  # noqa
from sklearn.linear_model import LogisticRegressionCV
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import VotingRegressor
!pip install xgboost
from xgboost import XGBClassifier
import xgboost as xgb
from sklearn.ensemble import HistGradientBoostingRegressor
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn import metrics
from sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, auc, roc_auc_score
from sklearn.metrics import classification_report
```

THE **ENVIRONMENT**

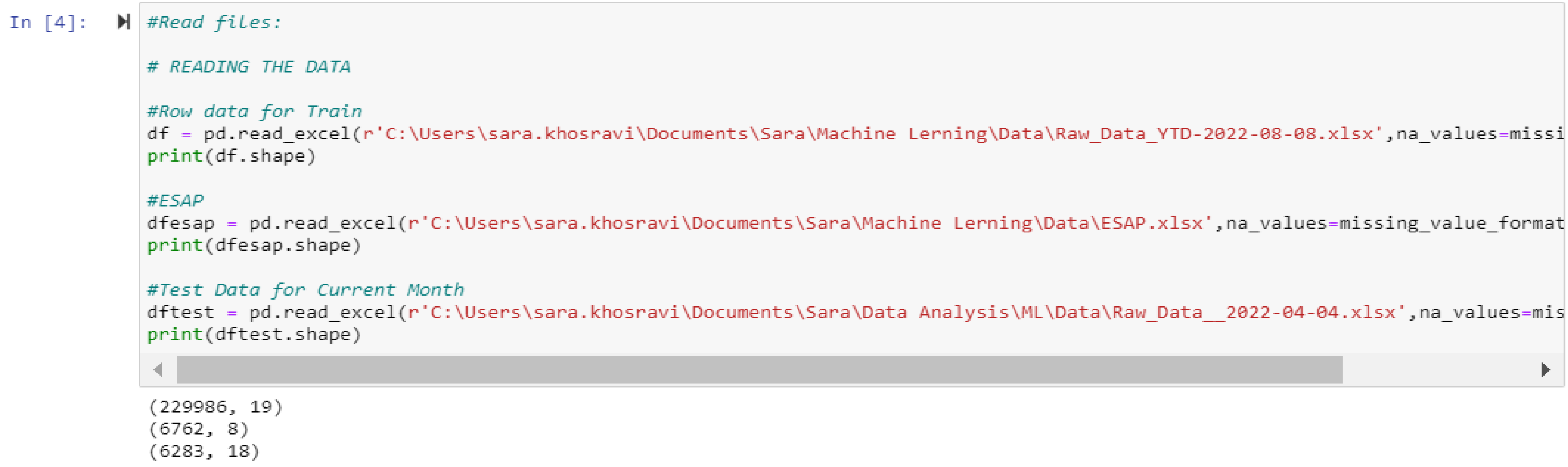
READING THE DATABASE

SETTING UP WORKING DIRECTORY



```
In [1]:  # SETTING UP WORKING DIRECTORY
         import os
         os.getcwd()
         os.chdir (r'C:\Users\iramk\OneDrive\Desktop\Data Science Class Note\MLBDA\MLProject')
         os.getcwd()

Out[1]:  'C:\\Users\\iramk\\OneDrive\\Desktop\\Data Science Class Note\\MLBDA\\MLProject'
```

Train Dataset: 229986 records and **19** features
Test Dataset: 6283 records and **18** features
ESAP Dataset: 6762 records and **8** features



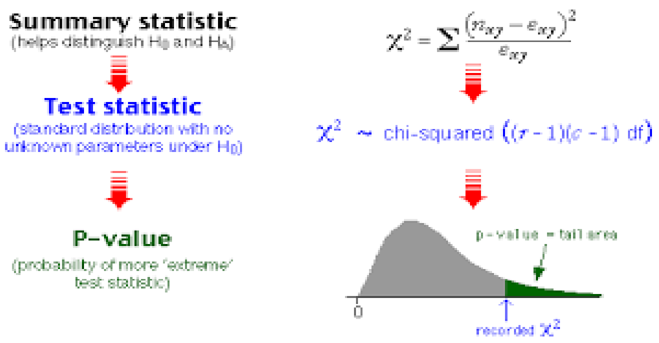
```
In [4]:  #Read files:

         # READING THE DATA

         #Row data for Train
         df = pd.read_excel(r'C:\Users\sara.khosravi\Documents\Sara\Machine Lerning\Data\Raw_Data_YTD-2022-08-08.xlsx',na_values=missi
         print(df.shape)

         #ESAP
         dfesap = pd.read_excel(r'C:\Users\sara.khosravi\Documents\Sara\Machine Lerning\Data\ESAP.xlsx',na_values=missing_value_format
         print(dfesap.shape)

         #Test Data for Current Month
         dftest = pd.read_excel(r'C:\Users\sara.khosravi\Documents\Sara\Data Analysis\ML\Data\Raw_Data__2022-04-04.xlsx',na_values=mis
         print(dftest.shape)

         (229986, 19)
         (6762, 8)
         (6283, 18)
```

HYPOTHESIS

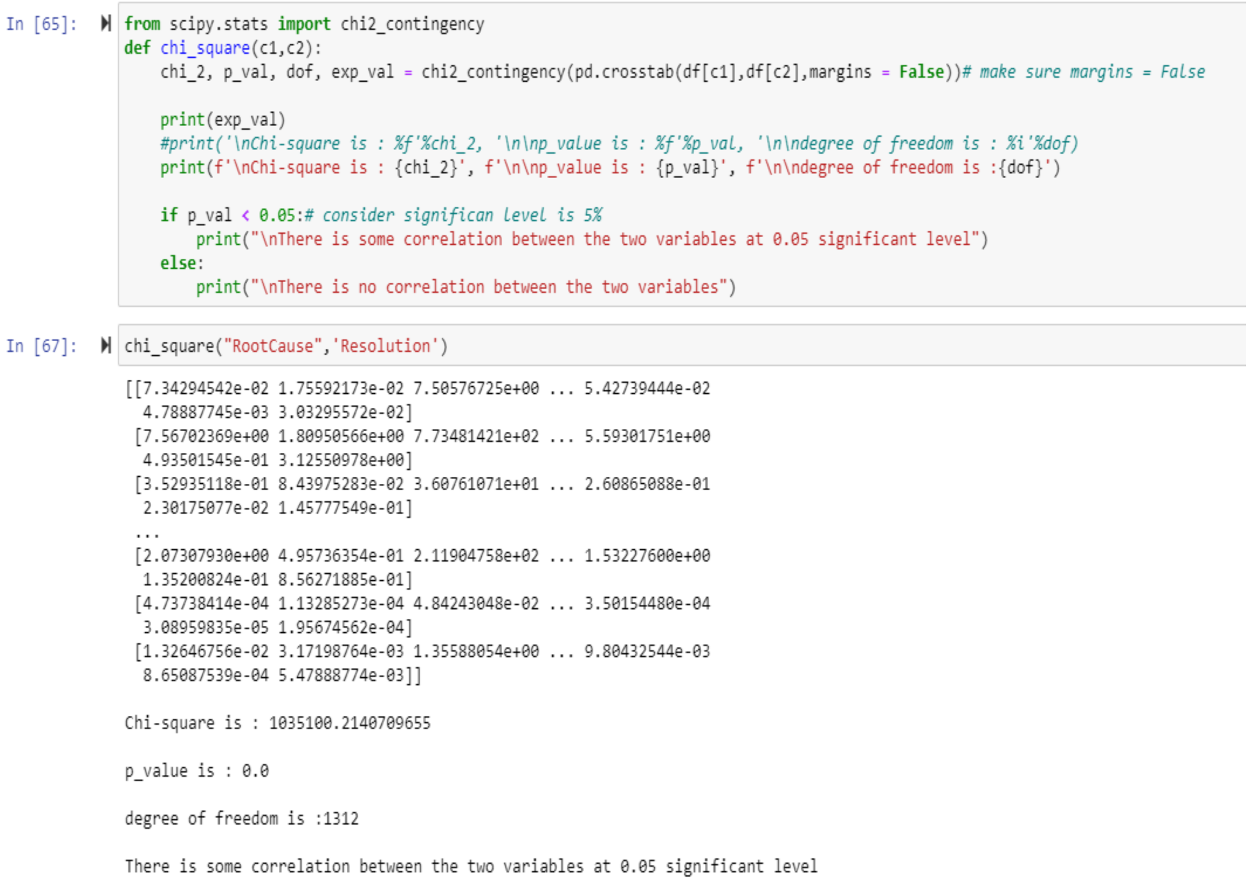
THE **HYPOTHESIS**

POSSIBLE OUTCOME

- ❑ FOR IMT TICKETS RESOLVED BY NOC, THERE ARE ROOT CAUSE AND ACTION TAKEN THAT RESOLVE EACH ISSUE. THE GOAL IS TO PRE-DETERMINE AN APPROPRIATE ACTION/ROOT CAUSE FOR FUTURE IMT BASED ON HISTORICAL INFORMATION.
- ❑ We are interested in knowing if there is a relationship between 'ROOTCAUSE' and (‘rule name', 'Resolution', 'Responsibility', 'Bot', 'month’,..).



Summary statistic
(helps distinguish H_0 and H_A)
Test statistic
(standard distribution with no unknown parameters under H_0)
P–value
(probability of more ‘extreme’ test statistic)
$\chi^2 = \sum \frac{(n_{xy} - e_{xy})^2}{e_{xy}}$
χ^2 ~ chi-squared ((r - 1)(c - 1) df)
p-value = tail area
0
recorded χ^2



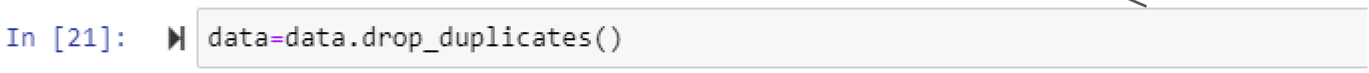
```
In [65]:  from scipy.stats import chi2_contingency
          def chi_square(c1,c2):
              chi_2, p_val, dof, exp_val = chi2_contingency(pd.crosstab(df[c1],df[c2],margins = False))# make sure margins = False

              print(exp_val)
              #print('\nChi-square is : %f'%chi_2, '\n\np_value is : %f'%p_val, '\n\ndegree of freedom is : %i'%dof)
              print(f'\nChi-square is : {chi_2}', f'\n\np_value is : {p_val}', f'\n\ndegree of freedom is :{dof}')

              if p_val < 0.05:# consider significan level is 5%
                  print("\nThere is some correlation between the two variables at 0.05 significant level")
              else:
                  print("\nThere is no correlation between the two variables")

In [67]:  chi_square("RootCause",'Resolution')

          [[7.34294542e-02 1.75592173e-02 7.50576725e+00 ... 5.42739444e-02
            4.78887745e-03 3.03295572e-02]
           [7.56702369e+00 1.80950566e+00 7.73481421e+02 ... 5.59301751e+00
            4.93501545e-01 3.12550978e+00]
           [3.52935118e-01 8.43975283e-02 3.60761071e+01 ... 2.60865088e-01
            2.30175077e-02 1.45777549e-01]
           ...
           [2.07307930e+00 4.95736354e-01 2.11904758e+02 ... 1.53227600e+00
            1.35200824e-01 8.56271885e-01]
           [4.73738414e-04 1.13285273e-04 4.84243048e-02 ... 3.50154480e-04
            3.08959835e-05 1.95674562e-04]
           [1.32646756e-02 3.17198764e-03 1.35588054e+00 ... 9.80432544e-03
            8.65087539e-04 5.47888774e-03]]

          Chi-square is : 1035100.2140709655

          p_value is : 0.0

          degree of freedom is :1312

          There is some correlation between the two variables at 0.05 significant level
```

DATA CLEANING

DATA **CLEANING**

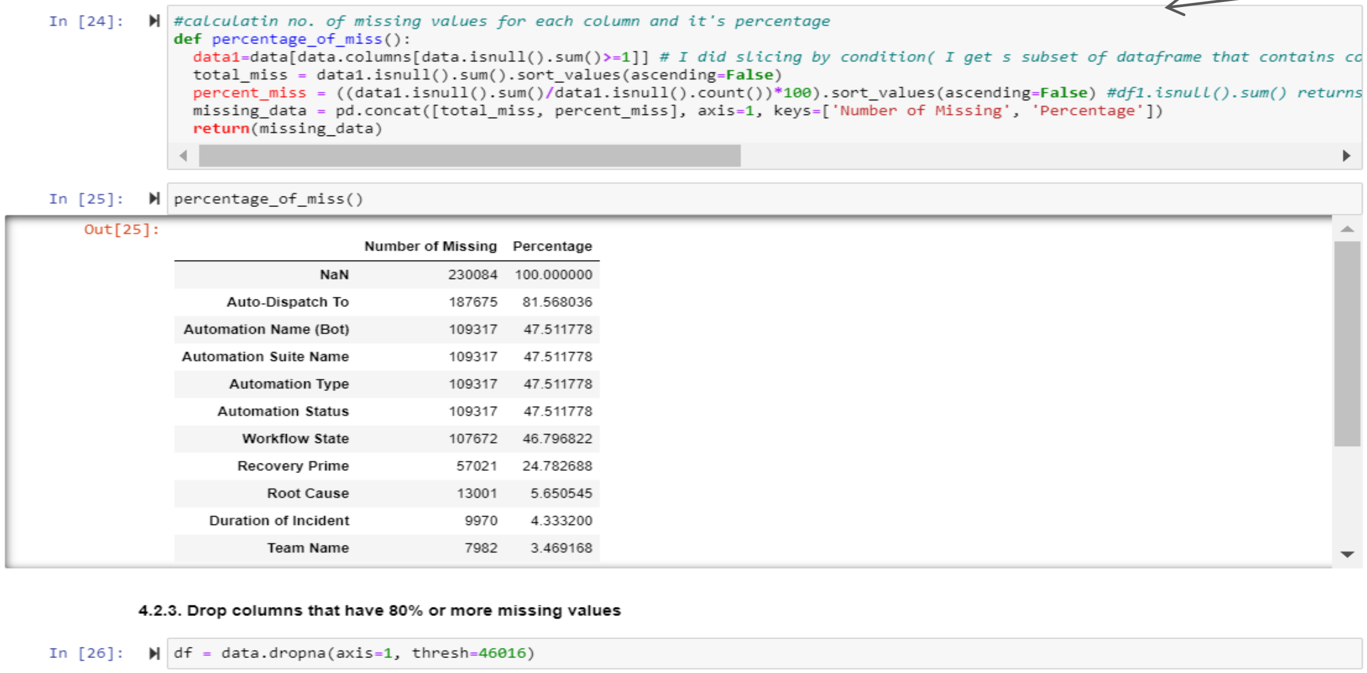
CHECKING MISSING VALUES, FIND OUTLIERS, TRANSFORM VARIABLES, CREATE VARIABLES, AND DUPLICATE DATA

HANDLING Duplicate Data



```
In [21]:    data=data.drop_duplicates()
```

HANDLING Missing Value

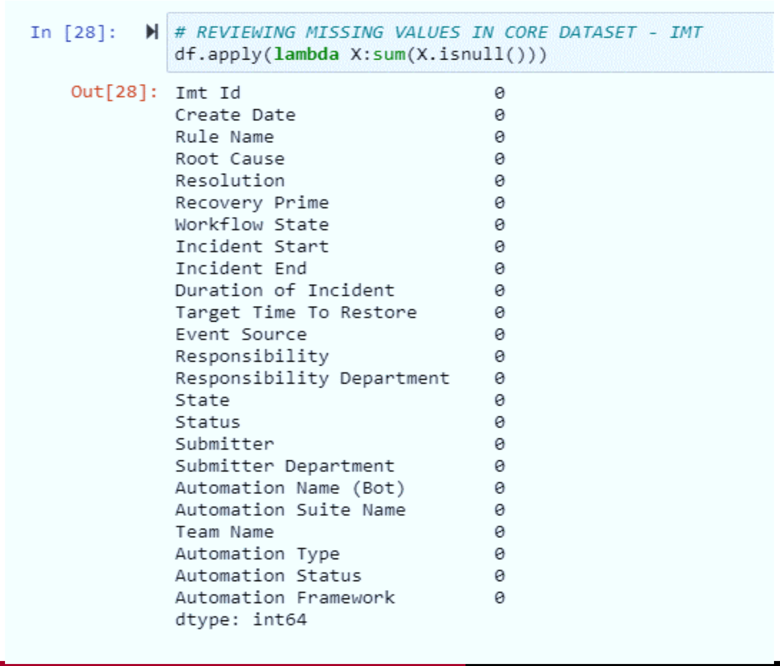


```
In [24]:  #calculatin no. of missing values for each column and it's percentage
          def percentage_of_miss():
            data1=data[data.columns[data.isnull().sum()>=1]] # I did slicing by condition( I get s subset of dataframe that contains co
            total_miss = data1.isnull().sum().sort_values(ascending=False)
            percent_miss = ((data1.isnull().sum()/data1.isnull().count())*100).sort_values(ascending=False) #df1.isnull().sum() returns
            missing_data = pd.concat([total_miss, percent_miss], axis=1, keys=['Number of Missing', 'Percentage'])
            return(missing_data)

In [25]:  percentage_of_miss()
Out[25]:
```

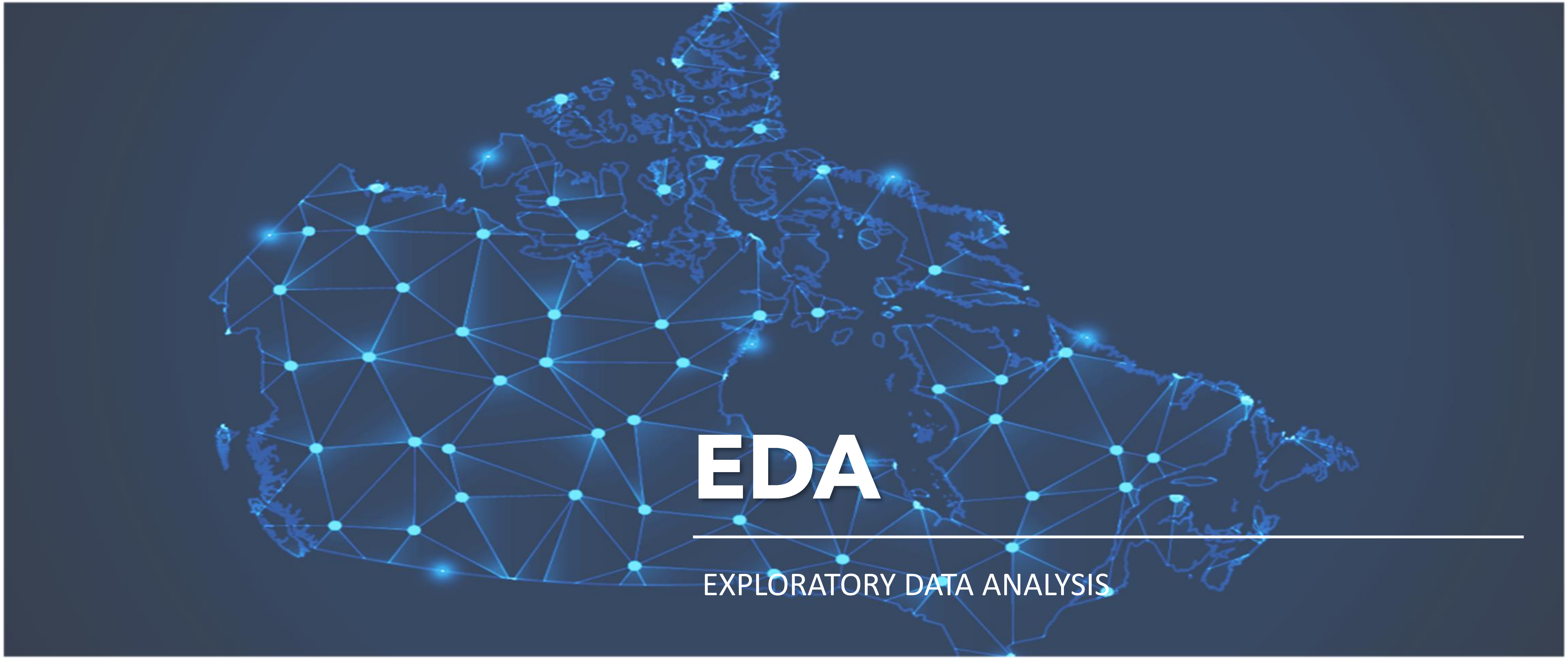
	Number of Missing	Percentage
NaN	230084	100.000000
Auto-Dispatch To	187675	81.568036
Automation Name (Bot)	109317	47.511778
Automation Suite Name	109317	47.511778
Automation Type	109317	47.511778
Automation Status	109317	47.511778
Workflow State	107672	46.796822
Recovery Prime	57021	24.782688
Root Cause	13001	5.650545
Duration of Incident	9970	4.333200
Team Name	7982	3.469168

4.2.3. Drop columns that have 80% or more missing values

```
In [26]:  df = data.dropna(axis=1, thresh=46016)
```



```
In [28]:  # REVIEWING MISSING VALUES IN CORE DATASET - IMT
          df.apply(lambda X:sum(X.isnull()))

Out[28]:  Imt Id                       0
          Create Date                  0
          Rule Name                    0
          Root Cause                   0
          Resolution                   0
          Recovery Prime               0
          Workflow State               0
          Incident Start               0
          Incident End                 0
          Duration of Incident         0
          Target Time To Restore       0
          Event Source                 0
          Responsibility               0
          Responsibility Department    0
          State                        0
          Status                       0
          Submitter                    0
          Submitter Department         0
          Automation Name (Bot)        0
          Automation Suite Name        0
          Team Name                    0
          Automation Type              0
          Automation Status            0
          Automation Framework         0
          dtype: int64
```



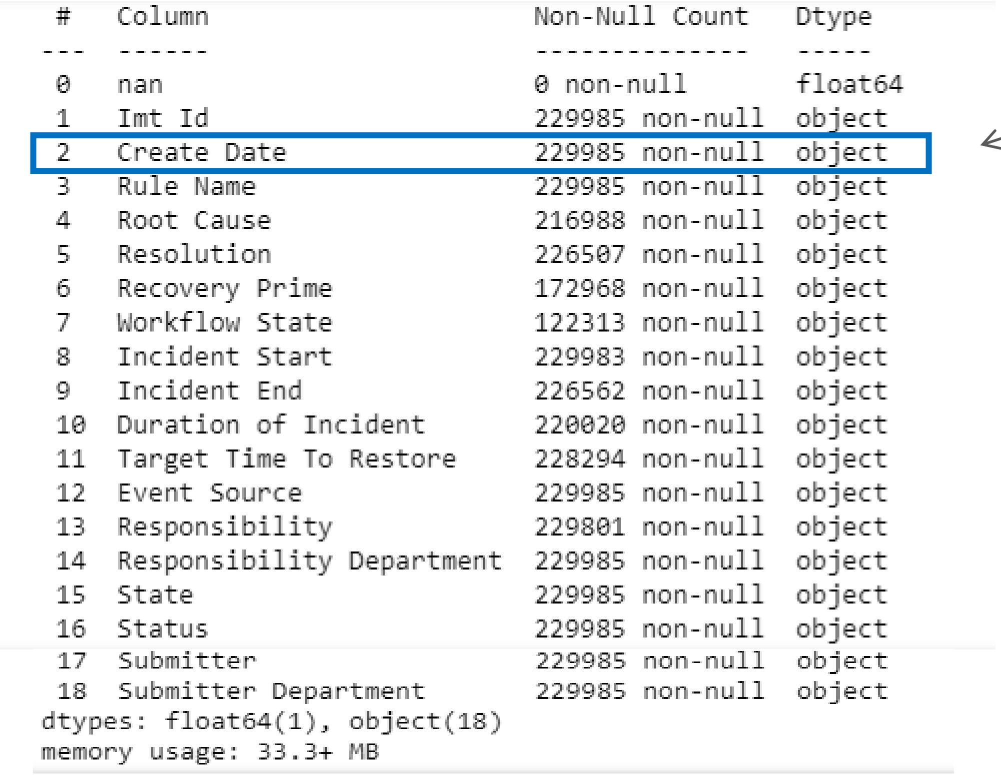
EDA

EXPLORATORY DATA ANALYSIS

REVIEW **THE DATA TYPES**

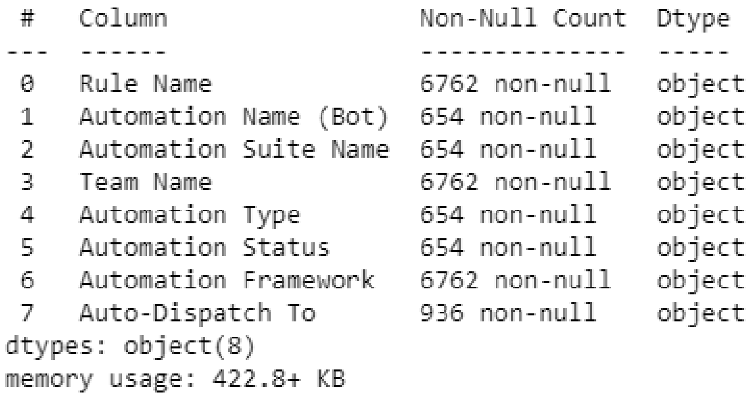
DESCRIPTION

For each Tickets provided relevant information are the following:



```
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   nan                        0 non-null       float64
 1   Imt Id                     229985 non-null  object
 2   Create Date                229985 non-null  object
 3   Rule Name                  229985 non-null  object
 4   Root Cause                 216988 non-null  object
 5   Resolution                 226507 non-null  object
 6   Recovery Prime             172968 non-null  object
 7   Workflow State             122313 non-null  object
 8   Incident Start             229983 non-null  object
 9   Incident End               226562 non-null  object
 10  Duration of Incident       220020 non-null  object
 11  Target Time To Restore     228294 non-null  object
 12  Event Source               229985 non-null  object
 13  Responsibility             229801 non-null  object
 14  Responsibility Department  229985 non-null  object
 15  State                      229985 non-null  object
 16  Status                     229985 non-null  object
 17  Submitter                  229985 non-null  object
 18  Submitter Department       229985 non-null  object
dtypes: float64(1), object(18)
memory usage: 33.3+ MB
```

CONVERT TO YEAR AND MONTH



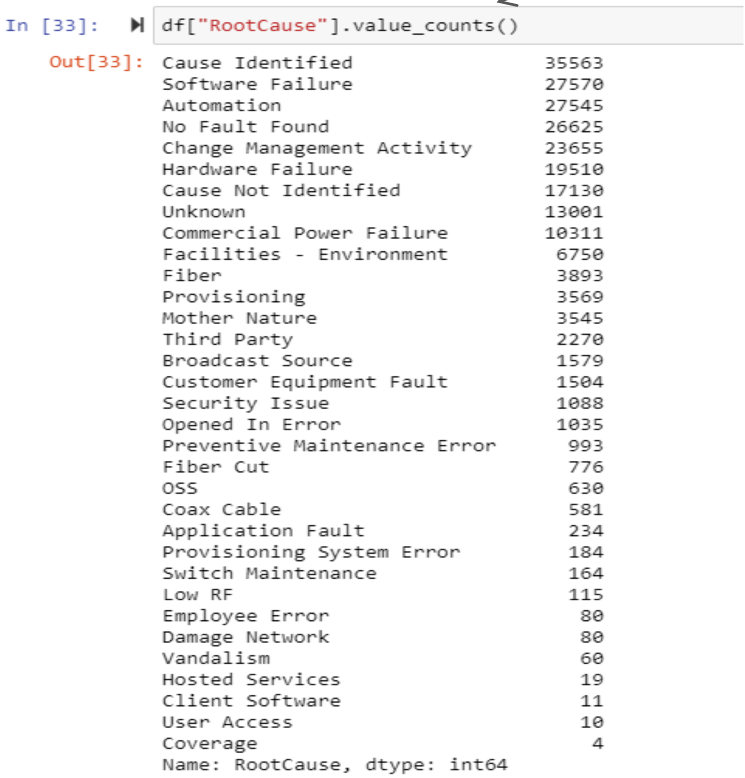
```
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Rule Name               6762 non-null   object
 1   Automation Name (Bot)   654 non-null    object
 2   Automation Suite Name   654 non-null    object
 3   Team Name               6762 non-null   object
 4   Automation Type         654 non-null    object
 5   Automation Status       654 non-null    object
 6   Automation Framework    6762 non-null   object
 7   Auto-Dispatch To        936 non-null    object
dtypes: object(8)
memory usage: 422.8+ KB
```

EXPLORATORY **DATA ANALYSIS**

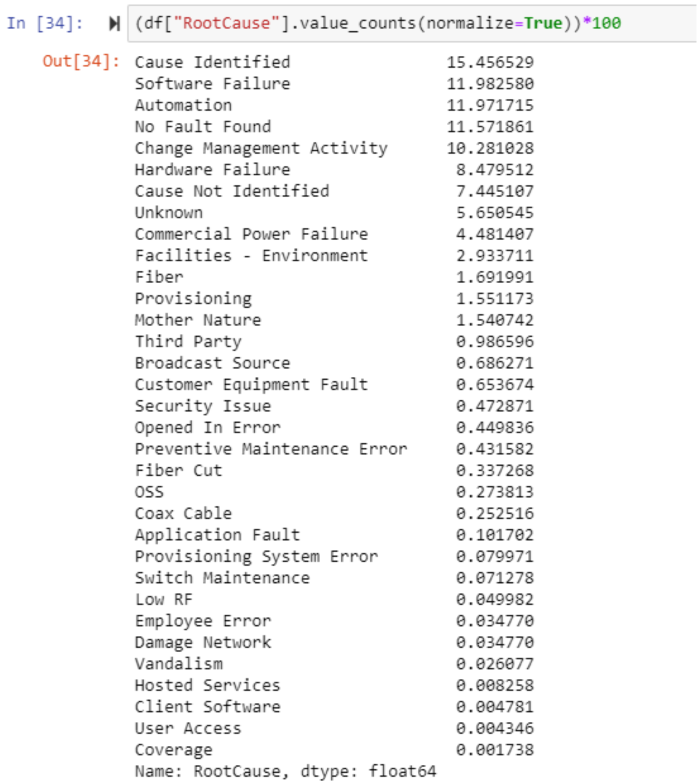
UNDERSTANDING FEATURES

COUNTS VALUE OF ROOT CAUSE

PERCENTAGE OF VALUE ROOT CAUSE



```
In [33]:  df["RootCause"].value_counts()

Out[33]:  Cause Identified                 35563
          Software Failure                 27570
          Automation                       27545
          No Fault Found                   26625
          Change Management Activity       23655
          Hardware Failure                 19510
          Cause Not Identified             17130
          Unknown                          13001
          Commercial Power Failure         10311
          Facilities - Environment          6750
          Fiber                             3893
          Provisioning                      3569
          Mother Nature                     3545
          Third Party                       2270
          Broadcast Source                  1579
          Customer Equipment Fault          1504
          Security Issue                    1088
          Opened In Error                   1035
          Preventive Maintenance Error       993
          Fiber Cut                          776
          OSS                                630
          Coax Cable                         581
          Application Fault                  234
          Provisioning System Error          184
          Switch Maintenance                 164
          Low RF                             115
          Employee Error                      80
          Damage Network                      80
          Vandalism                           60
          Hosted Services                     19
          Client Software                     11
          User Access                         10
          Coverage                             4
          Name: RootCause, dtype: int64
```



```
In [34]:  (df["RootCause"].value_counts(normalize=True))*100

Out[34]:  Cause Identified                15.456529
          Software Failure                11.982580
          Automation                      11.971715
          No Fault Found                  11.571861
          Change Management Activity      10.281028
          Hardware Failure                 8.479512
          Cause Not Identified             7.445107
          Unknown                          5.650545
          Commercial Power Failure         4.481407
          Facilities - Environment         2.933711
          Fiber                            1.691991
          Provisioning                     1.551173
          Mother Nature                    1.540742
          Third Party                      0.986596
          Broadcast Source                 0.686271
          Customer Equipment Fault         0.653674
          Security Issue                   0.472871
          Opened In Error                  0.449836
          Preventive Maintenance Error     0.431582
          Fiber Cut                        0.337268
          OSS                              0.273813
          Coax Cable                       0.252516
          Application Fault                0.101702
          Provisioning System Error        0.079971
          Switch Maintenance               0.071278
          Low RF                           0.049982
          Employee Error                   0.034770
          Damage Network                   0.034770
          Vandalism                        0.026077
          Hosted Services                  0.008258
          Client Software                  0.004781
          User Access                      0.004346
          Coverage                         0.001738
          Name: RootCause, dtype: float64
```

CORRELATION **ANALYSIS**

CORRELATION BETWEEN VARIABLES

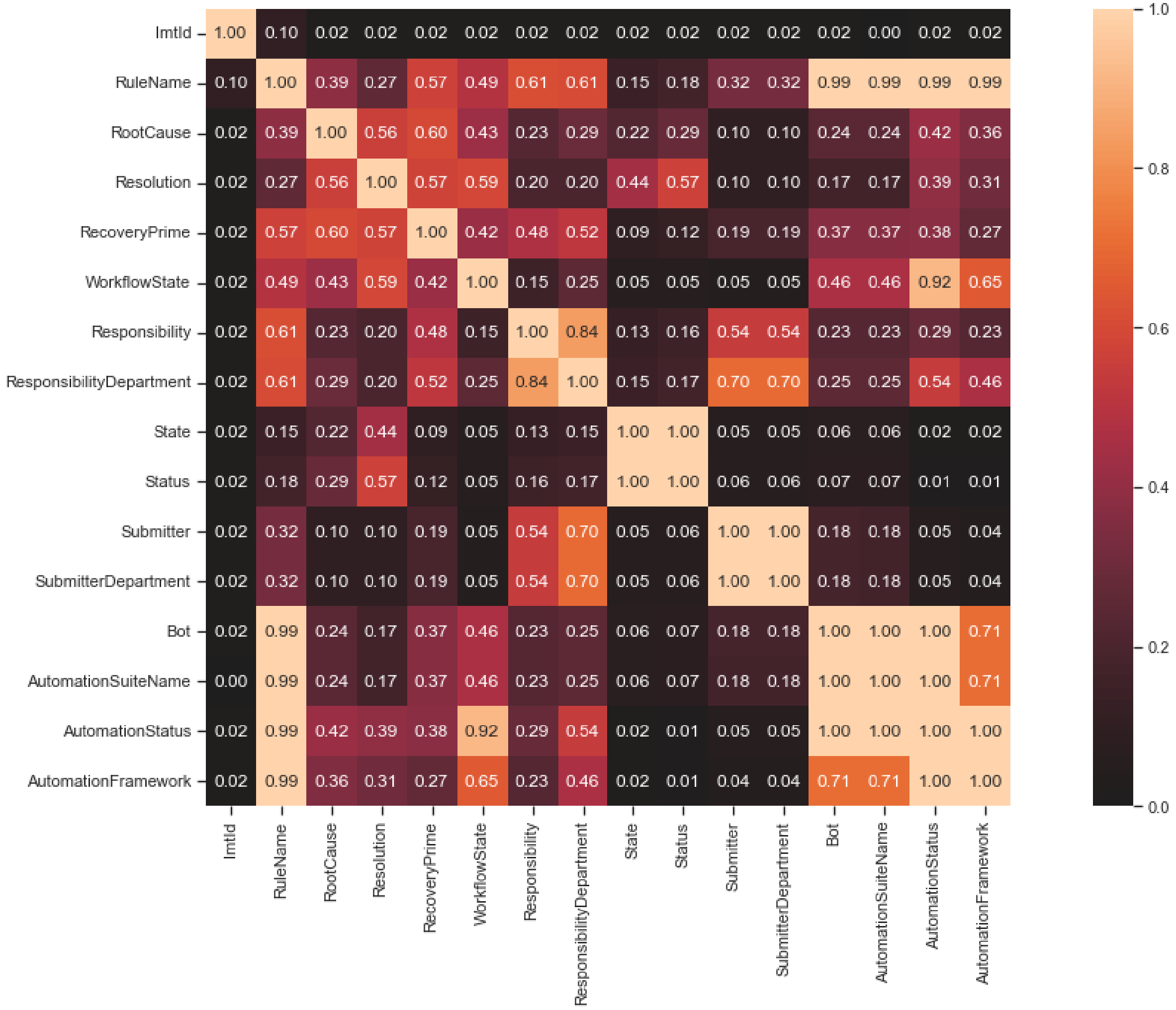
BIVARIATE ANALYSIS: **CATEGORICAL VS. CATEGORICAL**

FOR SUMMARIZATION: CONTINGENCY TABLE (TWO-WAY TABLE)

FOR VISUALIZATION :STACKED BAR CHART, GROUPED BAR CHART,...

FOR TEST OF INDEPENDENCE: CHI-SQUARE TEST

❖ **THERE IS POSITIVE CORRELATION BETWEEN ROOT CAUSE AND RECOVERY PRIME**

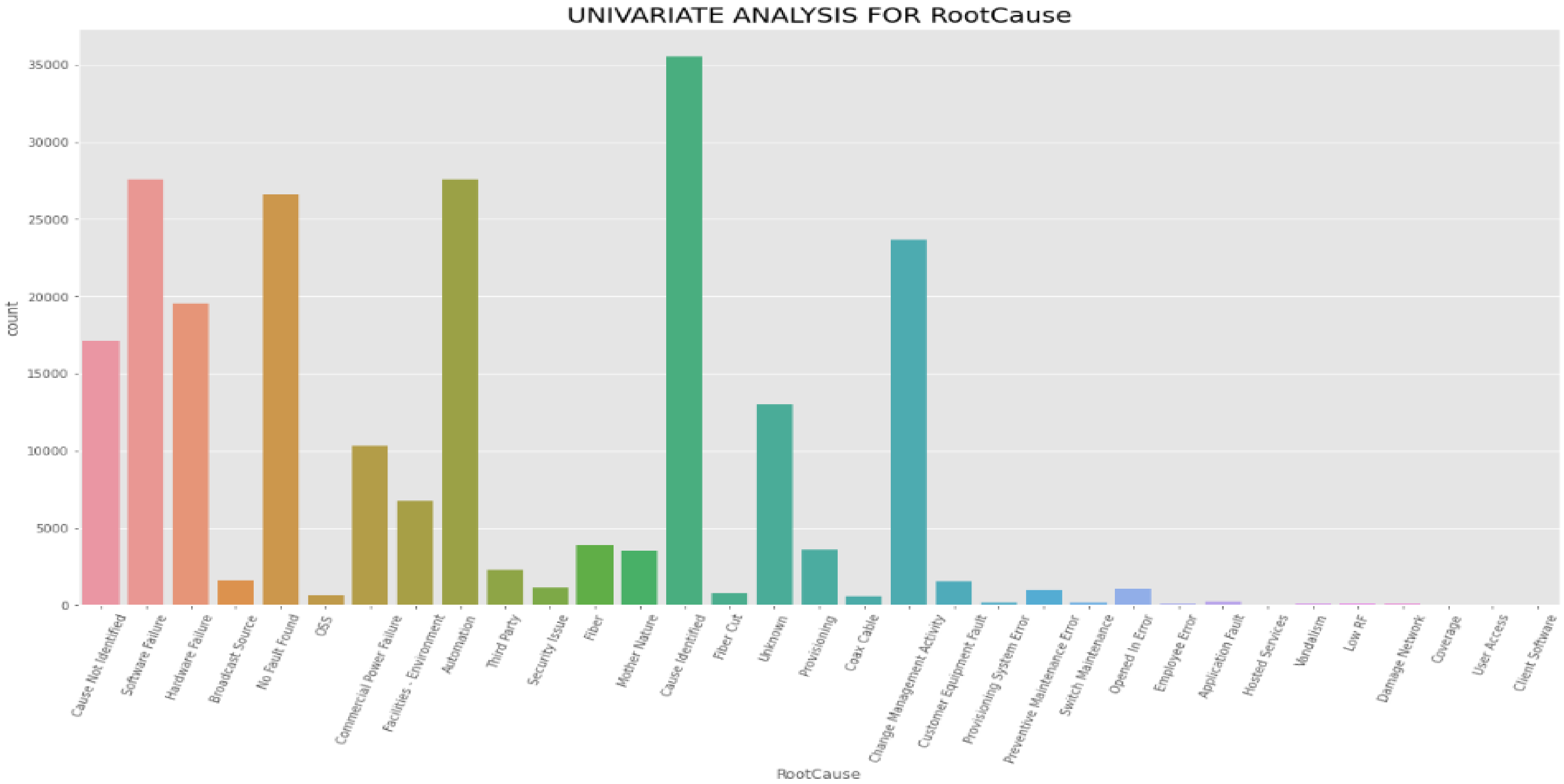


	ImtId	RuleName	RootCause	Resolution	RecoveryPrime	WorkflowState	Responsibility	ResponsibilityDepartment	State	Status	Submitter	SubmitterDepartment	Bot	AutomationSuiteName	AutomationStatus	AutomationFramework
ImtId	1.00	0.10	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.02	0.02
RuleName	0.10	1.00	0.39	0.27	0.57	0.49	0.61	0.61	0.15	0.18	0.32	0.32	0.99	0.99	0.99	0.99
RootCause	0.02	0.39	1.00	0.56	0.60	0.43	0.23	0.29	0.22	0.29	0.10	0.10	0.24	0.24	0.42	0.36
Resolution	0.02	0.27	0.56	1.00	0.57	0.59	0.20	0.20	0.44	0.57	0.10	0.10	0.17	0.17	0.39	0.31
RecoveryPrime	0.02	0.57	0.60	0.57	1.00	0.42	0.48	0.52	0.09	0.12	0.19	0.19	0.37	0.37	0.38	0.27
WorkflowState	0.02	0.49	0.43	0.59	0.42	1.00	0.15	0.25	0.05	0.05	0.05	0.05	0.46	0.46	0.92	0.65
Responsibility	0.02	0.61	0.23	0.20	0.48	0.15	1.00	0.84	0.13	0.16	0.54	0.54	0.23	0.23	0.29	0.23
ResponsibilityDepartment	0.02	0.61	0.29	0.20	0.52	0.25	0.84	1.00	0.15	0.17	0.70	0.70	0.25	0.25	0.54	0.46
State	0.02	0.15	0.22	0.44	0.09	0.05	0.13	0.15	1.00	1.00	0.05	0.05	0.06	0.06	0.02	0.02
Status	0.02	0.18	0.29	0.57	0.12	0.05	0.16	0.17	1.00	1.00	0.06	0.06	0.07	0.07	0.01	0.01
Submitter	0.02	0.32	0.10	0.10	0.19	0.05	0.54	0.70	0.05	0.06	1.00	1.00	0.18	0.18	0.05	0.04
SubmitterDepartment	0.02	0.32	0.10	0.10	0.19	0.05	0.54	0.70	0.05	0.06	1.00	1.00	0.18	0.18	0.05	0.04
Bot	0.02	0.99	0.24	0.17	0.37	0.46	0.23	0.25	0.06	0.07	0.18	0.18	1.00	1.00	1.00	0.71
AutomationSuiteName	0.00	0.99	0.24	0.17	0.37	0.46	0.23	0.25	0.06	0.07	0.18	0.18	1.00	1.00	1.00	0.71
AutomationStatus	0.02	0.99	0.42	0.39	0.38	0.92	0.29	0.54	0.02	0.01	0.05	0.05	1.00	1.00	1.00	1.00
AutomationFramework	0.02	0.99	0.36	0.31	0.27	0.65	0.23	0.46	0.02	0.01	0.04	0.04	0.71	0.71	1.00	1.00

DATA **VISUALIZATION**

UNIVARIATE ANALYSIS

Visualization: BAR CHART

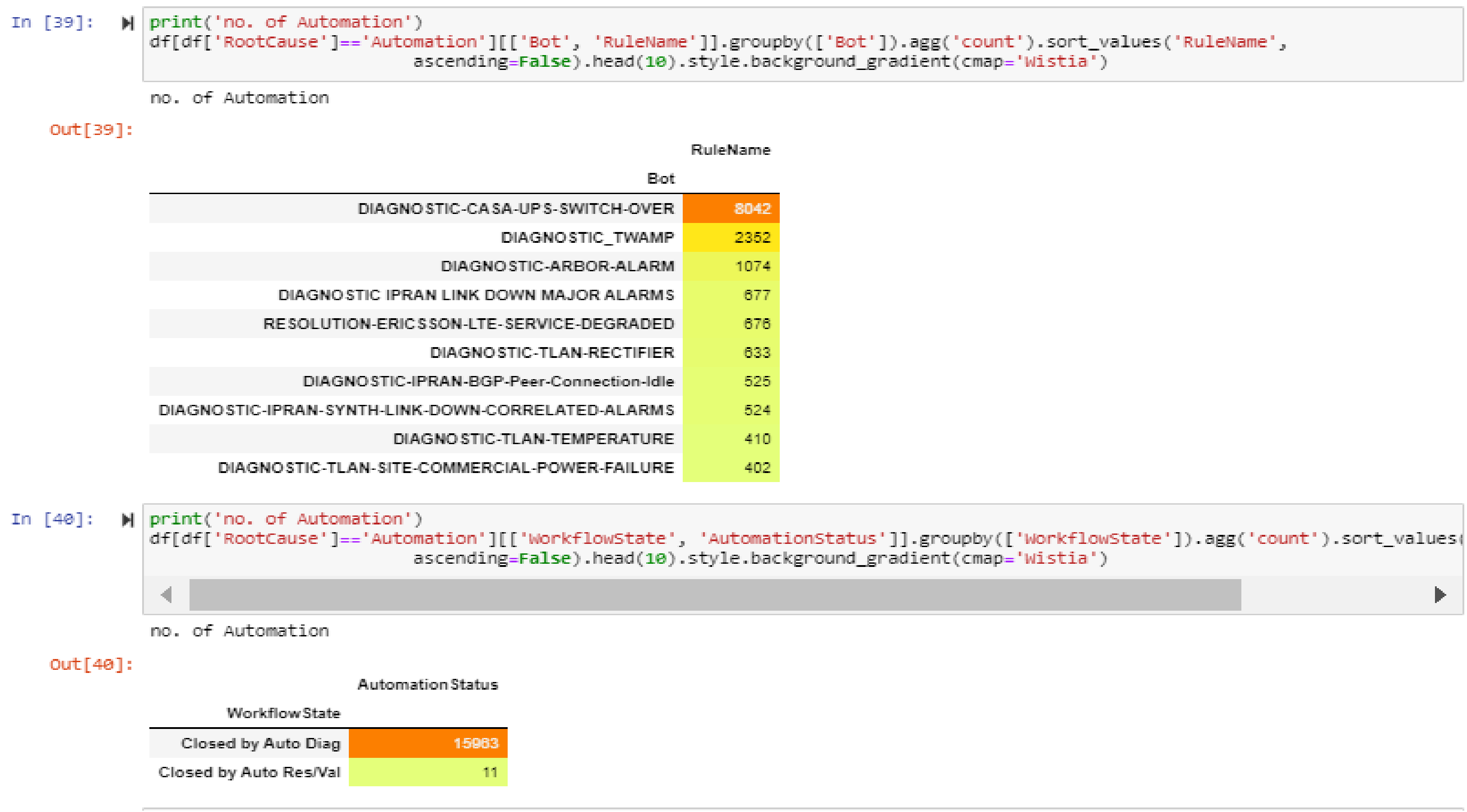


UNIVARIATE ANALYSIS FOR RootCause

DATA **VISUALIZATION**

BIVARIATE ANALYSIS

contingency table (two-way table)

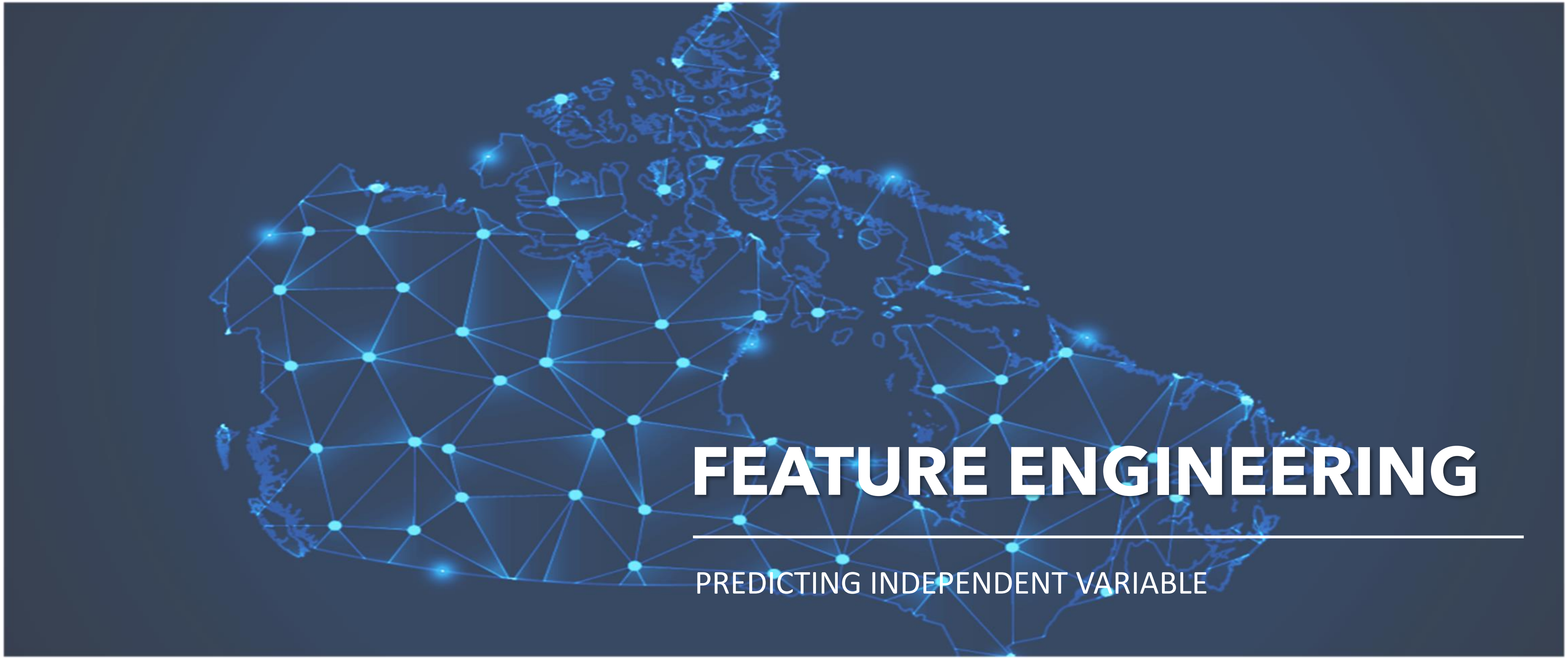


```
In [39]:  print('no. of Automation')
          df[df['RootCause']=='Automation'][['Bot', 'RuleName']].groupby(['Bot']).agg('count').sort_values('RuleName',
                                                  ascending=False).head(10).style.background_gradient(cmap='Wistia')

          no. of Automation
Out[39]:
```

	RuleName
Bot	
DIAGNOSTIC-CASA-UPS-SWITCH-OVER	8042
DIAGNOSTIC_TWAMP	2352
DIAGNOSTIC-ARBOR-ALARM	1074
DIAGNOSTIC IPRAN LINK DOWN MAJOR ALARMS	677
RESOLUTION-ERICSSON-LTE-SERVICE-DEGRADED	676
DIAGNOSTIC-TLAN-RECTIFIER	633
DIAGNOSTIC-IPRAN-BGP-Peer-Connection-Idle	525
DIAGNOSTIC-IPRAN-SYNTH-LINK-DOWN-CORRELATED-ALARMS	524
DIAGNOSTIC-TLAN-TEMPERATURE	410
DIAGNOSTIC-TLAN-SITE-COMMERCIAL-POWER-FAILURE	402

```
In [40]:  print('no. of Automation')
          df[df['RootCause']=='Automation'][['WorkflowState', 'AutomationStatus']].groupby(['WorkflowState']).agg('count').sort_values(
                                                  ascending=False).head(10).style.background_gradient(cmap='Wistia')

          no. of Automation
Out[40]:
```

	Automation Status
Workflow State	
Closed by Auto Diag	15963
Closed by Auto Res/Val	11



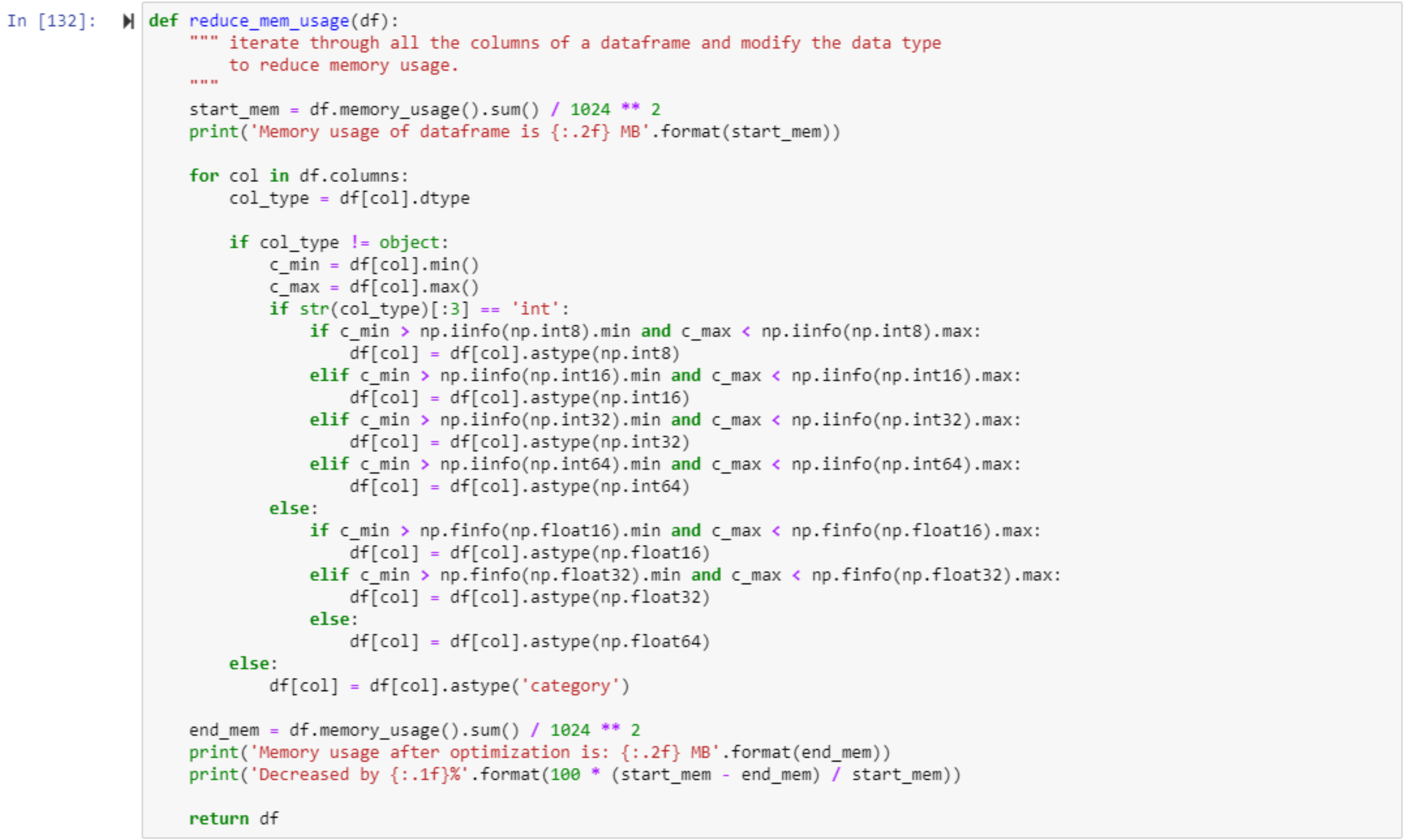
FEATURE ENGINEERING

PREDICTING INDEPENDENT VARIABLE

FEATURE **ENGINEERING**

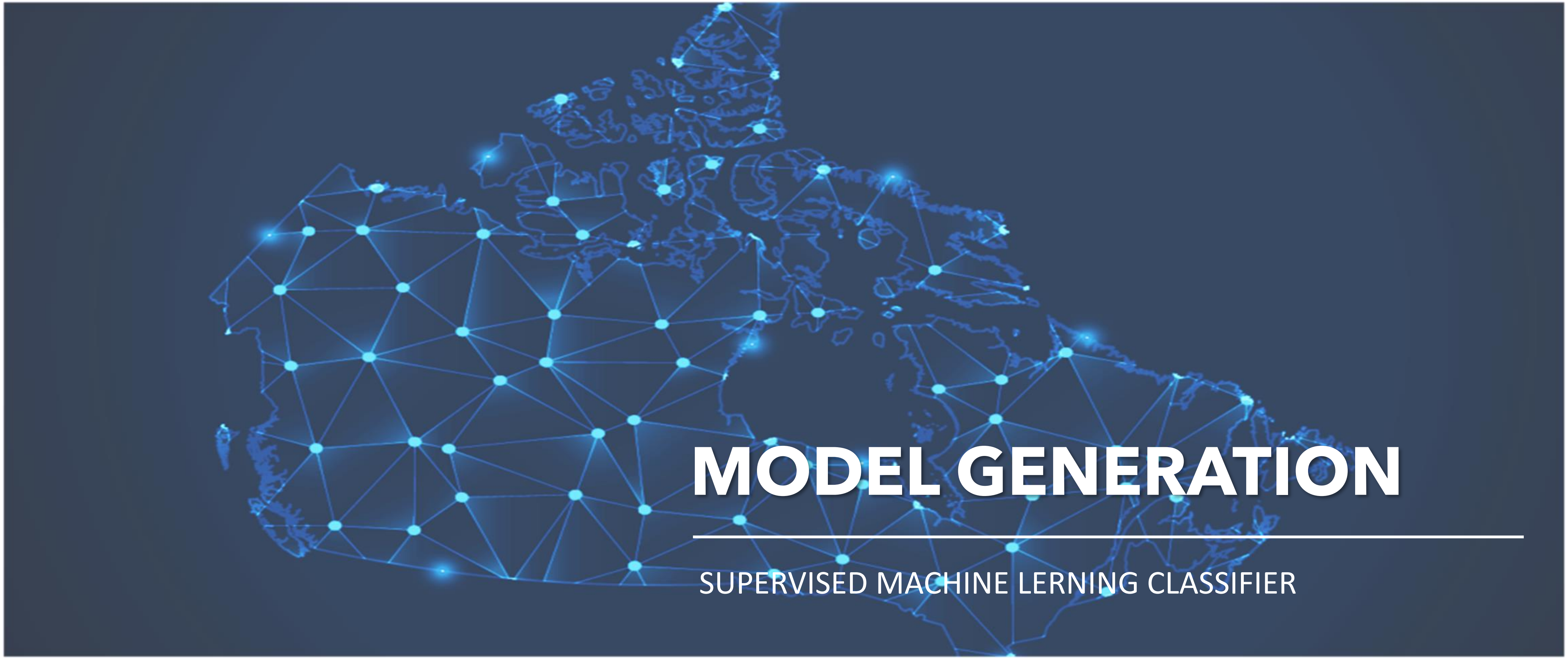
MEMORY REDUCTION

FEATURE ENGINEERING: MEMORY REDUCTION



In [132]:

```
def reduce_mem_usage(df):
    """ iterate through all the columns of a dataframe and modify the data type
        to reduce memory usage.
    """
    start_mem = df.memory_usage().sum() / 1024 ** 2
    print('Memory usage of dataframe is {:.2f} MB'.format(start_mem))

    for col in df.columns:
        col_type = df[col].dtype

        if col_type != object:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.float16).max:
                    df[col] = df[col].astype(np.float16)
                elif c_min > np.finfo(np.float32).min and c_max < np.finfo(np.float32).max:
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
        else:
            df[col] = df[col].astype('category')

    end_mem = df.memory_usage().sum() / 1024 ** 2
    print('Memory usage after optimization is: {:.2f} MB'.format(end_mem))
    print('Decreased by {:.1f}%'.format(100 * (start_mem - end_mem) / start_mem))

    return df
```



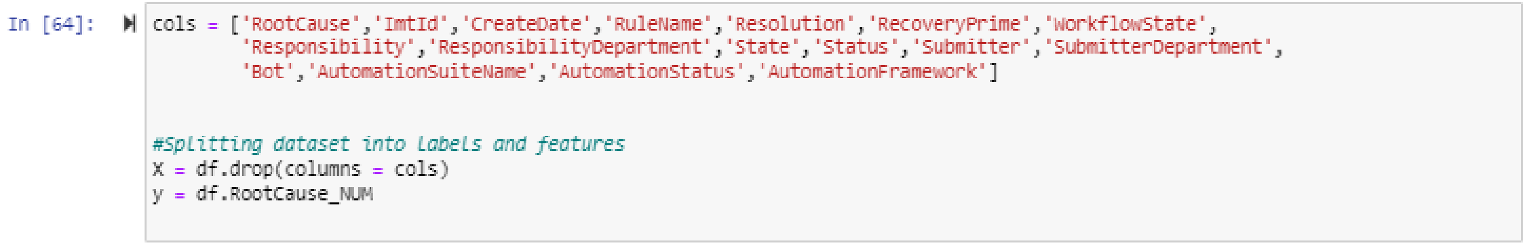
MODEL GENERATION

SUPERVISED MACHINE LERNING CLASSIFIER

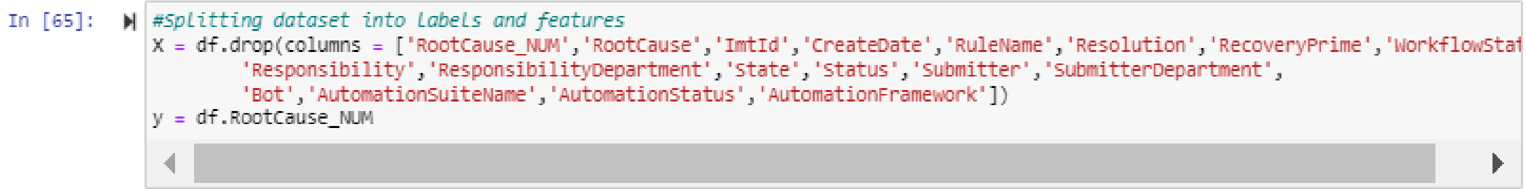
SUPERVISED **MACHINE LERNING CLASSIFIER**

VARIABLE SELECTION

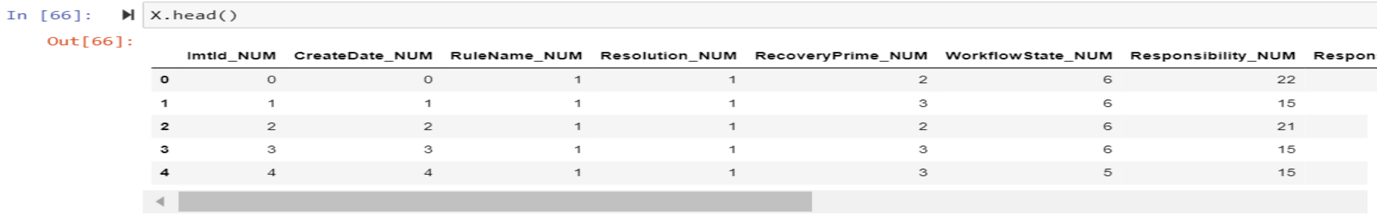
Defining 2 dataset :
Dependent variable (y)
Independent variables (X)



```
In [64]:  cols = ['RootCause','ImtId','CreateDate','RuleName','Resolution','RecoveryPrime','WorkflowState',
                 'Responsibility','ResponsibilityDepartment','State','Status','Submitter','SubmitterDepartment',
                 'Bot','AutomationSuiteName','AutomationStatus','AutomationFramework']


          #Splitting dataset into Labels and features
          X = df.drop(columns = cols)
          y = df.RootCause_NUM
```

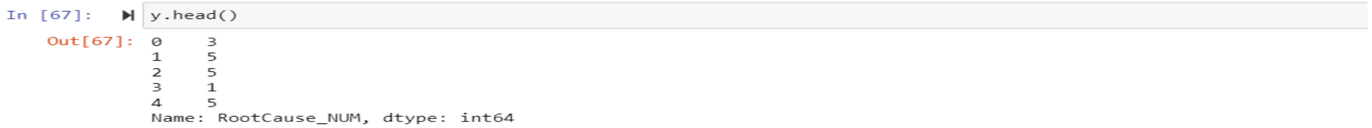


```
In [65]:  #Splitting dataset into Labels and features
          X = df.drop(columns = ['RootCause_NUM','RootCause','ImtId','CreateDate','RuleName','Resolution','RecoveryPrime','WorkflowStat
                 'Responsibility','ResponsibilityDepartment','State','Status','Submitter','SubmitterDepartment',
                 'Bot','AutomationSuiteName','AutomationStatus','AutomationFramework'])
          y = df.RootCause_NUM
```

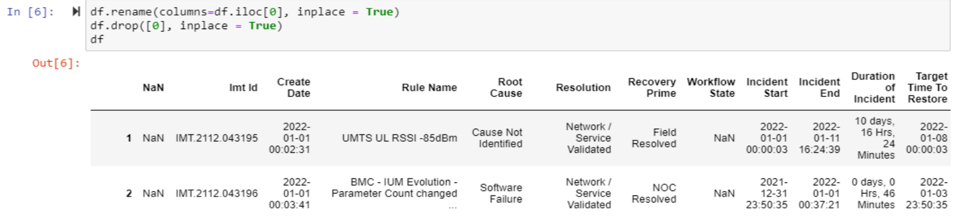


```
In [66]:  X.head()
Out[66]:
```

	ImtId_NUM	CreateDate_NUM	RuleName_NUM	Resolution_NUM	RecoveryPrime_NUM	WorkflowState_NUM	Responsibility_NUM	ResponsibilityDepartment
0	0	0	1	1	2	6	22	
1	1	1	1	1	3	6	15	
2	2	2	1	1	2	6	21	
3	3	3	1	1	3	6	15	
4	4	4	1	1	3	5	15	



```
In [67]:  y.head()
Out[67]:  0    3
          1    5
          2    5
          3    1
          4    5
          Name: RootCause_NUM, dtype: int64
```



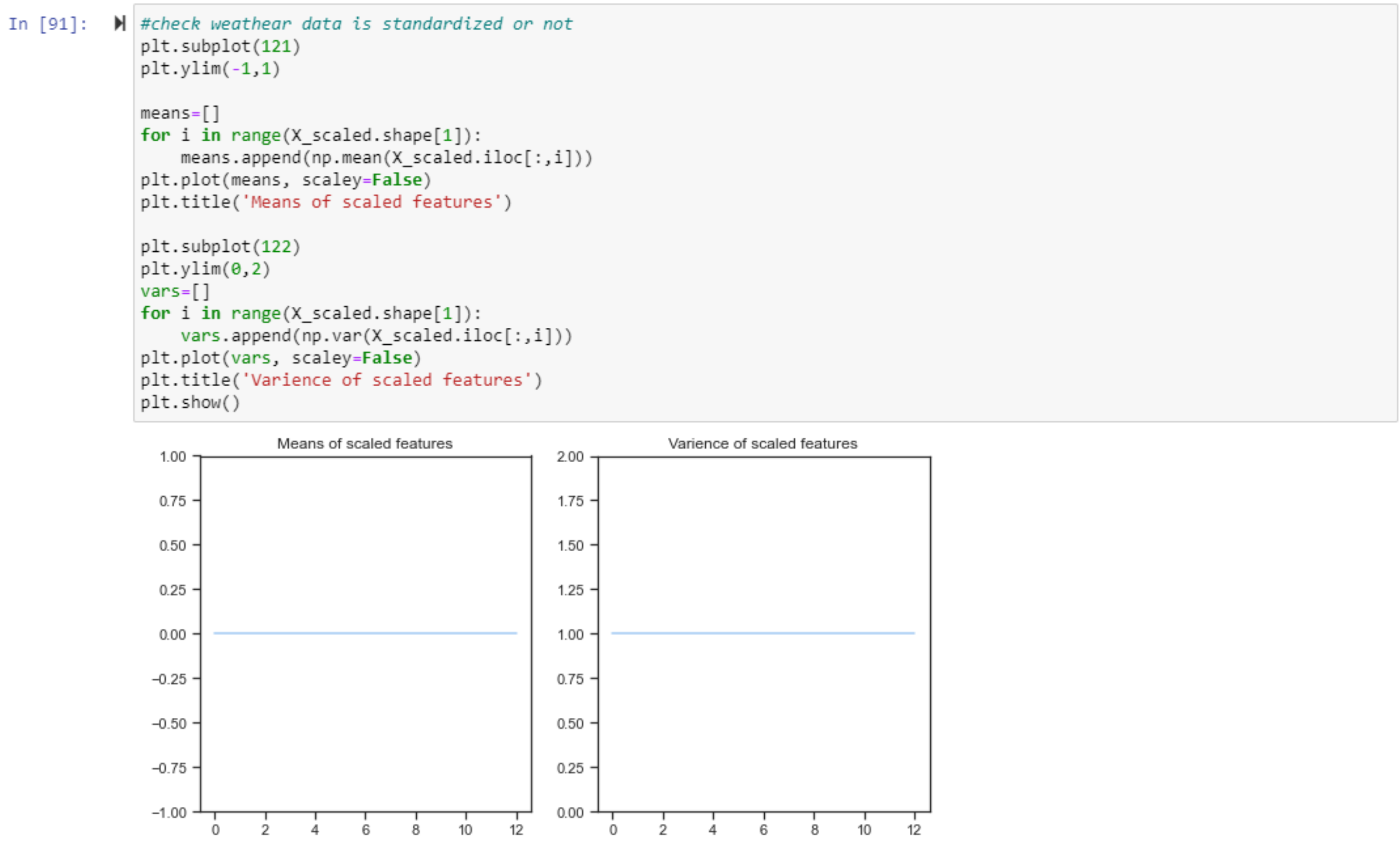
```
In [6]:  df.rename(columns=df.iloc[0], inplace = True)
         df.drop([0], inplace = True)
         df
Out[6]:
```

	NaN	Imt Id	Create Date	Rule Name	Root Cause	Resolution	Recovery Prime	Workflow State	Incident Start	Incident End	Duration of Incident	Target Time To Restore
1	NaN	IMT.2112.043195	2022-01-01 00:02:31	UMTS UL RSSI -85dBm	Cause Not Identified	Network / Service Validated	Field Resolved	NaN	2022-01-01 00:00:03	2022-01-11 16:24:39	10 days, 16 Hrs, 24 Minutes	2022-01-08 00:00:03
2	NaN	IMT.2112.043196	2022-01-01 00:03:41	BMC - IUM Evolution - Parameter Count changed ...	Software Failure	Network / Service Validated	NOC Resolved	NaN	2021-12-31 23:50:35	2022-01-01 00:37:21	0 days, 0 Hrs, 46 Minutes	2022-01-03 23:50:35

ROGERS.

SUPERVISED **MACHINE LERNING CLASSIFIER**

VARIABLE STANDARDIZED



```
In [91]:  #check weathear data is standardized or not
          plt.subplot(121)
          plt.ylim(-1,1)

          means=[]
          for i in range(X_scaled.shape[1]):
              means.append(np.mean(X_scaled.iloc[:,i]))
          plt.plot(means, scaley=False)
          plt.title('Means of scaled features')

          plt.subplot(122)
          plt.ylim(0,2)
          vars=[]
          for i in range(X_scaled.shape[1]):
              vars.append(np.var(X_scaled.iloc[:,i]))
          plt.plot(vars, scaley=False)
          plt.title('Varience of scaled features')
          plt.show()
```

GETTING VARIANCE AND STANDARDIZED

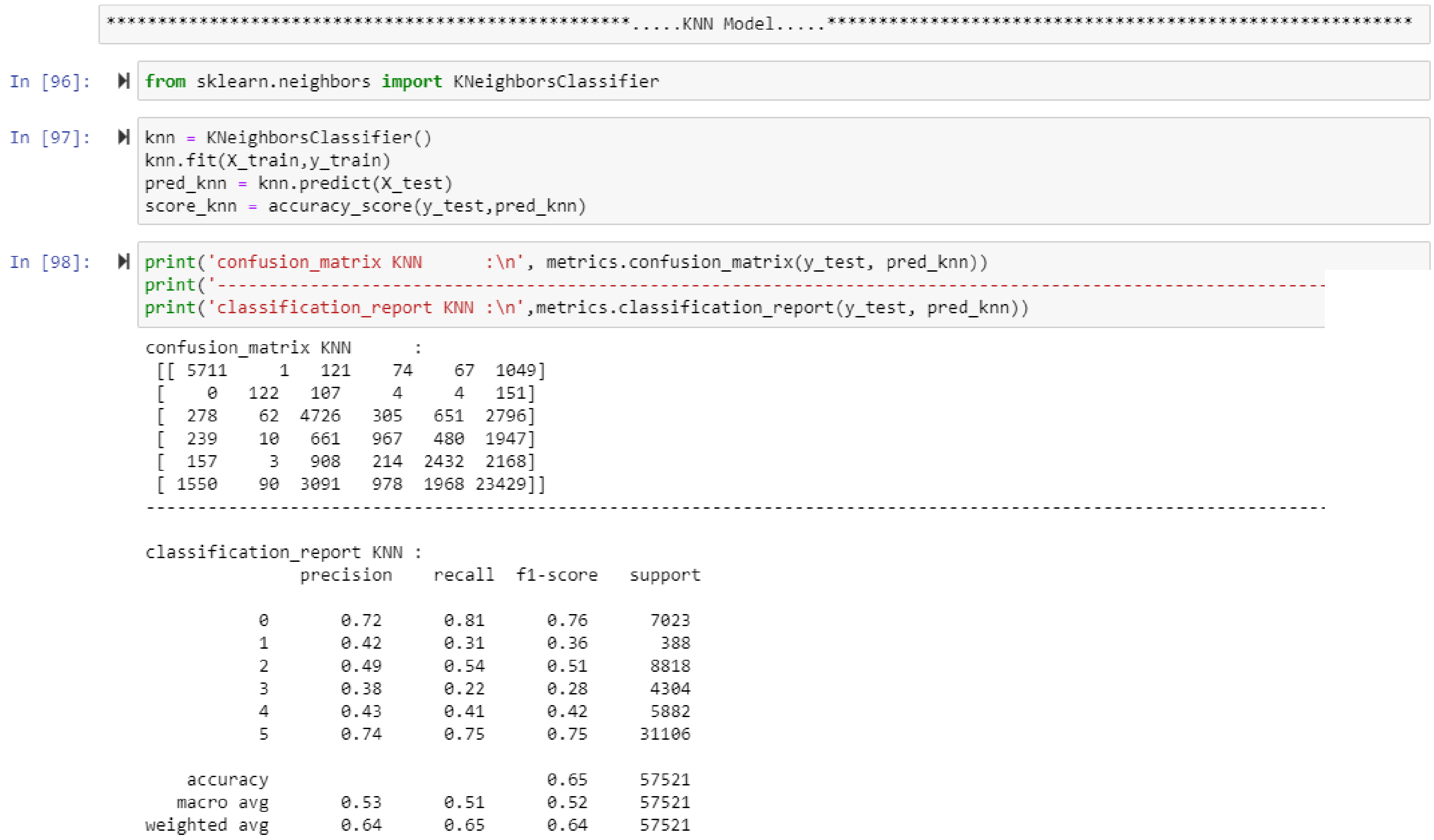
$$\sigma^2 = \frac{\Sigma\,(x - \mu)^2}{N}$$ **Population Variance**

$$s^2 = \frac{\Sigma\,(x - \bar{x})^2}{n - 1}$$ **Sample Variance**

$$s = \sqrt{\frac{\Sigma(x - \bar{x})^2}{n - 1}}$$ Sample Standard Deviation

SUPERVISED **MACHINE LERNING CLASSIFIER**

KNN



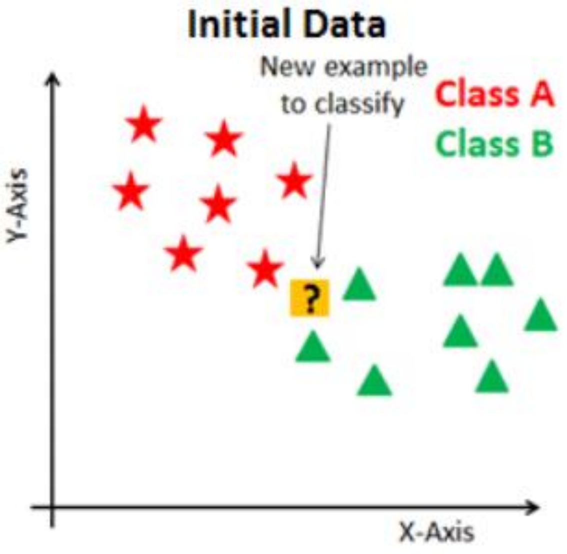
```
***************************************************.....KNN Model.....*********************************************************
```

```
In [96]:  from sklearn.neighbors import KNeighborsClassifier
```

```
In [97]:  knn = KNeighborsClassifier()
           knn.fit(X_train,y_train)
           pred_knn = knn.predict(X_test)
           score_knn = accuracy_score(y_test,pred_knn)
```

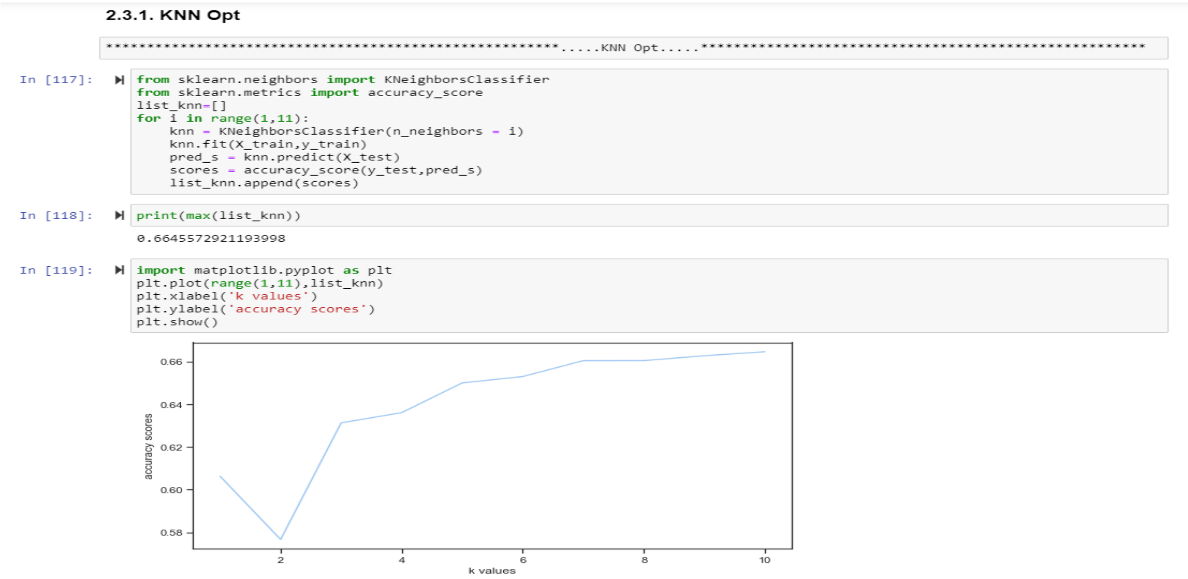
```
In [98]:  print('confusion_matrix KNN      :\n', metrics.confusion_matrix(y_test, pred_knn))
           print('-------------------------------------------------------------------------------------------------------------------
           print('classification_report KNN :\n',metrics.classification_report(y_test, pred_knn))
```

```
confusion_matrix KNN      :
 [[ 5711     1   121    74    67  1049]
 [    0   122   107     4     4   151]
 [  278    62  4726   305   651  2796]
 [  239    10   661   967   480  1947]
 [  157     3   908   214  2432  2168]
 [ 1550    90  3091   978  1968 23429]]
-------------------------------------------------------------------------------------------------------------------

classification_report KNN :
               precision    recall  f1-score   support

           0       0.72      0.81      0.76      7023
           1       0.42      0.31      0.36       388
           2       0.49      0.54      0.51      8818
           3       0.38      0.22      0.28      4304
           4       0.43      0.41      0.42      5882
           5       0.74      0.75      0.75     31106

    accuracy                           0.65     57521
   macro avg       0.53      0.51      0.52     57521
weighted avg       0.64      0.65      0.64     57521
```



SUPERVISED **MACHINE LERNING CLASSIFIER**

KNN-OPTIMIZED



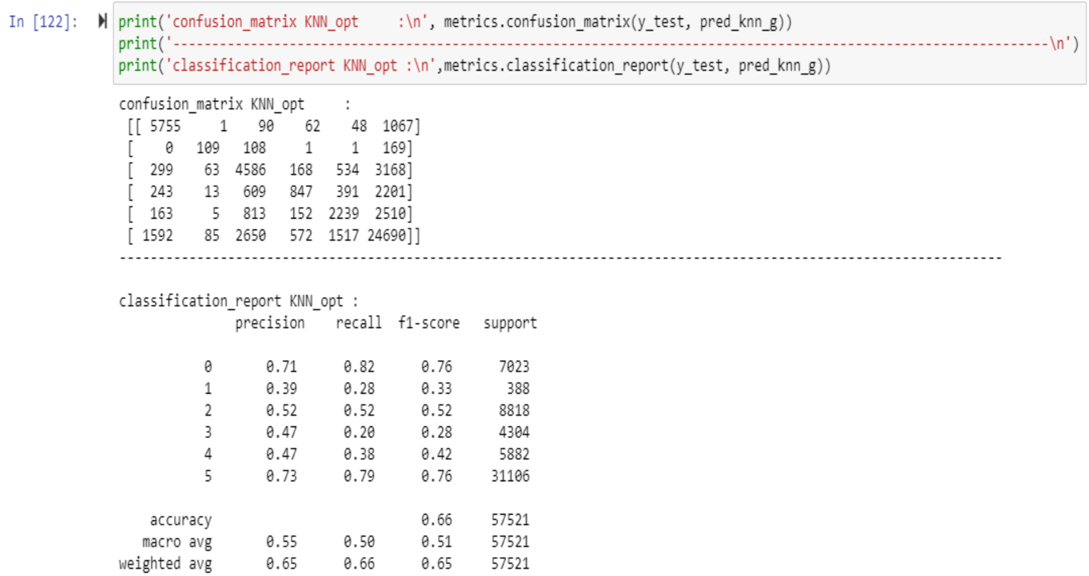
2.3.1. KNN Opt

```
*******************************************************.....KNN Opt.....*******************************************************
```

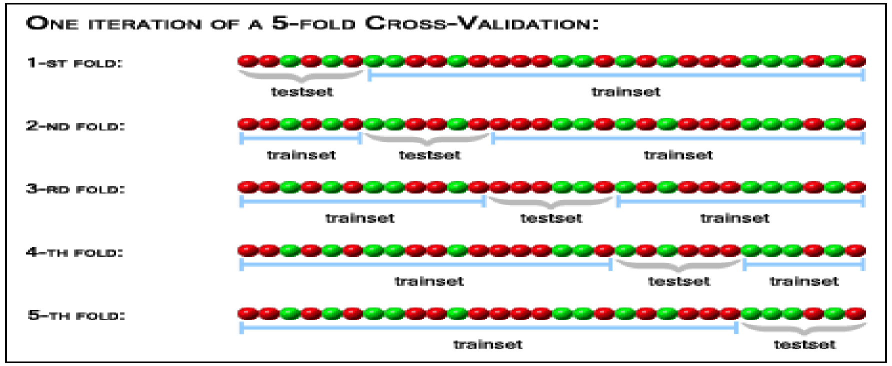
```
In [117]:  from sklearn.neighbors import KNeighborsClassifier
           from sklearn.metrics import accuracy_score
           list_knn=[]
           for i in range(1,11):
               knn = KNeighborsClassifier(n_neighbors = i)
               knn.fit(X_train,y_train)
               pred_s = knn.predict(X_test)
               scores = accuracy_score(y_test,pred_s)
               list_knn.append(scores)
```

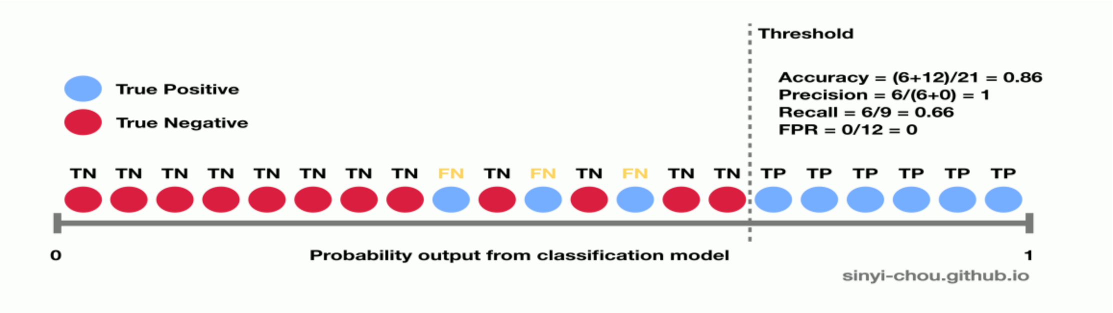
```
In [118]:  print(max(list_knn))

           0.6645572921193998
```

```
In [119]:  import matplotlib.pyplot as plt
           plt.plot(range(1,11),list_knn)
           plt.xlabel('k values')
           plt.ylabel('accuracy scores')
           plt.show()
```



```
In [122]:  print('confusion_matrix KNN_opt     :\n', metrics.confusion_matrix(y_test, pred_knn_g))
           print('---------------------------------------------------------------------------------------------\n')
           print('classification_report KNN_opt :\n',metrics.classification_report(y_test, pred_knn_g))

           confusion_matrix KNN_opt     :
            [[ 5755     1    90    62    48  1067]
            [    0   109   108     1     1   169]
            [  299    63  4586   168   534  3168]
            [  243    13   609   847   391  2201]
            [  163     5   813   152  2239  2510]
            [ 1592    85  2650   572  1517 24690]]
           ---------------------------------------------------------------------------------------------

           classification_report KNN_opt :
                          precision    recall  f1-score   support

                      0       0.71      0.82      0.76      7023
                      1       0.39      0.28      0.33       388
                      2       0.52      0.52      0.52      8818
                      3       0.47      0.20      0.28      4304
                      4       0.47      0.38      0.42      5882
                      5       0.73      0.79      0.76     31106

               accuracy                           0.66     57521
              macro avg       0.55      0.50      0.51     57521
           weighted avg       0.65      0.66      0.65     57521
```





Accuracy = (6+12)/21 = 0.86
Precision = 6/(6+0) = 1
Recall = 6/9 = 0.66
FPR = 0/12 = 0

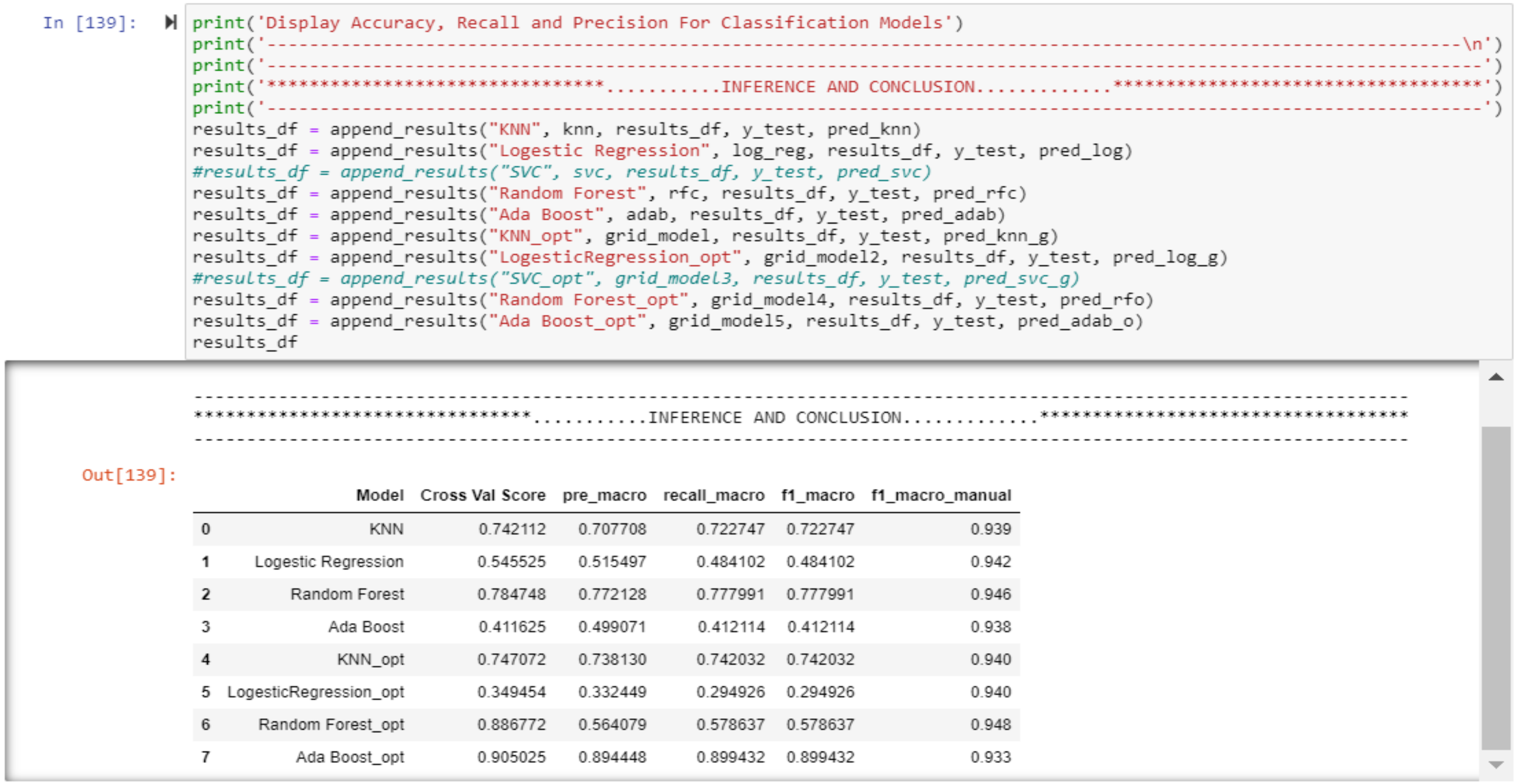
CONCLUSION

DECODING INFERENCE

CONCLUSION

BEST MODEL

B. COMPARE ALL MODELS



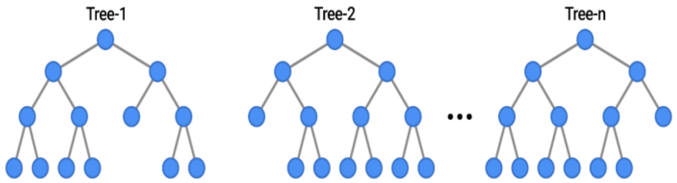
```
In [139]:  print('Display Accuracy, Recall and Precision For Classification Models')
           print('---------------------------------------------------------------------------------------------------------\n')
           print('-----------------------------------------------------------------------------------------------------------')
           print('********************************..........INFERENCE AND CONCLUSION............***********************************')
           print('-----------------------------------------------------------------------------------------------------------')
           results_df = append_results("KNN", knn, results_df, y_test, pred_knn)
           results_df = append_results("Logestic Regression", log_reg, results_df, y_test, pred_log)
           #results_df = append_results("SVC", svc, results_df, y_test, pred_svc)
           results_df = append_results("Random Forest", rfc, results_df, y_test, pred_rfc)
           results_df = append_results("Ada Boost", adab, results_df, y_test, pred_adab)
           results_df = append_results("KNN_opt", grid_model, results_df, y_test, pred_knn_g)
           results_df = append_results("LogesticRegression_opt", grid_model2, results_df, y_test, pred_log_g)
           #results_df = append_results("SVC_opt", grid_model3, results_df, y_test, pred_svc_g)
           results_df = append_results("Random Forest_opt", grid_model4, results_df, y_test, pred_rfo)
           results_df = append_results("Ada Boost_opt", grid_model5, results_df, y_test, pred_adab_o)
           results_df
```

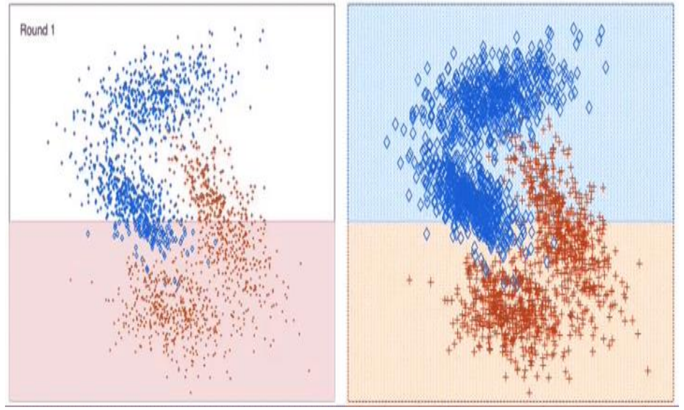
```
-----------------------------------------------------------------------------------------------------------
********************************..........INFERENCE AND CONCLUSION............***********************************
-----------------------------------------------------------------------------------------------------------
```

Out[139]:

	Model	Cross Val Score	pre_macro	recall_macro	f1_macro	f1_macro_manual
0	KNN	0.742112	0.707708	0.722747	0.722747	0.939
1	Logestic Regression	0.545525	0.515497	0.484102	0.484102	0.942
2	Random Forest	0.784748	0.772128	0.777991	0.777991	0.946
3	Ada Boost	0.411625	0.499071	0.412114	0.412114	0.938
4	KNN_opt	0.747072	0.738130	0.742032	0.742032	0.940
5	LogesticRegression_opt	0.349454	0.332449	0.294926	0.294926	0.940
6	Random Forest_opt	0.886772	0.564079	0.578637	0.578637	0.948
7	Ada Boost_opt	0.905025	0.894448	0.899432	0.899432	0.933

EXAMPLES



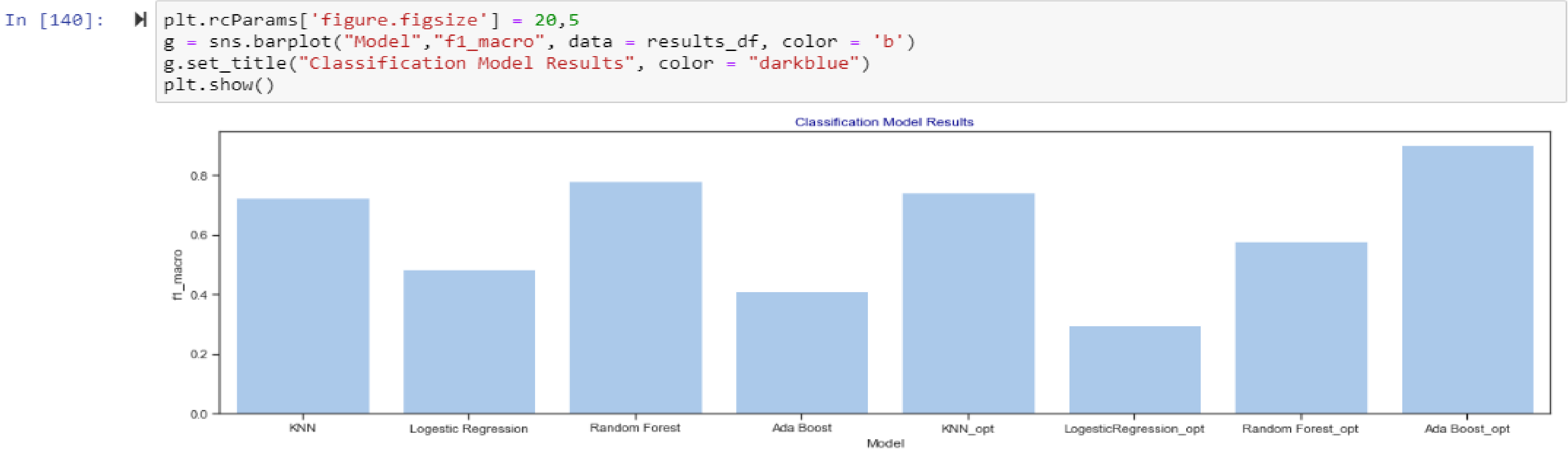


CONCLUSION

BEST MODEL

The model is acceptable because with an accuracy of over (60%)

A different model (non-linear) will be better to predict the output variable as the correlation study suggests.



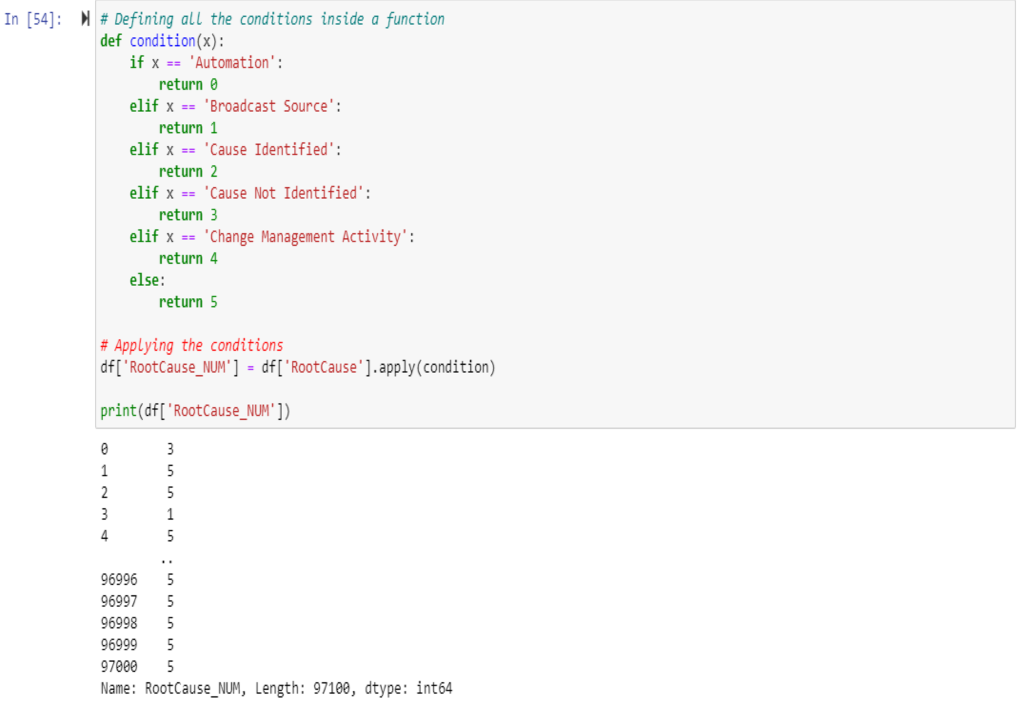
```
In [140]:  plt.rcParams['figure.figsize'] = 20,5
           g = sns.barplot("Model","f1_macro", data = results_df, color = 'b')
           g.set_title("Classification Model Results", color = "darkblue")
           plt.show()
```

INFERENCE

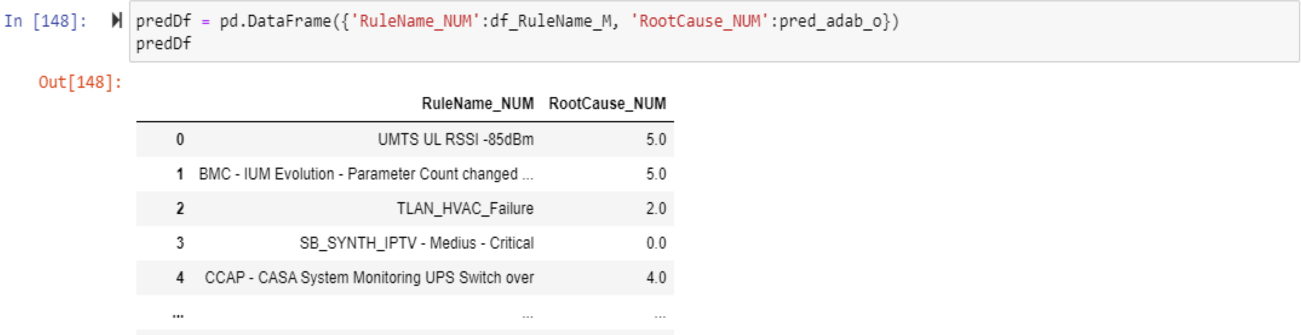
INTERPRETING THE RESULTS

Data Prediction based on data history

After selecting the model, data analysis is performed based on the predicted data.



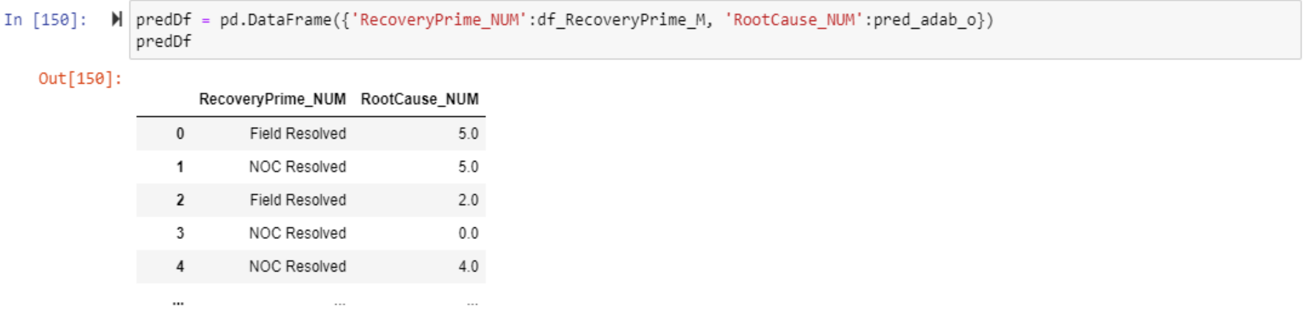
```
In [54]:  # Defining all the conditions inside a function
          def condition(x):
              if x == 'Automation':
                  return 0
              elif x == 'Broadcast Source':
                  return 1
              elif x == 'Cause Identified':
                  return 2
              elif x == 'Cause Not Identified':
                  return 3
              elif x == 'Change Management Activity':
                  return 4
              else:
                  return 5

          # Applying the conditions
          df['RootCause_NUM'] = df['RootCause'].apply(condition)

          print(df['RootCause_NUM'])

          0        3
          1        5
          2        5
          3        1
          4        5
                  ..
          96996    5
          96997    5
          96998    5
          96999    5
          97000    5
          Name: RootCause_NUM, Length: 97100, dtype: int64
```



```
In [148]:  predDf = pd.DataFrame({'RuleName_NUM':df_RuleName_M, 'RootCause_NUM':pred_adab_o})
           predDf
```

Out[148]:

	RuleName_NUM	RootCause_NUM
0	UMTS UL RSSI -85dBm	5.0
1	BMC - IUM Evolution - Parameter Count changed ...	5.0
2	TLAN_HVAC_Failure	2.0
3	SB_SYNTH_IPTV - Medius - Critical	0.0
4	CCAP - CASA System Monitoring UPS Switch over	4.0
...	...	...



```
In [150]:  predDf = pd.DataFrame({'RecoveryPrime_NUM':df_RecoveryPrime_M, 'RootCause_NUM':pred_adab_o})
           predDf
```

Out[150]:

	RecoveryPrime_NUM	RootCause_NUM
0	Field Resolved	5.0
1	NOC Resolved	5.0
2	Field Resolved	2.0
3	NOC Resolved	0.0
4	NOC Resolved	4.0
...	...	...

RECOMMENDATION

RECOMMENDATION

PREDICTIVE MAINTENANCE AND IMPROVE NETWORK OPTIMIZATION

Total IMT in the ESAP for **PY** : 283033 **, Average in a Month: 23586**
Total IMT for PY: 424565

Total IMT in the ESAP for **YTD** : 245743, **Average in a Month: 31709**
Total IMT for YTD: 355573

1

Problem Statement

- Detect Network Congestion (Network Monitoring & Network Device)
- Prevent power outages, by using AI/ML Predictive Maintenance, and make customer satisfaction.
- Identify Network Problems and issues fast by using ML

2

Business Value

- According to the forecast, we can reduce the time, which leads to saving money and improve business processes, and make customer satisfy.
- By prediction, it is possible to determine the workload of network teams, which leads to handling or the new definition of projects in the system,

3

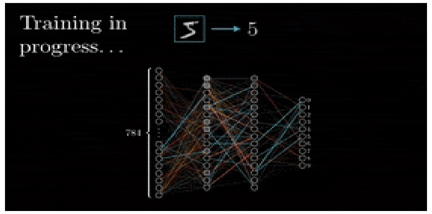
Data

- Enable cross team collaboration
- Identified Gaps and Limitations such as data and cloud environment

4

Model Generation

- Using High level Model
- Due to many fluctuated in top Flow and Rule Name, we need to use algorithms that are suitable for getting the bias.



Thank You !

SARA!