

```

import sys
!{sys.executable} -m pip install -U pandas-profiling[notebook]
!jupyter nbextension enable --py widgetsnbextension
!pip install matplotlib
!pip install graphviz

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-packages (from pandas!=1.4.0,<1.6,>1
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Requirement already satisfied: pycparser in /usr/local/lib/python3.9/dist-packages (from cffi>=1.0.1->argon2-cffi
Enabling notebook extension jupyter-js-widgets/extension...
Paths used for configuration of notebook:
  /root/.jupyter/nbconfig/notebook.json
Paths used for configuration of notebook:

- Validating: OK
Paths used for configuration of notebook:
  /root/.jupyter/nbconfig/notebook.json
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: matplotlib in /usr/local/lib/python3.9/dist-packages (3.5.3)
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Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: graphviz in /usr/local/lib/python3.9/dist-packages (0.10.1)

```

```

import pandas as pd
import numpy as np

df= pd.read_csv("/content/drive/MyDrive/CIND 820 Capstone Project/merged_completdedata.csv")
print(df.dtypes)

```

```

RecordID      int64
X              float64
Y              float64

```

```
FID                int64
BusinessID         int64
Name               object
Address            object
StreetNo           int64
StreetName         object
BldgNo             object
UnitNo             object
PostalCode         object
Location           object
Ward               int64
NAICSCode          int64
NAICSCat           object
NAICSDescr         object
Phone              object
Fax                object
TollFree           object
EMail              object
WebAddress         object
EmplRange          int64
CENT_X             float64
CENT_Y             float64
Year               int64
isnew              object
Closed             object
dtype: object
```

```
df = df[df['Year'] == 2019] #if we just look at closed from 2019
```

```
df.drop(['Year'], axis=1, inplace=True) #if we just look at closed from 2019
```

```
#NAICSCode back to object as it is nominal not ordinal
df['NAICSCode'] = df['NAICSCode'].astype(str)
```

```
# Let's display first 10 records
df.head(10)
```

	RecordID		X	Y	FID	BusinessID	Name	Address	StreetNo	StreetName	BldgNo	...	Phone	F
	46689	46690	-79.665386	43.684736	1	7	Peel Car & Truck Rentals	7050 Bramalea Rd	7050	Bramalea Rd	Yes	...	905- 670- 2442	9C 67 64
	46690	46691	-79.642760	43.593515	2	4246	Real Fruit Bubble Tea	100 City Centre Dr	100	City Centre Dr	No	...		

```
# look at meta information about data, such as null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16518 entries, 46689 to 63206
Data columns (total 27 columns):
#   Column          Non-Null Count  Dtype
---  -
0   RecordID        16518 non-null  int64
1   X               16518 non-null  float64
2   Y               16518 non-null  float64
3   FID             16518 non-null  int64
4   BusinessID      16518 non-null  int64
5   Name            16518 non-null  object
6   Address         16518 non-null  object
7   StreetNo        16518 non-null  int64
8   StreetName      16518 non-null  object
9   BldgNo          16518 non-null  object
10  UnitNo          16518 non-null  object
11  PostalCode      16518 non-null  object
12  Location        16518 non-null  object
13  Ward            16518 non-null  int64
14  NAICSCode       16518 non-null  object
15  NAICSCat        16518 non-null  object
16  NAICSDescr      16518 non-null  object
17  Phone           16518 non-null  object
18  Fax             16518 non-null  object
19  TollFree        16518 non-null  object
20  EMail           16518 non-null  object
21  WebAddress      16518 non-null  object
22  EmplRange       16518 non-null  int64
23  CENT_X          16518 non-null  float64
24  CENT_Y          16518 non-null  float64
25  isnew           16518 non-null  object
26  Closed          16518 non-null  object
dtypes: float64(4), int64(6), object(17)
memory usage: 3.5+ MB
```

```
# Let's see meta information about numeric data, we can also see if there any extreme values
df.describe()
```

	RecordID	X	Y	FID	BusinessID	StreetNo	Ward	EmplRange	CE
count	16518.000000	16518.000000	16518.000000	16518.000000	16518.000000	16518.000000	16518.000000	16518.000000	16518.00
mean	54948.500000	-79.657689	43.601356	8259.500000	38317.374803	2949.933285	5.372927	2.183981	608803.89
std	4768.480209	0.046612	0.056180	4768.480209	32183.768108	2364.551005	2.452044	1.450311	3622.9E
min	46690.000000	-79.802980	43.485170	1.000000	7.000000	1.000000	1.000000	1.000000	596627.93
25%	50819.250000	-79.697599	43.560065	4130.250000	10300.250000	1050.250000	5.000000	1.000000	606962.72
50%	54948.500000	-79.655443	43.600388	8259.500000	20467.000000	2380.000000	5.000000	2.000000	609549.25
75%	59077.750000	-79.622510	43.643674	12388.750000	57398.250000	5144.500000	7.000000	3.000000	611124.36
max	63207.000000	-79.550935	43.732864	16518.000000	93823.000000	7895.000000	11.000000	9.000000	616985.05

```
df.drop(['RecordID', 'FID', 'BusinessID', 'StreetNo', 'Ward', 'CENT_X', 'CENT_Y', 'EmplRange'], axis=1, inplace=True)

# First split the data into train and test set
from sklearn.model_selection import train_test_split

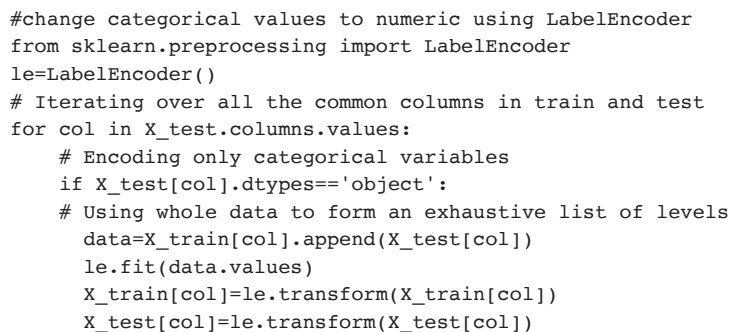
# Split dataset into training set and test set
# Our class column is Closed and everything else will be used as features
class_col_name='Closed'

feature_names=df.columns[df.columns != class_col_name ]
# 80% training and 20% test
X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names], df[class_col_name], test_size=0.2, random_

#plot the distribution of continuous variables

import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

X_train[X_train.dtypes[(X_train.dtypes=="float64")|(X_train.dtypes=="int64")]]
        .index.values].hist(figsize=[17,17])
from IPython.display import set_matplotlib_formats # for better resolution in pdf export
set_matplotlib_formats('pdf', 'svg')
```

[illegible]

```
#help(tree.DecisionTreeClassifier)

#Decision tree 5 levels deep
from sklearn import tree
clf = tree.DecisionTreeClassifier(max_depth=5)
clf = clf.fit(X_train, y_train)
print("Successfully trained the decision tree...")

    Successfully trained the decision tree...

#plot the decision tree
import graphviz
#Get unique class values to display on the tree
class_values=df[class_col_name].unique()
print ("Class Names",class_values)

dot_data = tree.export_graphviz(clf, out_file=None,
                                feature_names=feature_names,
                                class_names=class_values,
                                filled=True)

# Plot tree
graph = graphviz.Source(dot_data, format="png")
graph
```

```

Class Names ['No' 'Yes']

# Let's make the predictions on the test set that we set aside earlier using the trained tree
y_pred = clf.predict(X_test)

from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, y_pred)
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
print ("TP: ", tp," , FP: ", fp," , TN: ", tn," , FN:", fn)

Confusion Matrix
[[2752   10]
 [ 538    4]]
TP:  4 , FP:  10 , TN:  2752 , FN:  538

value = [1345 4221]

#print precision, recall, and accuracy from the perspective of each of the class (0 and 1 for the dataset)
from sklearn.metrics import classification_report
from sklearn import metrics

print(classification_report(y_test, y_pred))

              precision    recall  f1-score   support

    No         0.84         1.00         0.91         2762
    Yes         0.29         0.01         0.01          542

 accuracy         0.83         0.83         0.83         3304
 macro avg         0.56         0.50         0.46         3304
weighted avg         0.75         0.83         0.76         3304

samples = 40 | samples = 1697 | samples = 202 |

#Similarly we can Train and Test in Bayes
#from sklearn.naive_bayes import MultinomialNB
#Since we have negative values in the X column use GaussianNB instead of MultinomialNB
from sklearn.naive_bayes import GaussianNB
#####from sklearn.naive_bayes import MultinomialNB

#Create a MultiNomial NB Classifier
#####nb = MultinomialNB()
nb = GaussianNB()

#Train the model using the training sets
nb.fit(X_train, y_train)

#Predict the response for test dataset
y_pred = nb.predict(X_test)

print ("Total Columns (including class)",len(df.columns))

Total Columns (including class) 19

#print("Number of features used ",nb.n_features_)
print("Classes ",nb.classes_)
print("Number of records for classes ",nb.class_count_)
#print("Log prior probability for classes ", nb.class_log_prior_)
print("Probability of each class", nb.class_prior_)
#print("Log conditional probability for each feature given a class\n",nb.feature_log_prob_)
print("float absolute additive value to variances", nb.epsilon_)
#print("array,shape variance of each feature per class",nb.sigma_)
print("array,shape mean of each feature per class",nb.theta_)

```

```

Classes      ['No' 'Yes']
Number of records for classes      [11042.  2172.]
Probability of each class [0.83562888 0.16437112]
float absolute additive value to variances 0.021032330650500256
array,shape mean of each feature per class [[-7.96575960e+01  4.36025371e+01  7.72517171e+03  2.89902373e+03
  2.74015577e+02  5.11682666e-02  6.55859446e-01  1.32051259e+01
  3.16664554e+01  1.31677232e+01  9.71418221e+00  3.22962145e+02
  7.66111212e+03  2.82494584e+03  1.49972831e-01  6.10215541e-01
  7.42800217e-01  1.00978084e-01]
[-7.96598839e+01  4.35966464e+01  7.57958057e+03  2.84230617e+03
  2.75028085e+02  4.41988950e-02  7.05340700e-01  1.33462247e+01
  3.40626151e+01  1.23678637e+01  1.02808471e+01  3.22968232e+02
  7.21436326e+03  2.51757689e+03  1.66666667e-01  5.92081031e-01
  7.23296501e-01  1.36740331e-01]]

```

```

from sklearn.metrics import classification_report
from sklearn import metrics

```

```
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
No	0.84	1.00	0.91	2762
Yes	0.19	0.01	0.01	542
accuracy			0.83	3304
macro avg	0.51	0.50	0.46	3304
weighted avg	0.73	0.83	0.76	3304

```

#describe categorical data
df.describe(include='O')

```

	Name	Address	StreetName	BldgNo	UnitNo	PostalCode	Location	NAICSCode	NAISCCat	NAICSDescr	Phone	Fax
count	16518	16518	16518	16518	16518	16518	16518	16518	16518	16518	16518	16518
unique	15233	5959	598	2	2	34	56	24	19	687	15531	94
top	Subway	100 City Centre Dr	Dundas St E	No	Yes	L4W	Northeast EA (West)	81	Retail Trade	Limited-service eating places		
freq	43	222	667	15689	10986	2714	4131	1873	2303	808	403	6



```

#drop columns that have unique values
#df.drop(['Name','Address','StreetName','NAICSDescr'], axis=1, inplace=True)
df.drop(['Name','Address','StreetName','NAICSDescr',"PostalCode", "BldgNo", "NAISCCat", "NAICSCode", "Phone", "Fax", "TollFree"], axis=1, inplace=True)

#Let's create a list for our categorical columns for the dataset, we need this later
#cat_cols=["PostalCode", "BldgNo", "UnitNo","NAISCCat","NAICSCode", "Phone", "Fax", "TollFree","WebAddress","isnew","EMail","Location"]
cat_cols=["UnitNo","WebAddress","isnew","EMail","Location"]

# Create a copy of the data frame in memory with a different name
df_onehot=df.copy()
#convert only categorical variables/features to dummy/one-hot features
df_onehot = pd.get_dummies(df, columns=cat_cols, prefix = cat_cols)
#print the dataset
df_onehot

```


	X	Y	Closed	UnitNo_No	UnitNo_Yes	WebAddress_No	WebAddress_Yes	isnew_No	isnew_Yes	EEmail_
46689	-79.665386	43.684736	No	0	1	0	1	1	0	
46690	-79.642760	43.593515	No	0	1	0	1	0	1	
46691	-79.667311	43.682752	No	0	1	0	1	1	0	
46692	-79.629235	43.698932	No	0	1	0	1	0	1	
46693	-79.629235	43.698932	No	0	1	1	0	0	1	
...
63202	-79.697599	43.517559	Yes	1	0	0	1	0	1	
63203	-79.697599	43.517559	No	1	0	0	1	0	1	
63204	-79.697599	43.517559	Yes	1	0	0	1	0	1	
63205	-79.697599	43.517559	No	0	1	1	0	0	1	

```
#X column has negative values. Those column values won't work with Naive Bayes. So run the following
# line of code for the data set to make negative values to 0. Note that it is not necessary for decision tree to remove
df_onehot["X"]=df_onehot["X"].apply(lambda x: 0 if x<0 else x)
```

```
#Repeat the train test set split
from sklearn.model_selection import train_test_split
```

```
# Uncomment following line for class name for the dataset
class_col_name="Closed"
```

```
one_hot_feature_names=df_onehot.columns[df_onehot.columns != class_col_name]
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(df_onehot.loc[:, one_hot_feature_names], df_onehot[class_col_name],
```

```
# Repeat Naive Bayes modeling
from sklearn.naive_bayes import MultinomialNB
```

```
#Create a MultiNomial NB Classifier
nb = MultinomialNB()
print ("Succesfully NB done..")
#Train the model using the training sets
nb.fit(X_train, y_train)
print ("Succesfully fit done..")
#Predict the response for test dataset
y_pred = nb.predict(X_test)
print ("Succesfully done..")
```

```
Succesfully NB done..
Succesfully fit done..
Succesfully done..
```

```
#print("Number of features used ",nb.n_features_)
print("Classes ",nb.classes_)
print("Number of records for classes ",nb.class_count_)
print("Log prior probability for classes ", nb.class_log_prior_)
print("Log conditional probability for each feature given a class\n",nb.feature_log_prob_)
```

```
Classes  ['No' 'Yes']
Number of records for classes  [11036. 2178.]
Log prior probability for classes  [-0.18011422 -1.80286985]
Log conditional probability for each feature given a class
[[-13.19270961 -0.10868217 -4.95232449 -4.30436674 -5.22959755
  -4.1850976 -3.99282369 -6.15217322 -4.833809 -4.37245324
  -7.63202798 -8.51988077 -8.01092606 -8.29486981 -8.94421437
 -13.19270961 -9.00305487 -8.48317941 -9.93461307 -9.03382652
 -8.94421437 -7.79908206 -9.55512345 -7.65537534 -7.14062044
 -10.05721539 -8.71537279 -6.70960226 -7.90950588 -9.03382652
 -9.01832234 -8.9732019 -8.23688255 -6.77761265 -8.34852252
 -8.6818501 -10.19697733 -8.02222561 -9.20372556 -9.06557522
```

```

-8.64941483 -7.7288778 -6.89376036 -9.3215086 -9.14965834
-9.38604712 -9.55512345 -9.97383378 -7.6281892 -5.26466401
-8.24394972 -9.16735792 -9.7269737 -9.14965834 -8.82326176
-9.18537642 -9.30088931 -9.97383378 -9.50383015 -8.34067934
-11.5832717 -8.11130524 -9.26088397 -11.80641525 -8.88864451
-5.84863676]
[-11.57034002 -0.10918715 -5.09029546 -4.23862505 -5.18514562
-4.2007393 -4.02865692 -5.88336467 -4.76240508 -4.41963857
-7.23960668 -8.86228982 -8.62590104 -8.73712668 -9.49089848
-11.57034002 -9.96090211 -8.93128269 -9.26775493 -8.93128269
-9.00539067 -7.74169863 -9.26775493 -8.01499196 -7.12768877
-10.47172773 -8.67996827 -6.85184115 -8.3514642 -9.49089848
-9.37311545 -9.37311545 -8.20304419 -6.82540789 -8.3514642
-9.00539067 -9.62442987 -8.0439795 -11.57034002 -9.17244475
-9.26775493 -7.72019242 -6.67999089 -9.00539067 -9.26775493
-10.18404566 -9.08543337 -10.87719284 -7.95942211 -5.25317534
-8.31224349 -9.49089848 -9.37311545 -9.00539067 -9.49089848
-8.7977513 -9.49089848 -10.18404566 -10.47172773 -7.95942211
-11.57034002 -8.20304419 -9.77858055 -11.57034002 -8.73712668
-5.48584061]]

```

```

from sklearn.metrics import confusion_matrix
cf=confusion_matrix(y_test, y_pred)
print ("Confusion Matrix")
print(cf)
tn, fp, fn, tp=cf.ravel()
print ("TP: ", tp, ", FP: ", fp, ", TN: ", tn, ", FN:", fn)

```

```

Confusion Matrix
[[2768    0]
 [ 536    0]]
TP:  0 , FP:  0 , TN:  2768 , FN: 536

```

```

from sklearn.metrics import classification_report
from sklearn import metrics

```

```
print(classification_report(y_test, y_pred))
```

```

              precision    recall  f1-score   support

     No         0.84         1.00         0.91         2768
     Yes         0.00         0.00         0.00          536

 accuracy         0.84         0.84         0.84         3304
 macro avg         0.42         0.50         0.46         3304
 weighted avg         0.70         0.84         0.76         3304

```

```

/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision
_warn_prf(average, modifier, msg_start, len(result))

```

```

from sklearn import tree
clf = tree.DecisionTreeClassifier(max_depth=5)
clf = clf.fit(X_train, y_train)
import graphviz
#Get unique class values to display on the tree
class_values=df_onehot[class_col_name].unique()
print ("class Names",class_values)

dot_data = tree.export_graphviz(clf, out_file=None,
                                feature_names=one_hot_feature_names,
                                class_names=class_values,
                                filled=True)

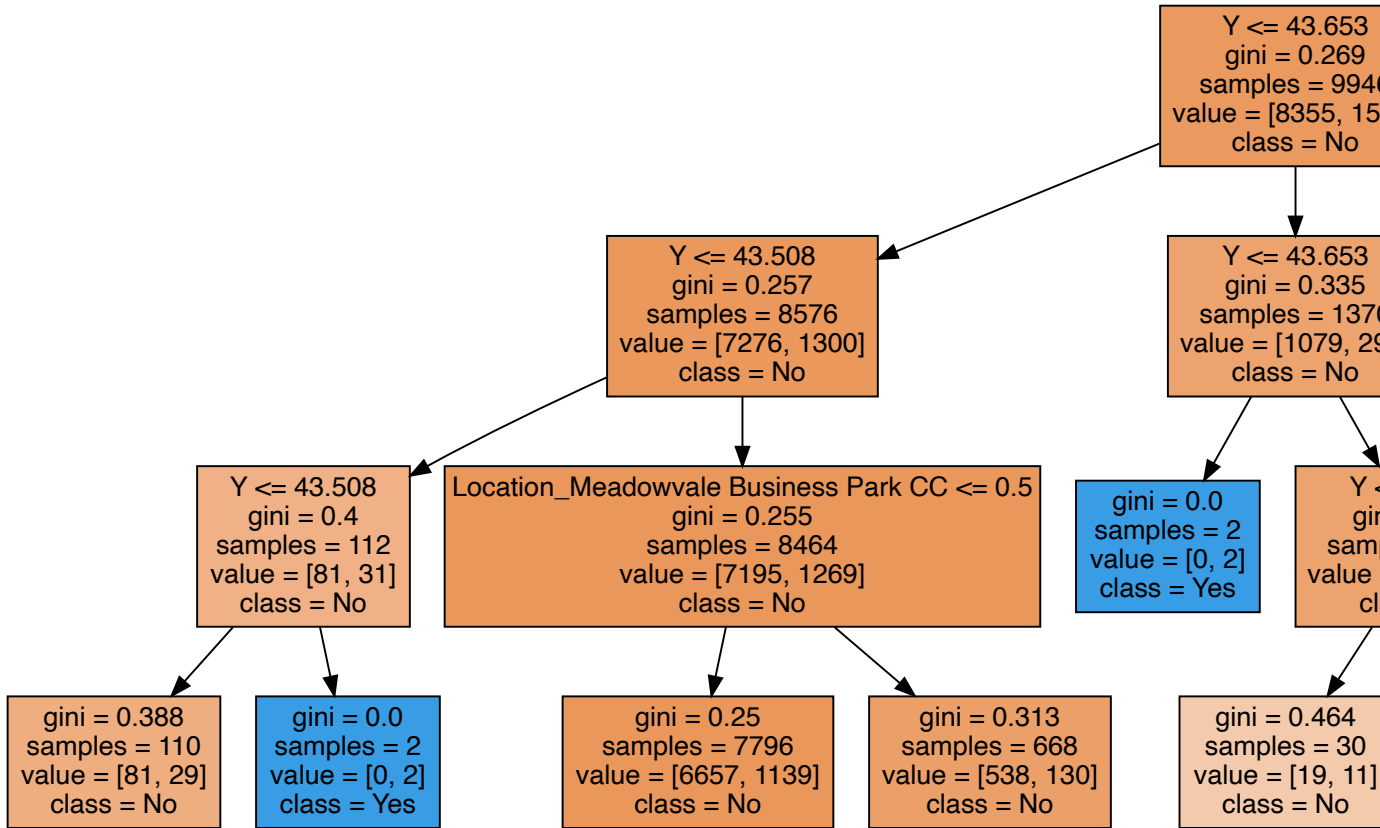
```

```

# Draw graph
graph = graphviz.Source(dot_data, format="png")
graph

```

```
class Names ['No' 'Yes']
```



```
# Perform prediction on the test set
y_pred = clf.predict(X_test)

# Get classification report
from sklearn.metrics import classification_report
from sklearn import metrics

print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
No	0.84	1.00	0.91	2768
Yes	0.29	0.00	0.01	536
accuracy			0.84	3304
macro avg	0.56	0.50	0.46	3304
weighted avg	0.75	0.84	0.76	3304

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