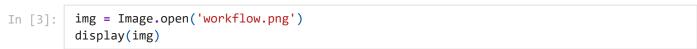
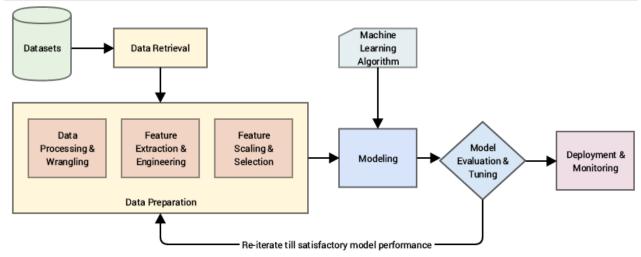
```
In [1]: from IPython.core.interactiveshell import InteractiveShell #Allowing for multiline ou
InteractiveShell.ast_node_interactivity = "all"
```

Importing Modules and Creating Workflow

```
import os
In [2]:
         import time
         from PIL import Image
         import numpy as np
         import pandas as pd
         import pandas flavor as pf
         import matplotlib.pyplot as plt
         import seaborn as sns
         from statistics import mean
         from statistics import stdev
         import xgboost as xgb
         from xgboost import XGBClassifier
         from sklearn.impute import SimpleImputer
         from sklearn.preprocessing import StandardScaler
         from sklearn.model selection import train test split
         from sklearn.compose import make column transformer
         from sklearn.pipeline import make_pipeline
         from sklearn.metrics import f1_score, accuracy_score, confusion_matrix
         from sklearn.metrics import roc curve
         from sklearn.metrics import roc auc score
         from sklearn.metrics import accuracy score, confusion matrix, classification report
         import scikitplot as skplt
```





Data Exploration

cwd = os.getcwd() directory = os.fsencode(cwd) files = [] for file in os.listdir(directory): filename = os.fsdecode(file) if filename.endswith(".csv"): print(filename.split('.')[0])

```
In [4]: #Reading in different data files and analyzing first few rows of each data set
    training_df = pd.read_csv('FoodDelivery.csv') #Airport_codes -> ac
    pd.set_option('display.max_columns', None)
    pd.set_option('display.max_rows', None)
```

localhost:8889/lab 1/10

```
training df.shape # We will split training data into training and validation
In [5]:
Out[5]: (388, 50)
In [6]:
          training df.head()
            Age Gender Marital_Status Occupation Monthly_Income Educational_Qualifications Family_size la
Out[6]:
                                 Single
                                                        No Income
                                                                              Post Graduate
                                                                                                    4 1
         0
           NaN
                 Female
                                           Student
            24.0
                 Female
                                 Single
                                           Student
                                                     Below Rs.10000
                                                                                  Graduate
                                                                                                    3 1
         1
         2
            22.0
                                 Single
                                           Student
                                                     Below Rs.10000
                                                                              Post Graduate
                                                                                                    3 1
                    Male
            22.0
                 Female
                                 Single
                                           Student
                                                        No Income
                                                                                  Graduate
                                                                                                    6 1
            22.0
                                 Single
                                                     Below Rs.10000
                                                                              Post Graduate
                    Male
                                           Student
                                                                                                    4 1
         training_df.info()
In [7]:
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 388 entries, 0 to 387
         Data columns (total 50 columns):
          #
              Column
                                                            Non-Null Count
                                                                             Dtype
          0
                                                            379 non-null
                                                                             float64
              Age
          1
              Gender
                                                            388 non-null
                                                                             object
          2
              Marital Status
                                                            388 non-null
                                                                             object
          3
              Occupation
                                                            388 non-null
                                                                             object
          4
              Monthly Income
                                                            388 non-null
                                                                             object
          5
              Educational Qualifications
                                                            388 non-null
                                                                             object
          6
              Family size
                                                            388 non-null
                                                                             int64
          7
              latitude
                                                            388 non-null
                                                                             float64
          8
              longitude
                                                            388 non-null
                                                                             float64
          9
              Meal(P1)
                                                            388 non-null
                                                                             object
          10
             Meal(P2)
                                                            388 non-null
                                                                             object
              Perference(P1)
          11
                                                            388 non-null
                                                                             object
              Perference(P2)
                                                                             object
          12
                                                            388 non-null
                                                            388 non-null
          13
              Ease and convenient
                                                                             object
          14
              Time saving
                                                            388 non-null
                                                                             object
          15
              More_restaurant_choices
                                                            388 non-null
                                                                             object
              Easy Payment option
                                                            388 non-null
                                                                             object
          16
              More Offers and Discount
                                                                             object
          17
                                                            388 non-null
          18
              Good Food quality
                                                            388 non-null
                                                                             object
          19
              Good_Tracking_system
                                                            388 non-null
                                                                             object
          20
              Self_Cooking
                                                            388 non-null
                                                                             object
          21
              Health Concern
                                                            388 non-null
                                                                             object
          22
              Late Delivery
                                                            388 non-null
                                                                             object
              Poor_Hygiene
                                                            388 non-null
                                                                             object
          23
          24
              Bad past experience
                                                            388 non-null
                                                                             object
```

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```
25 Unavailability
                                                         388 non-null
                                                                         object
         26 Unaffordable
                                                         388 non-null
                                                                         object
         27
             Long delivery time
                                                                         object
                                                         388 non-null
             Delay of delivery person getting assigned
                                                         388 non-null
                                                                         object
         29
             Delay_of_delivery_person_picking_up_food
                                                         388 non-null
                                                                         object
         30 Wrong_order_delivered
                                                         388 non-null
                                                                         object
                                                                         object
         31 Missing item
                                                         388 non-null
         32 Order placed by mistake
                                                         388 non-null
                                                                         object
         33 Influence_of_time
                                                         388 non-null
                                                                         object
         34 Order_Time
                                                         388 non-null
                                                                         object
         35 Maximum wait time
                                                         388 non-null
                                                                         object
         36 Residence_in_busy_location
                                                         388 non-null
                                                                         object
                                                                         object
         37 Good_Road_Condition
                                                         388 non-null
         38 Low_quantity_low_time
                                                         388 non-null
                                                                         object
         39 Delivery person ability
                                                         388 non-null
                                                                         object
                                                         388 non-null
         40 Influence_of_rating
                                                                         object
                                                         388 non-null
         41 Less_Delivery_time
                                                                         object
         42 High_Quality_of_package
                                                         388 non-null
                                                                         object
         43
             Number of calls
                                                         388 non-null
                                                                         object
         44
             Politeness
                                                         388 non-null
                                                                         object
         45 Freshness
                                                         388 non-null
                                                                         object
         46 Temperature
                                                         388 non-null
                                                                         object
         47 Good Taste
                                                         388 non-null
                                                                         object
         48 Good Quantity
                                                         388 non-null
                                                                         object
         49
             orderAgain
                                                         388 non-null
                                                                         object
        dtypes: float64(3), int64(1), object(46)
        memory usage: 151.7+ KB
In [8]:
         def missing values table(df):
             mis_val = df.isnull().sum()
             mis_val_percent = 100 * df.isnull().sum() / len(df)
             mis val table = pd.concat([mis val, mis val percent], axis=1)
             mis_val_table_ren_columns = mis_val_table.rename(
             columns = {0 : 'Missing Values', 1 : '% of Total Values'})
             mis val table ren columns = mis val table ren columns[
                 mis val table ren columns.iloc[:,1] != 0].sort values(
             '% of Total Values', ascending=False).round(1)
             print ("Your selected dataframe has " + str(df.shape[1]) + " columns.\n"
                 "There are " + str(mis_val_table_ren_columns.shape[0]) +
                      " columns that have missing values.")
             return mis val table ren columns
         missing_values_table(training_df)
        Your selected dataframe has 50 columns.
        There are 1 columns that have missing values.
Out[8]:
             Missing Values % of Total Values
```

Age 9 2.3

Data Preparation

```
training_df['orderAgain'].value_counts()
 In [9]:
         Yes
                 301
 Out[9]:
         No
                 87
         Name: orderAgain, dtype: int64
In [10]:
          def impute mode(X):
              return training_df[X].fillna(value=training_df[X].mode()[0], inplace=True)
```

localhost:8889/lab 3/10

```
impute_mode('Age')

In [11]: training_df['Age'].isnull().any()

Out[11]: False

In [41]: import pandas_profiling
    profile = training_df.profile_report(title="Pandas Profiling Report")
    profile
```

localhost:8889/lab 4/10

Overview

Dataset statistics

Number of variables	50
Number of observations	388
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	64
Duplicate rows (%)	16.5%
Total size in memory	151.7 KiB
Average record size in memory	400.3 B

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Variable types

Numeric	4
Categorical	45
Boolean	1

Alerts

```
Dataset has 64 (16.5%) duplicate rows

Meal(P1) is highly correlated with Meal(P2)

High correlation
```

Out[41]:

```
In [12]: train_df, valid_df = train_test_split(training_df,test_size=0.3, stratify= training_df[
In [13]: train_df.shape, valid_df.shape
Out[13]: ((271, 50), (117, 50))
```

localhost:8889/lab 5/10

```
train_df.reset_index(drop=True, inplace=True)
In [14]:
                valid df.reset index(drop=True, inplace=True)
               train df.columns
In [15]:
Out[15]: Index(['Age', 'Gender', 'Marital_Status', 'Occupation', 'Monthly_Income',
                          'Educational_Qualifications', 'Family_size', 'latitude', 'longitude',
                         'Meal(P1)', 'Meal(P2)', 'Perference(P1)', 'Perference(P2)', 'Ease_and_convenient', 'Time_saving', 'More_restaurant_choices', 'Easy_Payment_option', 'More_Offers_and_Discount', 'Good_Food_quality', 'Good_Tracking_system', 'Self_Cooking', 'Health_Concern',
                         'Late_Delivery', 'Poor_Hygiene', 'Bad_past_experience', 'Unavailability', 'Unaffordable', 'Long_delivery_time',
                         'Delay_of_delivery_person_getting_assigned',
                         'Delay_of_delivery_person_picking_up_food', 'Wrong_order_delivered', 'Missing_item', 'Order_placed_by_mistake', 'Influence_of_time',
                         'Order_Time', 'Maximum_wait_time', 'Residence_in_busy_location',
                         'Good_Road_Condition', 'Low_quantity_low_time',
                         'Delivery_person_ability', 'Influence_of_rating', 'Less_Delivery_time', 'High_Quality_of_package', 'Number_of_calls', 'Politeness', 'Freshness', 'Temperature', 'Good_Taste', 'Good_Quantity', 'orderAgain'],
                        dtype='object')
             Spliting into X and y
               X train = train df.drop(columns = ['orderAgain'],axis = 1)
In [16]:
```

```
y_train = train_df.orderAgain
           y train.replace({'Yes':1,'No':0},inplace = True)
          X valid = train df.drop(columns = ['orderAgain'],axis = 1)
In [17]:
           y_valid= train_df.orderAgain
           y valid.replace({'Yes':1,'No':0},inplace = True)
          X_train.shape , y_train.shape , X_valid.shape , y_valid.shape
In [18]:
Out[18]: ((271, 49), (271,), (271, 49), (271,))
          y train.head()
In [19]:
Out[19]: 0
               1
               1
               1
          3
               1
          Name: orderAgain, dtype: int64
          from sklearn.preprocessing import OrdinalEncoder
In [21]:
           std = StandardScaler()
           ord enc = OrdinalEncoder()
           preprocess = make_column_transformer((ord_enc, ['Gender', 'Marital_Status', 'Occupation')
                   'Educational_Qualifications', 'Family_size','Meal(P1)', 'Meal(P2)', 'Perference(
                   'Ease_and_convenient', 'Time_saving', 'More_restaurant_choices',
                   'Easy_Payment_option', 'More_Offers_and_Discount', 'Good_Food_quality',
                   'Good_Tracking_system', 'Self_Cooking', 'Health_Concern',
                   'Late_Delivery', 'Poor_Hygiene', 'Bad_past_experience', 'Unavailability', 'Unaffordable', 'Long_delivery_time',
                   'Delay of delivery person getting assigned',
```

6/10 localhost:8889/lab

```
'Delay_of_delivery_person_picking_up_food', 'Wrong_order_delivered',
    'Missing_item', 'Order_placed_by_mistake', 'Influence_of_time',
    'Order_Time', 'Maximum_wait_time', 'Residence_in_busy_location',
    'Good_Road_Condition', 'Low_quantity_low_time',
    'Delivery_person_ability', 'Influence_of_rating', 'Less_Delivery_time',
    'High_Quality_of_package', 'Number_of_calls', 'Politeness', 'Freshness',
    'Temperature', 'Good_Taste', 'Good_Quantity']),
(std, ['Age','latitude','longitude']), remainder = 'passthrough')
```

In []:

Training Model

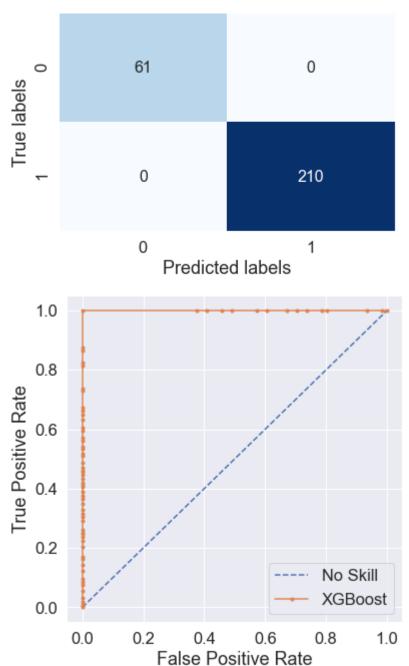
XG BOOST Classifier

```
In [38]:
          xgb clf.fit(X train, y train)
          # Predicting on the test data
          pred_test = xgb_clf.predict(X_valid)
          #Calculating and printing the f1 score
          f1 test = f1 score(y valid, pred test)
          print('The f1 score for the testing data:', f1_test)
          #Ploting the confusion matrix
          conf matrix(y valid, pred test)
          lr_probs = xgb_clf.predict_proba(X_valid)
          lr_probs = lr_probs[:, 1]
          ns_probs = [0 for _ in range(len(y_valid))]
          ns_auc = roc_auc_score(y_valid, ns_probs)
          lr auc = roc auc score(y valid, lr probs)
          print('No Skill: ROC AUC=%.3f' % (ns auc))
          print('Logistic: ROC AUC=%.3f' % (lr_auc))
          ns_fpr, ns_tpr, _ = roc_curve(y_valid, ns_probs)
          lr_fpr, lr_tpr, _ = roc_curve(y_valid, lr_probs)
          # plot the roc curve for the model
          plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
          plt.plot(lr_fpr, lr_tpr, marker='.', label='XGBoost')
          # axis labels
          plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          # show the Legend
          plt.legend()
          # show the plot
          plt.show()
```

localhost:8889/lab 7/10

[14:33:37] WARNING: C:/Users/Administrator/workspace/xgboost-win64 release 1.4.0/src/lea rner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with the obj ective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval metr ic if you'd like to restore the old behavior. C:\Users\AKASH\anaconda3\lib\site-packages\xgboost\sklearn.py:1146: UserWarning: The use of label encoder in XGBClassifier is deprecated and will be removed in a future release. To remove this warning, do the following: 1) Pass option use label encoder=False when co nstructing XGBClassifier object; and 2) Encode your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num class - 1]. warnings.warn(label encoder deprecation msg, UserWarning) Out[38]: Pipeline(steps=[('columntransformer', ColumnTransformer(remainder='passthrough', transformers=[('ordinalencoder', OrdinalEncoder(), ['Gender', 'Marital_Status', 'Occupation', 'Monthly_Income', 'Educational_Qualifications', 'Family size', 'Meal(P1)', 'Meal(P2)', 'Perference(P1)', 'Perference(P2)', 'Ease and convenient', 'Time_saving', 'More restaurant choices', 'Eas... colsample_bytree=1, gamma=0, gpu_id=-1, importance type='gain', interaction_constraints='', learning_rate=0.300000012, max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan, monotone_constraints='()', n_estimators=100, n_jobs=12, num_parallel_tree=1, random_state=0, reg alpha=0, reg lambda=1, scale pos weight=1, subsample=1, tree_method='exact', validate parameters=1, verbosity=None))]) The f1 score for the testing data: 1.0 No Skill: ROC AUC=0.500 Logistic: ROC AUC=1.000 Out[38]: [<matplotlib.lines.Line2D at 0x1df799cb400>] Out[38]: [<matplotlib.lines.Line2D at 0x1df799cb880>] Out[38]: Text(0.5, 0, 'False Positive Rate') Out[38]: Text(0, 0.5, 'True Positive Rate') Out[38]: <matplotlib.legend.Legend at 0x1df799cb7c0>

localhost:8889/lab 8/10



Conclusion

Overall, the dataset had very little misisng value. We imputed the missing value with the mode.

The dataset was split on the strata of the target to ensure we had enough instances.

Ordinal Encoding was done to the variables to ensure it captures the weight in the repsonses. Strongly Agree being strongest and Strongly Disagree being weakest

localhost:8889/lab

Overall, we ran a simple classifier and a boosted classifier. Given the amount of information in the survey dataset the boosted model performs extremely well with good predicitve power.

In []:	:	

localhost:8889/lab 10/10