



MACHINE LEARNING PREDICTING AIRLINE PASSENGER SATISFACTION

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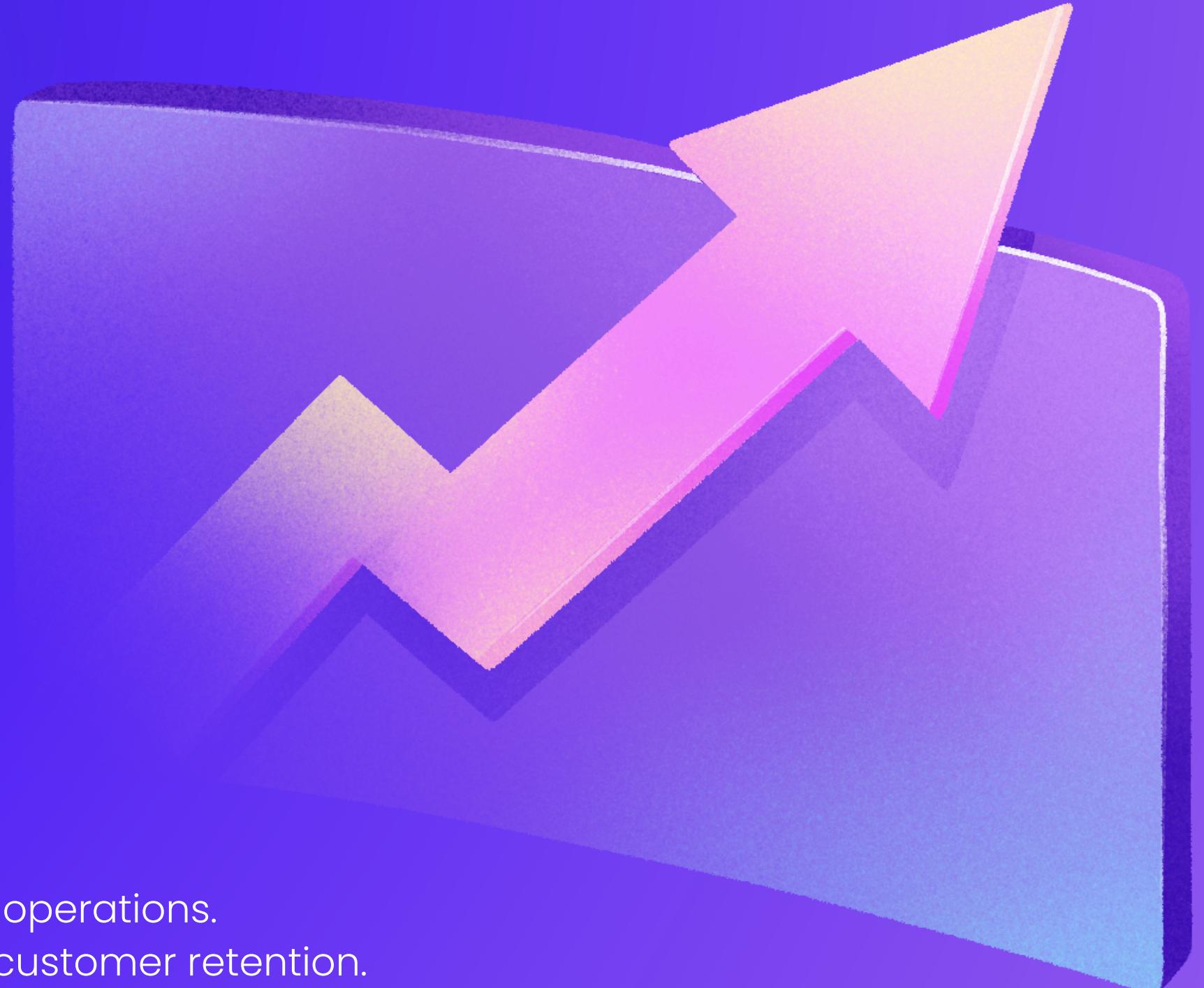
TABLE OF CONTENTS

- Introduction
- Dataset Description
- Data Preprocessing
- Machine Learning Approach
- Results
- Deployment
- References
- Conclusion



INTRODUCTION

In today's highly competitive aviation industry, customer satisfaction is a critical factor in maintaining loyalty and driving business growth. Airlines must identify and address key drivers of passenger satisfaction to enhance the overall travel experience. The challenge lies in leveraging data analytics to accurately predict passenger satisfaction and uncover actionable insights.



Significance of the Project:

- Helps airlines prioritize improvements in service and operations.
- Supports data-driven decision-making to enhance customer retention.
- Contributes to long-term competitiveness in the aviation industry.

DATASET DESCRIPTION



Source

Dataset: [Airline Passenger Satisfaction](#)

Key Features/Variables

Demographics: Gender, Age, Travel Class, Customer Type

Flight Information: Flight Distance, Type of Travel, In-flight Service

Service Ratings: Seat Comfort, Food and Beverage, Cleanliness, Online Check-in, Gate Location, In-flight Entertainment, ...

Delays: Arrival Delay in Minutes, Departure Delay in Minutes

Dataset Size

Total Records: 129,880 passengers

Features: 25 columns (24 predictors + 1 target variable)

Target Variable

Satisfaction: Indicates whether the passenger was satisfied (Satisfied) or not (Neutral or Dissatisfied).

DATA CLEANING AND PREPROCESSING

- Checking For Null Values

Checking For Null Values

```
df.isnull().sum()  
4] ✓ 2.3s  
.. Unnamed: 0          0  
id                  0  
Gender              0  
Customer Type       0  
Age                 0  
Type of Travel       0  
Class                0  
Flight Distance      0  
Inflight wifi service 0  
Departure/Arrival time convenient 0  
Ease of Online booking 0  
Gate location        0  
Food and drink       0  
Online boarding       0  
Seat comfort          0  
Inflight entertainment 0  
On-board service      0  
Leg room service      0
```

DATA CLEANING AND PREPROCESSING

- Feature Engineering

Getting Rid of the object-type columns with Label Encoder

[9] ✓ 36.2s Python

```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
```

Extracting of features of type object

[10] ✓ 0.0s Python

```
encoded_need=[]
for i in data_cleaned.columns:
    if data_cleaned[i].dtype=='object':
        encoded_need.append(i)
```

[11] ✓ 0.2s Python

```
for i in encoded_need:
    data_cleaned[i]=label_encoder.fit_transform(data_cleaned[i])
```

[12] ✓ 0.1s Python

```
data_cleaned.head()
```

DATA CLEANING AND PREPROCESSING

- Data Splitting

Splitting The Data

```
[20] ✓ 2.1s
from sklearn.model_selection import train_test_split

[21] ✓ 0.0s
target=data_cleaned.iloc[:, -1]
X_train,X_test,y_train,y_test=train_test_split(features,target,test_size=0.2,random_state=42)
print(f"Shape of training set is : {X_train.shape} and test set is :{X_test.shape}" )
...
... Shape of training set is : (83123, 22) and test set is :(20781, 22)
```

MACHINE LEARNING APPROACH

Machine Learning Models Used



Logistic Regression
Establishes a baseline;
explains linear
relationships clearly.



**K-Nearest Neighbors
(KNN)**
Captures patterns in similar
passenger groups; models
non-linear trends.



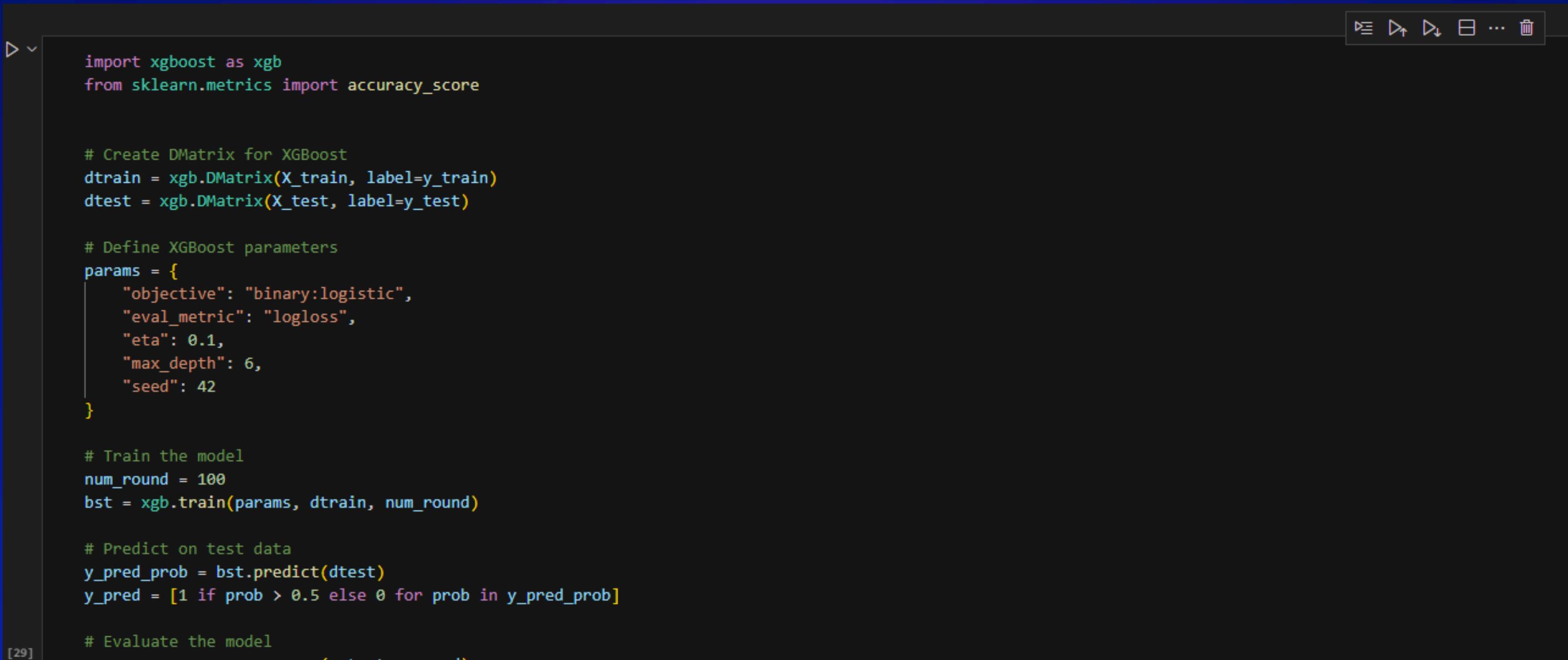
Decision Tree
Simple and interpretable;
identifies key factors
driving satisfaction.



XGBoost
High accuracy; handles
complex patterns and
prevents overfitting.

MACHINE LEARNING APPROACH

Implementing XGBOOST



The image shows a screenshot of a Jupyter Notebook cell. The cell contains Python code for implementing an XGBoost model. The code includes importing libraries, creating DMatrix for training and testing data, defining XGBoost parameters, training the model, predicting on test data, and evaluating the model. The code is syntax-highlighted in green, blue, and orange. The cell has a header with a dropdown arrow and a toolbar with icons for file operations. The bottom left corner of the cell shows the number [29].

```
import xgboost as xgb
from sklearn.metrics import accuracy_score

# Create DMatrix for XGBoost
dtrain = xgb.DMatrix(X_train, label=y_train)
dtest = xgb.DMatrix(X_test, label=y_test)

# Define XGBoost parameters
params = {
    "objective": "binary:logistic",
    "eval_metric": "logloss",
    "eta": 0.1,
    "max_depth": 6,
    "seed": 42
}

# Train the model
num_round = 100
bst = xgb.train(params, dtrain, num_round)

# Predict on test data
y_pred_prob = bst.predict(dtest)
y_pred = [1 if prob > 0.5 else 0 for prob in y_pred_prob]

# Evaluate the model
```

RESULTS(ACCURACY)

01

Logistic Regression Algorithm

```
from sklearn.metrics import ConfusionMatrixDisplay,confusion_matrix
from sklearn.metrics import accuracy_score
y_pred_lr=model_lr.predict(X_test)
accuracy=accuracy_score(y_pred_lr,y_test)
print(f"Accuracy of Logistic Regression is : {round(accuracy*100,2)} % .")
```

23] ✓ 0.0s

.. Accuracy of Logistic Regression is : 86.72 % .

RESULTS(ACCURACY)

02

K-Nearest Neighbors (KNN)

```
from sklearn.neighbors import KNeighborsClassifier  
knn=KNeighborsClassifier(n_neighbors=5)  
#fit the model with trained data  
knn.fit(X_train,y_train)  
  
#Predict the accuracy of the model  
y_pred_knn=knn.predict(X_test)  
  
accuracy=accuracy_score(y_pred_knn,y_test)  
print(f"Accuracy of KNN is : {round(accuracy*100,2)} % .")
```

✓ 4.8s

Accuracy of KNN is : 74.76 % .

RESULTS(ACCURACY)

03

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier

DecisionTree=DecisionTreeClassifier(criterion='gini', splitter='best',max_features=6,random_state=1234)
#fit the model with trained data
DecisionTree.fit(X_train,y_train)

#Predict the accuracy of the model
y_pred_dt=DecisionTree.predict(X_test)

accuracy=accuracy_score(y_pred_dt,y_test)
print(f"Accuracy of Decision Tree is : {round(accuracy*100,2)} % .")

[27] ✓ 0.6s
...
... Accuracy of Decision Tree is : 93.75 % .
```

04

XGBoost

RESULTS(ACCURACY)

```
dtrain = xgb.DMatrix(X_train, label=y_train)
dtest = xgb.DMatrix(X_test, label=y_test)

# Define XGBoost parameters
params = {
    "objective": "binary:logistic",
    "eval_metric": "logloss",
    "eta": 0.1,
    "max_depth": 6,
    "seed": 42
}

# Train the model
num_round = 100
bst = xgb.train(params, dtrain, num_round)

# Predict on test data
y_pred_prob = bst.predict(dtest)
y_pred = [1 if prob > 0.5 else 0 for prob in y_pred_prob]

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
```

✓ 1.3s

· Accuracy: 0.96



A close-up photograph of a human hand reaching out towards a robotic hand. The robotic hand is made of dark, metallic components with glowing red and blue lights at its joints. The background is dark, creating a dramatic contrast with the illuminated hands. The overall mood is futuristic and technological.

DEPLOYMENT

REFERENCES



ML-COSTUMER-
SATISFACTIONP-
RIVATE

kaggle

AIRLINE
PASSENGER
SATISFACTION
DATASET



WE USED
FASTAPI TO
DEPLOY OUR
MODEL



CONCLUSION

XGBoost outperformed other models with the highest accuracy.
Decision Tree provided interpretable insights into key factors influencing satisfaction.
Logistic Regression and KNN served as effective benchmarks for comparison.



THANK YOU!

