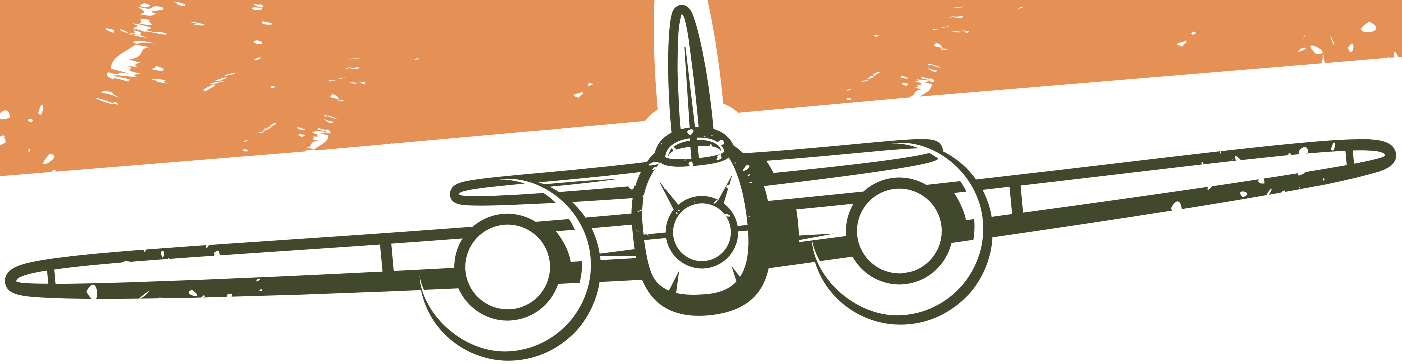
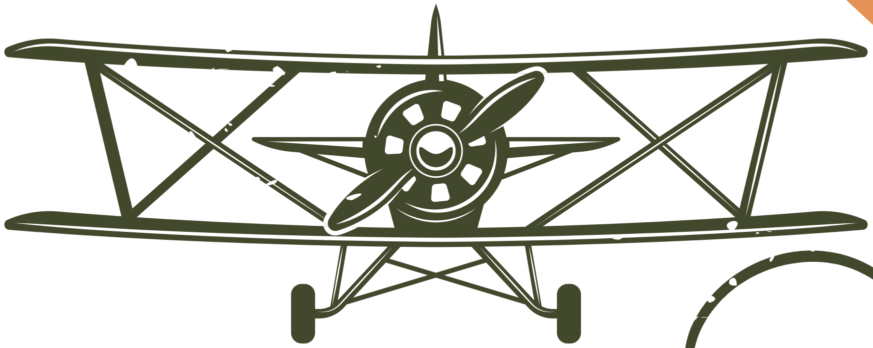


Airline Passenger Satisfaction

(Hokages)

Table of contents



01 Introduction

Introduction, problem statement, objective

Introduction

Customer satisfaction plays a major role in affecting the business of a company therefore analyzing and improving the factors that are closely related to customer satisfaction is important for the growth and reputation of a company.

Problem Statement

One of the problems of many airline industries is how to measure customer satisfaction concerning the experience of using online services.

The objective or goal of this project is to guide an airline company to determine the important factors that influence customer or passenger satisfaction.

02 Dataset

Description, preparation, preprocessing, Exploration

Dataset Description

This dataset contains an airline passenger satisfaction survey:

- Which factors are highly correlated to a satisfied (or dissatisfied) passenger?
- Can you predict passenger satisfaction?

About Dataset

Columns Description:

- Gender: Gender of the passengers (Female, Male)
- Customer Type: The customer type (Loyal customer, disloyal customer)
- Age: The actual age of the passengers
- Type of Travel: Purpose of the flight of the passengers (Personal Travel, Business Travel)
- Class: Travel class in the plane of the passengers (Business, Eco, Eco Plus)
- Flight distance: The flight distance of this journey

About Dataset

Columns Description:

- Inflight wifi service: Satisfaction level of the inflight wifi service (0:Not Applicable;1-5)
- Departure/Arrival time convenient: Satisfaction level of Departure/Arrival time convenient
- Ease of Online booking: Satisfaction level of online booking
- Gate location: Satisfaction level of Gate location
- Food and drink: Satisfaction level of Food and drink
- Online boarding: Satisfaction level of online boarding

About Dataset

Columns Description:

- Seat comfort: Satisfaction level of Seat comfort
- Inflight entertainment: Satisfaction level of inflight entertainment
- On-board service: Satisfaction level of On-board service
- Leg room service: Satisfaction level of Leg room service
- Baggage handling: Satisfaction level of baggage handling
- Check-in service: Satisfaction level of Check-in service

About Dataset

Columns Description:

- Inflight service: Satisfaction level of inflight service
- Cleanliness: Satisfaction level of Cleanliness
- Departure Delay in Minutes: Minutes delayed when departure
- Arrival Delay in Minutes: Minutes delayed when Arrival
- Satisfaction: Airline satisfaction level(Satisfaction, neutral or dissatisfaction)

Data Preparation

Connect to the Spark server

```
[3]  spark = pyspark.sql.SparkSession.builder.getOrCreate()
```

Obtain the Data

```
[4]  fullpath = 'Airline_Passenger_Satisfaction.csv'

     data = spark.read.csv(fullpath)

     data
```

```
DataFrame[_c0: string, _c1: string, _c2: string, _c3: string, _c4: string, _c5: string, _c6: string, _c7: string, _c8: string, _c9: string, _c10: string, _c11: string, _c12: string, _c13: string, _c14: string, _c15: string, _c16: string, _c17: string, _c18: string, _c19: string, _c20: string, _c21: string, _c22: string, _c23: string, _c24: string]
```

Data Preparation

```
data = spark.read.csv(fullpath,
                      sep=',',
                      inferSchema=True,
                      header=True,
                      multiLine=True)

data.printSchema()
```

```
data.printSchema()
```

```
root
 |-- Unnamed: 0: integer (nullable = true)
 |-- id: integer (nullable = true)
 |-- Gender: string (nullable = true)
 |-- CustomerType: string (nullable = true)
 |-- Age: integer (nullable = true)
 |-- TypeofTravel: string (nullable = true)
 |-- Class: string (nullable = true)
 |-- FlightDistance: integer (nullable = true)
 |-- Inflightwifiservice: integer (nullable = true)
 |-- Departure/Arrivaltimeconvenient: integer (nullable = true)
 |-- EaseofOnlinebooking: integer (nullable = true)
 |-- Gatelocation: integer (nullable = true)
 |-- Foodanddrink: integer (nullable = true)
 |-- Onlineboarding: integer (nullable = true)
 |-- Seatcomfort: integer (nullable = true)
 |-- Inflightentertainment: integer (nullable = true)
 |-- On-boardservice: integer (nullable = true)
 |-- Legroomservice: integer (nullable = true)
 |-- Baggagehandling: integer (nullable = true)
 |-- Checkinservice: integer (nullable = true)
 |-- Inflightservice: integer (nullable = true)
 |-- Cleanliness: integer (nullable = true)
 |-- DepartureDelayinMinutes: integer (nullable = true)
 |-- ArrivalDelayinMinutes: double (nullable = true)
 |-- satisfaction: integer (nullable = true)
```

Data Preprocessing

Data Cleaning

```
# these columns are useless to us, drop them
drop_cols = ['DepartureDelayinMinutes', 'ArrivalDelayinMinutes', '_c0', 'id']

data = data.drop(*drop_cols)
```

```
data = data.replace('other', None, subset=['Gender'])
```

```
data = data.replace('other', None, subset=['Class'])
```

Data Exploration

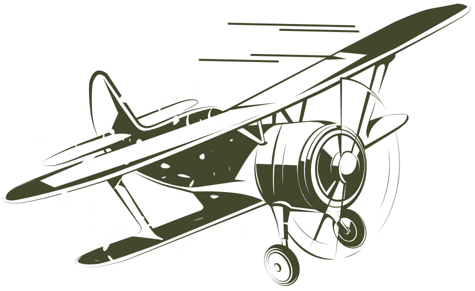
```
data.registerTempTable('data')

state_counts = spark.sql(r"""SELECT Gender, COUNT(Gender) AS total
                          FROM data
                          GROUP BY Gender
                          ORDER BY total desc """)
state_counts.show()
```

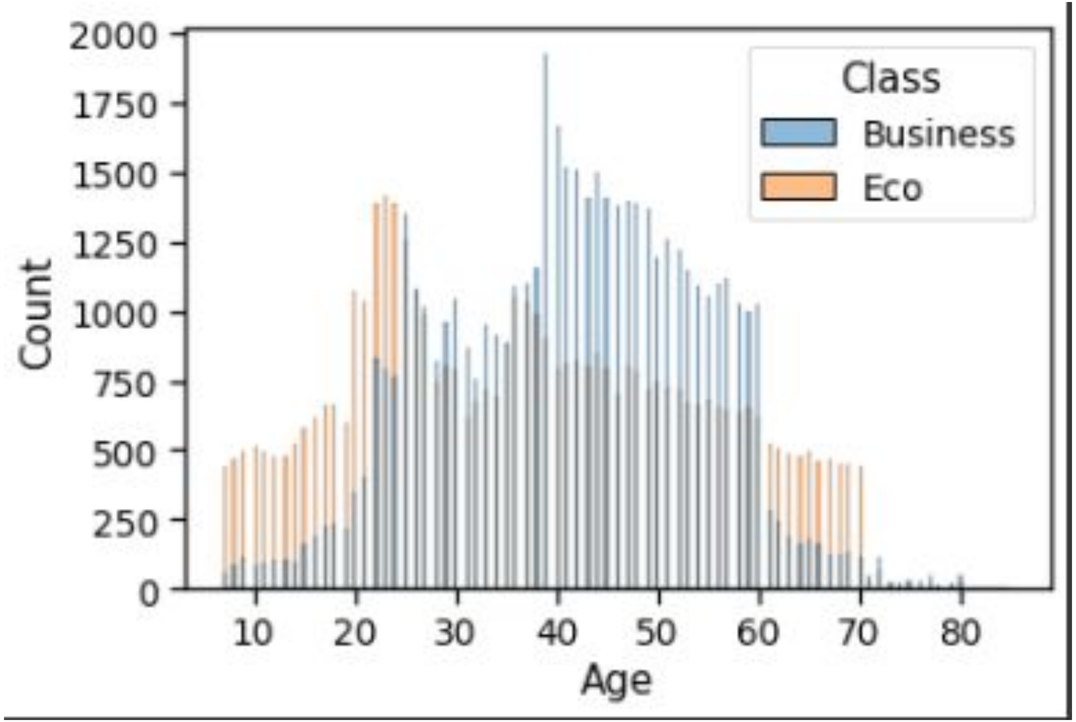
```
+------+-----+
|Gender|total|
+------+-----+
|Female|52727|
|  Male|51177|
+------+-----+
```

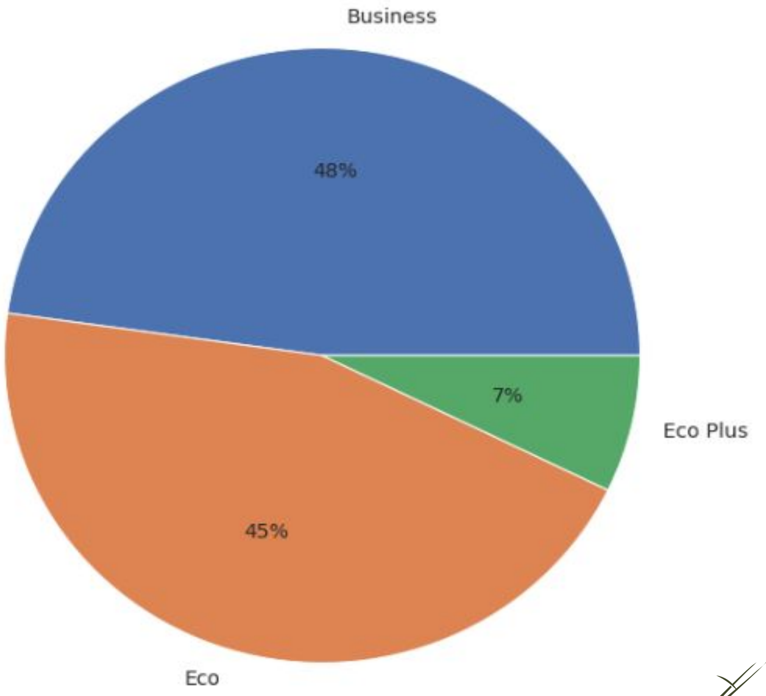
```
mfr_counts = spark.sql(r"""SELECT Class, COUNT(Class) as total
                        FROM data
                        GROUP BY Class
                        ORDER BY total desc""")

mfr_counts.show()
```

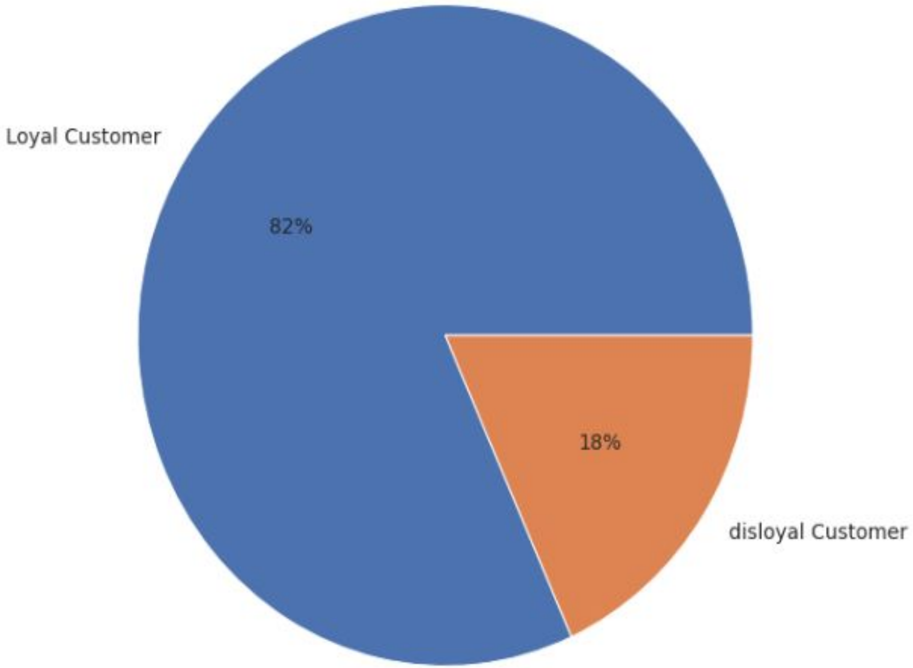
```
+--------+-----+
|   Class|total|
+--------+-----+
|Business|49665|
|     Eco|46745|
|Eco Plus| 7494|
+--------+-----+
```

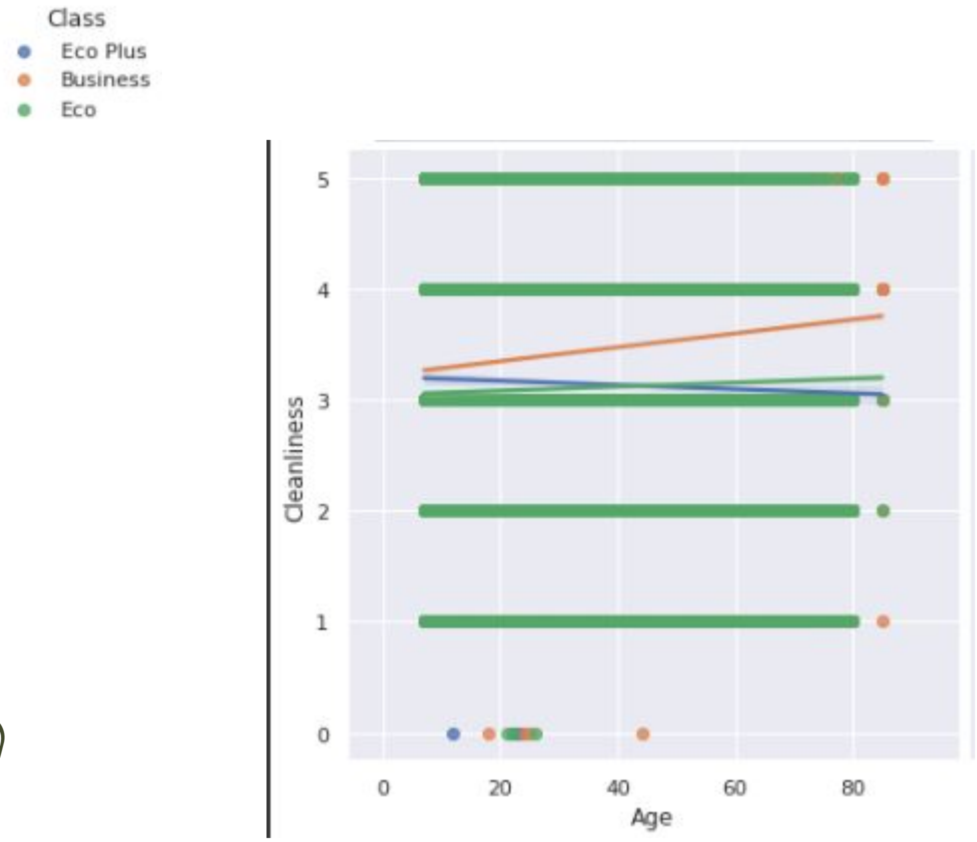
Exploratory Data Analysis (EDA)




Class
Business
Eco
Count
2000
1750
1500
1250
1000
750
500
250
0
10
20
30
40
50
60
70
80
Age


Business
48%
7%
Eco Plus
45%
Eco


Loyal Customer
82%
18%
disloyal Customer


Class
Eco Plus
Business
Eco
Cleanliness
Age
0
1
2
3
4
5
0
20
40
60
80

PySpark ML

03

Processing, Building a Model, Evaluation

Data Preparation

Category columns

```
cat_cols = ['Gender', 'CustomerType', 'TypeofTravel', 'Class','satisfaction']

n = 4

for col in cat_cols:
    most_freq = data.groupBy(col).count().orderBy('count', ascending=False).take(n - 1)
    most_freq = spark.createDataFrame(most_freq).toPandas()
    most_freq = most_freq[col].tolist()

    data = data.withColumn(col, F.when(F.col(col).isin(most_freq), F.col(col)))
```

On Categorical Columns, we will encode all the categorical columns using StringIndexer and drop the original columns.

```
[ ]  for col in cat_cols:
         indexer = StringIndexer(inputCol=col, outputCol=col+'_idx')
         data = indexer.fit(data).transform(data)

     data = data.drop(*cat_cols)
```

```python
cols = data.columns
cols.remove('satisfaction_idx') #remove -> we need this to be our label


assembler = VectorAssembler(inputCols=cols, outputCol='features')

data = assembler.transform(data)
```

```python
# We have created a new dataframe only consisting of the features column and the label column (actually price column but renamed)
df_data = data.select(F.col('features'), F.col('satisfaction_idx').alias('label'))

df_train, df_test = df_data.randomSplit([0.8, 0.2])
```

Building a Model

Building a Model

Model Building

```
evaluator = RegressionEvaluator() # Can specify what metrics we want to use. Default metric is Root Mean Squared Error (RMSE)
grid = ParamGridBuilder().build()
```

Initialize Regressors and Train

```
[ ] #Random Forest Regressor
    classifier_rf = RandomForestRegressor(featuresCol='features', labelCol='label')
    cv_rf = CrossValidator(estimator=classifier_rf, evaluator=evaluator, estimatorParamMaps=grid, numFolds=5)
    cv_model_rf = cv_rf.fit(df_train)
```

```
[ ] #Gradient Boosted Tree Regressor
    classifier_gbt = GBTRegressor(featuresCol="features", labelCol='label', maxIter=10)
    cv_gbt = CrossValidator(estimator=classifier_gbt, evaluator=evaluator, estimatorParamMaps=grid, numFolds=5)
    cv_model_gbt = cv_gbt.fit(df_train)
```

```
[ ] #Linear Regression
    classifier_lr = LinearRegression(maxIter=10, regParam=0.3, elasticNetParam=0.8)
    cv_lr = CrossValidator(estimator=classifier_lr, evaluator=evaluator, estimatorParamMaps=grid, numFolds=5)
    cv_model_lr = cv_lr.fit(df_train)
```

Model Evaluation

Model Evaluation

```
metrics = []
models = [cv_model_rf, cv_model_gbt, cv_model_lr]

for model in models:
    metrics.append(model.avgMetrics)
print (metrics)

for idx, model in enumerate(models):
    metrics[idx].append(RegressionEvaluator(predictionCol='prediction', labelCol='label', metricName='r2').evaluate(model.bestMod
    metrics[idx].append(RegressionEvaluator(predictionCol='prediction', labelCol='label', metricName='rmse').evaluate(model.bestM
    metrics[idx].append(RegressionEvaluator(predictionCol='prediction', labelCol='label', metricName='mae').evaluate(model.bestMo

df = pd.DataFrame(metrics, index = ['Random Forest Regressor', 'Gradient Boosted Tree Regressor',  'Linear Regression'], columns=

df
```

```
[[0.24528405092644592], [0.22446513982488212], [0.49549138181179944]]
```

	Average Metrics (CV)	Best Model R2 on Test Set	Best Model RMSE on Test Set	Best Model MAE on Test Set
Random Forest Regressor	0.245284	0.752917	0.246414	0.162691
Gradient Boosted Tree Regressor	0.224465	0.795455	0.224201	0.113253
Linear Regression	0.495491	-0.000013	0.495732	0.491257

Thanks!

Do you have any questions?

Done by:

- Shouq Alharbi
- Razan Alajlan
- Nada Oteif
- Hayam Alrashed
- Sarah Alrashidi