# **Holiday Package Prediction**

## Libraries

#### In [1]:

```
import numpy as np
import pandas as pd
import missingno as msno
import plotly.express as px
import plotly.graph_objs as go
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import KNNImputer
from sklearn.feature_selection import f_classif
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import accuracy_score, classification_report
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
```

# **Dataset**

## In [2]:

holiday = pd.read\_csv(r'C:\Users\Tanmayee\OneDrive\Documents\Personal\Other\AI\Adarsh\Tr

## Out[2]:

	CustomerID	ProdTaken	Age	TypeofContact	CityTier	DurationOfPitch	Occupation	G	
0	200000	1	41.0	Self Enquiry	3	6.0	Salaried	F	
1	200001	0	49.0	Company Invited	1	14.0	Salaried		
2	200002	1	37.0	Self Enquiry	1	8.0	Free Lancer		
3	200003	0	33.0	Company Invited	1	9.0	Salaried	F	
4	200004	0	NaN	Self Enquiry	1	8.0	Small Business		
				•••					
4883	204883	1	49.0	Self Enquiry	3	9.0	Small Business		
4884	204884	1	28.0	Company Invited	1	31.0	Salaried		
4885	204885	1	52.0	Self Enquiry	3	17.0	Salaried	F	
4886	204886	1	19.0	Self Enquiry	3	16.0	Small Business		
4887	204887	1	36.0	Self Enquiry	1	14.0	Salaried		
4888 r	4888 rows × 20 columns								

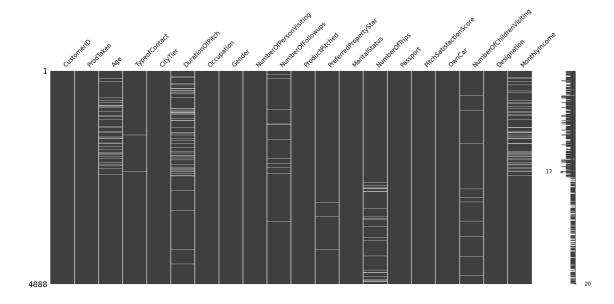
# **Checking Null Values**

## In [3]:

holiday.isnull().sum()
msno.matrix(holiday)

## Out[3]:

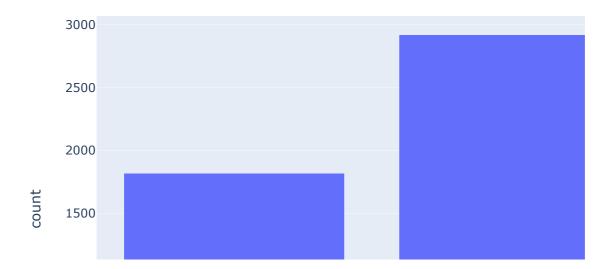
<AxesSubplot:>



# **Exploratory Data Analysis**

## In [4]:

```
fig = px.histogram(holiday,x='Gender')
fig.show()
```



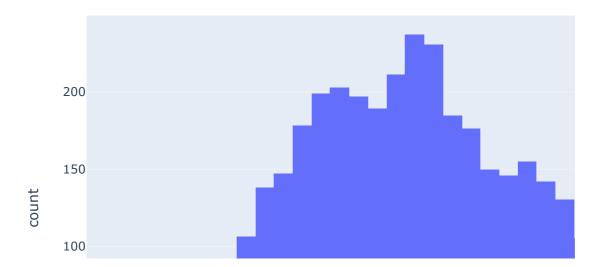
# In [5]:

```
fig = px.histogram(holiday,x='TypeofContact')
fig.show()
```



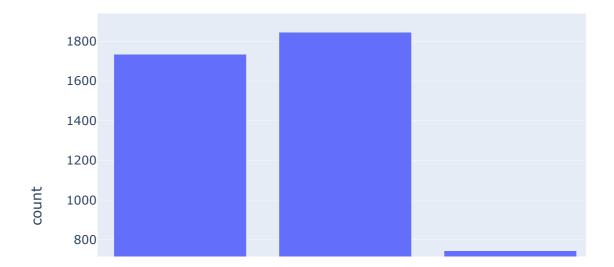
# In [6]:

```
fig = px.histogram(holiday,x='Age')
fig.show()
```



# In [7]:

```
fig = px.histogram(holiday,x='ProductPitched')
fig.show()
```



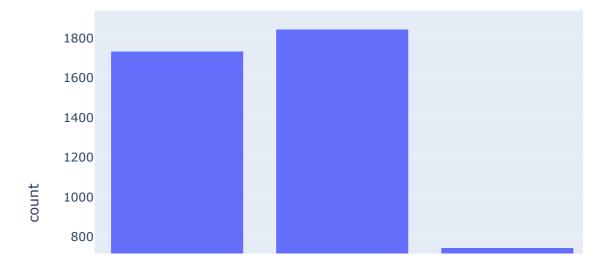
# In [8]:

```
fig = px.histogram(holiday,x='MaritalStatus')
fig.show()
```



## In [9]:

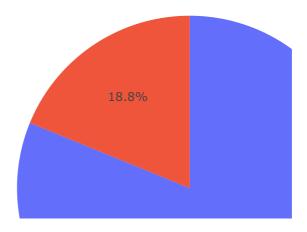
```
fig = px.histogram(holiday,x='Designation')
fig.show()
```



Using the df DataFrame and the data and labels supplied in the names and parameters, make a pie chart. The title of the chart is set using the title parameter. By adjusting the different options offered by the px.pie() method, you may change how the chart looks. Finally, you can use the fig.show() function to display the chart.

#### In [10]:

## Product Taken vs Not Taken Distribution



Code initially compiles a list of column names for all of the object- or int64-type columns in holiday. The unique values in each column are then extracted by iterating over each name of the column in this list. The output is formatted using the f-string in a manner that is similar to the original code.

#### In [11]:

```
categorical_cols = holiday.select_dtypes(include=['object', 'int64']).columns.tolist()

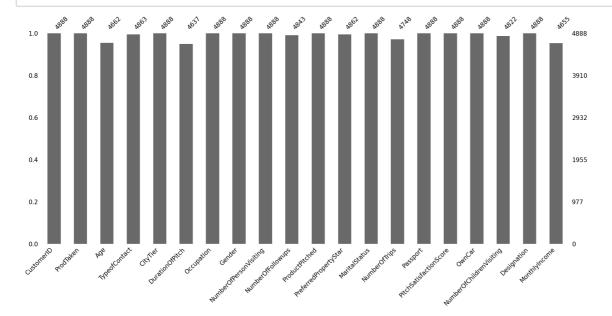
for col in categorical_cols:
    unique_vals = holiday[col].unique()
    #print(f"{col} {'-' * (50 - Len(col))} {unique_vals}")
```

#### In [12]:

```
holiday.replace('Fe Male','Female', inplace = True)
```

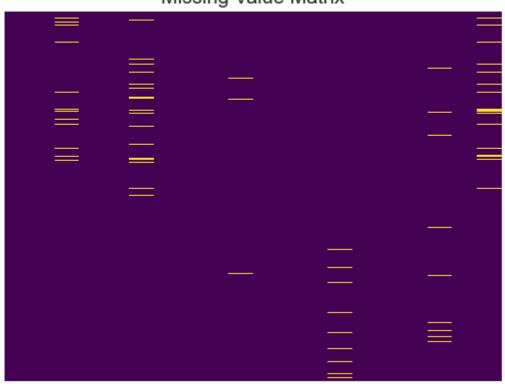
## In [13]:

# Generate the missing value matrix plot
msno\_bar = msno.bar(holiday)



## In [14]:

# Missing Value Matrix



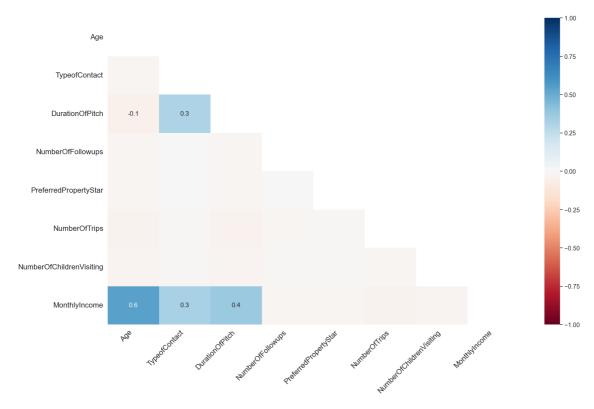
**NumberOfTrips PitchSatisfactionScore SpeofContact** Occupation **MaritalStatus** CustomerID ProdTaken NumberOfFollowups **Number Of Children Visiting** CityTier **DurationOfPitch** Gender **NumberOfPersonVisiting** ProductPitched **PreferredPropertyStar** Passport OwnCar Designation MonthlyIncome

## In [15]:

#### msno.heatmap(holiday)

#### Out[15]:

### <AxesSubplot:>



# **Pre-Processing**

## In [16]:

```
holiday = holiday.drop(['CustomerID'],axis=1)
```

## In [17]:

```
# Define the categorical columns
categorical = [col for col in holiday.columns if holiday[col].dtype == 'object' or holic
# Define the numerical columns
numerical = [col for col in holiday.columns if holiday[col].dtype in ['int64', 'float64']
```

## In [18]:

```
# Impute missing values for numerical columns using KNNImputer
imputer = KNNImputer(n_neighbors=1)
holiday[numerical] = imputer.fit_transform(holiday[numerical])

# Impute missing values for categorical columns using mode
for col in categorical:
    holiday[col].fillna(holiday[col].mode()[0], inplace=True)

# Check for any remaining missing values
holiday.isnull()
```

## Out[18]:

	ProdTaken	Age	TypeofContact	CityTier	DurationOfPitch	Occupation	Gender	Num
0	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	
4883	False	False	False	False	False	False	False	
4884	False	False	False	False	False	False	False	
4885	False	False	False	False	False	False	False	
4886	False	False	False	False	False	False	False	
4887	False	False	False	False	False	False	False	
4888 rows × 19 columns								
4								•

## In [19]:

y = holiday.ProdTaken

## In [20]:

```
cat_df = holiday[categorical].apply(LabelEncoder().fit_transform)
cat_df.head()
```

## Out[20]:

	ProdTaken	TypeofContact	CityTier	Occupation	Gender	NumberOfPersonVisiting	Numbe
0	1	1	2	2	0	2	
1	0	0	0	2	1	2	
2	1	1	0	0	1	2	
3	0	0	0	2	0	1	
4	0	1	0	3	1	1	
4							•

## In [21]:

scaler = MinMaxScaler(feature\_range=(0,1))
normalized\_numerical = pd.DataFrame(scaler.fit\_transform(holiday[numerical]), columns=nu
normalized\_numerical

## Out[21]:

Age	DurationOfPitch	MonthlyIncome
0.534884	0.008197	0.204683
0.720930	0.073770	0.195848
0.441860	0.024590	0.164725
0.348837	0.032787	0.173110
0.209302	0.024590	0.178832
0.720930	0.032787	0.261840
0.232558	0.213115	0.206925
0.790698	0.098361	0.315527
0.023256	0.090164	0.197475
0.418605	0.073770	0.235887
	0.534884 0.720930 0.441860 0.348837 0.209302  0.720930 0.232558 0.790698 0.023256	0.534884       0.008197         0.720930       0.073770         0.441860       0.024590         0.348837       0.032787         0.209302       0.024590             0.720930       0.032787         0.232558       0.213115         0.790698       0.098361         0.023256       0.090164

4888 rows × 3 columns

```
In [22]:
```

```
bestfeatures_num = SelectKBest(score_func=f_classif, k=3)
fit_num = bestfeatures_num.fit(normalized_numerical,y)
dfscores_num = pd.DataFrame(fit_num.scores_)
dfcolumns_num = pd.DataFrame(normalized_numerical.columns)
#concat two dataframes for better visualization
featureScores_num = pd.concat([dfcolumns_num,dfscores_num],axis=1)
featureScores_num.columns = ['Specs','Score'] #naming the dataframe columns
print(featureScores_num.nlargest(3,'Score')) #print best features
featureScores_num.nlargest(3,'Score').to_csv("numerical.csv")
```

```
Specs Score
0 Age 102.943931
2 MonthlyIncome 77.318846
1 DurationOfPitch 28.181641
```

#### In [23]:

```
df = holiday[['Passport', 'ProductPitched', 'MaritalStatus']]
df.head()
```

#### Out[23]:

	Passport	ProductPitched	MaritalStatus
0	1	Deluxe	Single
1	0	Deluxe	Divorced
2	1	Basic	Single
3	1	Basic	Divorced
4	0	Basic	Divorced

#### In [24]:

```
dog_df = pd.get_dummies(df)
dog_df.head()
```

#### Out[24]:

	Passport	ProductPitched_Basic	ProductPitched_Deluxe	ProductPitched_King	ProductPitc
0	1	0	1	0	_
1	0	0	1	0	
2	1	1	0	0	
3	1	1	0	0	
4	0	1	0	0	
4					•

#### In [25]:

```
num_dog_df = pd.concat([normalized_numerical, dog_df], axis=1)
df = pd.concat([y, num_dog_df], axis=1)
df.head()
```

#### Out[25]:

	ProdTaken	Age	DurationOfPitch	MonthlyIncome	Passport	ProductPitched_Basic	; P
0	1	0.534884	0.008197	0.204683	1	C	)
1	0	0.720930	0.073770	0.195848	0	C	)
2	1	0.441860	0.024590	0.164725	1	1	
3	0	0.348837	0.032787	0.173110	1	1	
4	0	0.209302	0.024590	0.178832	0	1	
4							•

## In [26]:

```
X = df.drop(['ProdTaken'], axis = 1)
y = df['ProdTaken']
```

#### **Train and Test**

#### In [27]:

```
X_train,X_test,y_train,y_test=train_test_split(X ,y,test_size=0.2,random_state=1)
```

## Logistic Regression

#### In [28]:

```
reg = 0.01
LogRegModel = LogisticRegression(C=1/reg, solver = 'liblinear').fit(X_train, y_train)
```

# Accuracy, Precision, Recall and F1 Score

#### In [29]:

```
accuracy_logi = LogRegModel.score(X_test, y_test)
preds = LogRegModel.predict(X_test)
recall_logi = metrics.recall_score(y_test, preds)
precision_logi = metrics.precision_score(y_test, preds)
f1_score_logi = metrics.f1_score(y_test, preds)
```

## **Printing Metrics**

#### In [30]:

```
print('accuracy:', accuracy_logi)
print('recall:', recall_logi)
print('precision:', precision_logi)
print('f1-score:', f1_score_logi)
```

accuracy: 0.8282208588957055 recall: 0.2205128205128205 precision: 0.7288135593220338 f1-score: 0.3385826771653543

#### **XGBoost**

#### In [31]:

```
# define the XGBClassifier model
xgb_model = xgb.XGBClassifier().fit(X_train, y_train)

# predict the labels on test data
y_pred = xgb_model.predict(X_test)

# calculate accuracy score
accuracy = accuracy_score(y_test, y_pred)
```

## Accuracy, Precision, Recall and F1 Score

#### In [32]:

```
accuracy_xgb = xgb_model.score(X_test, y_test)
preds = xgb_model.predict(X_test)
recall_xgb = metrics.recall_score(y_test, preds)
precision_xgb = metrics.precision_score(y_test, preds)
f1_score_xgb = metrics.f1_score(y_test, preds)
```

# Printing Accuracy, Precision, Recall and F1 Score

#### In [33]:

```
print('accuracy:', accuracy_xgb)
print('recall:', recall_xgb)
print('precision:', precision_xgb)
print('f1-score:', f1_score_xgb)
```

accuracy: 0.8793456032719836 recall: 0.5282051282051282 precision: 0.7984496124031008 f1-score: 0.6358024691358025

#### **Random Forest Tree**

```
In [34]:
```

```
# Create a random forest classifier with 100 trees
rf = RandomForestClassifier(n_estimators=100, random_state=42)
# Train the model on the training data
rf.fit(X_train, y_train)
# Predict on the test data
preds = rf.predict(X_test)
```

## Accuracy, Precision, Recall and F1 Score

#### In [35]:

```
accuracy_rf = rf.score(X_test, y_test)
preds = rf.predict(X_test)
recall_rf = metrics.recall_score(y_test, preds)
precision_rf = metrics.precision_score(y_test, preds)
f1_score_rf = metrics.f1_score(y_test, preds)
```

## Printing Accuracy, Precision, Recall and F1 Score

### In [36]:

```
print('accuracy:', accuracy_rf)
print('recall:', recall_rf)
print('precision:', precision_rf)
print('f1-score:', f1_score_rf)
```

accuracy: 0.8977505112474438 recall: 0.6153846153846154 precision: 0.8275862068965517 f1-score: 0.7058823529411765

## Storing data into Dataframes for plotting it

```
In [37]:
```

```
models = ['Logistic Regression', 'XGBoost', 'Random Forest']
accuracy = [accuracy_logi, accuracy_xgb, accuracy_rf]
recall = [recall_logi, recall_xgb, recall_rf]
precision = [precision_logi, precision_xgb, precision_rf]
f1_score = [f1_score_logi, f1_score_xgb, f1_score_rf]
```

```
In [38]:
```

```
# Create trace for accuracy
trace1 = go.Bar(x=models, y=accuracy, name='Accuracy', marker_color='pink')

# Create trace for recall
trace2 = go.Bar(x=models, y=recall, name='Recall', marker_color='cyan')

# Create trace for precision
trace3 = go.Bar(x=models, y=precision, name='Precision', marker_color='navy')

# Create trace for F1-score
trace4 = go.Bar(x=models, y=f1_score, name='F1-score', marker_color='teal')
```

## Plotting the graph

## In [39]:

## **Model Evaluation Metrics**



## In [ ]: