coupon_acceptance_prediction

July 2, 2025

0.1 Smart Coupon Targeting: Predicting User Acceptance for Personalized E-Commerce Deals

0.2 Data Overview

The dataset consists of **12,684 rows** and **25 columns**, capturing user demographics, behavioral patterns, driving context, coupon details, and a target variable indicating coupon acceptance.

0.2.1 Key Components:

- **User Demographics:** Gender, Age, Marital Status, Education, Income, etc.
- **Spending Behavior:** Frequency of visits to bars, coffee houses, restaurants, etc.
- **Driving Context:** Destination, Passenger, Weather, Temperature.
- **Coupon Details:** Type of coupon, expiration duration.
- **Travel Constraints:** Distance and direction to the coupon location.
- **Target Variable:** `Accept (Y/N)` indicating whether the user accepted the coupon.

0.3 Project Objective

In the modern e-commerce landscape, personalized marketing strategies play a crucial role in enhancing user engagement and driving sales. This project aims to leverage **machine learning techniques** to predict whether a user will accept a coupon based on various factors such as demographics, behavioral patterns, driving context, and coupon details.

By accurately identifying the factors influencing coupon acceptance, businesses can **optimize coupon distribution strategies** to target the right users at the right time, thereby improving conversion rates and customer satisfaction.

0.3.1 Key Goals:

- Analyze the impact of **user demographics, spending habits, and contextual factors** on coupon acceptance.
- Build and evaluate a **predictive model** to classify whether a user will accept a given coupon.
- Provide actionable insights to **enhance targeted marketing strategies** in e-commerce.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.io as pio
import plotly.offline as py
pd.options.plotting.backend = "plotly"
py.init_notebook_mode(connected=True)
pd.set_option('display.max_columns', None)
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
df = pd.read_csv("coupon_details.csv")
```

[3]:
```
df.head()
```

[3]:
```
        destination  passanger weather  temperature                 coupon  \
0  No Urgent Place      Alone   Sunny           55        Restaurant(<20)
1  No Urgent Place  Friend(s)   Sunny           80           Coffee House
2  No Urgent Place  Friend(s)   Sunny           80  Carry out & Take away
3  No Urgent Place  Friend(s)   Sunny           80           Coffee House
4  No Urgent Place  Friend(s)   Sunny           80           Coffee House

  expiration  gender age      maritalStatus  has_children  \
0         1d  Female  21  Unmarried partner             1
1         2h  Female  21  Unmarried partner             1
2         2h  Female  21  Unmarried partner             1
3         2h  Female  21  Unmarried partner             1
```

```
4         1d  Female  21  Unmarried partner            1

                  education  occupation            income  car    Bar  \
0  Some college - no degree  Unemployed  $37500 - $49999  NaN  never
1  Some college - no degree  Unemployed  $37500 - $49999  NaN  never
2  Some college - no degree  Unemployed  $37500 - $49999  NaN  never
3  Some college - no degree  Unemployed  $37500 - $49999  NaN  never
4  Some college - no degree  Unemployed  $37500 - $49999  NaN  never

  CoffeeHouse CarryAway RestaurantLessThan20 Restaurant20To50  \
0       never       NaN                  4~8              1~3
1       never       NaN                  4~8              1~3
2       never       NaN                  4~8              1~3
3       never       NaN                  4~8              1~3
4       never       NaN                  4~8              1~3

   toCoupon_GEQ5min  toCoupon_GEQ15min  toCoupon_GEQ25min  direction_same  \
0                 1                  0                  0               0
1                 1                  0                  0               0
2                 1                  1                  0               0
3                 1                  1                  0               0
4                 1                  1                  0               0

   direction_opp  Accept(Y/N?)
0              1             1
1              1             0
2              1             1
3              1             0
4              1             0
```

[4]:
```
def missing_plot(dataset):
    null_feat = pd.DataFrame(dataset.isnull().sum(),columns=['Count'])
    null_percentage = pd.DataFrame(dataset.isnull().sum()/
 ↪len(dataset),columns=['Count'])

    trace = go.Bar(x= null_feat.index, y = null_feat['Count'],opacity=0.8,
                   text = null_feat['Count'],textposition='auto',
                   marker=dict(color = '#D84E5F',
                               line = dict(color = '#000000',width = 1.5)))
    layout = dict(height=600,width = 1000,title = 'Missing values analysis by␣
 ↪Barplot')

    fig = dict(data=[trace], layout= layout)

    py.iplot(fig)

def check(df_):
```

```python
    print('SHAPE'.center(60,'*'))
    print('OBSERVATIONS -------->{}'.format(df_.shape[0]))
    print('FEATURES -------->{}'.format(df_.shape[1]))
    print('TYPES OF FETAURES'.center(60,'*'))
    print(df_.dtypes,'\n')
    print('Duplicate Values Analysis'.center(60,'*'))
    print('\n',df_.duplicated().sum(),'\n')
    print(''.center(60,'*'))
```

[5]:
```python
check(df)
missing_plot(df)
```

```
***************************SHAPE****************************
OBSERVATIONS -------->12684
FEATURES -------->25
*********************TYPES OF FETAURES**********************
destination             object
passanger               object
weather                 object
temperature              int64
coupon                  object
expiration              object
gender                  object
age                     object
maritalStatus           object
has_children             int64
education               object
occupation              object
income                  object
car                     object
Bar                     object
CoffeeHouse             object
CarryAway               object
RestaurantLessThan20    object
Restaurant20To50        object
toCoupon_GEQ5min         int64
toCoupon_GEQ15min        int64
toCoupon_GEQ25min        int64
direction_same           int64
direction_opp            int64
Accept(Y/N?)             int64
dtype: object

*****************Duplicate Values Analysis******************

 291

************************************************************
```

[6]:
```
df['age'].value_counts()
```

[6]:
```
age
21         2653
26         2559
31         2039
50plus     1788
36         1319
41         1093
46          686
below21     547
Name: count, dtype: int64
```

[7]:
```
df['age'] = df['age'].replace({'50plus': 50, 'below21': 20}).astype(int)
```

[15]:
```
df.drop(columns=['car'], inplace=True)
```

[17]:
```
cols = ['Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20',␣
 ↪'Restaurant20To50']

for col in cols:
    df[col].fillna(df[col].mode()[0], inplace=True)
```

[19]:
```
object_cols = df.select_dtypes(include='O').columns.tolist()
numeric_cols = df.select_dtypes(include=['int','float']).columns.tolist()

print("Object columns are: \n",object_cols,"\n")
print("Numeric columns are: \n",numeric_cols)
```

```
Object columns are:
 ['destination', 'passanger', 'weather', 'coupon', 'expiration', 'gender',
'maritalStatus', 'education', 'occupation', 'income', 'Bar', 'CoffeeHouse',
'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50']

Numeric columns are:
 ['temperature', 'age', 'has_children', 'toCoupon_GEQ5min', 'toCoupon_GEQ15min',
'toCoupon_GEQ25min', 'direction_same', 'direction_opp', 'Accept(Y/N?)']
```

[21]:
```
df.describe().T
```

[21]:

	count	mean	std	min	25%	50%	75%	max
temperature	12684.0	63.301798	19.154486	30.0	55.0	80.0	80.0	80.0
age	12684.0	32.296515	10.187216	20.0	21.0	31.0	41.0	50.0
has_children	12684.0	0.414144	0.492593	0.0	0.0	0.0	1.0	1.0
toCoupon_GEQ5min	12684.0	1.000000	0.000000	1.0	1.0	1.0	1.0	1.0
toCoupon_GEQ15min	12684.0	0.561495	0.496224	0.0	0.0	1.0	1.0	1.0
toCoupon_GEQ25min	12684.0	0.119126	0.323950	0.0	0.0	0.0	0.0	1.0
direction_same	12684.0	0.214759	0.410671	0.0	0.0	0.0	0.0	1.0

```
direction_opp      12684.0   0.785241   0.410671   0.0   1.0   1.0   1.0   1.0
Accept(Y/N?)       12684.0   0.568433   0.495314   0.0   0.0   1.0   1.0   1.0
```

0.4 EDA

Frequent Spender: This feature can be based on the frequency of visits to **bars**, **coffee houses**, and **restaurants**. - A user can be classified as a **Frequent Spender** if they visit any of these places more than a certain threshold (e.g., more than 5 times per month).

[25]:
```
def is_frequent_spender(value):
    if value in ['4~8', 'gt8']:
        return 1
    return 0

df['Frequent_Spender_Bar'] = df['Bar'].apply(is_frequent_spender)
df['Frequent_Spender_CoffeeHouse'] = df['CoffeeHouse'].
 ↪apply(is_frequent_spender)
df['Frequent_Spender_RestaurantLessThan20'] = df['RestaurantLessThan20'].
 ↪apply(is_frequent_spender)
df['Frequent_Spender_Restaurant20To50'] = df['Restaurant20To50'].
 ↪apply(is_frequent_spender)

df['Frequent_Spender'] = df[['Frequent_Spender_Bar',␣
 ↪'Frequent_Spender_CoffeeHouse',
                             'Frequent_Spender_RestaurantLessThan20',␣
 ↪'Frequent_Spender_Restaurant20To50']].sum(axis=1)

df['Frequent_Spender'] = df['Frequent_Spender'].apply(lambda x: 1 if x > 0 else␣
 ↪0)
```

Distance Sensitivity: Based on the `toCoupon_GEQ5min`, `toCoupon_GEQ15min`, and `toCoupon_GEQ25min` columns, a user can be classified as **Distance Sensitive** if they only accept coupons for nearby locations (e.g., within 5 minutes).

[28]:
```
df['Distance_Sensitive'] = df.apply(lambda x: 1 if (x['toCoupon_GEQ5min'] == 1␣
 ↪and x['toCoupon_GEQ15min'] == 1) else 0, axis=1)
```

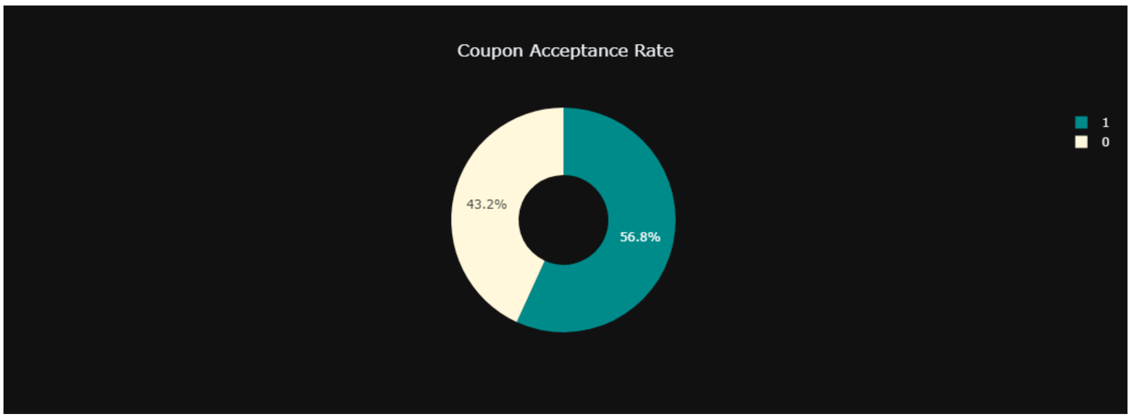
Weather Sensitive: A user could be labeled as **Weather Sensitive** if their coupon acceptance is higher in sunny weather compared to rainy or snowy conditions.

[31]:
```
df['Weather_Sensitive'] = df['weather'].apply(lambda x: 1 if x == 'Sunny' else␣
 ↪0)
```

- Coupon Acceptance Rate

[34]:
```
fig = px.pie(df,
             names="Accept(Y/N?)",
             title="Coupon Acceptance Rate",
             hole=0.4,
```

```
            color="Accept(Y/N?)",
            color_discrete_map={1: 'darkcyan',
                                0: 'cornsilk'})

fig.update_layout(title_x=0.5,
                 height=400,
                 width=600,
                 template='plotly_dark')

fig.show()
```



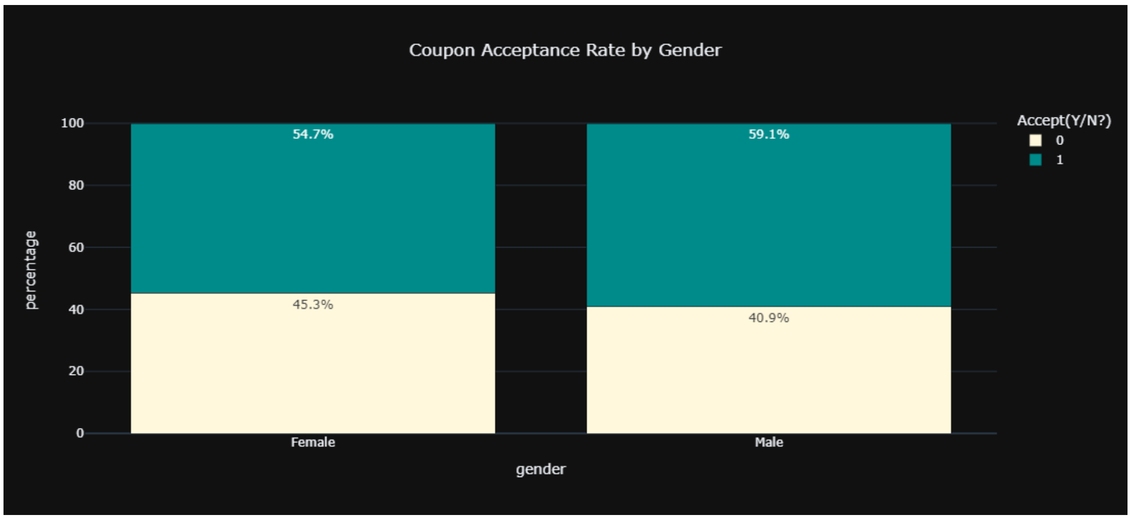
- 56.8% accept coupons, while 43.2% reject them.
- Coupons influence engagement but need optimization.
- Targeted, personalized offers can boost acceptance.

0.4.1 User Demographics vs. Coupon Acceptance

Acceptance by Gender

[39]:
```
df_grouped = df.groupby(["gender", "Accept(Y/N?)"]).size().
 ↪reset_index(name="count")
df_grouped["percentage"] = df_grouped["count"] / df_grouped.
 ↪groupby("gender")["count"].transform("sum") * 100
df_grouped["Accept(Y/N?)"] = df_grouped["Accept(Y/N?)"].astype(str)


custom_colors = {"1": 'darkcyan',
                 "0": 'cornsilk'}

fig = px.bar(df_grouped,
             x="gender",
             y="percentage",
             color="Accept(Y/N?)",
             title="Coupon Acceptance Rate by Gender",
```

```
            text=df_grouped["percentage"].apply(lambda x: f"{x:.1f}%"),
            color_discrete_map=custom_colors)

fig.update_layout(barmode="stack",
                  title_x=0.5,
                  height=500,
                  width=600,
                  template='plotly_dark')
fig.update_traces(textposition="inside")

fig.show()
```

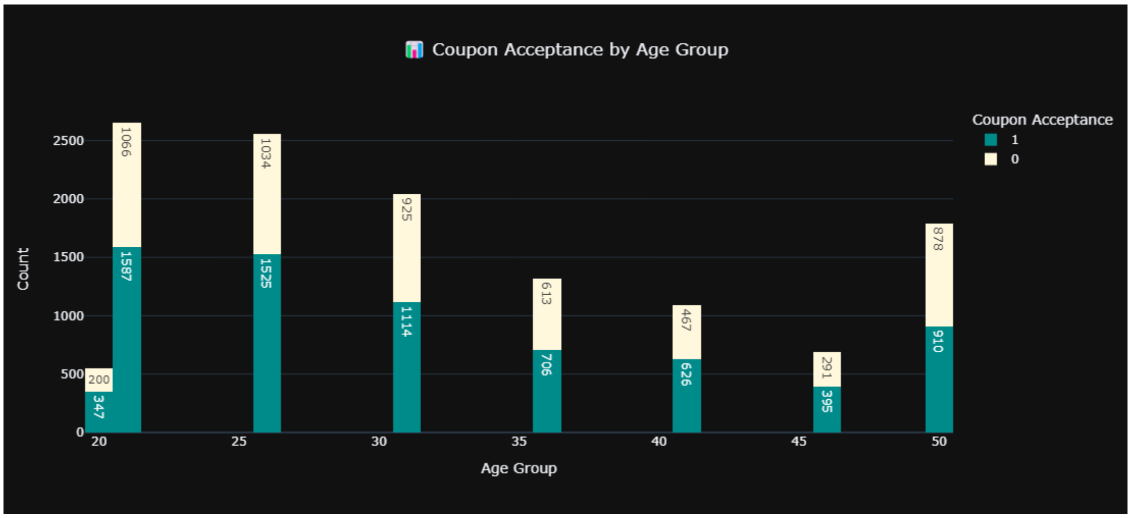


- Males (59.08%) accept coupons more than females (54.72%). Targeted offers for females and optimized coupon strategies can further boost engagement and conversions

Age Group vs. Acceptance

[43]:
```
df["Accept(Y/N?)"] = df["Accept(Y/N?)"].astype(str)

fig = px.histogram(df,
                   x="age",
                   color="Accept(Y/N?)",
                   barmode="stack",
                   title="  Coupon Acceptance by Age Group",
                   text_auto=True,
                   color_discrete_map={"1": "darkcyan", "0": "cornsilk"})

fig.update_layout(
    template="plotly_dark",
    title_x=0.5,
    xaxis_title="Age Group",
```

```
    yaxis_title="Count",
    legend_title="Coupon Acceptance",
    font=dict(size=12),
    height=500, width=700
)

fig.show()
```



- Younger users (21-26) have the highest coupon acceptance, gradually declining as age increases. Targeting personalized offers for younger demographics can maximize conversions, while customized incentives for older users may improve engagement.

0.4.2 Impact of Spending Behavior on Coupon Acceptance

Spending Habits vs. Acceptance

[48]:
```
custom_colors = ["#3498DB", "#E74C3C", "#2ECC71", "#F39C12"]

fig = make_subplots(rows=2, cols=2,
                    subplot_titles=["  Bar Visits", "  Coffee House Visits",
                                    "  Carry Away Orders", "  Restaurants <$20"])

fig.add_trace(go.Box(y=df["Bar"], name="Bar Visits",␣
 ↪marker_color=custom_colors[0], boxmean=True), row=1, col=1)
fig.add_trace(go.Box(y=df["CoffeeHouse"], name="Coffee House Visits",␣
 ↪marker_color=custom_colors[1], boxmean=True), row=1, col=2)
fig.add_trace(go.Box(y=df["CarryAway"], name="Carry Away Orders",␣
 ↪marker_color=custom_colors[2], boxmean=True), row=2, col=1)
fig.add_trace(go.Box(y=df["RestaurantLessThan20"], name="Restaurants <$20",␣
 ↪marker_color=custom_colors[3], boxmean=True), row=2, col=2)
```

```
fig.update_layout(
    title="  Spending Habits Distribution - Box Plot",
    template="plotly_dark",
    title_x=0.5,
    showlegend=False,
    height=700, width=900,
    font=dict(size=12),
    margin=dict(t=50, l=50, r=50, b=50)
)

fig.show()
```

- Most users rarely visit bars, with the median and mean below 1 visit per month. Coffee houses are more frequently visited, with a mean between 4-8 visits and a median slightly below 1. Carry-away orders and budget restaurants (<$20) are more popular, with median visits between 1-3 times per month, indicating a strong preference for quick, affordable food options. This suggests that targeting discount coupons for `coffee houses` and `takeout restaurants` could drive higher coupon acceptance.

[51]:
```
df['maritalStatus'] = df['maritalStatus'].astype(str)
df['has_children'] = df['has_children'].astype(str)
df['education'] = df['education'].astype(str)
df['occupation'] = df['occupation'].astype(str)
df['income'] = df['income'].astype(str)
```

```
df['Accept(Y/N?)'] = df['Accept(Y/N?)'].astype(str)

fig = make_subplots(
    rows=2, cols=2,
    subplot_titles=[
        "Marital Status Analysis  ",
        "Children and Spending Behavior  ",
        "Education Level and Coupon Acceptance  ",
        "Occupation and Income Trends  "
    ],
    horizontal_spacing=0.15,
    vertical_spacing=0.3
)

# Marital Status Analysis
marital_counts = df['maritalStatus'].value_counts()
fig.add_trace(
    go.Bar(x=marital_counts.index, y=marital_counts.values, name="Marital␣
 ↪Status", marker_color="lightblue"),
    row=1, col=1
)

# Children and Spending Behavior
children_counts = df.groupby("has_children")["Frequent_Spender"].sum()
fig.add_trace(
    go.Bar(x=children_counts.index, y=children_counts.values, name="Children &␣
 ↪Spending", marker_color="lightgreen"),
    row=1, col=2
)

# Education Level and Coupon Acceptance
edu_acceptance = df.groupby("education")["Accept(Y/N?)"].value_counts().
 ↪unstack()
fig.add_trace(
    go.Bar(x=edu_acceptance.index, y=edu_acceptance.iloc[:,1], name="Accepted␣
 ↪Coupons", marker_color="orange"),
    row=2, col=1
)
fig.add_trace(
    go.Bar(x=edu_acceptance.index, y=edu_acceptance.iloc[:,0], name="Rejected␣
 ↪Coupons", marker_color="red"),
    row=2, col=1
)

# Occupation and Income Trends
occupation_income = df.groupby("occupation")["income"].count().sort_values()
fig.add_trace(
```

```
    go.Bar(x=occupation_income.index, y=occupation_income.values, name="Income␣
↪by Occupation", marker_color="purple"),
    row=2, col=2
)

fig.update_layout(
    title="Consumer Behavior",
    title_x = 0.5,
    height = 1000,
    width = 1200,
    template="plotly_dark",
    showlegend=False
)

fig.show()
```

0.4.3 Business Insights Conclusion: Consumer Behavior & Coupon Acceptance

1 **Marital Status & Spending Habits**
- **Married partners** form the largest consumer group, followed by **single individuals**.
- Marketing strategies should **differentiate offers** for married vs. single consumers, as spending behaviors may vary.

2 **Children & Coupon Usage**
- Households **without children** outnumber those **with children (2:1 ratio)**.
- Families with children may respond **better to family-oriented coupons**, such as discounts on restaurants or grocery items.

3 **Education & Coupon Acceptance**
- **Higher-educated individuals (Bachelor's, Graduate degrees)** accept coupons **more frequently**.
- Premium or high-value coupons might be **more effective** for this segment, as they likely have **higher disposable income**.

4 **Occupation & Income Trends**
- **Students & Unemployed individuals** form a **large consumer base** (~34%).
- **Computer, Sales, and Management professionals** are key targets for **higher-value offers** since they have stable income streams.
- **Food service & healthcare workers** may respond well to **budget-friendly discounts** due to their demanding jobs.

0.4.4 Business Recommendations:

Targeted Coupon Campaigns based on **marital status & children**.
Educational & occupation-based promotions to drive engagement.
Customize discounts for students & unemployed groups.
Optimize coupon values for high-income earners to increase premium sales.

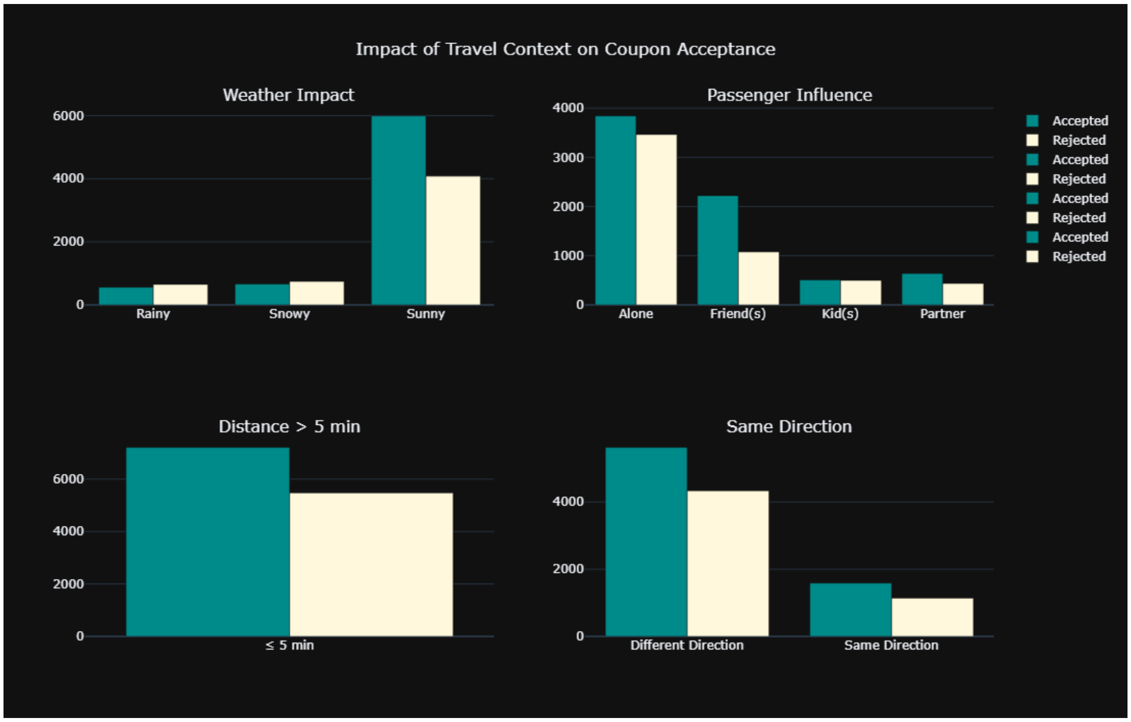
This analysis helps **tailor promotions**, **increase conversion rates**, and **improve customer retention** through data-driven marketing!

0.4.5 Impact of Travel Context on Coupon Usage

[55]:
```
colors = ["darkcyan", "cornsilk"]
fig = make_subplots(rows=2, cols=2,
                    subplot_titles=["Weather Impact", "Passenger Influence",␣
 ↪"Distance > 5 min", "Same Direction"])

# Weather Impact
weather_counts = df.groupby(["weather", "Accept(Y/N?)"]).size().unstack()
fig.add_trace(go.Bar(x=weather_counts.index,
                      y=weather_counts.iloc[:,1],
                      name="Accepted",
                      marker_color=colors[0]),
              row=1, col=1)
fig.add_trace(go.Bar(x=weather_counts.index,
```

```
                      y=weather_counts.iloc[:,0],
                      name="Rejected",
                      marker_color=colors[1]),
              row=1, col=1)

# Passenger Influence
passenger_counts = df.groupby(["passanger", "Accept(Y/N?)"]).size().unstack()
fig.add_trace(go.Bar(x=passenger_counts.index,
                      y=passenger_counts.iloc[:,1],
                      name="Accepted",
                      marker_color=colors[0]),
              row=1, col=2)
fig.add_trace(go.Bar(x=passenger_counts.index,
                      y=passenger_counts.iloc[:,0],
                      name="Rejected",
                      marker_color=colors[1]),
              row=1, col=2)

# Distance > 5 min
distance_counts = df.groupby(["toCoupon_GEQ5min", "Accept(Y/N?)"]).size().
 ↪unstack()
fig.add_trace(go.Bar(x=["  5 min", "> 5 min"],
                      y=distance_counts.iloc[:,1],
                      name="Accepted",
                      marker_color=colors[0]),
              row=2, col=1)
fig.add_trace(go.Bar(x=["  5 min", "> 5 min"],
                      y=distance_counts.iloc[:,0],
                      name="Rejected",
                      marker_color=colors[1]),
              row=2, col=1)

# Same Direction Influence
direction_counts = df.groupby(["direction_same", "Accept(Y/N?)"]).size().
 ↪unstack()
fig.add_trace(go.Bar(x=["Different Direction", "Same Direction"],
                      y=direction_counts.iloc[:,1],
                      name="Accepted",
                      marker_color=colors[0]),
              row=2, col=2)
fig.add_trace(go.Bar(x=["Different Direction", "Same Direction"],
                      y=direction_counts.iloc[:,0],
                      name="Rejected",
                      marker_color=colors[1]),
              row=2, col=2)

# Update layout
```

```
fig.update_layout(title="Impact of Travel Context on Coupon Acceptance",
                  title_x = 0.5,
                  template="plotly_dark",
                  barmode="group",
                  showlegend=True,
                  height=700, width=1000)

fig.show()
```



- **Weather Impact:** Coupons are more accepted on **sunny days** compared to **rainy or snowy** conditions, indicating weather influences customer behavior.

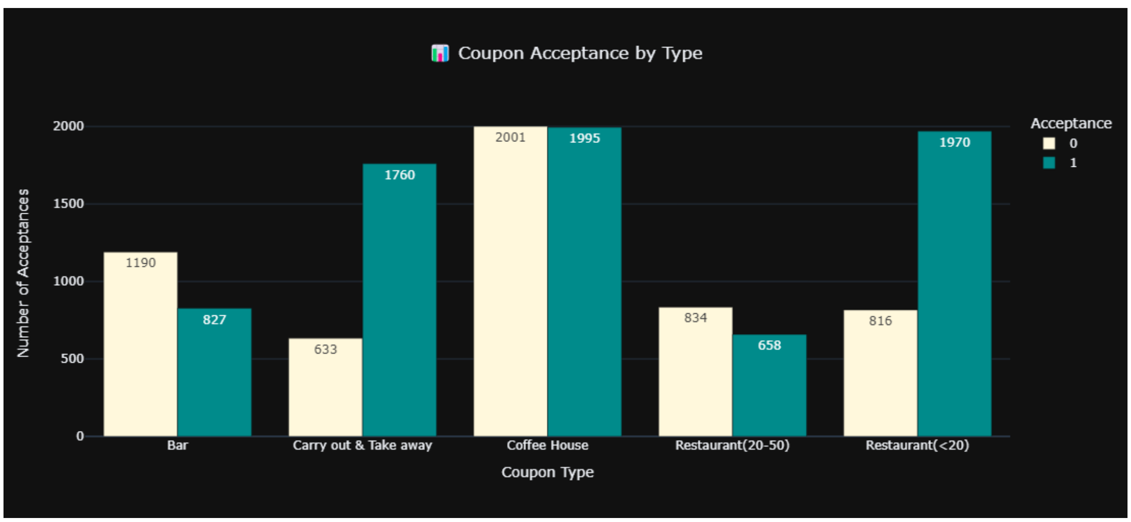
- **Passenger Influence:** People traveling **with friends or partners** show **higher coupon acceptance** than those traveling **alone**, suggesting social influence plays a role.

- **Travel Time:** A **higher percentage of users accept coupons regardless of travel time**, indicating convenience isn't a major barrier.

- **Direction Factor:** Customers traveling in the **same direction** as the coupon location accept more offers, highlighting the importance of route-based targeting.

Business Insight: Marketers should focus on targeting customers in **favorable weather, social settings, and aligned travel routes** to maximize coupon acceptance rates.

[58]:
```
df_grouped = df.groupby(["coupon", "Accept(Y/N?)"]).size().
↪reset_index(name="count")

fig = px.bar(df_grouped,
             x="coupon",
             y="count",
             color="Accept(Y/N?)",
             barmode="group",
             title="  Coupon Acceptance by Type",
             text_auto=True,
             color_discrete_map={"0":"cornsilk", "1":"darkcyan"}
            )

fig.update_layout(
    title_x=0.5,
    height=500,
    width=800,
    template='plotly_dark',
    xaxis_title="Coupon Type",
    yaxis_title="Number of Acceptances",
    font=dict(size=12),
    legend_title="Acceptance",
    bargap=0.2
)

fig.show()
```



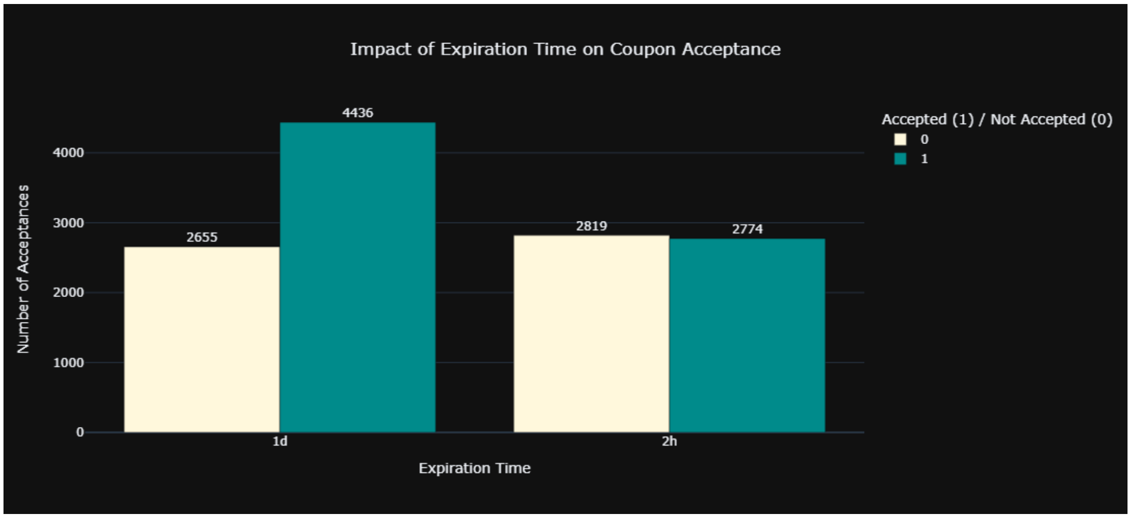
- **Carry Out & Take Away and Restaurant (<$20) coupons** have the **highest acceptance rates**, indicating that customers prefer discounts on quick and affordable dining options.

- **Coffee House coupons** show a **balanced acceptance**, suggesting steady customer interest in café deals.

- **Bar and Restaurant (20-50) coupons** have **lower acceptance rates**, implying that discounts for higher-end dining and bars are less appealing or relevant to customers.

- **Strategic Focus**: Businesses should **prioritize promotions** on **takeout and budget-friendly restaurants** to maximize coupon redemption and customer engagement.

[61]:
```
df_expiration = df.groupby(["expiration", "Accept(Y/N?)"]).size().
  ↪reset_index(name="count")

# Creating the bar chart
fig = px.bar(df_expiration,
             x="expiration",
             y="count",
             color="Accept(Y/N?)",
             barmode="group",
             title="Impact of Expiration Time on Coupon Acceptance",
             text_auto=True,
             color_discrete_map={"1": "darkcyan", "0": "cornsilk"}
            )

fig.update_layout(title_x=0.5,
                  height=500,
                  width=700,
                  template='plotly_dark',
                  xaxis_title="Expiration Time",
                  yaxis_title="Number of Acceptances",
                  legend_title="Accepted (1) / Not Accepted (0)",
                  bargap=0.2
                 )

fig.update_traces(textposition="outside")

fig.show()
```



Customers are more likely to accept **1-day expiration coupons (62.5%)** compared to **2-hour expiration coupons (49.6%)**. This suggests that offering a **longer validity period** increases coupon acceptance, allowing users more flexibility and improving conversion rates.

0.4.6 Selected Important Features Based on EDA Insights

After performing an in-depth EDA, the most relevant features for **coupon acceptance prediction** can be categorized into **demographics, behavioral traits, and contextual factors**:

0.4.7 1 Demographic Features (Who are the best targets?)

Age – Certain age groups (21-31) show higher coupon usage.
Gender – Coupon acceptance may vary by gender.
Marital Status – Married vs. single consumers exhibit different spending patterns.
Has Children – Families with children may prefer certain types of coupons.
Education – Higher-educated individuals show increased coupon acceptance.
Occupation – Certain job sectors (IT, Sales, Students) are key targets.
Income – Impacts spending behavior and willingness to redeem coupons.

0.4.8 2 Behavioral Features (What conditions lead to high acceptance?)

Frequent_Spender – Categorizes users based on restaurant/coffee shop visits.
Distance_Sensitive – Determines how distance impacts coupon usage.
Weather_Sensitive – Measures weather's influence on coupon redemption.
Bar, CoffeeHouse, RestaurantLessThan20, Restaurant20To50 – Frequency of visits indicates likelihood of using food-related coupons.

0.4.9 3 Coupon-Specific Features (Which coupons work best?)

Coupon Type – Restaurant vs. Coffee Shop vs. Bar acceptance trends.
Expiration – 1-day vs. 2-hour expiration impacts redemption rates.

0.4.10 4 Contextual Features (When & where should coupons be offered?)

toCoupon_GEQ5min, toCoupon_GEQ15min, toCoupon_GEQ25min – Measures travel time to coupon locations.
Destination – Work, home, or other locations impact coupon relevance.
direction_same & direction_opp – Whether a user is moving towards or away from the coupon location.
Weather & Temperature – Can affect willingness to go out for offers.

---

[65]:
```
df['Accept(Y/N?)'].value_counts()
```

[65]:
```
Accept(Y/N?)
1    7210
0    5474
Name: count, dtype: int64
```

[67]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score,␣
 ↪precision_score, recall_score, f1_score, confusion_matrix
from sklearn.metrics import precision_recall_curve, roc_curve, auc
```

[69]:
```
target = 'Accept(Y/N?)'
X = df.drop(columns=[target])
y = df[target].astype(int)

cat_features = X.select_dtypes(include=['object']).columns.tolist()
num_features = X.select_dtypes(include=['int64', 'int32']).columns.tolist()
```

[83]:
```
categorical_transformer = OneHotEncoder(handle_unknown='ignore')
numerical_transformer = StandardScaler()


preprocessor = ColumnTransformer(
```

```
    transformers=[
        ('num', numerical_transformer, num_features),
        ('cat', categorical_transformer, cat_features)
    ]
)

models = {
    "Logistic Regression": LogisticRegression(),
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
 ↪random_state=42),
    "SVM": SVC(probability=True)
}

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)

for name, model in models.items():
    pipeline = Pipeline(steps=[('preprocessor', preprocessor), ('classifier',␣
 ↪model)])
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    print(f"\n{name} Model Performance:\n")
    print(classification_report(y_test, y_pred))
    print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
Logistic Regression Model Performance:

              precision    recall  f1-score   support

           0       0.67      0.56      0.61      1095
           1       0.70      0.79      0.74      1442

    accuracy                           0.69      2537
   macro avg       0.68      0.67      0.68      2537
weighted avg       0.69      0.69      0.68      2537

Accuracy: 0.6890027591643674

Random Forest Model Performance:

              precision    recall  f1-score   support

           0       0.73      0.67      0.70      1095
           1       0.76      0.81      0.79      1442
```

```
    accuracy                           0.75      2537
   macro avg       0.75      0.74      0.74      2537
weighted avg       0.75      0.75      0.75      2537

Accuracy: 0.7504927079227434

XGBoost Model Performance:

              precision    recall  f1-score   support

           0       0.74      0.66      0.70      1095
           1       0.76      0.83      0.79      1442

    accuracy                           0.76      2537
   macro avg       0.75      0.75      0.75      2537
weighted avg       0.76      0.76      0.75      2537

Accuracy: 0.7567993693338589

SVM Model Performance:

              precision    recall  f1-score   support

           0       0.72      0.62      0.67      1095
           1       0.74      0.82      0.78      1442

    accuracy                           0.73      2537
   macro avg       0.73      0.72      0.72      2537
weighted avg       0.73      0.73      0.73      2537

Accuracy: 0.73433188805676
```

[71]:

```
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline

X = df.drop(columns=['Accept(Y/N?)'])
y = df['Accept(Y/N?)'].astype(int)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪stratify=y, random_state=42)
```

[73]:

```
num_features = ['temperature', 'age', 'toCoupon_GEQ5min', 'toCoupon_GEQ15min',␣
 ↪'toCoupon_GEQ25min']
cat_features = ['destination', 'passanger', 'weather', 'coupon', 'expiration',␣
 ↪'gender', 'maritalStatus', 'education',
                'occupation', 'income', 'Bar', 'CoffeeHouse', 'CarryAway',␣
 ↪'RestaurantLessThan20', 'Restaurant20To50']
```

```python
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), num_features),
        ('cat', OneHotEncoder(handle_unknown='ignore'), cat_features)
    ])

models = {
    "Logistic Regression": LogisticRegression(),
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
↪random_state=42),
    "SVM": SVC(probability=True)
}
```

[89]:

```python
results = {}

for model_name, model in models.items():
    print(f"\n  Training Model: {model_name} ...")


    pipeline = ImbPipeline(steps=[
        ('preprocessor', preprocessor),
        ('smote', SMOTE(sampling_strategy=0.85, random_state=42)),
        ('classifier', model)
    ])


    pipeline.fit(X_train, y_train)


    y_pred = pipeline.predict(X_test)


    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    results[model_name] = {
        "Accuracy": accuracy,
        "Precision": precision,
        "Recall": recall,
        "F1-Score": f1
    }
```

```
    print(f"  {model_name} - Accuracy: {accuracy:.4f}, Precision: {precision:.
↪4f}, Recall: {recall:.4f}, F1-Score: {f1:.4f}")
```

```
 Training Model: Logistic Regression …
 Logistic Regression - Accuracy: 0.6768, Precision: 0.7071, Recall: 0.7365,
F1-Score: 0.7215

 Training Model: Random Forest …
 Random Forest - Accuracy: 0.7497, Precision: 0.7572, Recall: 0.8239, F1-Score:
0.7891

 Training Model: XGBoost …
 XGBoost - Accuracy: 0.7544, Precision: 0.7640, Recall: 0.8218, F1-Score:
0.7918

 Training Model: SVM …
 SVM - Accuracy: 0.7477, Precision: 0.7577, Recall: 0.8176, F1-Score: 0.7865
```

[91]:

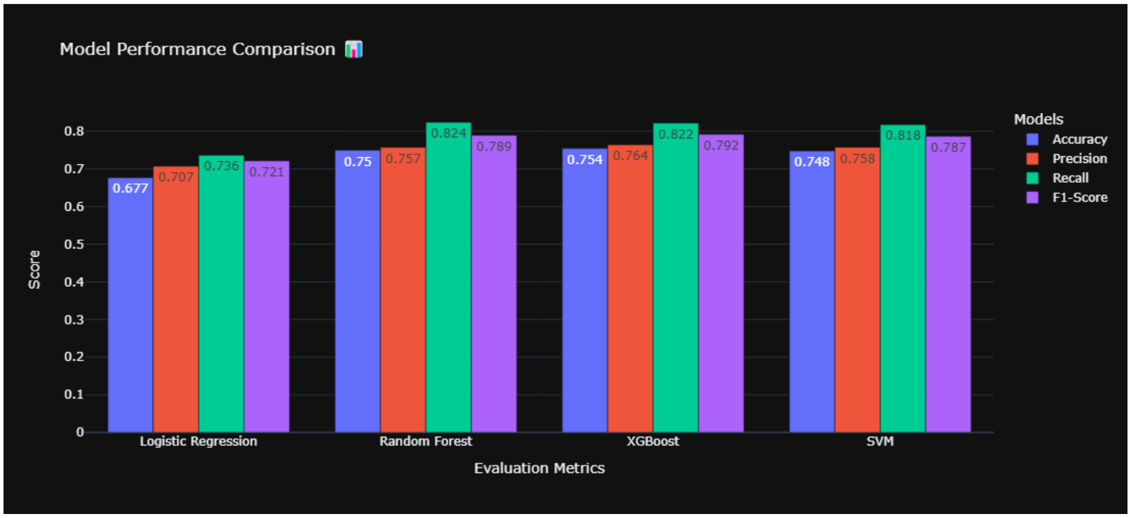
```
results_df = pd.DataFrame(results).T
print("\n  Final Model Performance:")
print(results_df)
```

```
 Final Model Performance:
                     Accuracy  Precision    Recall  F1-Score
Logistic Regression  0.676784   0.707057  0.736477  0.721467
Random Forest        0.749704   0.757170  0.823856  0.789107
XGBoost              0.754434   0.764023  0.821775  0.791848
SVM                  0.747734   0.757712  0.817614  0.786524
```

[93]:

```
fig = go.Figure()

colors = ['#636EFA', '#EF553B', '#00CC96', '#AB63FA']

for i, model in enumerate(results_df.columns):
    fig.add_trace(go.Bar(
        x=results_df.index,
        y=results_df[model],
        text= results_df[model].round(3),
        name=model,
        marker_color=colors[i]
    ))

fig.update_layout(
    title="Model Performance Comparison  ",
    xaxis_title="Evaluation Metrics",
    yaxis_title="Score",
```

```
    template="plotly_dark",
    barmode='group',
    legend_title="Models",
    height = 500,
    width = 700
)

fig.show()
```



[80]:
```
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder

education_levels = ['Some college - no degree', 'Bachelors degree', 'Associates␣
↪degree', 'High School Graduate', 'Graduate degree (Masters or Doctorate)',␣
↪'Some High School']
marital_status_levels = ['Unmarried partner', 'Single', 'Married partner',␣
↪'Divorced','Widowed']

num_features = ['temperature', 'age', 'toCoupon_GEQ5min', 'toCoupon_GEQ15min',␣
↪'toCoupon_GEQ25min']
cat_nominal_features = ['destination', 'passanger', 'weather', 'coupon',␣
↪'expiration', 'gender', 'occupation', 'income',
                        'Bar', 'CoffeeHouse', 'CarryAway',␣
↪'RestaurantLessThan20', 'Restaurant20To50']
cat_ordinal_features = ['maritalStatus', 'education']

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), num_features),
```

```
        ('cat_nominal', OneHotEncoder(handle_unknown='ignore'),␣
 ↪cat_nominal_features),
        ('cat_ordinal', OrdinalEncoder(categories=[marital_status_levels,␣
 ↪education_levels]), cat_ordinal_features)
    ])


X = preprocessor.fit_transform(df)

print("Processed Data Shape:", X.shape)
```

```
Processed Data Shape: (12684, 85)
```

[82]:
```
y = df['Accept(Y/N?)'].astype(int)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪stratify=y, random_state=42)
```

[84]:
```
smote = SMOTE(sampling_strategy=0.85, random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

[85]:
```
baseline_model = XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='logloss')
baseline_model.fit(X_train_resampled,y_train_resampled)

y_pred_baseline = baseline_model.predict(X_test)
print("Baseline Model:")
print(classification_report(y_test, y_pred_baseline))
```

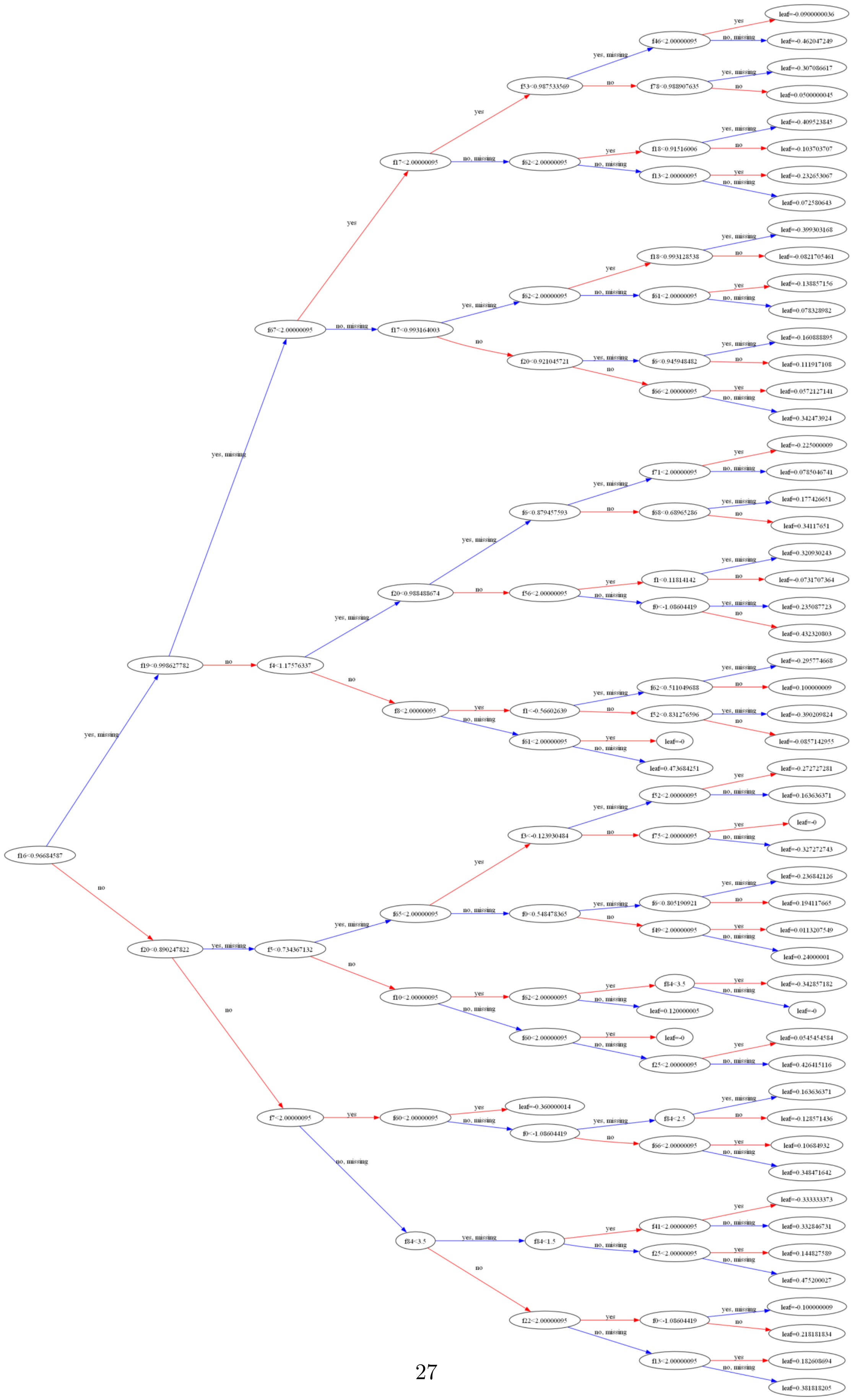
```
Baseline Model:
              precision    recall  f1-score   support

           0       0.73      0.66      0.70      1095
           1       0.76      0.82      0.79      1442

    accuracy                           0.75      2537
   macro avg       0.75      0.74      0.74      2537
weighted avg       0.75      0.75      0.75      2537
```

[107]:
```
from xgboost import plot_tree

num_trees = baseline_model.get_booster().best_iteration + 1 if baseline_model.
 ↪get_booster().best_iteration is not None else baseline_model.get_booster().
 ↪num_boosted_rounds()

dump = baseline_model.get_booster().get_dump(with_stats=True)
tree_depths = []
```

```python
for tree in dump:
    lines = tree.split('\n')
    max_depth = max([line.count('\t') for line in lines if line.strip() != ''])
    tree_depths.append(max_depth)

print(f"Number of trees: {len(tree_depths)}")
print(f"Max depth across all trees: {max(tree_depths)}")
print(f"Average depth: {sum(tree_depths)/len(tree_depths):.2f}")
```

```
Number of trees: 100
Max depth across all trees: 6
Average depth: 6.00
```

[115]:
```python
import os
os.environ["PATH"] += os.pathsep + 'C:\\Program Files\\Graphviz\\bin'

import matplotlib.pyplot as plt
from xgboost import plot_tree

fig, ax = plt.subplots(figsize=(60, 30))
plot_tree(baseline_model, num_trees=0, ax=ax, rankdir='LR')
fig.savefig("tree_visualization.png", dpi=300, bbox_inches='tight')
```



[117]:
```
from sklearn.model_selection import GridSearchCV
param_grid = {
    'max_depth': [3, 4, 5, 6, 7, 8, 10],
    'min_child_weight': [1, 3, 5]
}


grid_search = GridSearchCV(
    estimator=XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='logloss'),
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    verbose=1
)

grid_search.fit(X_train_resampled,y_train_resampled)
print("Best parameters:", grid_search.best_params_)
```

```
Fitting 3 folds for each of 21 candidates, totalling 63 fits
Best parameters: {'max_depth': 8, 'min_child_weight': 3}
```

[121]:
```
param_grid = {'gamma': [0, 0.2, 0.4, 0.6, 0.8]}

grid_search = GridSearchCV(
    estimator=XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='logloss',
                             max_depth=8,
                             min_child_weight=3),
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    verbose=1
)

grid_search.fit(X_train_resampled,y_train_resampled)
print("Best parameters:", grid_search.best_params_)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Best parameters: {'gamma': 0.4}
```

[125]:
```
param_grid = {
    'subsample': [0.8, 1.0, 1.2, 1.4, 1.6],
    'colsample_bytree': [0.6, 0.8, 1.0, 1.2, 1.4, 1.6]
}
```

```
grid_search = GridSearchCV(
    estimator=XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='logloss',
                             max_depth=8,
                             min_child_weight=3,
                             gamma=0.4),
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    verbose=1
)

grid_search.fit(X_train_resampled,y_train_resampled)
print("Best parameters:", grid_search.best_params_)
```

```
Fitting 3 folds for each of 30 candidates, totalling 90 fits
Best parameters: {'colsample_bytree': 1.0, 'subsample': 1.0}
```

[127]:

```
param_grid = {
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'n_estimators': [100, 200, 300, 500]
}


grid_search = GridSearchCV(
    estimator=XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='logloss',
                             max_depth=8,
                             min_child_weight=3,
                             gamma=0.4,
                             subsample=1.0,
                             colsample_bytree=1.0),
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    verbose=1
)

grid_search.fit(X_train_resampled,y_train_resampled)
print("Best parameters:", grid_search.best_params_)
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
Best parameters: {'learning_rate': 0.1, 'n_estimators': 300}
```

[129]:

```
param_grid = {
    'scale_pos_weight': [5, 10, 15, 20, 25]
```

```
}

grid_search = GridSearchCV(
    estimator=XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='logloss',
                             max_depth=8,
                             min_child_weight=3,
                             gamma=0.4,
                             subsample=1.0,
                             colsample_bytree=1.0,
                             learning_rate = 0.1,
                             n_estimators=300
                         ),
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    verbose=1
)
grid_search.fit(X_train_resampled,y_train_resampled)

best_scale_pos_weight = grid_search.best_params_['scale_pos_weight']
print(f"Best scale_pos_weight: {best_scale_pos_weight}")
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Best scale_pos_weight: 5
```

[88]:
```
final_model = XGBClassifier(random_state=42,␣
 ↪use_label_encoder=False,eval_metric='logloss',
                            scale_pos_weight = 5,
                            max_depth=8,
                            min_child_weight=3,
                            gamma=0.4,
                            subsample=1.0,
                            colsample_bytree=1.0,
                            learning_rate = 0.1,
                            n_estimators=300
                           )
final_model.fit(X_train_resampled,y_train_resampled)
```

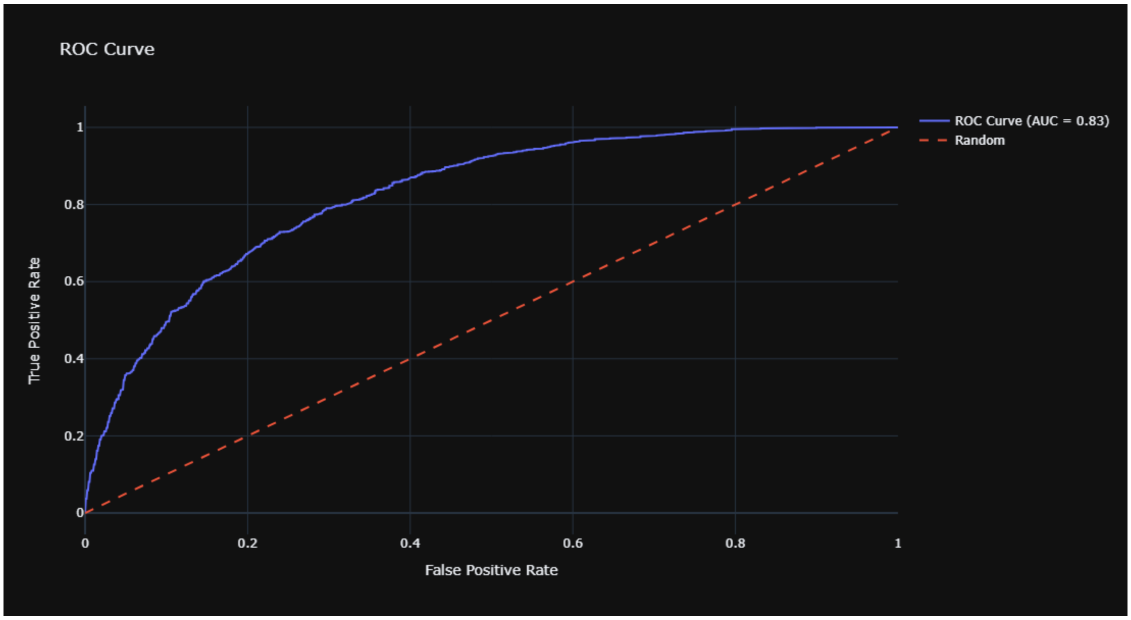
[88]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1.0,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric='logloss', gamma=0.4, gpu_id=-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.1, max_bin=256,
              max_cat_to_onehot=4, max_delta_step=0, max_depth=8, max_leaves=0,
              min_child_weight=3, missing=nan, monotone_constraints='()',
```

```
                n_estimators=300, n_jobs=0, num_parallel_tree=1, predictor='auto',
                random_state=42, reg_alpha=0, reg_lambda=1, …)
```

[90]:

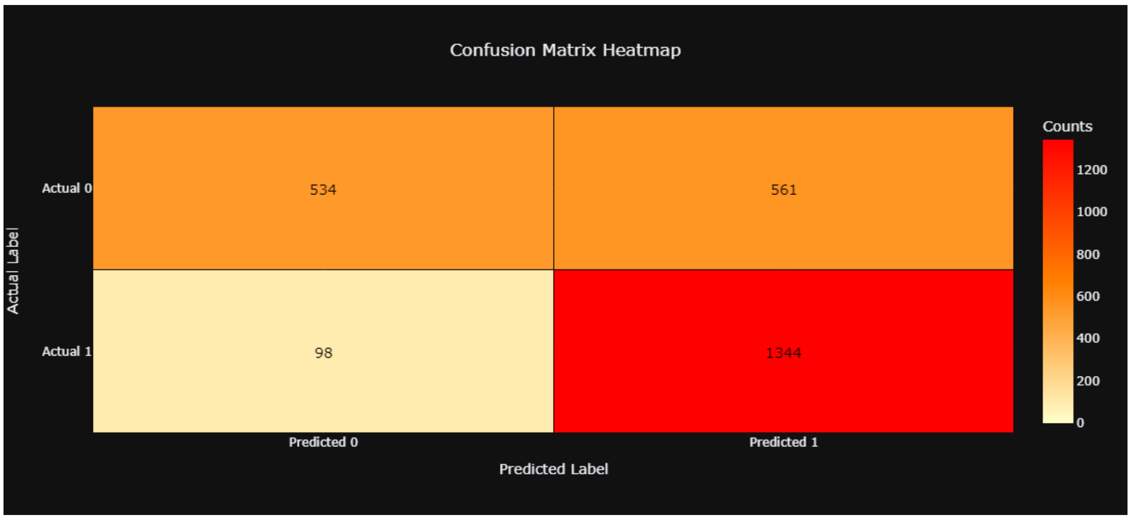
```python
y_pred = final_model.predict(X_test)
y_pred_prob = final_model.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)

fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

fig = go.Figure()
fig.add_trace(go.Scatter(x=fpr, y=tpr, mode='lines', name=f'ROC Curve (AUC =␣
 ↪{roc_auc:.2f})'))
fig.add_trace(go.Scatter(x=[0, 1], y=[0, 1], mode='lines', name='Random',␣
 ↪line=dict(dash='dash')))
fig.update_layout(title='ROC Curve', xaxis_title='False Positive Rate',␣
 ↪yaxis_title='True Positive Rate',height=600,width=800,template="plotly_dark")
fig.show()
```

```
              precision    recall  f1-score   support

           0       0.84      0.49      0.62      1095
           1       0.71      0.93      0.80      1442

    accuracy                           0.74      2537
   macro avg       0.78      0.71      0.71      2537
weighted avg       0.77      0.74      0.72      2537

Confusion Matrix:
 [[ 534  561]
 [  98 1344]]
```



[92]:
```
cm = confusion_matrix(y_test, y_pred)
annotations = np.array([["{:.0f}".format(value) for value in row] for row in cm])

trace = go.Heatmap(
    z=cm,
    x=['Predicted 0', 'Predicted 1'],
    y=['Actual 0', 'Actual 1'],
    colorscale=[[0, 'rgb(255, 255, 204)'], [0.5, 'rgb(255, 128, 0)'], [1, 'rgb(255, 0, 0)']],
    zmin=0,
    xgap=1,
    ygap=1,
    zmax=cm.max(),
    colorbar=dict(title='Counts')
)

layout = go.Layout(
    title='Confusion Matrix Heatmap',
    title_x=0.5,
    xaxis=dict(title='Predicted Label'),
    yaxis=dict(title='Actual Label', autorange='reversed'),
    annotations=[
        dict(
            x=j,
            y=i,
            text=annotations[i][j],
```

```
                showarrow=False,
                font=dict(color='black', size=14)
            )
            for i in range(cm.shape[0])
            for j in range(cm.shape[1])
        ]
)

fig = go.Figure(data=[trace], layout=layout)
fig.update_layout(height=500,width=500,template="plotly_dark")
fig.show()
```



[94]:
```
y_probs = final_model.predict_proba(X_test)[:, 1]

# Try a lower threshold (e.g., 0.4)
threshold = 0.4
y_pred_thresh = (y_probs >= threshold).astype(int)


print(f"=== Evaluation at Threshold = {threshold} ===")
print(classification_report(y_test, y_pred_thresh))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_thresh))
```

```
=== Evaluation at Threshold = 0.4 ===
              precision    recall  f1-score   support

           0       0.87      0.42      0.57      1095
           1       0.68      0.95      0.80      1442

    accuracy                           0.72      2537
```

```
   macro avg       0.78      0.69      0.68      2537
weighted avg       0.77      0.72      0.70      2537

Confusion Matrix:
 [[ 462  633]
 [  68 1374]]
```

[98]:

```python
from sklearn.model_selection import GridSearchCV
param_grid = {
    'max_depth': [7, 8, 9, 10],
    'scale_pos_weight': [1, 2, 3, 4, 5, 6]
}

grid_search = GridSearchCV(
    estimator=XGBClassifier(
        random_state=42,
        use_label_encoder=False,
        eval_metric='logloss',
        min_child_weight=3,
        gamma=0.4,
        subsample=1.0,
        colsample_bytree=1.0,
        learning_rate=0.1,
        n_estimators=300
    ),
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    verbose=1,
    n_jobs=-1
)

grid_search.fit(X_train_resampled, y_train_resampled)

print("Best Parameters:", grid_search.best_params_)
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Best Parameters: {'max_depth': 9, 'scale_pos_weight': 3}
```

[145]:

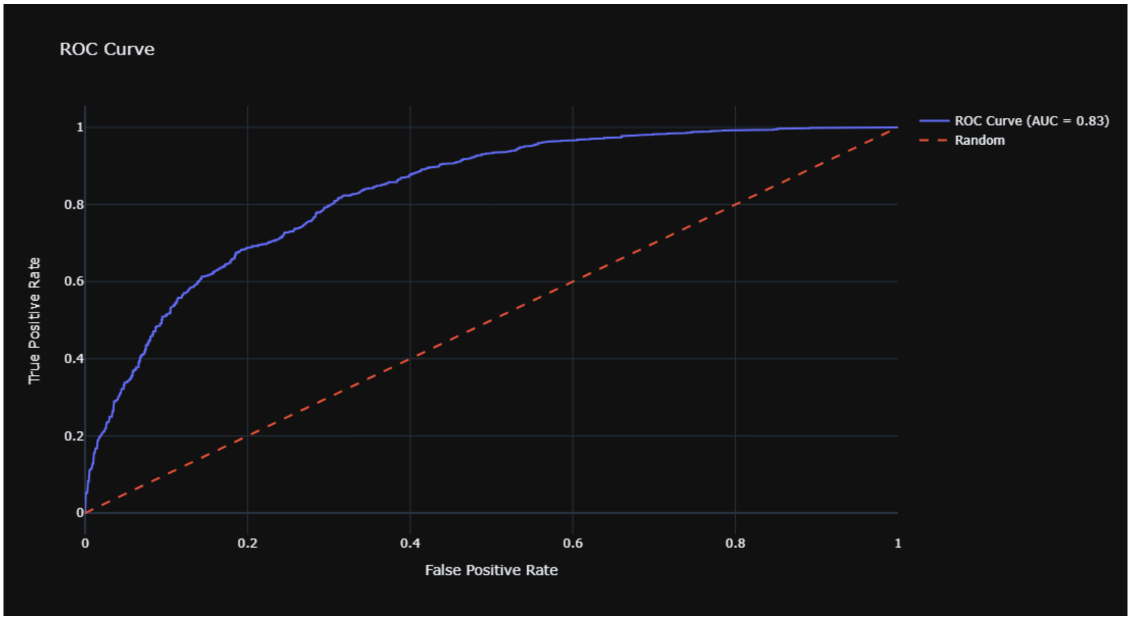
```python
final_model_new = XGBClassifier(random_state=42,␣
 ↪use_label_encoder=False,eval_metric='logloss',
                            scale_pos_weight = 3,
                            max_depth=9,
                            min_child_weight=3,
                            gamma=0.4,
                            subsample=1.0,
                            colsample_bytree=1.0,
                            learning_rate = 0.1,
```

```
                              n_estimators=300
                             )
final_model_new.fit(X_train_resampled,y_train_resampled)
```

[145]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1.0,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric='logloss', gamma=0.4, gpu_id=-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.1, max_bin=256,
              max_cat_to_onehot=4, max_delta_step=0, max_depth=9, max_leaves=0,
              min_child_weight=3, missing=nan, monotone_constraints='()',
              n_estimators=300, n_jobs=0, num_parallel_tree=1, predictor='auto',
              random_state=42, reg_alpha=0, reg_lambda=1, …)
```

[147]:
```
y_pred = final_model_new.predict(X_test)
y_pred_prob = final_model_new.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)

fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

fig = go.Figure()
fig.add_trace(go.Scatter(x=fpr, y=tpr, mode='lines', name=f'ROC Curve (AUC =␣
 ↪{roc_auc:.2f})'))
fig.add_trace(go.Scatter(x=[0, 1], y=[0, 1], mode='lines', name='Random',␣
 ↪line=dict(dash='dash')))
fig.update_layout(title='ROC Curve', xaxis_title='False Positive Rate',␣
 ↪yaxis_title='True Positive Rate',height=600,width=800,template="plotly_dark")
fig.show()
```

```
              precision    recall  f1-score   support

           0       0.81      0.56      0.66      1095
           1       0.73      0.90      0.81      1442

    accuracy                           0.75      2537
   macro avg       0.77      0.73      0.74      2537
weighted avg       0.76      0.75      0.75      2537

Confusion Matrix:
 [[ 618  477]
 [ 146 1296]]
```



[149]:
```
y_probs = final_model_new.predict_proba(X_test)[:, 1]

for thresh in np.arange(0.3, 0.6, 0.05):
    y_pred_thresh = (y_probs >= thresh).astype(int)
    print(f"\nThreshold = {thresh:.2f}")
    print(classification_report(y_test, y_pred_thresh))
    print(confusion_matrix(y_test, y_pred_thresh))
```

```
Threshold = 0.30
              precision    recall  f1-score   support

           0       0.89      0.44      0.59      1095
           1       0.69      0.96      0.80      1442

    accuracy                           0.74      2537
   macro avg       0.79      0.70      0.70      2537
weighted avg       0.78      0.74      0.71      2537

[[ 485  610]
 [  61 1381]]

Threshold = 0.35
              precision    recall  f1-score   support

           0       0.86      0.47      0.61      1095
           1       0.70      0.94      0.80      1442
```

```
    accuracy                           0.74      2537
   macro avg       0.78      0.71      0.71      2537
weighted avg       0.77      0.74      0.72      2537

[[ 515  580]
 [  84 1358]]

Threshold = 0.40
              precision    recall  f1-score   support

           0       0.85      0.51      0.64      1095
           1       0.71      0.93      0.81      1442

    accuracy                           0.75      2537
   macro avg       0.78      0.72      0.72      2537
weighted avg       0.77      0.75      0.74      2537

[[ 560  535]
 [ 100 1342]]

Threshold = 0.45
              precision    recall  f1-score   support

           0       0.83      0.54      0.65      1095
           1       0.72      0.91      0.81      1442

    accuracy                           0.75      2537
   macro avg       0.77      0.73      0.73      2537
weighted avg       0.77      0.75      0.74      2537

[[ 588  507]
 [ 123 1319]]

Threshold = 0.50
              precision    recall  f1-score   support

           0       0.81      0.56      0.66      1095
           1       0.73      0.90      0.81      1442

    accuracy                           0.75      2537
   macro avg       0.77      0.73      0.74      2537
weighted avg       0.76      0.75      0.75      2537

[[ 618  477]
 [ 146 1296]]

Threshold = 0.55
```

```
              precision    recall  f1-score   support

           0       0.79      0.59      0.68      1095
           1       0.74      0.88      0.80      1442

    accuracy                           0.76      2537
   macro avg       0.77      0.74      0.74      2537
weighted avg       0.76      0.76      0.75      2537

[[ 651  444]
 [ 173 1269]]
```

0.5 Model Deployement

[239]:
```
final_threshold = 0.45

import joblib

joblib.dump(final_model_new, "xgb_coupon_model.pkl")

with open("threshold.txt", "w") as f:
    f.write(str(final_threshold))
```

[241]:
```
new_data = pd.DataFrame({
    'destination': ['No Urgent Place', 'Work', 'Home', 'Work', 'No Urgent␣
 ↪Place',
                    'Work', 'Home', 'No Urgent Place', 'Work', 'Home'],
    'passanger': ['Alone', 'Friend(s)', 'Partner', 'Kid(s)', 'Alone',
                  'Partner', 'Alone', 'Friend(s)', 'Kid(s)', 'Partner'],
    'weather': ['Sunny', 'Rainy', 'Snowy', 'Sunny', 'Rainy',
                'Snowy', 'Sunny', 'Rainy', 'Snowy', 'Sunny'],
    'temperature': [60, 75, 40, 55, 80, 33, 45, 70, 85, 65],
    'coupon': ['Coffee House', 'Restaurant(<20)', 'Carry out & Take away',␣
 ↪'Bar', 'Restaurant(20-50)',
               'Coffee House', 'Bar', 'Carry out & Take away',␣
 ↪'Restaurant(20-50)', 'Restaurant(<20)'],
    'expiration': ['2h', '1d', '2h', '2h', '1d',
                   '2h', '1d', '1d', '2h', '2h'],
    'gender': ['Female', 'Male', 'Female', 'Female', 'Male',
               'Female', 'Male', 'Female', 'Male', 'Male'],
    'age': [25, 30, 45, 22, 36, 52, 40, 28, 19, 33],
    'maritalStatus': ['Single', 'Married partner', 'Unmarried partner',␣
 ↪'Single', 'Divorced',
                      'Single', 'Widowed', 'Married partner', 'Single',␣
 ↪'Unmarried partner'],
    'has_children': [0, 1, 1, 0, 1, 0, 1, 0, 0, 1],
```

```
    'education': ['Bachelors degree', 'Some college - no degree', 'Graduate␣
↪degree (Masters or Doctorate)',
                  'High School Graduate', 'Associates degree', 'Some High␣
↪School',
                  'Bachelors degree', 'Some college - no degree', 'Graduate␣
↪degree (Masters or Doctorate)',
                  'High School Graduate'],
    'occupation': ['Unemployed', 'Student', 'Professional', 'Executive',␣
↪'Military',
                   'Unemployed', 'Retired', 'Student', 'Executive',␣
↪'Professional'],
    'income': ['$12500 - $24999', '$25000 - $37499', '$37500 - $49999', '$50000␣
↪- $62499',
               '$62500 - $74999', '$87500 - $99999', '$100000 or More', '$25000␣
↪- $37499',
               '$37500 - $49999', '$50000 - $62499'],
    'car': ['Scooter and motorcycle', 'Mazda', 'BMW', 'Ford', 'Toyota',
            'Other', 'None', 'Honda', 'Hyundai', 'Chevrolet'],
    'Bar': ['1~3', 'never', '4~8', '1~3', 'less1',
            'never', 'gt8', 'never', '1~3', 'less1'],
    'CoffeeHouse': ['4~8', '1~3', 'less1', 'never', 'never',
                    '1~3', 'never', '4~8', '1~3', 'never'],
    'CarryAway': ['1~3', 'less1', '1~3', '4~8', '1~3',
                  'less1', '4~8', 'never', '1~3', 'gt8'],
    'RestaurantLessThan20': ['1~3', '4~8', 'never', 'less1', 'less1',
                             '1~3', 'never', 'never', '1~3', '1~3'],
    'Restaurant20To50': ['never', '1~3', 'less1', 'never', 'never',
                         'never', 'never', '1~3', 'less1', 'less1'],
    'toCoupon_GEQ5min': [1, 1, 1, 0, 1, 1, 1, 1, 0, 1],
    'toCoupon_GEQ15min': [1, 1, 1, 1, 1, 0, 1, 1, 0, 1],
    'toCoupon_GEQ25min': [1, 1, 1, 1, 1, 1, 1, 1, 1, 0],
    'direction_same': [1, 0, 1, 0, 1, 0, 1, 0, 1, 0],
    'direction_opp': [0, 1, 0, 1, 0, 1, 0, 1, 0, 1]
})
```

[243]:
```
education_levels = ['Some college - no degree', 'Bachelors degree', 'Associates␣
↪degree',
                    'High School Graduate', 'Graduate degree (Masters or␣
↪Doctorate)',
                    'Some High School']
marital_status_levels = ['Unmarried partner', 'Single', 'Married partner',␣
↪'Divorced', 'Widowed']

num_features = ['temperature', 'age', 'toCoupon_GEQ5min', 'toCoupon_GEQ15min',␣
↪'toCoupon_GEQ25min']
```

```
cat_nominal_features = ['destination', 'passanger', 'weather', 'coupon',␣
↪'expiration', 'gender',
                        'occupation', 'income', 'Bar', 'CoffeeHouse',␣
↪'CarryAway',
                        'RestaurantLessThan20', 'Restaurant20To50']
cat_ordinal_features = ['maritalStatus', 'education']

# Build the preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), num_features),
        ('cat_nominal', OneHotEncoder(handle_unknown='ignore'),␣
↪cat_nominal_features),
        ('cat_ordinal', OrdinalEncoder(categories=[marital_status_levels,␣
↪education_levels]), cat_ordinal_features)
    ]
)

# Assume `df` is your original raw training DataFrame before preprocessing
preprocessor.fit(df)  # fit only on training data

# Save the fitted preprocessor
joblib.dump(preprocessor, "xgb_coupon_preprocessor.pkl")
```

[243]:
```
['xgb_coupon_preprocessor.pkl']
```

[245]:
```
model = joblib.load("xgb_coupon_model.pkl")
preprocessor = joblib.load("xgb_coupon_preprocessor.pkl")

with open("threshold.txt") as f:
    threshold = float(f.read())

processed_data = preprocessor.transform(new_data)


y_prob = model.predict_proba(processed_data)[:, 1]
y_pred = (y_prob >= threshold).astype(int)

print("Predicted Acceptance:", y_pred)
```

```
Predicted Acceptance: [1 1 1 1 0 0 1 1 0 1]
```

0.5.1 Wrap into a Function

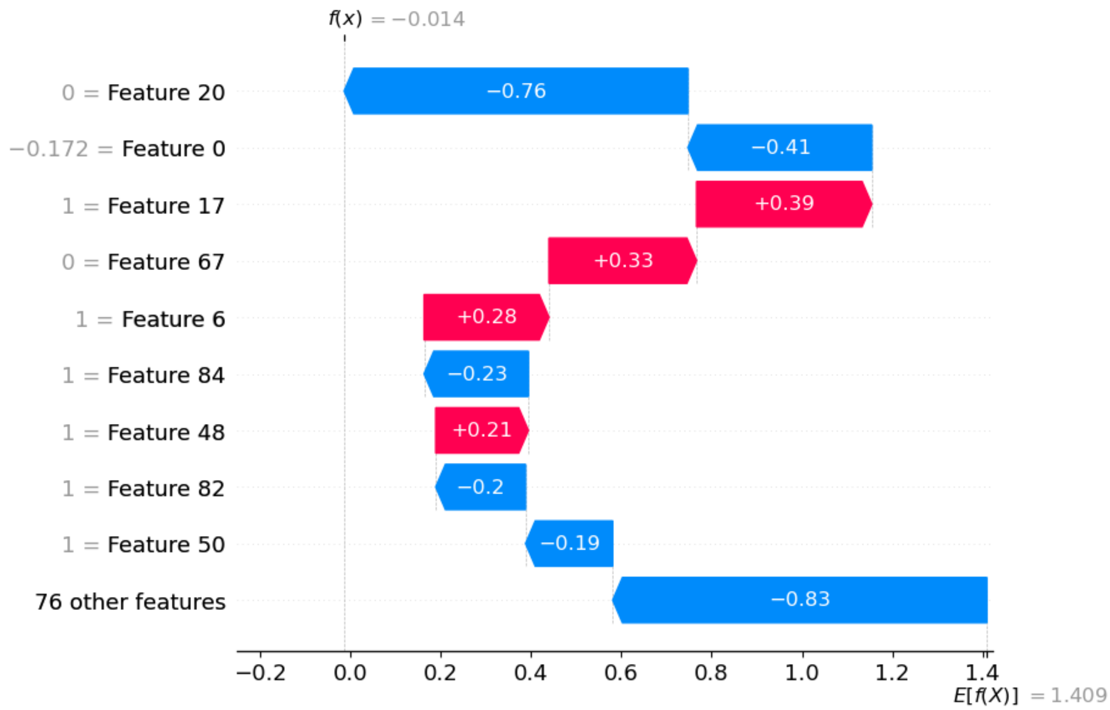
[253]:
```
def predict_coupon_acceptance(new_data):
    model = joblib.load("xgb_coupon_model.pkl")
    preprocessor = joblib.load("xgb_coupon_preprocessor.pkl")
```

```
    with open("threshold.txt") as f:
        threshold = float(f.read())


    processed = preprocessor.transform(new_data)


    y_prob = model.predict_proba(processed)[:, 1]
    y_pred = (y_prob >= threshold).astype(int)

    return y_pred
```

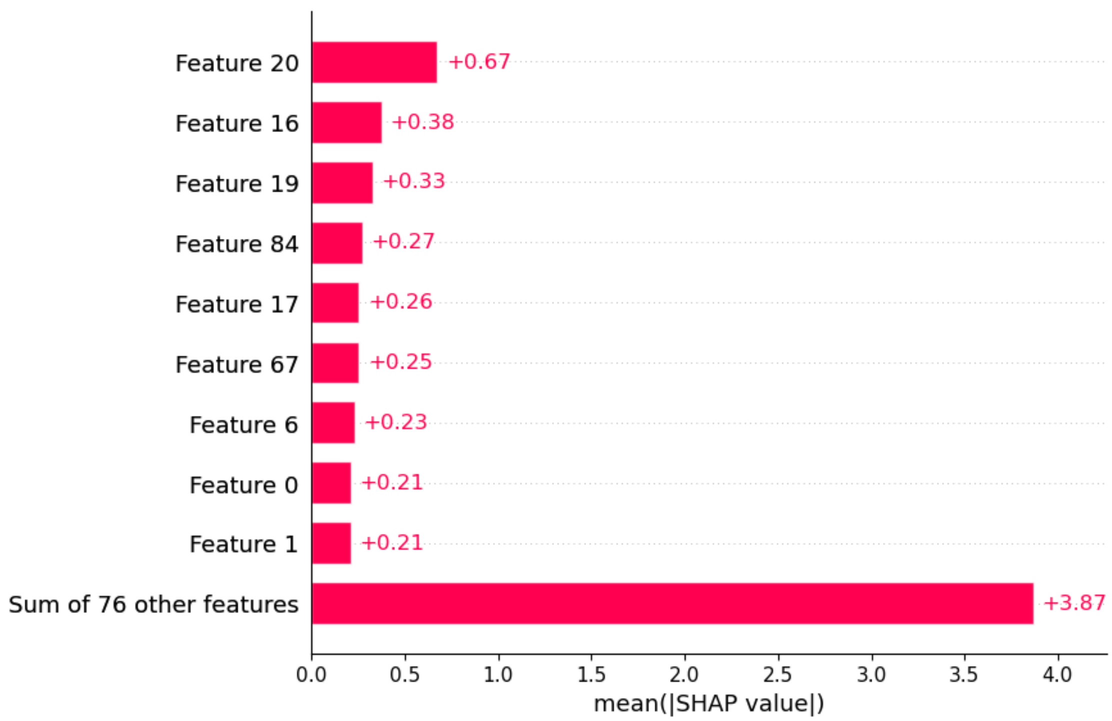
[255]:
```
preds = predict_coupon_acceptance(new_data)
new_data["PredictedAcceptance"] = preds
```

0.5.2 Explainability Using SHAP (Why the Model Predicts It)

[258]:
```
import shap

model = joblib.load("xgb_coupon_model.pkl")

processed = preprocessor.transform(new_data)

explainer = shap.Explainer(model)
shap_values = explainer(processed)

shap.plots.waterfall(shap_values[0])
```



[260]:
```
shap.plots.bar(shap_values)
```



0.5.3 Final Conclusion on Coupon Acceptance Prediction

1 Business Insights from EDA

- **Marital Status & Children**: Married individuals and those with children showed distinct spending behaviors.

- **Education Level & Coupon Acceptance**: Higher education levels correlated with increased coupon acceptance.

- **Occupation & Income Trends**: Professionals in higher-income jobs were more likely to accept coupons.

**** Feature Engineering & Selection****

- Performed **Chi-Square and Mutual Information tests** to retain only statistically significant features.

- Created additional features like **Frequent_Spender & Distance_Sensitive** to enhance model performance.

2 Model Training & Evaluation

- Applied **SMOTE** to balance class distribution.

- Used a **Pipeline approach with ColumnTransformer** for seamless preprocessing.

- Trained multiple models (**Logistic Regression, Random Forest, XGBoost, SVM**).

- XGBoost showed the **best performance** before tuning (F1-score = **0.7918**).

- Hyperparameter tuning via **GridSearchCV** further optimized XGBoost.

3 Final Model Performance (XGBoost - Tuned) **Overall Accuracy**: **76%**
Precision: **0.79 (class 0), 0.74 (class 1)**
Recall: **0.60 (class 0), 0.88 (class 1)**
F1-Score: **0.68 (class 0), 0.81 (class 1)**

4 Key Observations **High Recall for Class 1 (Coupon Accepted - 88%)**: The model effectively captures users who are likely to accept coupons.
Lower Recall for Class 0 (Coupon Rejected - 60%): Some non-acceptors are misclassified as acceptors.
Balanced Trade-off: Model performs well in identifying coupon acceptance behavior but slightly struggles in correctly predicting rejections.