Dataset uploading

```
from google.colab import files
uploaded = files.upload()
# prompt: handle missing values for an csv file in google colab

import pandas as pd

# Load the CSV file into a pandas DataFrame
df = pd.read_csv('customer.csv')
```

```
Choose files No file chosen  Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable
```

Handling Missing Values

```
# Check for missing values
print(df.isnull().sum())

# Fill missing values with mean for numerical columns
numerical_cols = df.select_dtypes(include=['number']).columns
df[numerical_cols] = df[numerical_cols].fillna(df[numerical_cols].mean())

# Fill missing values with mode for categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
df[categorical_cols] = df[categorical_cols].fillna(df[categorical_cols].mode().iloc[0])

# Verify if missing values are filled
print(df.isnull().sum())
```

```
Year                          0
Date                          0
Question_Number               0
Question                      0
Number_of_Respondents         0
Very_Satisfied                0
Satisfied                     0
Neutral                       0
Dissatisfied                  0
Very_Dissatisfied             0
Very_Satisfied_or_Satisfied   0
ObjectId                      0
dtype: int64
Year                          0
Date                          0
Question_Number               0
Question                      0
Number_of_Respondents         0
Very_Satisfied                0
Satisfied                     0
Neutral                       0
Dissatisfied                  0
Very_Dissatisfied             0
Very_Satisfied_or_Satisfied   0
ObjectId                      0
dtype: int64
```

Duplicate records

```
# Check for duplicate rows
duplicate_rows = df[df.duplicated()]

# Print the duplicate rows
print("Duplicate Rows:")
print(duplicate_rows)

# Remove duplicate rows
df = df.drop_duplicates()

# Print the DataFrame after removing duplicates
print("\nDataFrame after removing duplicates:")
```

```
df
```

```
Duplicate Rows:
Empty DataFrame
Columns: [Year, Date, Question_Number, Question, Number_of_Respondents, Very_Satisfied, Satisfied, Neutral, Dissatisfied, Very_Dissa
Index: []

DataFrame after removing duplicates:
```

	Year	Date	Question_Number	Question	Number_of_Respondents	Very_Satisfied	Satisfied	Neutral	Dissatisfied	Very_Dis
0	2017	2017/10/31 07:00:00+00	7-13	Overall quality of customer service	882	22.16	47.61	25.03	3.15	
1	2016	2016/10/31 07:00:00+00	26	Overall quality of customer service	1202	22.39	47.83	23.37	4.35	
2	2015	2015/10/31 07:00:00+00	Survey Not Conducted	Survey Not Conducted	99999	99999.00	99999.00	99999.00	99999.00	
3	2014	2014/10/31 07:00:00+00	10b	How easy was the City to contact	493	35.95	46.07	8.26	7.44	
4	2014	2014/10/31 07:00:00+00	10c	The way you were treated	493	44.15	40.25	8.83	4.72	
5	2014	2014/10/31 07:00:00+00	10d	The accuracy of the information you were given	493	36.76	40.55	14.08	6.51	
6	2014	2014/10/31 07:00:00+00	10e	How quickly staff responded to your request	493	38.05	37.63	13.10	7.69	
7	2014	2014/10/31 07:00:00+00	10f	How well your issue was handled	493	37.92	34.58	12.50	8.96	
8	2013	2013/10/31 07:00:00+00	14b	How easy was the City to contact	428	37.68	44.31	8.06	7.58	
9	2013	2013/10/31 07:00:00+00	14c	The way you were treated	428	44.47	40.14	8.17	4.09	
				The accuracy						

Outliers

```
import pandas as pd
import numpy as np

# Assuming 'df' is your DataFrame with numerical features

def find_outliers_iqr(data):
    Q1 = np.percentile(data, 25)
    Q3 = np.percentile(data, 75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[(data < lower_bound) | (data > upper_bound)]
    return outliers


numerical_features = df.select_dtypes(include=np.number).columns
for col in numerical_features:
    outliers = find_outliers_iqr(df[col])
    print(f"Outliers in {col}:")
    print(outliers)
    print("-" * 20)
```

```
Outliers in Year:
Series([], Name: Year, dtype: int64)
--------------------
Outliers in Number_of_Respondents:
0      882
1     1202
2    99999
Name: Number_of_Respondents, dtype: int64
--------------------
Outliers in Very_Satisfied:
0       22.16
1       22.39
2    99999.00
Name: Very_Satisfied, dtype: float64
--------------------
Outliers in Satisfied:
2    99999.0
Name: Satisfied, dtype: float64
--------------------
Outliers in Neutral:
0       25.03
1       23.37
2    99999.00
Name: Neutral, dtype: float64
--------------------
Outliers in Dissatisfied:
2    99999.0
Name: Dissatisfied, dtype: float64
--------------------
Outliers in Very_Dissatisfied:
2    99999.0
Name: Very_Dissatisfied, dtype: float64
--------------------
Outliers in Very_Satisfied_or_Satisfied:
2    99999.0
Name: Very_Satisfied_or_Satisfied, dtype: float64
--------------------
Outliers in ObjectId:
Series([], Name: ObjectId, dtype: int64)
--------------------
```

Standardization

```
from sklearn.preprocessing import StandardScaler

# Assuming 'df' is your DataFrame with numerical features

# Create a StandardScaler object
scaler = StandardScaler()

# Select numerical columns for standardization
numerical_cols = df.select_dtypes(include=np.number).columns

# Fit and transform the numerical columns
df[numerical_cols] = scaler.fit_transform(df[numerical_cols])

# Print the standardized DataFrame
print("\nStandardized DataFrame:")
df
```

Standardized DataFrame:

	Year	Date	Question_Number	Question	Number_of_Respondents	Very_Satisfied	Satisfied	Neutral	Dissatisfied	Very
0	2.483682	2017/10/31 07:00:00+00	7-13	Overall quality of customer service	-0.170565	-0.193284	-0.192013	-0.191776	-0.192621	
1	1.940376	2016/10/31 07:00:00+00	26	Overall quality of customer service	-0.153239	-0.193271	-0.192001	-0.191865	-0.192557	
2	1.397071	2015/10/31 07:00:00+00	Survey Not Conducted	Survey Not Conducted	5.195945	5.196152	5.196152	5.196152	5.196152	
3	0.853766	2014/10/31 07:00:00+00	10b	How easy was the City to contact	-0.191626	-0.192540	-0.192096	-0.192679	-0.192390	
4	0.853766	2014/10/31 07:00:00+00	10c	The way you were treated	-0.191626	-0.192098	-0.192409	-0.192649	-0.192537	
5	0.853766	2014/10/31 07:00:00+00	10d	The accuracy of the information you were given	-0.191626	-0.192497	-0.192393	-0.192366	-0.192440	
6	0.853766	2014/10/31 07:00:00+00	10e	How quickly staff responded to your request	-0.191626	-0.192427	-0.192551	-0.192419	-0.192377	
7	0.853766	2014/10/31 07:00:00+00	10f	How well your issue was handled	-0.191626	-0.192434	-0.192715	-0.192451	-0.192308	
8	0.310460	2013/10/31 07:00:00+00	14b	How easy was the City to contact	-0.195146	-0.192447	-0.192190	-0.192690	-0.192382	
9	0.310460	2013/10/31 07:00:00+00	14c	The way you were treated	-0.195146	-0.192081	-0.192415	-0.192684	-0.192571	
				The accuracy						

EDA

```
import matplotlib.pyplot as plt
import seaborn as sns

# Univariate Analysis

# Histograms for numerical features
for col in numerical_features:
    plt.figure(figsize=(8, 6))
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.show()

# Box plots for numerical features
for col in numerical_features:
    plt.figure(figsize=(8, 6))
    sns.boxplot(df[col])
    plt.title(f'Box Plot of {col}')
    plt.ylabel(col)
    plt.show()

# Count plots for categorical features
for col in categorical_cols:
```

```
    plt.figure(figsize=(8, 6))
    sns.countplot(x=col, data=df)
    plt.title(f'Count Plot of {col}')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.xticks(rotation=45, ha='right') # Rotate x-axis labels for better readability
    plt.show()


# Bivariate Analysis

# Scatter plots for numerical features
for col1 in numerical_features:
    for col2 in numerical_features:
        if col1 != col2:
            plt.figure(figsize=(8, 6))
            sns.scatterplot(x=col1, y=col2, data=df)
            plt.title(f'Scatter Plot of {col1} vs {col2}')
            plt.xlabel(col1)
            plt.ylabel(col2)
            plt.show()

# Correlation Heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(df[numerical_cols].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap of Numerical Features')
plt.show()

# Box plots for numerical features grouped by a categorical feature
for col in numerical_features:
  for cat_col in categorical_cols:
    plt.figure(figsize=(10,6))
    sns.boxplot(x = cat_col, y = col, data=df)
    plt.title(f"Box plot of {col} grouped by {cat_col}")
    plt.show()
```

Show hidden output

Feature Engineering

```
from sklearn.preprocessing import StandardScaler


# Create a StandardScaler object
scaler = StandardScaler()

# Select numerical columns for standardization
numerical_cols = df.select_dtypes(include=np.number).columns

# Fit and transform the numerical columns
# Instead of directly assigning to df[numerical_cols], create a new DataFrame
scaled_data = scaler.fit_transform(df[numerical_cols])
scaled_df = pd.DataFrame(scaled_data, columns=numerical_cols, index=df.index)

# Update the original DataFrame with the scaled values
df[numerical_cols] = scaled_df[numerical_cols]


# Print the standardized DataFrame
print("\nStandardized DataFrame:")
df
```

Standardized DataFrame:

	Year	Date	Question_Number	Question	Number_of_Respondents	Very_Satisfied	Satisfied	Neutral	Dissatisfied	Very
0	2.483682	2017/10/31 07:00:00+00	7-13	Overall quality of customer service	-0.170565	-0.193284	-0.192013	-0.191776	-0.192621	
1	1.940376	2016/10/31 07:00:00+00	26	Overall quality of customer service	-0.153239	-0.193271	-0.192001	-0.191865	-0.192557	
2	1.397071	2015/10/31 07:00:00+00	Survey Not Conducted	Survey Not Conducted	5.195945	5.196152	5.196152	5.196152	5.196152	
3	0.853766	2014/10/31 07:00:00+00	10b	How easy was the City to contact	-0.191626	-0.192540	-0.192096	-0.192679	-0.192390	
4	0.853766	2014/10/31 07:00:00+00	10c	The way you were treated	-0.191626	-0.192098	-0.192409	-0.192649	-0.192537	
5	0.853766	2014/10/31 07:00:00+00	10d	The accuracy of the information you were given	-0.191626	-0.192497	-0.192393	-0.192366	-0.192440	
6	0.853766	2014/10/31 07:00:00+00	10e	How quickly staff responded to your request	-0.191626	-0.192427	-0.192551	-0.192419	-0.192377	
7	0.853766	2014/10/31 07:00:00+00	10f	How well your issue was handled	-0.191626	-0.192434	-0.192715	-0.192451	-0.192308	
8	0.310460	2013/10/31 07:00:00+00	14b	How easy was the City to contact	-0.195146	-0.192447	-0.192190	-0.192690	-0.192382	
9	0.310460	2013/10/31 07:00:00+00	14c	The way you were treated	-0.195146	-0.192081	-0.192415	-0.192684	-0.192571	
				The accuracy						

Model Building

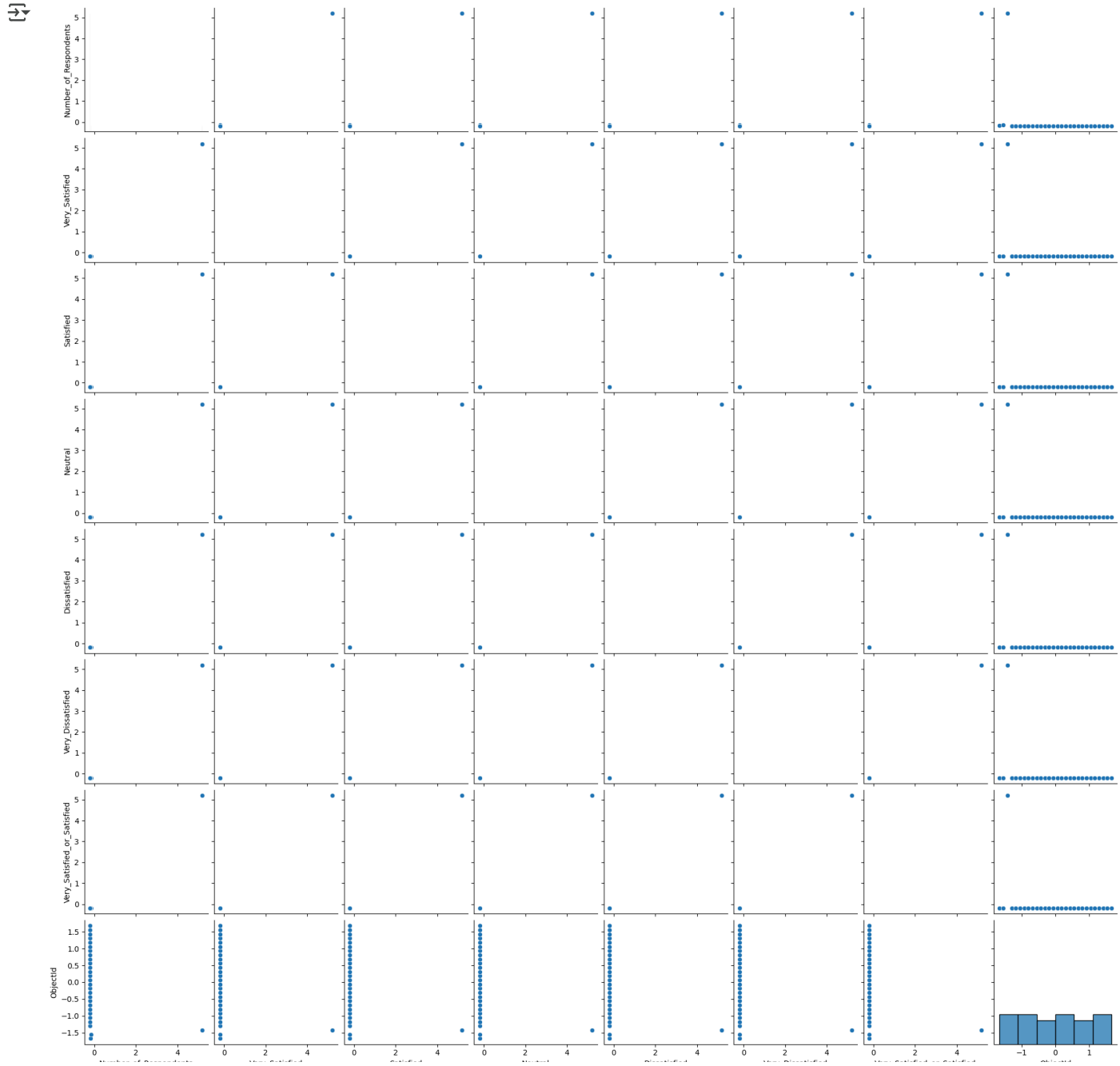
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Assuming your target variable is 'Exited'
# Check if 'Exited' column exists in the DataFrame
if 'Exited' not in df.columns:
    # If not found, print an error message and stop
    print("Error: 'Exited' column not found in the DataFrame.")
    # You might need to investigate why 'Exited' is missing and fix it
    # For example, if it's a typo, correct the column name
    # Or if it's missing from the data, you need to add it
else:
    X = df.drop('Exited', axis=1)
    y = df['Exited']

    # Convert categorical features to numerical using one-hot encoding
    X = pd.get_dummies(X, drop_first=True)

    # Split data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Initialize and train a Logistic Regression model
    model = LogisticRegression()
```

```
    model.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = model.predict(X_test)

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

    print(classification_report(y_test, y_pred))
    print(confusion_matrix(y_test, y_pred))
```

```
Error: 'Exited' column not found in the DataFrame.
```

Visualization

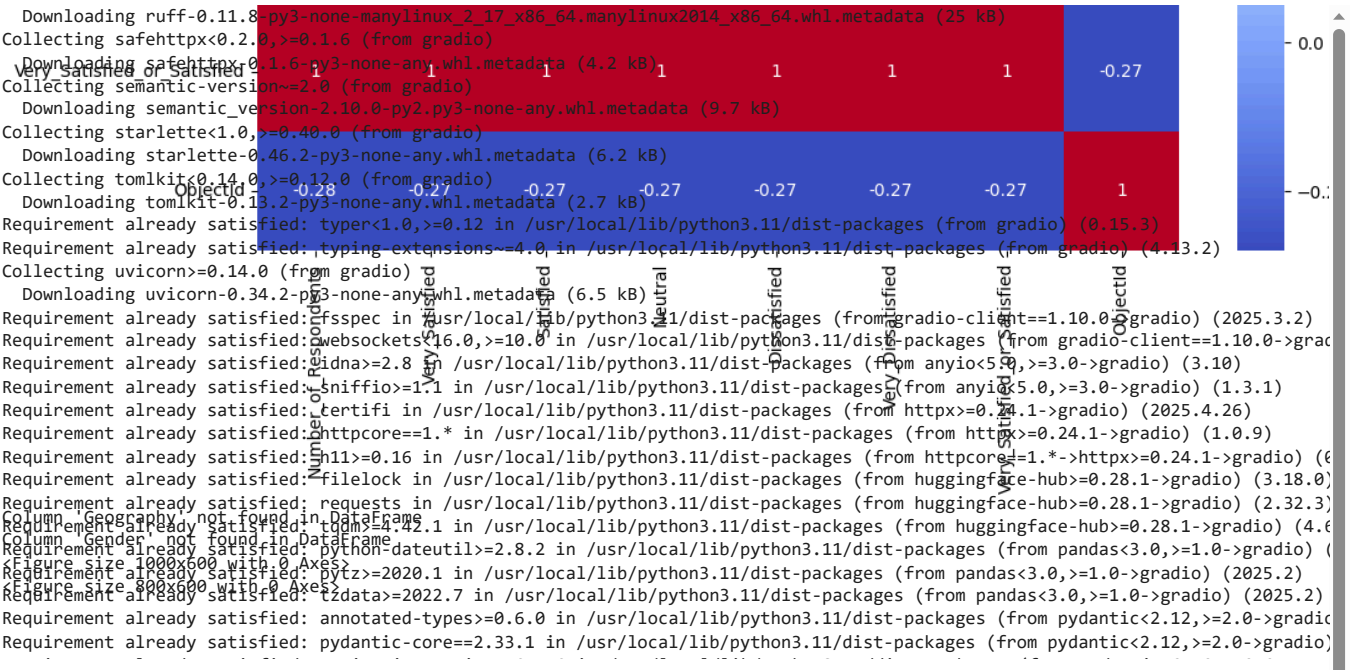
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

# Assuming 'df' is your DataFrame (loaded from customer.csv as in your code)

# Convert 'Year' column to datetime objects
# df['Year'] = pd.to_datetime(df['Year'])  # Assuming 'Year' is the problematic column

# Extract numerical features for correlation
numerical_features = df.select_dtypes(include=np.number).columns

# Example 1: Pairplot for numerical features
sns.pairplot(df[numerical_features])
plt.show()


# Example 2: Correlation heatmap for numerical features only
plt.figure(figsize=(12, 10))
sns.heatmap(df[numerical_features].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()

# Example 3: Boxplot for a specific numerical feature grouped by a categorical feature
plt.figure(figsize=(10, 6))
# Check if 'Geography' is in the columns before plotting
if 'Geography' in df.columns:
    sns.boxplot(x='Geography', y='CreditScore', data=df)  # Replace 'Geography' and 'CreditScore' as needed
    plt.title("CreditScore Distribution by Geography")
    plt.show()
else:
    print("Column 'Geography' not found in DataFrame")

# Example 4: Countplot for a categorical feature
plt.figure(figsize=(8, 6))
# Check if 'Gender' is in the columns before plotting
if 'Gender' in df.columns:
    sns.countplot(x='Gender', data=df) # Replace 'Gender' as needed
    plt.title("Count of Gender")
    plt.show()
else:
    print("Column 'Gender' not found in DataFrame")
```




```
pip install gradio
```

```
Collecting gradio
  Downloading gradio-5.29.0-py3-none-any.whl.metadata (16 kB)
Collecting aiofiles<25.0,>=22.0 (from gradio)
  Downloading aiofiles-24.1.0-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: anyio<5.0,>=3.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (4.9.0)
Collecting fastapi<1.0,>=0.115.2 (from gradio)
  Downloading fastapi-0.115.12-py3-none-any.whl.metadata (27 kB)
Collecting ffmpy (from gradio)
  Downloading ffmpy-0.5.0-py3-none-any.whl.metadata (3.0 kB)
Collecting gradio-client==1.10.0 (from gradio)
  Downloading gradio_client-1.10.0-py3-none-any.whl.metadata (7.1 kB)
Collecting groovy~=0.1 (from gradio)
  Downloading groovy-0.1.2-py3-none-any.whl.metadata (6.1 kB)
Requirement already satisfied: httpx>=0.24.1 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.28.1)
Requirement already satisfied: huggingface-hub>=0.28.1 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.30.2)
Requirement already satisfied: jinja2<4.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.1.6)
Requirement already satisfied: markupsafe<4.0,>=2.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.0.2)
Requirement already satisfied: numpy<3.0,>=1.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.0.2)
Requirement already satisfied: orjson~=3.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.10.17)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from gradio) (24.2)
Requirement already satisfied: pandas<3.0,>=1.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.2.2)
Requirement already satisfied: pillow<12.0,>=8.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (11.2.1)
Requirement already satisfied: pydantic<2.12,>=2.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.11.3)
Collecting pydub (from gradio)
  Downloading pydub-0.25.1-py2.py3-none-any.whl.metadata (1.4 kB)
Collecting python-multipart>=0.0.18 (from gradio)
  Downloading python_multipart-0.0.20-py3-none-any.whl.metadata (1.8 kB)
Requirement already satisfied: pyyaml<7.0,>=5.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (6.0.2)
Collecting ruff>=0.9.3 (from gradio)
```

```
  Downloading ruff-0.11.8-py3-none-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (25 kB)
Collecting safehttpx<0.2.0,>=0.1.6 (from gradio)
  Downloading safehttpx-0.1.6-py3-none-any.whl.metadata (4.2 kB)
Collecting semantic-version~=2.0 (from gradio)
  Downloading semantic_version-2.10.0-py2.py3-none-any.whl.metadata (9.7 kB)
Collecting starlette<1.0,>=0.40.0 (from gradio)
  Downloading starlette-0.46.2-py3-none-any.whl.metadata (6.2 kB)
Collecting tomlkit<0.14.0,>=0.12.0 (from gradio)
  Downloading tomlkit-0.13.2-py3-none-any.whl.metadata (2.7 kB)
Requirement already satisfied: typer<1.0,>=0.12 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.15.3)
Requirement already satisfied: typing-extensions~=4.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (4.13.2)
Collecting uvicorn>=0.14.0 (from gradio)
  Downloading uvicorn-0.34.2-py3-none-any.whl.metadata (6.5 kB)
Requirement already satisfied: fsspec in /usr/local/lib/python3.11/dist-packages (from gradio-client==1.10.0->gradio) (2025.3.2)
Requirement already satisfied: websockets<16.0,>=10.0 in /usr/local/lib/python3.11/dist-packages (from gradio-client==1.10.0->grad
Requirement already satisfied: idna>=2.8 in /usr/local/lib/python3.11/dist-packages (from anyio<5.0,>=3.0->gradio) (3.10)
Requirement already satisfied: sniffio>=1.1 in /usr/local/lib/python3.11/dist-packages (from anyio<5.0,>=3.0->gradio) (1.3.1)
Requirement already satisfied: certifi in /usr/local/lib/python3.11/dist-packages (from httpx>=0.24.1->gradio) (2025.4.26)
Requirement already satisfied: httpcore==1.* in /usr/local/lib/python3.11/dist-packages (from httpx>=0.24.1->gradio) (1.0.9)
Requirement already satisfied: h11>=0.16 in /usr/local/lib/python3.11/dist-packages (from httpcore==1.*->httpx>=0.24.1->gradio) (0
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.28.1->gradio) (3.18.0)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.28.1->gradio) (2.32.3)
Requirement already satisfied: tqdm>=4.42.1 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.28.1->gradio) (4.6
Column 'Gender' not found in DataFrame
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas<3.0,>=1.0->gradio) (
<Figure size 1000x600 with 0 Axes>
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas<3.0,>=1.0->gradio) (2025.2)
<Figure size 800x600 with 0 Axes>
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas<3.0,>=1.0->gradio) (2025.2)
Requirement already satisfied: annotated-types>=0.6.0 in /usr/local/lib/python3.11/dist-packages (from pydantic<2.12,>=2.0->gradio
Requirement already satisfied: pydantic-core==2.33.1 in /usr/local/lib/python3.11/dist-packages (from pydantic<2.12,>=2.0->gradio)
```




```
import gradio as gr

def predict_exit(CreditScore,Geography,Gender,Age,Tenure,Balance,NumOfProducts,HasCrCard,IsActiveMember,EstimatedSalary):
  # Replace this with your actual prediction logic
  # This is a placeholder that always predicts 0
  return 0

iface = gr.Interface(
    fn=predict_exit,
    inputs=[
        gr.Number(label="CreditScore"),
        gr.Dropdown(["France", "Spain", "Germany"], label="Geography"),
        gr.Radio(["Male", "Female"], label="Gender"),
        gr.Number(label="Age"),
        gr.Number(label="Tenure"),
        gr.Number(label="Balance"),
        gr.Number(label="NumOfProducts"),
        gr.Checkbox(label="HasCrCard"),
        gr.Checkbox(label="IsActiveMember"),
        gr.Number(label="EstimatedSalary"),
    ],
    outputs=gr.Textbox(label="Prediction"),
    title="Customer Churn Prediction",
    description="Predict customer churn based on various features.",
)
```