nl7ln1a8n

January 26, 2025

1 Q1

Given information:

```
\begin{split} &P(\text{Disease}) = 1 \; / \; 10,\!000 = 0.0001 \\ &P(\text{No Disease}) = 1 \; \text{-} \; P(\text{Disease}) = 0.9999 \\ &P(\text{Positive}|\text{Disease}) = 0.99 \\ &P(\text{Negative}|\text{No Disease}) = 0.99 \\ &P(\text{Positive}|\text{No Disease}) = 1 \; \text{-} \; 0.99 = 0.01 \end{split}
```

Try to find answer P(Disease|Positive)

Solution:

- 1. P(Disease|Positive) = P(Positive|Disease)P(Disease) / P(Positive) = 0.99 0.0001 / P(Positive)
- 2. Then the question is finding P(Positive)
- 3. P(Positive) = P(Positive|Disease) * P(Disease) + P(Positive|No Disease) * P(No Disease) = 0.99 * 0.0001 + 0.01 * 0.9999 = 0.010098
- 4. P(Disease|Positive) = 0.99 * 0.0001 / P(Positive) = 0.99 * 0.0001 / 0.010098 = 0.00980392157 \sim = 0.01

So the answer of the question is 0.98%, nearly 1% chances that you actually have this disease.

2 Q2

Import dataset

```
[954]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OrdinalEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import (
    classification_report,
    roc_auc_score,
    roc_curve,
    accuracy_score
)

data = pd.read_csv('KaggleV2-May-2016.csv')
```

Data preprocessing – Including data exploration (33 pts)

I utilized several features for training my model.

["Age", "Neighbourhood", "Scholarship", "AppointmentDiff", "SMS_received"]

Gender

Missing value detection

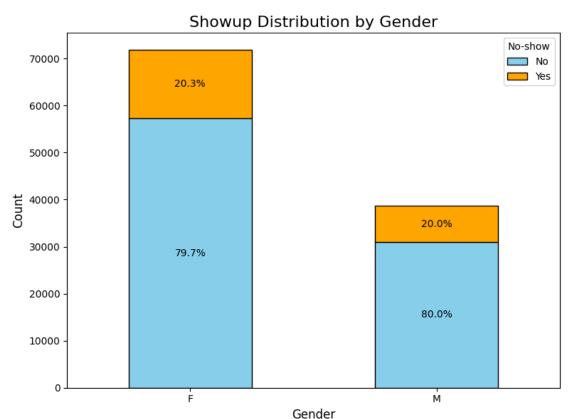
```
[955]: print(f"Number of missing value for Gender is {data['Gender'].isna().sum()}")
```

Number of missing value for Gender is O

Distribution and relationship to the target

```
[956]: # Calculate counts for each combination of gender and showup
       counts = data.groupby(['Gender', 'No-show']).size().unstack(fill_value=0)
       # Calculate percentages
       percentages = counts.div(counts.sum(axis=1), axis=0) * 100
       # Plot stacked bar chart
       fig, ax = plt.subplots(figsize=(8, 6))
       counts.plot(kind='bar', stacked=True, ax=ax, color=['skyblue', 'orange'],
        ⇔edgecolor='black')
       # Add percentage text on bars
       for i, gender in enumerate(counts.index):
           total = counts.loc[gender].sum()
           for j, showup_status in enumerate(counts.columns):
               count = counts.loc[gender, showup status]
              percentage = percentages.loc[gender, showup_status]
               if count > 0:
                   ax.text(i, count - count / 2 if j == 0 else total - count / 2, #
        → Text position
                           f"{percentage:.1f}%", ha='center', va='center', u
        ⇔color='black')
       # Customize plot
```

```
plt.title('Showup Distribution by Gender', fontsize=16)
plt.xlabel('Gender', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend(title='No-show', labels=counts.columns, fontsize=10)
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



From what we observed above, gender has little influence on predicting the No-show. Since neither gender has a No-show rate of 20%

Age

Missing values detection and an error value detected As far as we directly observe the dataset, we will find that there are abnormal value of age in this dataset as shown below. There should not be no patiants' age is less than 0. So I consider it as an error value when the age is less than 0. As a result, I impute it the most common data.

```
[957]: print(f"Number of missing value for Age is {data['Age'].isna().sum()}")
age_negative_rows = data[data['Age'] < 0]
# Display the filtered rows</pre>
```

```
print(age_negative_rows)

error_mask = data['Age'] == -1

# Calculate the mode (most common value) excluding the error value

mode_value = data.loc[data['Age'] != -1, 'Age'].mode()[0]

# Replace error values with the mode

data.loc[error_mask, 'Age'] = mode_value
```

```
Number of missing value for Age is 0
PatientId AppointmentID Gender ScheduledDay \
99832 4.659432e+14 5775010 F 2016-06-06T08:58:13Z

AppointmentDay Age Neighbourhood Scholarship Hipertension \
99832 2016-06-06T00:00:00Z -1 ROMÃO 0 0

Diabetes Alcoholism Handcap SMS_received No-show
99832 0 0 0 0 No
```

Before exploring the data, I aggregate this features by age group. I transfer exact age to different age groups from 0-20, 20-40, 40-60 and 60+. Turning this numerical data to categorical data. Then applying ordinal encoder on the age feature to generate an encoded age feature for future training

```
[958]: # Define bins and labels for age groups
bins = [0, 20, 40, 60, float('inf')] # Bin edges
labels = ['0-20', '20-40', '40-60', '60+'] # Category labels

# Create a new column for age groups
data['AgeGroup'] = pd.cut(data['Age'], bins=bins, labels=labels, right=False)

encoder = OrdinalEncoder(categories=[labels]) # Ensure the correct order
data['AgeEncoded'] = encoder.fit_transform(data[['AgeGroup']])
```

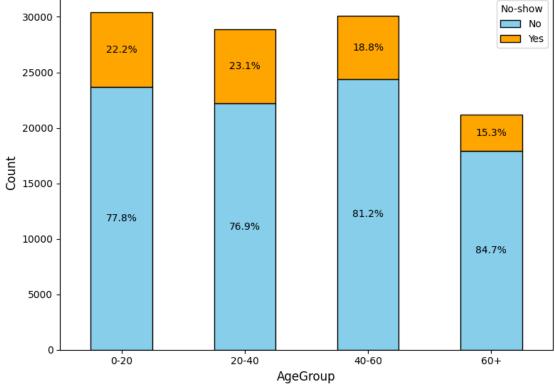
Distribution and relationship to the target

```
for j, showup_status in enumerate(counts.columns):
        count = counts.loc[gender, showup_status]
        percentage = percentages.loc[gender, showup_status]
        if count > 0:
            ax.text(i, count - count / 2 if j == 0 else total - count / 2, #__
 \hookrightarrow Text position
                    f"{percentage:.1f}%", ha='center', va='center',
 ⇔color='black')
# Customize plot
plt.title('Showup Distribution by AgeGroup', fontsize=16)
plt.xlabel('AgeGroup', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend(title='No-show', labels=counts.columns, fontsize=10)
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```

<ipython-input-959-647d28f80eb9>:2: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.

counts = data.groupby(['AgeGroup', 'No-show']).size().unstack(fill_value=0)





Neighborhood

Missing value detection

```
[960]: print(f"Number of missing value for Neighbourhood is {data['Age'].isna(). sum()}")
```

Number of missing value for Neighbourhood is O

Data preprocessing - oridinal Encoder

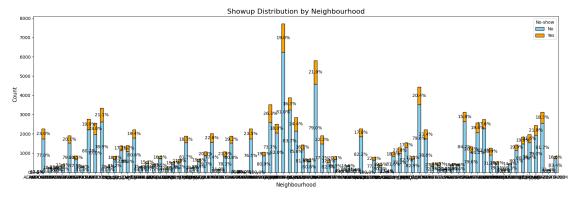
```
[961]: encoder = OrdinalEncoder() # Ensure the correct order
data['NeighborhoodEncoded'] = encoder.fit_transform(data[['Neighbourhood']])
```

Distribution and relationship to the target

I tried to adjust the figure size to make it clear, but there are too many neighborhoods in this figure. But we can still see there is a relationship to the target value

```
[962]: # Calculate counts for each combination of gender and showup
       counts = data.groupby(['Neighbourhood', 'No-show']).size().unstack(fill_value=0)
       # Calculate percentages
       percentages = counts.div(counts.sum(axis=1), axis=0) * 100
       # Plot stacked bar chart
       fig, ax = plt.subplots(figsize=(18, 6))
       counts.plot(kind='bar', stacked=True, ax=ax, color=['skyblue', 'orange'],__
        ⇔edgecolor='black')
       # Add percentage text on bars
       for i, gender in enumerate(counts.index):
           total = counts.loc[gender].sum()
           for j, showup_status in enumerate(counts.columns):
               count = counts.loc[gender, showup_status]
              percentage = percentages.loc[gender, showup_status]
               if count > 0:
                   ax.text(i, count - count / 2 if j == 0 else total - count / 2, \#
        → Text position
                           f"{percentage:.1f}%", ha='center', va='center',
        ⇔color='black')
       # Customize plot
       plt.title('Showup Distribution by Neighbourhood', fontsize=16)
       plt.xlabel('Neighbourhood', fontsize=12)
       plt.ylabel('Count', fontsize=12)
       plt.legend(title='No-show', labels=counts.columns, fontsize=10)
```

```
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



Scholarship

Missing value detection

```
[963]: print(f"Number of missing value for Gender is {data['Age'].isna().sum()}")
```

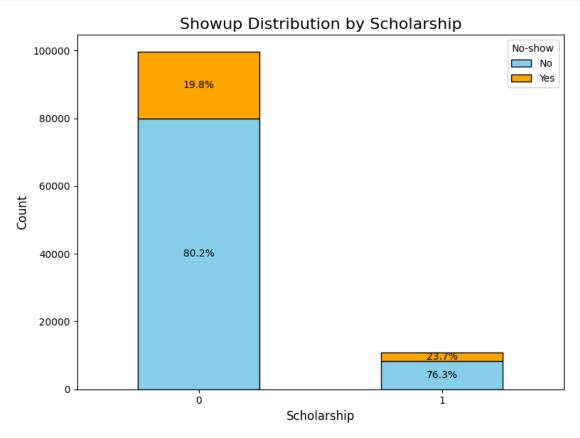
Number of missing value for Gender is O

Distribution and relationship to the target

```
[964]: # Calculate counts for each combination of gender and showup
       counts = data.groupby(['Scholarship', 'No-show']).size().unstack(fill_value=0)
       # Calculate percentages
       percentages = counts.div(counts.sum(axis=1), axis=0) * 100
       # Plot stacked bar chart
       fig, ax = plt.subplots(figsize=(8, 6))
       counts.plot(kind='bar', stacked=True, ax=ax, color=['skyblue', 'orange'], __
        ⇔edgecolor='black')
       # Add percentage text on bars
       for i, gender in enumerate(counts.index):
           total = counts.loc[gender].sum()
           for j, showup_status in enumerate(counts.columns):
               count = counts.loc[gender, showup status]
               percentage = percentages.loc[gender, showup_status]
               if count > 0:
                   ax.text(i, count - count / 2 if j == 0 else total - count / 2, #_\dots
        \hookrightarrow Text position
```

```
f"{percentage:.1f}%", ha='center', va='center',
color='black')

# Customize plot
plt.title('Showup Distribution by Scholarship', fontsize=16)
plt.xlabel('Scholarship', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend(title='No-show', labels=counts.columns, fontsize=10)
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



Hipertension

Missing value detection

```
[965]: print(f"Number of missing value for Hipertension is {data['Hipertension']. 

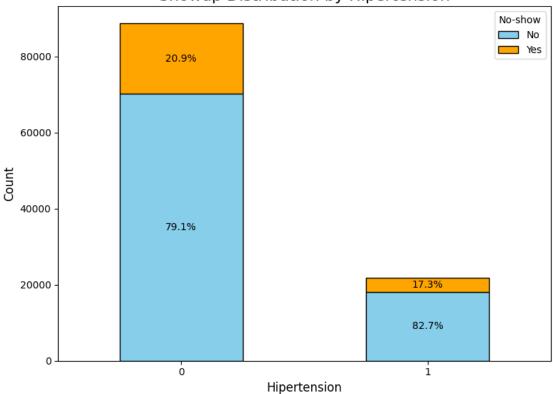
→isna().sum()}")
```

Number of missing value for Hipertension is O

Distribution and relationshio to the target

```
[966]: # Calculate counts for each combination of gender and showup
      counts = data.groupby(['Hipertension', 'No-show']).size().unstack(fill_value=0)
       # Calculate percentages
      percentages = counts.div(counts.sum(axis=1), axis=0) * 100
      # Plot stacked bar chart
      fig, ax = plt.subplots(figsize=(8, 6))
      counts.plot(kind='bar', stacked=True, ax=ax, color=['skyblue', 'orange'],__
       ⇔edgecolor='black')
      # Add percentage text on bars
      for i, gender in enumerate(counts.index):
          total = counts.loc[gender].sum()
          for j, showup_status in enumerate(counts.columns):
              count = counts.loc[gender, showup_status]
              percentage = percentages.loc[gender, showup status]
              if count > 0:
                  ax.text(i, count - count / 2 if j == 0 else total - count / 2, #u
        → Text position
                          f"{percentage:.1f}%", ha='center', va='center',
        # Customize plot
      plt.title('Showup Distribution by Hipertension', fontsize=16)
      plt.xlabel('Hipertension', fontsize=12)
      plt.ylabel('Count', fontsize=12)
      plt.legend(title='No-show', labels=counts.columns, fontsize=10)
      plt.xticks(rotation=0)
      plt.tight_layout()
      plt.show()
```





Diabetes

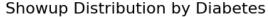
Missing value detection

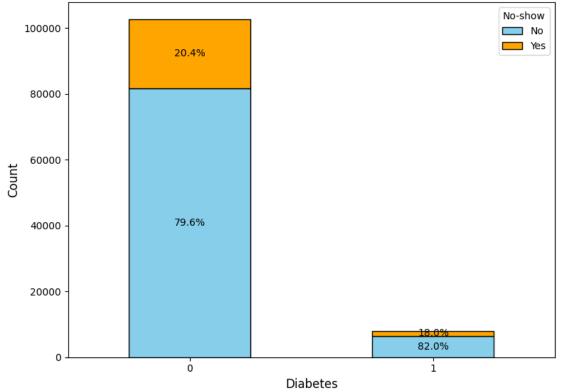
```
[967]: print(f"Number of missing value for Hipertension is {data['Diabetes'].isna(). sum()}")
```

Number of missing value for Hipertension is O

Distribution and relationshio to the target

```
# Add percentage text on bars
for i, gender in enumerate(counts.index):
    total = counts.loc[gender].sum()
    for j, showup_status in enumerate(counts.columns):
        count = counts.loc[gender, showup_status]
        percentage = percentages.loc[gender, showup_status]
        if count > 0:
            ax.text(i, count - count / 2 if j == 0 else total - count / 2, \#_{\sqcup}
 → Text position
                    f"{percentage:.1f}%", ha='center', va='center', u
 ⇔color='black')
# Customize plot
plt.title('Showup Distribution by Diabetes', fontsize=16)
plt.xlabel('Diabetes', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend(title='No-show', labels=counts.columns, fontsize=10)
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```





SMS received

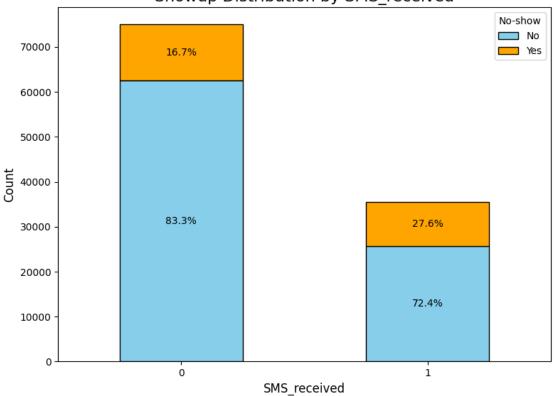
Missing value detection

Number of missing value for Hipertension is O

Distribution and relationshio to the target

```
[970]: # Calculate counts for each combination of gender and showup
       counts = data.groupby(['SMS_received', 'No-show']).size().unstack(fill_value=0)
       # Calculate percentages
       percentages = counts.div(counts.sum(axis=1), axis=0) * 100
       # Plot stacked bar chart
       fig, ax = plt.subplots(figsize=(8, 6))
       counts.plot(kind='bar', stacked=True, ax=ax, color=['skyblue', 'orange'],__
        ⇔edgecolor='black')
       # Add percentage text on bars
       for i, gender in enumerate(counts.index):
           total = counts.loc[gender].sum()
           for j, showup_status in enumerate(counts.columns):
               count = counts.loc[gender, showup_status]
               percentage = percentages.loc[gender, showup_status]
               if count > 0:
                   ax.text(i, count - count / 2 if j == 0 else total - count / 2, \#
        → Text position
                           f"{percentage:.1f}%", ha='center', va='center',
        ⇔color='black')
       # Customize plot
       plt.title('Showup Distribution by SMS_received', fontsize=16)
       plt.xlabel('SMS_received', fontsize=12)
       plt.ylabel('Count', fontsize=12)
       plt.legend(title='No-show', labels=counts.columns, fontsize=10)
       plt.xticks(rotation=0)
       plt.tight_layout()
       plt.show()
```



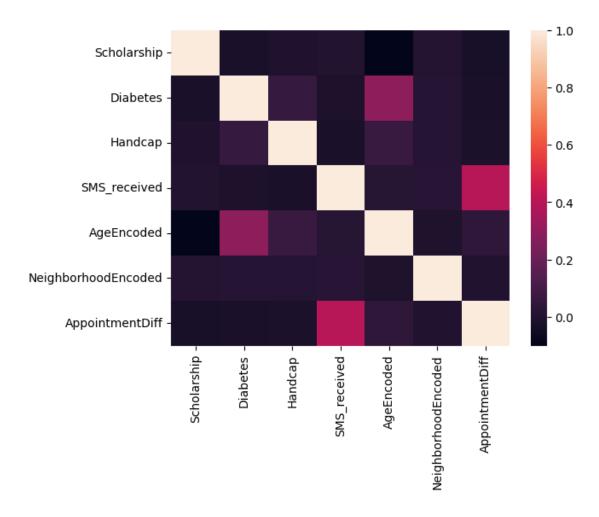


Time between appointment date and schedule date

Correlation heat map

As shown below, there is no high correlated features

```
[972]: <Axes: >
```



Train test data split

Utilized SMOTE for imbalanced data preprocessing

Utilized StandardScaler on input data to avoid Logistic Regression hitting the maximum number of iterations allowed before fully converging

```
[973]: from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
X, y = smote.fit_resample(X, y)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, \( \text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{
```

```
scaler = StandardScaler()
       X_train = scaler.fit_transform(X_train)
       X_test = scaler.transform(X_test)
       print(X_train.shape, y_train.shape) # Training data
       print(X_test.shape, y_test.shape) # Test data
      (149953, 7) (149953,)
      (26463, 7) (26463,)
      Build the prediction model and use 10-fold cross validation (17 pts) 1. using Logistic Regression
[974]: | lr model = LogisticRegression()
       lr_model.fit(X_train, y_train)
       # Make predictions
       y_pred_lr = lr_model.predict(X_test)
       y_pred_lr_prob = lr_model.predict_proba(X_test)[:,1]
       # Evaluate the model
       cv_scores = cross_val_score(lr_model, X_train, y_train, cv=10,_
        ⇔scoring="accuracy")
       # Print the results
       print(f"10-Fold Cross-Validation Scores: {cv_scores}")
       print(f"Mean Score: {np.mean(cv_scores):.4f}")
       print(f"Standard Deviation: {np.std(cv_scores):.4f}")
      10-Fold Cross-Validation Scores: [0.63023473 0.63870365 0.63176847 0.62907636
      0.63227743 0.62887629
       0.63441147 0.63007669 0.62720907 0.62734245]
      Mean Score: 0.6310
      Standard Deviation: 0.0033
        2. using Decision Tree
[975]: dt_model = DecisionTreeClassifier(random_state=24)
       dt_model.fit(X_train, y_train)
       # Make predictions
       y_pred_dt = dt_model.predict(X_test)
       y_pred_dt_prob = dt_model.predict_proba(X_test)[:,1]
       # Evaluate the model
       cv_scores = cross_val_score(dt_model, X_train, y_train, cv=10,_
        ⇔scoring="accuracy")
       # Print the results
```

```
print(f"10-Fold Cross-Validation Scores: {cv_scores}")
       print(f"Mean Score: {np.mean(cv_scores):.4f}")
       print(f"Standard Deviation: {np.std(cv_scores):.4f}")
      10-Fold Cross-Validation Scores: [0.75353428 0.75453454 0.7521339 0.74698233
      0.75405135 0.74884962
       0.74904968 0.74864955 0.75025008 0.74771591]
      Mean Score: 0.7506
      Standard Deviation: 0.0026
        3. Random Forest
[976]: # Train Random Forest Classifier
       rf model = RandomForestClassifier(random state=24)
       rf_model.fit(X_train, y_train)
       # Make predictions
       y pred rf = rf model.predict(X test)
       y_pred_rf_prob = rf_model.predict_proba(X_test)[:,1]
       # Evaluate the model
       cv_scores = cross_val_score(rf_model, X_train, y_train, cv=10,__

¬scoring="accuracy")
       # Print the results
       print(f"10-Fold Cross-Validation Scores: {cv_scores}")
       print(f"Mean Score: {np.mean(cv_scores):.4f}")
       print(f"Standard Deviation: {np.std(cv_scores):.4f}")
      10-Fold Cross-Validation Scores: [0.75693518 0.75660176 0.75380101 0.74738246
      0.75691897 0.75578526
       0.75251751 0.75405135 0.75045015 0.75251751]
      Mean Score: 0.7537
      Standard Deviation: 0.0029
      Report the following metrics: Precision, Recall, F-Score, AUC, Plot the ROC curve (20 points)
[977]: # Plot the ROC Curve
       plt.figure(figsize=(8, 6))
       for model_name, y_pred, y_pred_prob in [("Logistic Regression", y_pred_lr,__

y_pred_lr_prob),
         ("Decision Tree", y_pred_dt, y_pred_dt_prob),
         ("Random Forest", y_pred_rf, y_pred_rf_prob)]:
        print(model_name + "Classification Report:")
         print(classification_report(y_test, y_pred))
         # Compute AUC
         auc_score = roc_auc_score(y_test, y_pred_prob)
         fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
         plt.plot(fpr, tpr, label=model_name + f"ROC Curve (AUC = {auc_score:.2f})")
```

```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

Logistic RegressionClassification Report:

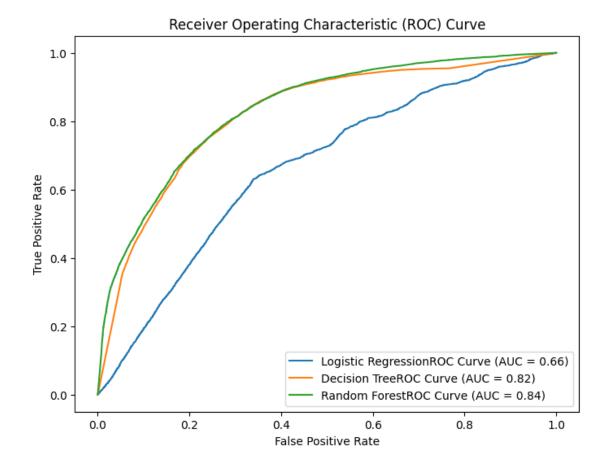
	precision	recall	f1-score	support
0	0.61	0.71	0.65	13182
1	0.65	0.55	0.60	13281
accuracy			0.63	26463
macro avg	0.63	0.63	0.63	26463
weighted avg	0.63	0.63	0.63	26463

Decision TreeClassification Report:

	precision	recall	f1-score	support
0	0.75	0.75	0.75	13182
1	0.76	0.76	0.76	13281
accuracy			0.75	26463
macro avg	0.75	0.75	0.75	26463
weighted avg	0.75	0.75	0.75	26463

Random ForestClassification Report:

	precision	recall	f1-score	support
0	0.77	0.74	0.75	13182
1	0.75	0.78	0.76	13281
accuracy			0.76	26463
macro avg	0.76	0.76	0.76	26463
weighted avg	0.76	0.76	0.76	26463



3 Q3

To transfer the regression problem of predicting the length of stay to classification problem, follow these step below

1. Analyze the distribution of Data and define categories

By observing the distribution of data and understand our demand. We can split the distribution into different categories. For an example, we could categorize the data into three groups [0-1, 2-3, 3+] by the length of stay. But this is mainly on our prediction demand. If we want to predict exact number of time, we could categorize like [0,1,2,3,4,5,6,7+]

2. labels those categories

The final step is giving each category a label so that machien would understand. An optional step is using categorical encoder to transfer these string values into binary values. For an example, I will label 0-1 as short_stay, 2-3 as a medium_stay, 3+ as long_stay. Further more, if adding encoder. 0-1 would be 1, 1-2 would be 2, 3+ would be 3.

Here is a pd.cut example on how to label numerical data into categorical data

```
[978]: import pandas as pd
import numpy as np

# Example data
data = {'LengthOfStay': [1, 3, 8, 2, 2, 3, 2, 0, 5, 4]}
df = pd.DataFrame(data)

# Define bins and labels
bins = [0, 2, 4, np.inf] # Intervals
labels = ['short_stay', 'medium_stay', 'long_stay']

# Create the 'StayCategory' column
df ['StayCategory'] = pd.cut(df['LengthOfStay'], bins=bins, labels=labels, uright=False)

print(df)
```

```
LengthOfStay StayCategory
0
             1
                 short_stay
1
             3 medium_stay
2
             8
                  long_stay
3
             2 medium_stay
             2 medium_stay
4
5
             3 medium_stay
6
             2 medium_stay
7
             0 short_stay
8
             5 long_stay
9
             4
                  long_stay
```