```python
# 3.1 Problem 1. Data Read, Write and Inspect:
# Complete the following task:
# - Dataset for the task: "bank.csv"

# 1. Load the provided dataset and import in pandas DataFrame.
df = pd.read_csv('!!!!!!!!!!!!!!!!!!!link afei hal tala
pani!!!!!!!!!!!!!!!!!!!!!!!!!!!!')

# 2. Check info of the DataFrame and identify following:

# (a) columns with dtypes=object
object_columns = df.select_dtypes(include=['object']).columns
print(f"Columns with dtype = object:\n {list(object_columns)}\n")

# (b) unique values of those columns.
unique_values = {}
for col in object_columns:
    unique_values[col] = df[col].unique()

print("Unique values for object dtype columns:\n")

for col, values in unique_values.items():
    print(f"{col}: {values}")

# (c) check for the total number of null values in each column.
null_values = df.isnull().sum()
print("\nNull values in each column:\n")
print(null_values)

# 3. Drop columns with dtype=object and store the resulting DataFrame
in "banknumericdata.csv"
df_numeric = df.drop(columns=object_columns)
df_numeric.to_csv('banknumericdata.csv')

# 4. Read "banknumericdata.csv" and find the summary statistics
df_numeric_read = pd.read_csv('banknumericdata.csv')
summary = df_numeric_read.describe()
print("\nSummary statistics:\n")
print(summary)
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Columns with dtype = object:
 ['job', 'marital', 'education', 'default', 'housing', 'loan',
'contact', 'month', 'poutcome', 'y']

Unique values for object dtype columns:

job: ['management' 'technician' 'entrepreneur' 'blue-collar' 'unknown'
 'retired' 'admin.' 'services' 'self-employed' 'unemployed'
'housemaid'
 'student']
marital: ['married' 'single' 'divorced']
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education: ['tertiary' 'secondary' 'unknown' 'primary']
default: ['no' 'yes']
housing: ['yes' 'no']
loan: ['no' 'yes']
contact: ['unknown' 'cellular' 'telephone']
month: ['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'jan' 'feb' 'mar'
'apr' 'sep']
poutcome: ['unknown' 'failure' 'other' 'success']
y: ['no' 'yes']

Null values in each column:

age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64

Summary statistics:

         Unnamed: 0           age        balance           day
duration  \
count  45211.000000  45211.000000   45211.000000  45211.000000
45211.000000
mean   22605.000000     40.936210    1362.272058     15.806419
258.163080
std    13051.435847     10.618762    3044.765829      8.322476
257.527812
min        0.000000     18.000000   -8019.000000      1.000000
0.000000
25%    11302.500000     33.000000      72.000000      8.000000
103.000000
50%    22605.000000     39.000000     448.000000     16.000000
180.000000
75%    33907.500000     48.000000    1428.000000     21.000000
319.000000
max    45210.000000     95.000000  102127.000000     31.000000
```

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4918.000000

           campaign         pdays      previous
count  45211.000000  45211.000000  45211.000000
mean       2.763841     40.197828      0.580323
std        3.098021    100.128746      2.303441
min        1.000000     -1.000000      0.000000
25%        1.000000     -1.000000      0.000000
50%        2.000000     -1.000000      0.000000
75%        3.000000     -1.000000      0.000000
max       63.000000    871.000000    275.000000
```

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# 3.1 Problem 2. Data Imputations:
# Complete all the following Task:

# 1. Load the provided dataset and import in pandas DataFrame
df = pd.read_csv('./medical_student.csv')

# 2. Check info of the DataFrame and identify columns with missing
(null) values
print("\nDataFrame Info:\n")
print(df.info())

# Identify columns with missing values
missing_values = df.isnull().sum()
print("\nMissing values in each column:\n")
print(missing_values[missing_values > 0])

# 3. For the column with missing values fill the values using various
techniques we discussed above.
# Try to explain why did you select the particular methods for
particular column.
print("\nFilling missing values:\n")
for column in missing_values[missing_values > 0].index:
    if df[column].dtype == 'float64' or df[column].dtype == 'int64':
        # Fill numeric columns with mean/average value of that column
        df[column] = df[column].fillna(df[column].mean())
        print(f"\nFilled missing values in '{column}' with average
value of the column.")

    elif df[column].dtype == 'object':
        # Fill object columns with mode/most common value from the
column
        df[column] = df[column].fillna(df[column].mode()[0])
        print(f"\nFilled missing values in '{column}' with most common
value in the column.")

# 4. Check for any duplicate values
print("\nChecking for duplicate rows...")
duplicates_count = df.duplicated().sum()
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print(f"Number of duplicate rows: {duplicates_count}")

# Drop duplicates if any exist
if duplicates_count > 0:
    df = df.drop_duplicates()
    print("Duplicate rows dropped.")

# Final output
print("\nFinal DataFrame Info:")
print(df.info())
```

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DataFrame Info:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 13 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   Student ID      180000 non-null  float64
 1   Age             180000 non-null  float64
 2   Gender          180000 non-null  object 
 3   Height          180000 non-null  float64
 4   Weight          180000 non-null  float64
 5   Blood Type      180000 non-null  object 
 6   BMI             180000 non-null  float64
 7   Temperature     180000 non-null  float64
 8   Heart Rate      180000 non-null  float64
 9   Blood Pressure  180000 non-null  float64
 10  Cholesterol     180000 non-null  float64
 11  Diabetes        180000 non-null  object 
 12  Smoking         180000 non-null  object 
dtypes: float64(9), object(4)
memory usage: 19.8+ MB
None

Missing values in each column:

Student ID        20000
Age               20000
Gender            20000
Height            20000
Weight            20000
Blood Type        20000
BMI               20000
Temperature       20000
Heart Rate        20000
Blood Pressure    20000
Cholesterol       20000
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Diabetes          20000
Smoking           20000
dtype: int64

Filling missing values:


Filled missing values in 'Student ID' with average value of the
column.

Filled missing values in 'Age' with average value of the column.

Filled missing values in 'Gender' with most common value in the
column.

Filled missing values in 'Height' with average value of the column.

Filled missing values in 'Weight' with average value of the column.

Filled missing values in 'Blood Type' with most common value in the
column.

Filled missing values in 'BMI' with average value of the column.

Filled missing values in 'Temperature' with average value of the
column.

Filled missing values in 'Heart Rate' with average value of the
column.

Filled missing values in 'Blood Pressure' with average value of the
column.

Filled missing values in 'Cholesterol' with average value of the
column.

Filled missing values in 'Diabetes' with most common value in the
column.

Filled missing values in 'Smoking' with most common value in the
column.

Checking for duplicate rows...
Number of duplicate rows: 12572
Duplicate rows dropped.

Final DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
Index: 187428 entries, 0 to 199999
Data columns (total 13 columns):
 #   Column          Non-Null Count   Dtype
```

```
---  ------          --------------   -----
 0   Student ID      187428 non-null  float64
 1   Age             187428 non-null  float64
 2   Gender          187428 non-null  object
 3   Height          187428 non-null  float64
 4   Weight          187428 non-null  float64
 5   Blood Type      187428 non-null  object
 6   BMI             187428 non-null  float64
 7   Temperature     187428 non-null  float64
 8   Heart Rate      187428 non-null  float64
 9   Blood Pressure  187428 non-null  float64
 10  Cholesterol     187428 non-null  float64
 11  Diabetes        187428 non-null  object
 12  Smoking         187428 non-null  object
dtypes: float64(9), object(4)
memory usage: 20.0+ MB
None
Cleaned dataset saved as 'cleaned_medical_student.csv'.
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# 3.2 Problem 1. Create a DataFrame that is subsetted for the columns
’Name’, ’Pclass’, ’Sex’, ’Age’, ’Fare’, and ’Survived’.
# Retain only those rows where ’Pclass’ is equal to 1, representing
first-class passengers. What is the mean,
# median, maximum value, and minimum value of the ’Fare’ column?

df = pd.read_csv('Titanic-Dataset.csv')

# Subsetted dataframe
subset_df = df[['Name', 'Pclass', 'Sex', 'Age', 'Fare', 'Survived']]

# filter rows where Pclass is 1.
first_class_df = subset_df[subset_df['Pclass'] == 1]

# Calculate the mean, median, max, and min of the 'Fare' column
mean_fare = first_class_df['Fare'].mean()
median_fare = first_class_df['Fare'].median()
max_fare = first_class_df['Fare'].max()
min_fare = first_class_df['Fare'].min()

# Print the results
print("Problem 1:\n")
print(f"Mean Fare: {mean_fare}")
print(f"Median Fare: {median_fare}")
print(f"Maximum Fare: {max_fare}")
print(f"Minimum Fare: {min_fare}")

# 3.2 Problem 2. How many null values are contained in the ’Age’
column in your subsetted DataFrame?
# Once you’ve found this out, drop them from your DataFrame.
print("\nProblem 2:\n")
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# Count the number of null values in the 'Age' column
null_age_count = first_class_df['Age'].isnull().sum()
print(f"Number of null values in 'Age' column: {null_age_count}")

# Drop the rows where 'Age' is null
first_class_df_cleaned = first_class_df.dropna(subset=['Age'])

# Verify that null values are dropped
null_age_count_after_drop =
first_class_df_cleaned['Age'].isnull().sum()
print(f"Number of null values in 'Age' column after dropping:
{null_age_count_after_drop}")
```

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Problem 1:
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Mean Fare: 84.1546875
Median Fare: 60.287499999999994
Maximum Fare: 512.3292
Minimum Fare: 0.0
```

```
Problem 2:
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Number of null values in 'Age' column: 30
Number of null values in 'Age' column after dropping: 0
```

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# 3.2 Problem 3. The ’Embarked’ column in the Titanic dataset contains
categorical data representing the ports of embarkation:
# • ’C’ for Cherbourg
# • ’Q’ for Queenstown
# • ’S’ for Southampton

df = pd.read_csv('Titanic-Dataset.csv')

# Tasks:
# 1. Use one-hot encoding to convert the ’Embarked’ column into
separate binary columns (’Embarked C’, ’Embarked Q’, ’Embarked S’).
embarked_dummies = pd.get_dummies(df['Embarked'], prefix='Embarked')

# 2. Add these new columns to the original DataFrame.
df = pd.concat([df, embarked_dummies], axis=1)

# 3. Drop the original ’Embarked’ column.
df.drop(columns=['Embarked'], inplace=True)

# 4. Print the first few rows of the modified DataFrame to verify the
changes.
print(df.head())
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
```

```
2             3          1       3
3             4          1       1
4             5          0       3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
0

   Parch            Ticket     Fare Cabin  Embarked_C  Embarked_Q
Embarked_S
0      0         A/5 21171   7.2500   NaN       False       False
True
1      0          PC 17599  71.2833   C85        True       False
False
2      0  STON/O2. 3101282   7.9250   NaN       False       False
True
3      0            113803  53.1000  C123       False       False
True
4      0            373450   8.0500   NaN       False       False
True

# 3.2 Problem 4. Compare the mean survival rates ('Survived') for the
different groups in the 'Sex' column.
df = pd.read_csv('Titanic-Dataset.csv')

mean_survival_by_gender = df.groupby('Sex')['Survived'].mean()
print(f"Mean survival rate by gender:\n{mean_survival_by_gender}")

# Bar plot to show the mean survival rate by gender
plt.figure(figsize=(6, 4))
plt.bar(mean_survival_by_gender.index, mean_survival_by_gender.values,
color=['blue', 'pink'])
plt.title('Mean Survival Rate by Gender')
plt.xlabel('Gender')
plt.ylabel('Mean Survival Rate')
plt.show()

Mean survival rate by gender:
Sex
female    0.742038
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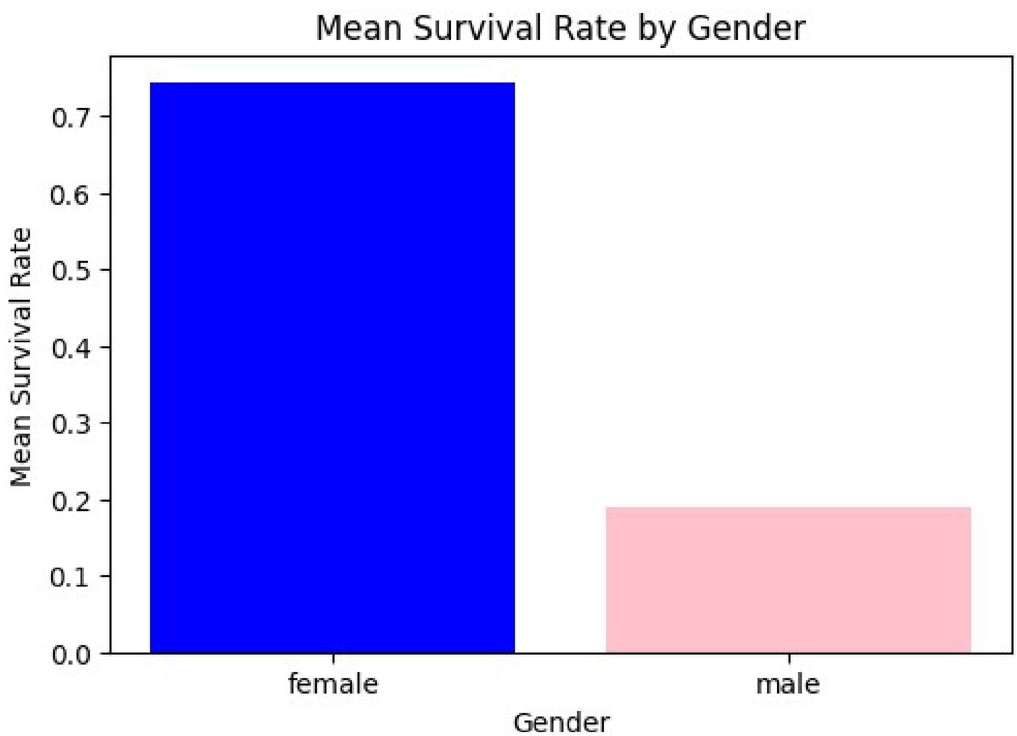
male      0.188908
Name: Survived, dtype: float64
```

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# 3.2 Problem 5. Draw a visualization that breaks your visualization
from Exercise 3 down by the port of embarkation
# (’Embarked’). In this instance, compare the ports ’C’ (Cherbourg),
’Q’ (Queenstown), and ’S’ (Southampton).

mean_survival_by_gender_and_embarked = df.groupby(['Sex', 'Embarked'])
['Survived'].mean().unstack()
print(f"Mean survival rate by gender and embarkation port:\
n{mean_survival_by_gender_and_embarked}")

# Bar plot to show the mean survival rate by gender and embarkation
port
mean_survival_by_gender_and_embarked.plot(kind='bar', figsize=(8, 6),
color=['blue', 'pink', 'lightgreen'])
plt.title('Mean Survival Rate by Gender and Embarkation Port')
plt.xlabel('Gender')
plt.ylabel('Mean Survival Rate')
plt.xticks(rotation=0)  # Rotate x-axis labels to make them readable
plt.legend(title='Embarked', labels=['Cherbourg (C)', 'Queenstown
(Q)', 'Southampton (S)'])
plt.show()
```
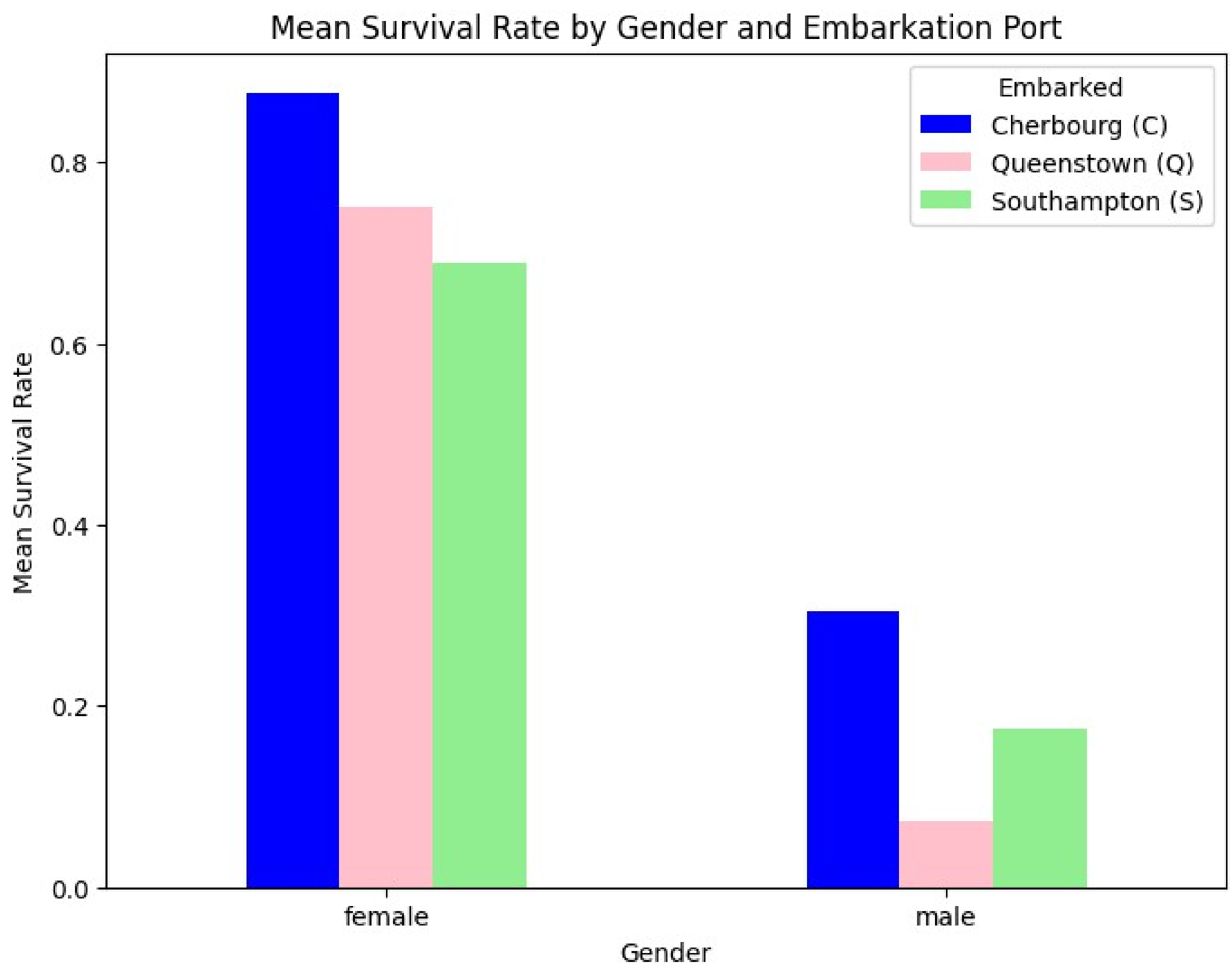

```
Mean survival rate by gender and embarkation port:
Embarked         C         Q         S
Sex
female    0.876712  0.750000  0.689655
male      0.305263  0.073171  0.174603
```




```
# 3.2 Problem 6. (optional) Show how the survival rates ('Survived')
vary by age group and passenger class ('Pclass').
# Break up the 'Age' column into five quantiles in your DataFrame, and
then compare the means of 'Survived' by class and age group.
# Draw a visualization using a any plotting library to represent this
graphically.

age_quantiles = pd.qcut(df['Age'], 5, labels=['Q1', 'Q2', 'Q3', 'Q4',
'Q5'])
df['AgeGroup'] = age_quantiles

mean_survival_by_class_and_age = df.groupby(['Pclass', 'AgeGroup'],
observed=False)['Survived'].mean().unstack()
```

```
print(f"Mean survival rate by Pclass and Age Group:\
n{mean_survival_by_class_and_age}")

# Plot the mean survival rate by Pclass and Age Group
mean_survival_by_class_and_age.plot(kind='bar', figsize=(10, 6),
color=['blue', 'orange', 'green', 'red', 'purple'])
plt.title('Mean Survival Rate by Passenger Class and Age Group')
plt.xlabel('Passenger Class')
plt.ylabel('Mean Survival Rate')
plt.xticks(rotation=0)  # Rotate x-axis labels for better readability
plt.legend(title='Age Group', loc='upper left', labels=['Q1', 'Q2',
'Q3', 'Q4', 'Q5'])
plt.show()

Mean survival rate by Pclass and Age Group:
AgeGroup         Q1        Q2        Q3        Q4        Q5
Pclass
1          0.809524  0.761905  0.666667  0.777778  0.506667
2          0.742857  0.400000  0.416667  0.461538  0.363636
3          0.333333  0.197674  0.283582  0.166667  0.088235
```