Introduction to Data Science
Assignment 1

Name: Shashini Shanmugan
Course: BCA(Sec A)
Registration Number - 2411021240013
Github Repository link -
https://github.com/ShashiniShanmugan/Data-Science/upload/main

Part 1: Theoretical Understanding

1. Define Data Science
Q. What is Data Science? Discuss its key components and the CRISP-DM process.

Data Science is an interdisciplinary field that uses mathematics, statistics, computer science, and domain knowledge to extract meaningful insights from data.

Key Components:

- Data Collection: Gathering raw data from various sources.
- Data Processing: Cleaning and organizing the data.
- Data Analysis: Using statistical and computational methods to derive insights.
- Visualization: Presenting results in an understandable format (e.g., graphs, dashboards).
- Decision-Making: Applying insights to solve real-world problems.

CRISP-DM process:
1. Business Understanding: Define objectives and questions.
2. Data Understanding: Explore the data to understand its structure.
3. Data Preparation: Clean, transform, and organize the data.
4. Modeling: Apply algorithms to analyze and predict.
5. Evaluation: Check if the model answers the problem.
6. Deployment: Implement the solution in real-world scenarios.

Q.Explain how the CRISP-DM framework is applied in solving real-world problems (e.g., predicting customer churn or recommending movies).

Predicting Customer Churn in Telecom

Problem Statement How can a telecom company predict which customers are likely to stop using their services?

Dataset

Source: Telco Customer Churn[https://www.kaggle.com/datasets/blastchar/telcocustomer-churn]

Columns:
Customer ID
Demographics: Gender, age group, etc.
Service details: Internet service, contract type, monthly charges.
Churn (Yes/No).

CRISP DM Process

1. Business Understanding:
Goal: Reduce churn rate by identifying at-risk customers.
Impact: Increase revenue by targeting retention efforts.

2. Data Understanding:
Analyze churn rate across demographics.
Understand correlations between service features and churn.

3. Data Preparation:
Handle missing values (e.g., impute missing charges).
Convert categorical variables (e.g., gender, contract type) to numerical data.
Scale numerical features like monthly charges.

4. Modeling:
Train a classification model (e.g., Logistic Regression, Random Forest) to predict churn.
Use features like contract type, monthly charges, and tenure.

5. Evaluation:
Use metrics like Accuracy, Precision, Recall, and F1 Score.
Evaluate the model on a confusion matrix to understand false positives and negatives.

6. Deployment:
Provide alerts for high-risk customers to customer service teams.
Implement proactive offers and discounts to retain customers.

Netflix Recommendation System

Problem Statement: How can Netflix recommend personalized movies or TV shows to users based on their preferences?

Dataset
Source: MovieLens Dataset (Free public dataset). [https://grouplens.org/datasets/movielens/]

Columns:
- User ID
- Movie ID
- Rating (1-5)
- Timestamp
- Movie metadata (title, genres, release year).

CRISP-DM Process-

1. Business Understanding:
Goal: Improve user engagement by suggesting content they're likely to enjoy.
Impact: Increased user satisfaction and retention.

2. Data Understanding:
Explore the dataset: Number of users, movies, and ratings.
Analyze distribution of ratings and popular genres.

3. Data Preparation:
Handle missing data in movie metadata.
Transform timestamp into human-readable format.
One-hot encode genres for analysis.

4. Modeling:
Use Collaborative Filtering to predict user preferences:
Find similar users and suggest movies they liked.
Train a recommendation model (e.g., Singular Value Decomposition).
Alternative: Content-based filtering using movie metadata.

5. Evaluation:
Split data into training and test sets.
Use metrics like Root Mean Square Error (RMSE) to measure model accuracy.

6. Deployment:
Integrate the model into a recommendation engine.
rovide real-time recommendations on the Netflix platform.

2. Case Study Questions:

From the case studies in the "Module 1 Case Studies" file, answer the following:

Q.What is the main business objective of the Netflix Recommendation System?

The main business objective of the Netflix Recommendation System is to improve user engagement by suggesting content they're likely to enjoy. This will increase the user satisfaction and retention.

Part 2: **Data Manipulation and Joins Use the following two CSV files for practical tasks:**

File 1: students.csv:

```
StudentID,Name,Marks
101,Alice,85
102,Bob,90
103,Charlie,88
104,David,92
```

File 2: details.csv:

```
StudentID,Age,Grade
101,20,A
102,21,B
103,22,A
105,19,C
```

Tasks:

1. Load the Datasets:

Load students.csv and details.csv into pandas DataFrames.

2. Perform Joins:

Merge the two DataFrames using the following join types:

Inner Join

Left Join

Right Join

Outer Join

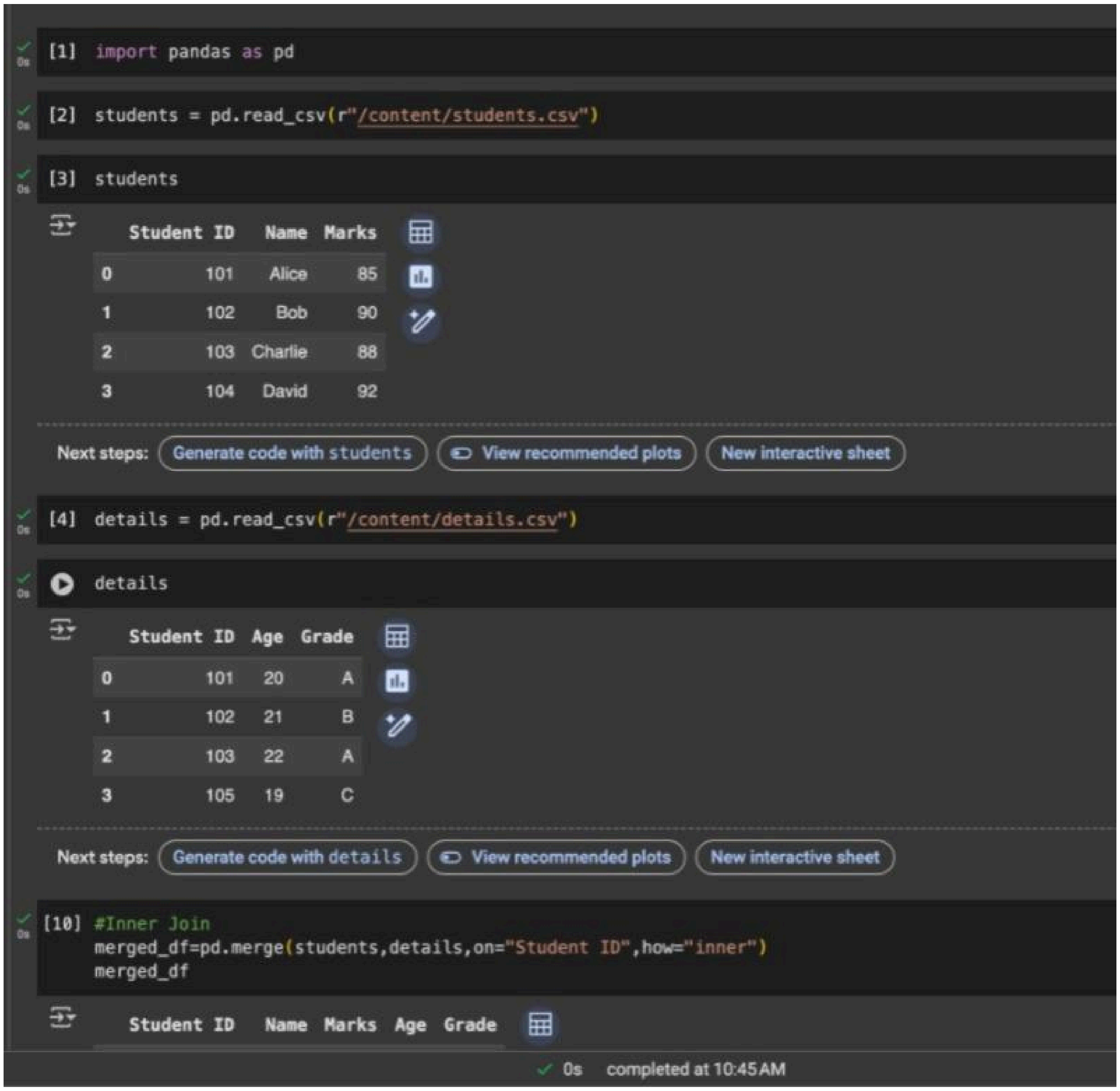
For each join type, describe the difference in the results.

3. Set Index:

Set StudentID as the index for the merged DataFrame.

Reset the index back to default.

4. Save the Results: Save the result of the outer join to a new CSV file called merged_students_details.csv.



```
[1] import pandas as pd
```

```
[2] students = pd.read_csv(r"/content/students.csv")
```

```
[3] students
```

```
   Student ID     Name  Marks
0         101    Alice     85
1         102      Bob     90
2         103  Charlie     88
3         104    David     92
```

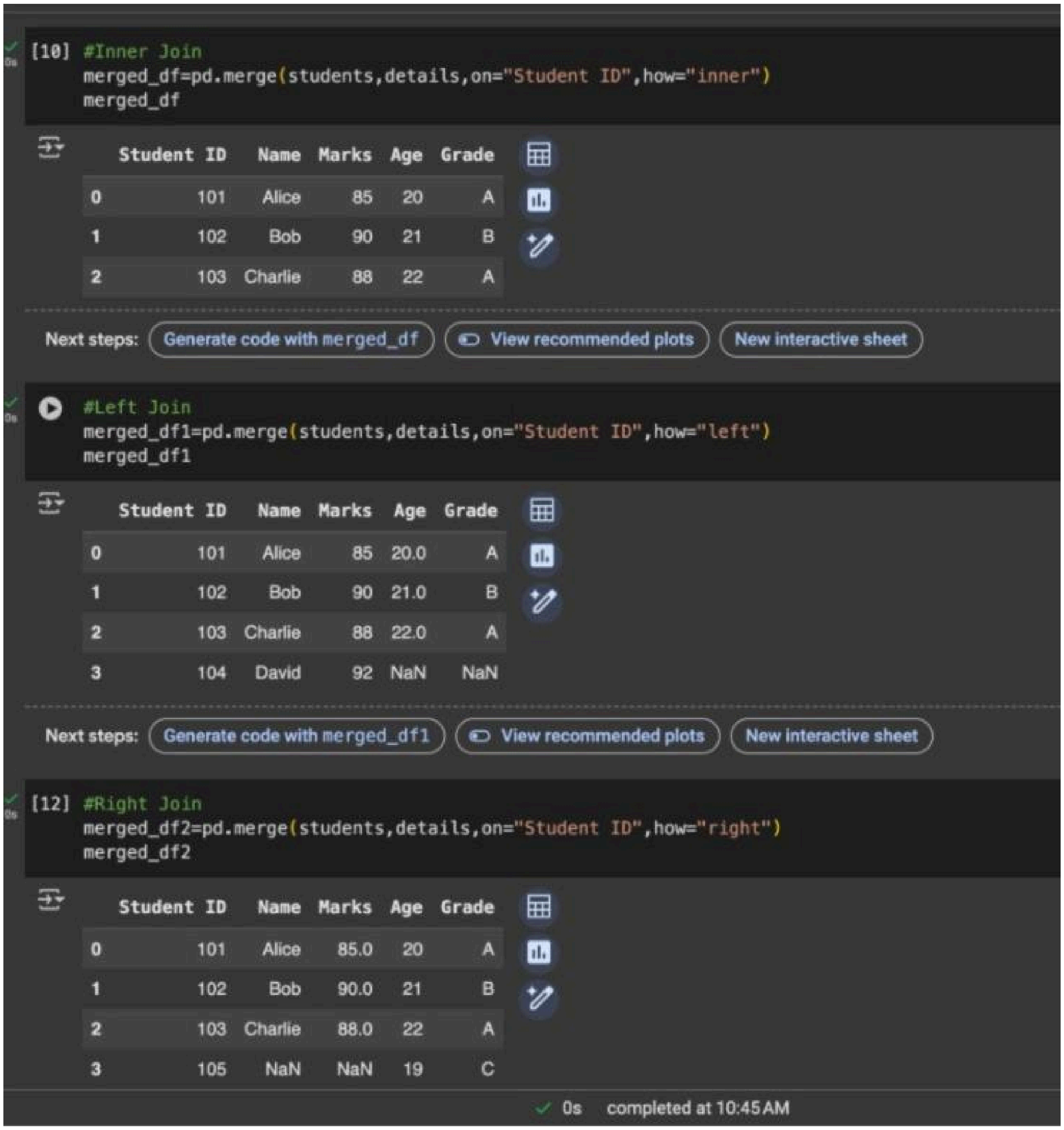
```
[4] details = pd.read_csv(r"/content/details.csv")
```

```
details
```

```
   Student ID  Age  Grade
0         101   20      A
1         102   21      B
2         103   22      A
3         105   19      C
```

```
[10] #Inner Join
     merged_df=pd.merge(students,details,on="Student ID",how="inner")
     merged_df
```

```
   Student ID  Name  Marks  Age  Grade
```



```
[10] #Inner Join
     merged_df=pd.merge(students,details,on="Student ID",how="inner")
     merged_df
```

```
   Student ID     Name  Marks  Age  Grade
0         101    Alice     85   20      A
1         102      Bob     90   21      B
2         103  Charlie     88   22      A
```

Next steps: Generate code with merged_df | View recommended plots | New interactive sheet

```
     #Left Join
     merged_df1=pd.merge(students,details,on="Student ID",how="left")
     merged_df1
```

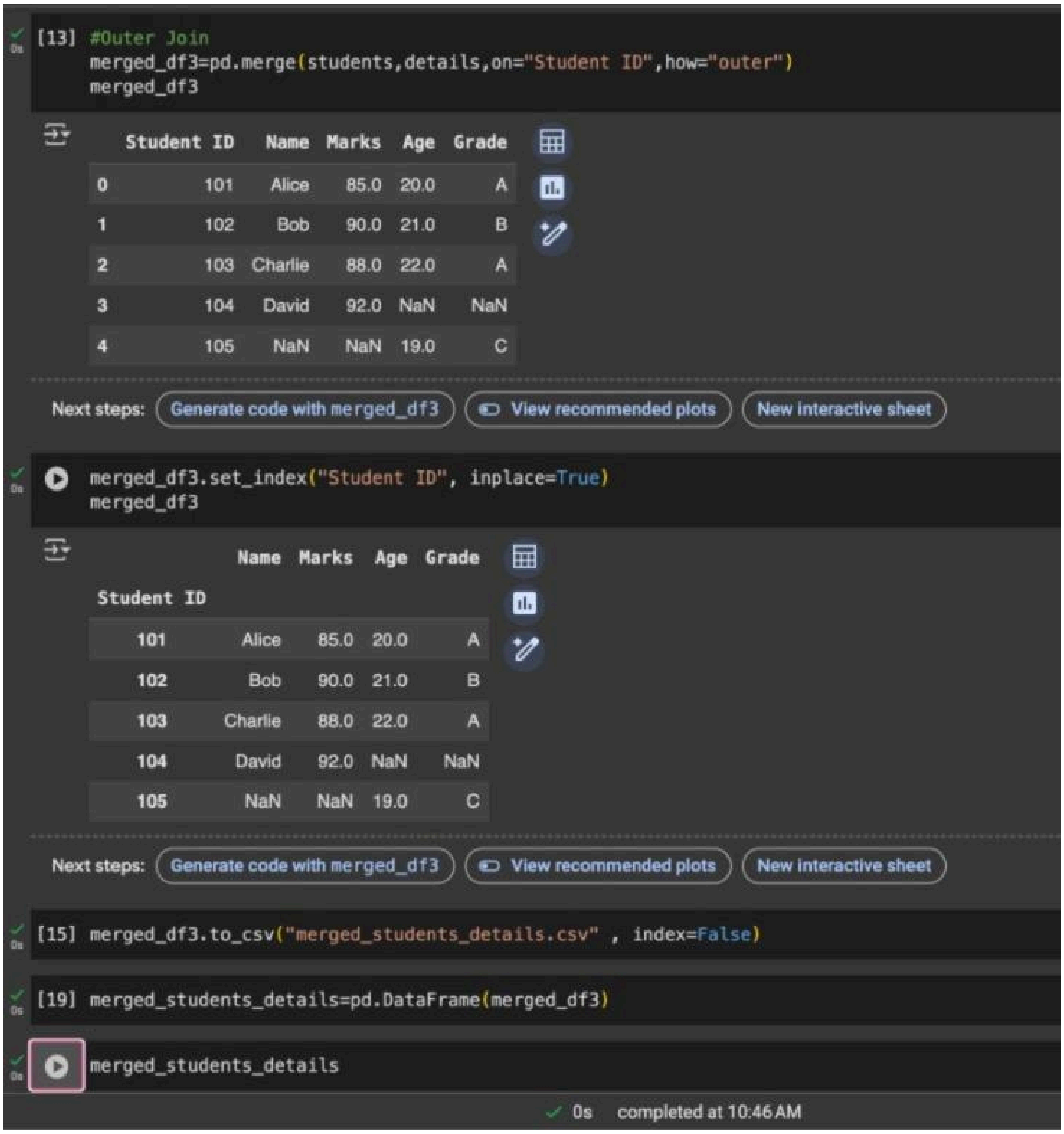
```
   Student ID     Name  Marks   Age  Grade
0         101    Alice     85  20.0      A
1         102      Bob     90  21.0      B
2         103  Charlie     88  22.0      A
3         104    David     92   NaN    NaN
```

Next steps: Generate code with merged_df1 | View recommended plots | New interactive sheet

```
[12] #Right Join
     merged_df2=pd.merge(students,details,on="Student ID",how="right")
     merged_df2
```

```
   Student ID     Name  Marks  Age  Grade
0         101    Alice   85.0   20      A
1         102      Bob   90.0   21      B
2         103  Charlie   88.0   22      A
3         105      NaN    NaN   19      C
```

✓ 0s completed at 10:45 AM



```
[13] #Outer Join
     merged_df3=pd.merge(students,details,on="Student ID",how="outer")
     merged_df3
```

```
   Student ID     Name  Marks   Age Grade
0         101    Alice   85.0  20.0     A
1         102      Bob   90.0  21.0     B
2         103  Charlie   88.0  22.0     A
3         104    David   92.0   NaN   NaN
4         105      NaN    NaN  19.0     C
```

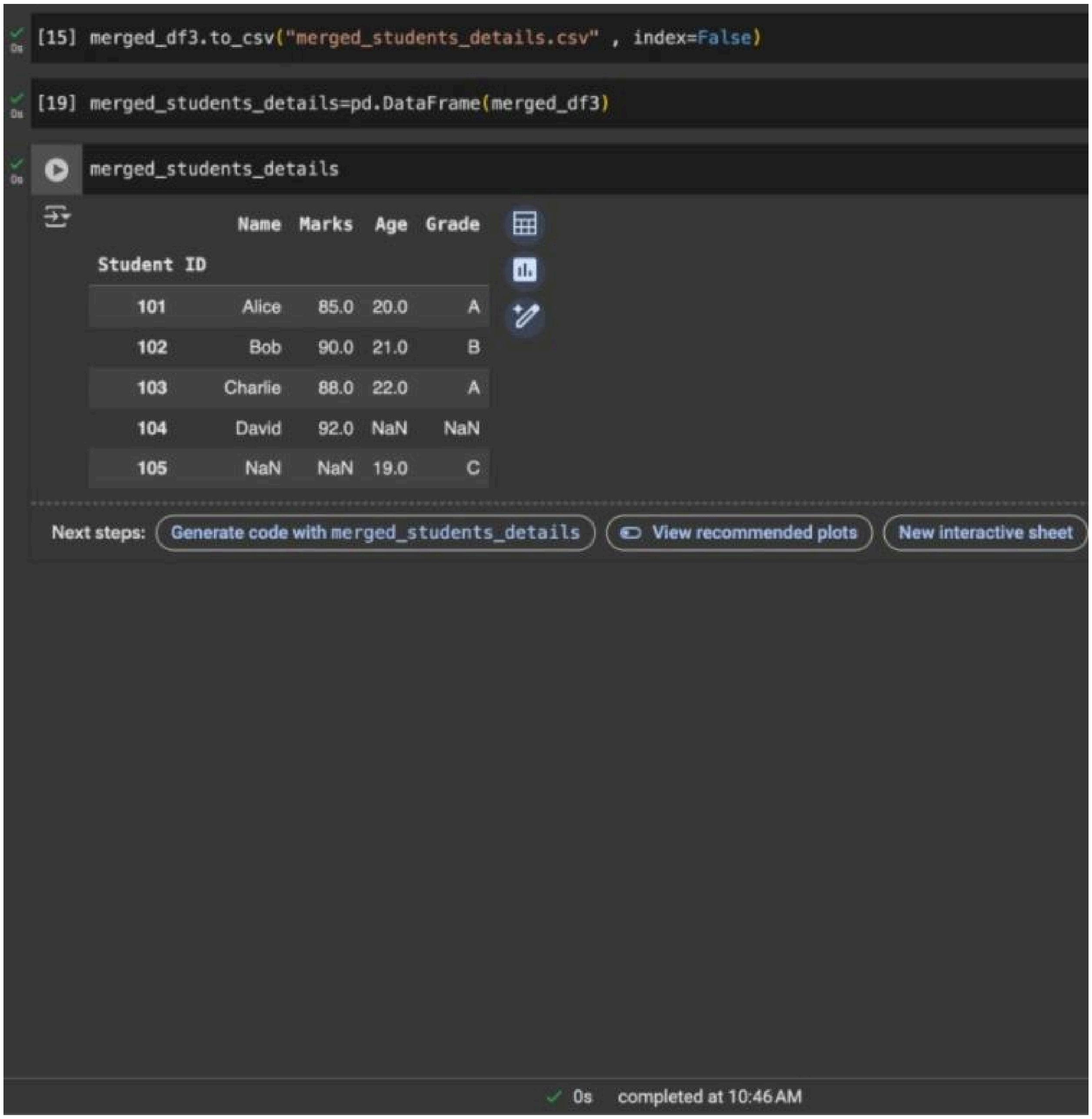
```
merged_df3.set_index("Student ID", inplace=True)
merged_df3
```

```
               Name  Marks   Age Grade
Student ID
101           Alice   85.0  20.0     A
102             Bob   90.0  21.0     B
103         Charlie   88.0  22.0     A
104           David   92.0   NaN   NaN
105             NaN    NaN  19.0     C
```

```
[15] merged_df3.to_csv("merged_students_details.csv" , index=False)

[19] merged_students_details=pd.DataFrame(merged_df3)

merged_students_details
```



```
[15] merged_df3.to_csv("merged_students_details.csv" , index=False)
```

```
[19] merged_students_details=pd.DataFrame(merged_df3)
```

```
merged_students_details
```

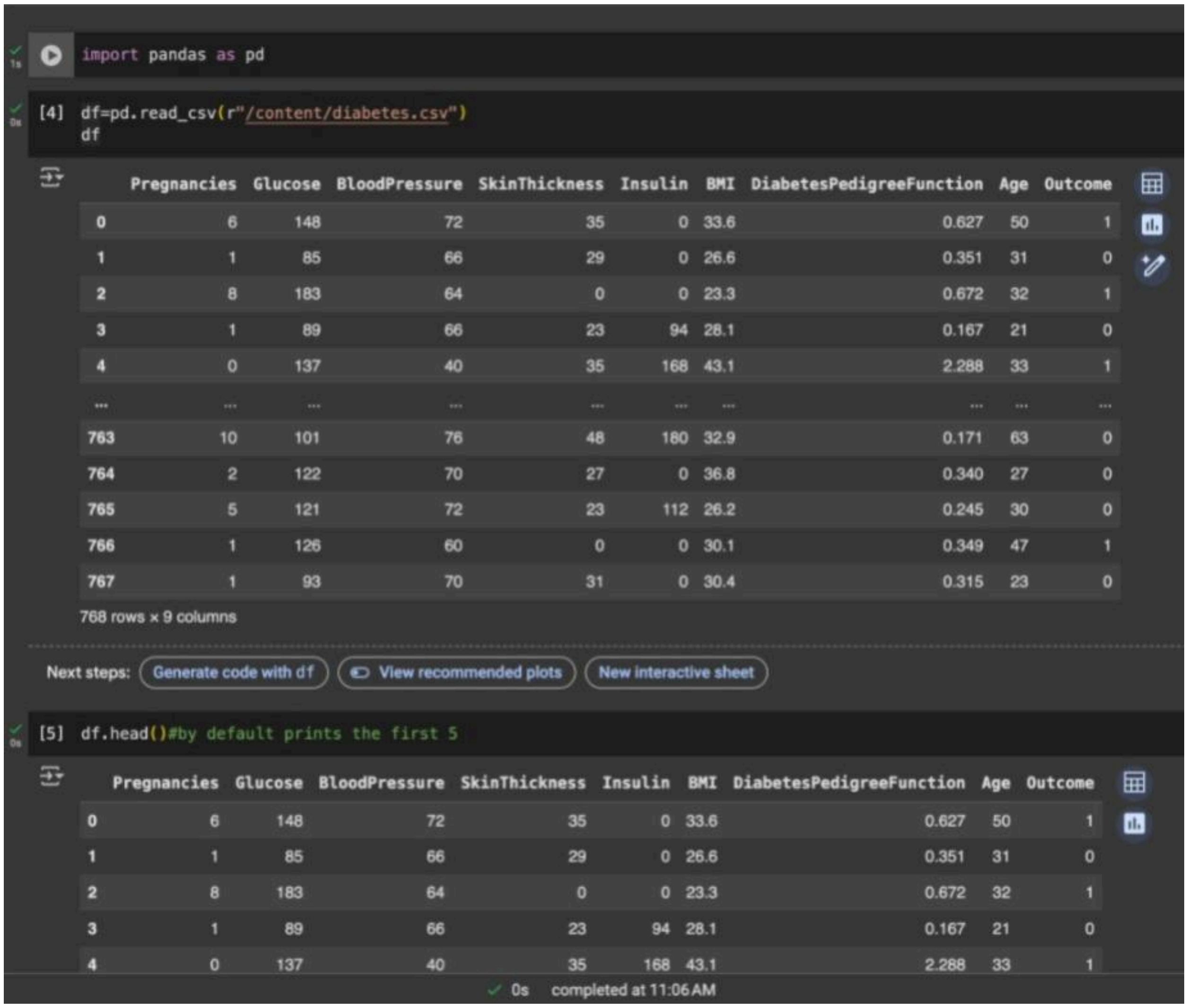
```
               Name  Marks   Age  Grade
Student ID
       101    Alice   85.0  20.0      A
       102      Bob   90.0  21.0      B
       103  Charlie   88.0  22.0      A
       104    David   92.0   NaN    NaN
       105      NaN    NaN  19.0      C
```

Part 3 - Exploratory Data Analysis (EDA)

Dataset: PIMA Indians Diabetes Dataset (use the dataset in the attached case studies or download it from Kaggle).

Tasks:
1. Load the Dataset:
Load the dataset into a pandas DataFrame.
Display its first five rows, shape, and basic statistics.

2. Handle Missing Values:
Identify and replace zeros in columns like Glucose or BMI with the median value of the respective column.



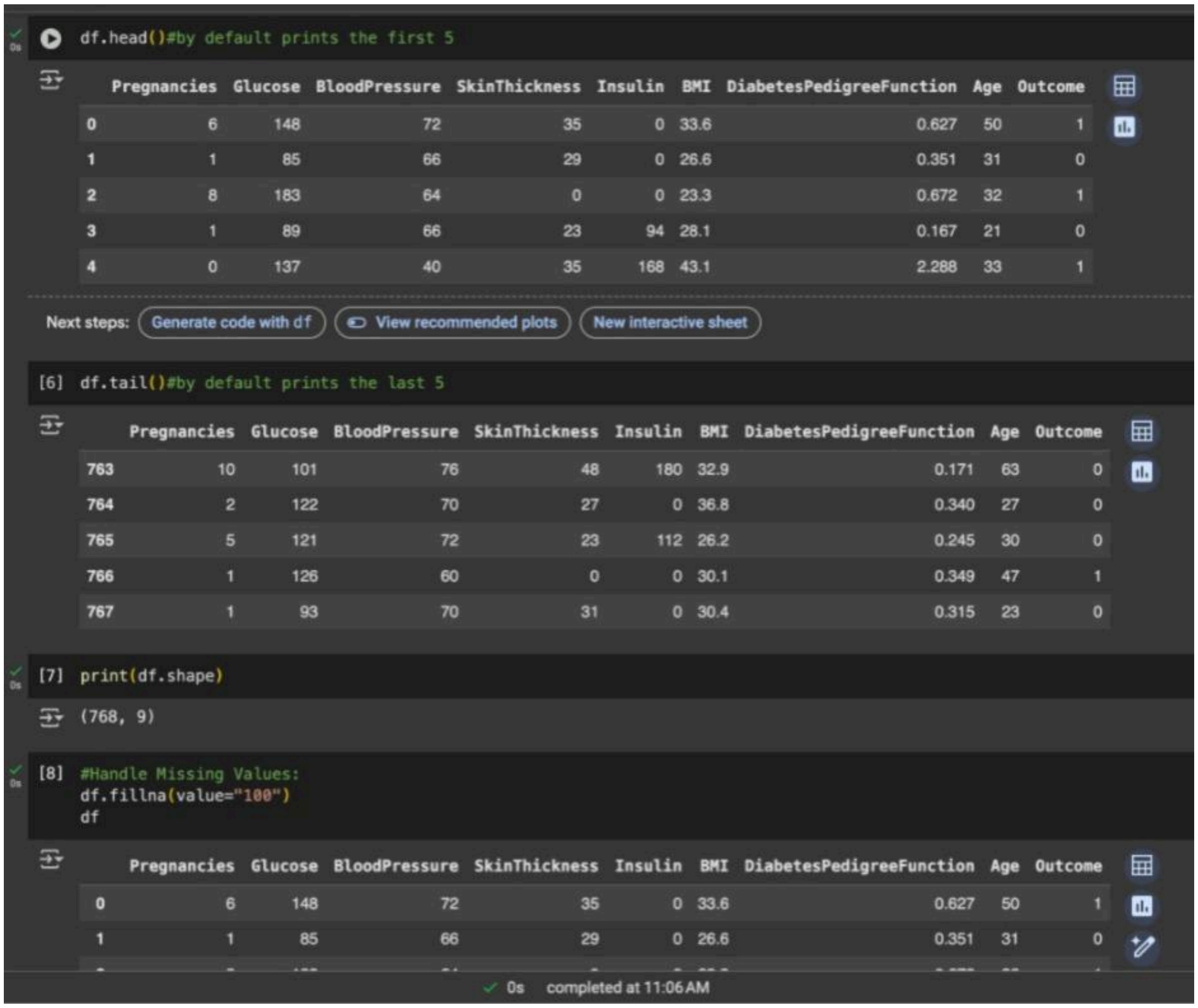
```
import pandas as pd
```

```
[4] df=pd.read_csv(r"/content/diabetes.csv")
    df
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0              6      148             72             35        0  33.6                     0.627   50        1
1              1       85             66             29        0  26.6                     0.351   31        0
2              8      183             64              0        0  23.3                     0.672   32        1
3              1       89             66             23       94  28.1                     0.167   21        0
4              0      137             40             35      168  43.1                     2.288   33        1
...          ...      ...            ...            ...      ...   ...                       ...  ...      ...
763           10      101             76             48      180  32.9                     0.171   63        0
764            2      122             70             27        0  36.8                     0.340   27        0
765            5      121             72             23      112  26.2                     0.245   30        0
766            1      126             60              0        0  30.1                     0.349   47        1
767            1       93             70             31        0  30.4                     0.315   23        0
768 rows × 9 columns
```

```
[5] df.head()#by default prints the first 5
```

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0            6      148             72             35        0  33.6                     0.627   50        1
1            1       85             66             29        0  26.6                     0.351   31        0
2            8      183             64              0        0  23.3                     0.672   32        1
3            1       89             66             23       94  28.1                     0.167   21        0
4            0      137             40             35      168  43.1                     2.288   33        1
```



```
df.head()#by default prints the first 5
```

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0            6      148             72             35        0  33.6                     0.627   50        1
1            1       85             66             29        0  26.6                     0.351   31        0
2            8      183             64              0        0  23.3                     0.672   32        1
3            1       89             66             23       94  28.1                     0.167   21        0
4            0      137             40             35      168  43.1                     2.288   33        1
```

```
[6] df.tail()#by default prints the last 5
```

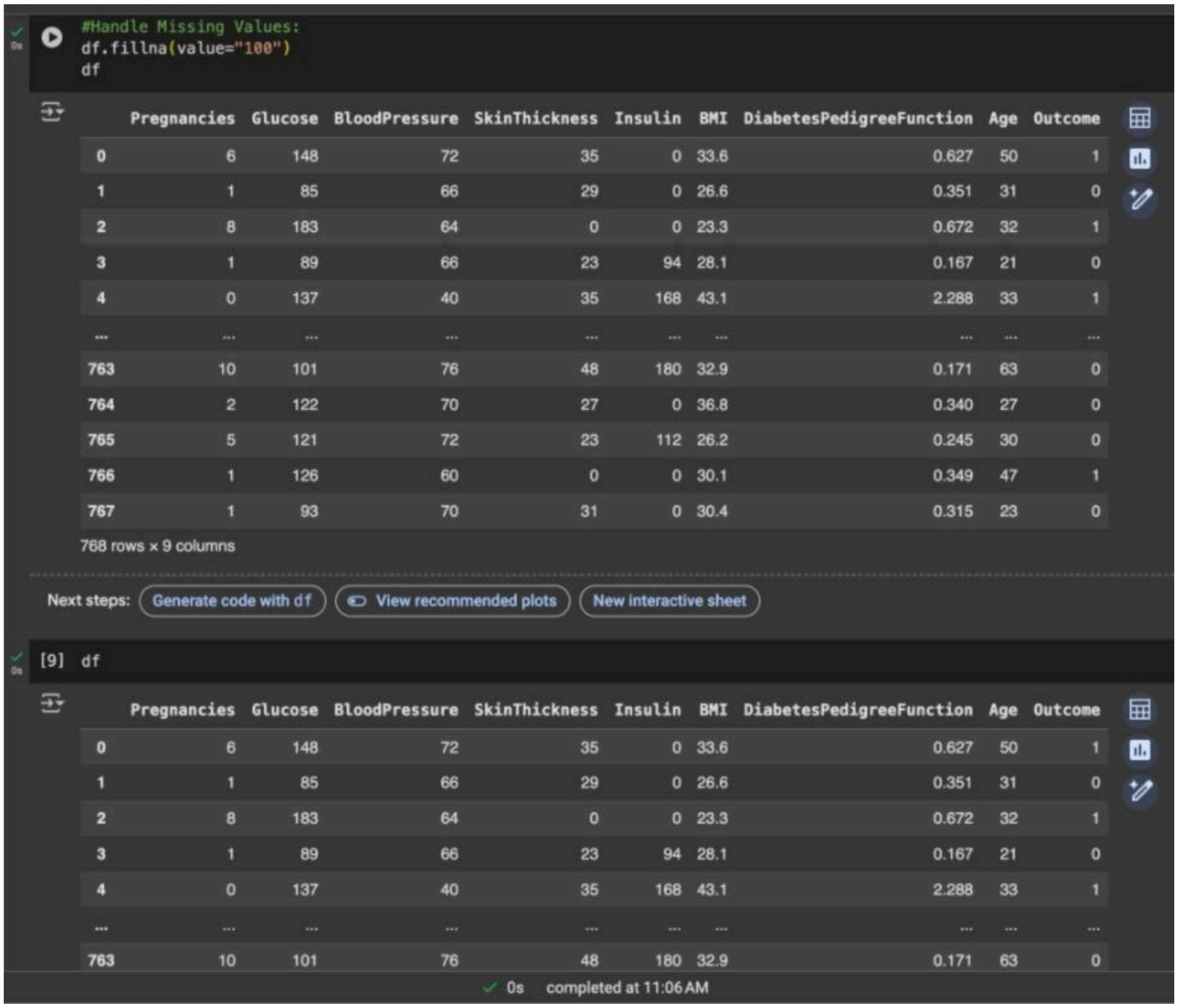
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
763           10      101             76             48      180  32.9                     0.171   63        0
764            2      122             70             27        0  36.8                     0.340   27        0
765            5      121             72             23      112  26.2                     0.245   30        0
766            1      126             60              0        0  30.1                     0.349   47        1
767            1       93             70             31        0  30.4                     0.315   23        0
```

```
[7] print(df.shape)
```

```
(768, 9)
```

```
[8] #Handle Missing Values:
    df.fillna(value="100")
    df
```

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0            6      148             72             35        0  33.6                     0.627   50        1
1            1       85             66             29        0  26.6                     0.351   31        0
```

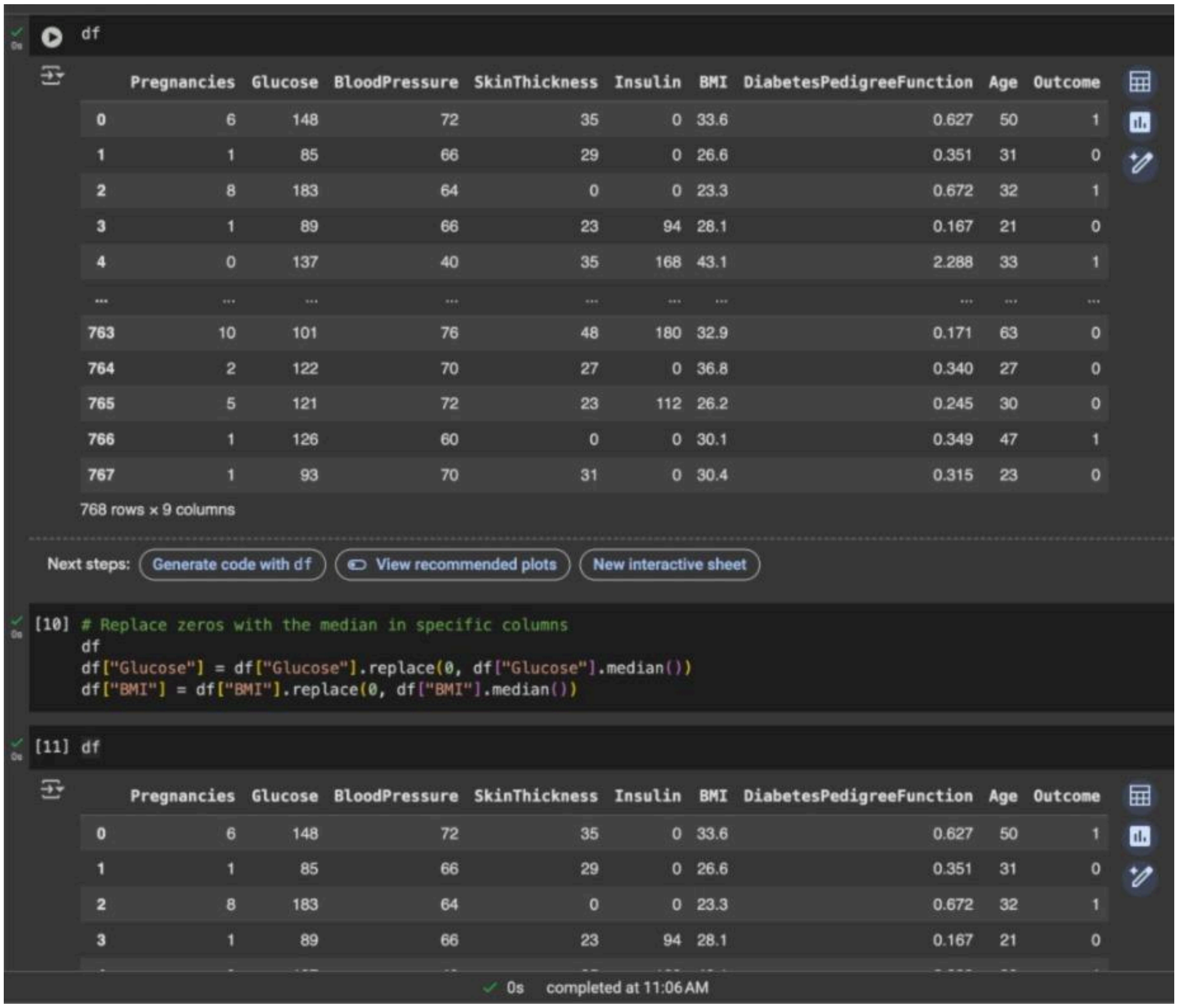


```
#Handle Missing Values:
df.fillna(value="100")
df
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0              6      148             72             35        0  33.6                     0.627   50        1
1              1       85             66             29        0  26.6                     0.351   31        0
2              8      183             64              0        0  23.3                     0.672   32        1
3              1       89             66             23       94  28.1                     0.167   21        0
4              0      137             40             35      168  43.1                     2.288   33        1
...          ...      ...            ...            ...      ...   ...                       ...  ...      ...
763           10      101             76             48      180  32.9                     0.171   63        0
764            2      122             70             27        0  36.8                     0.340   27        0
765            5      121             72             23      112  26.2                     0.245   30        0
766            1      126             60              0        0  30.1                     0.349   47        1
767            1       93             70             31        0  30.4                     0.315   23        0
768 rows × 9 columns
```

```
[9] df
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0              6      148             72             35        0  33.6                     0.627   50        1
1              1       85             66             29        0  26.6                     0.351   31        0
2              8      183             64              0        0  23.3                     0.672   32        1
3              1       89             66             23       94  28.1                     0.167   21        0
4              0      137             40             35      168  43.1                     2.288   33        1
...          ...      ...            ...            ...      ...   ...                       ...  ...      ...
763           10      101             76             48      180  32.9                     0.171   63        0
```



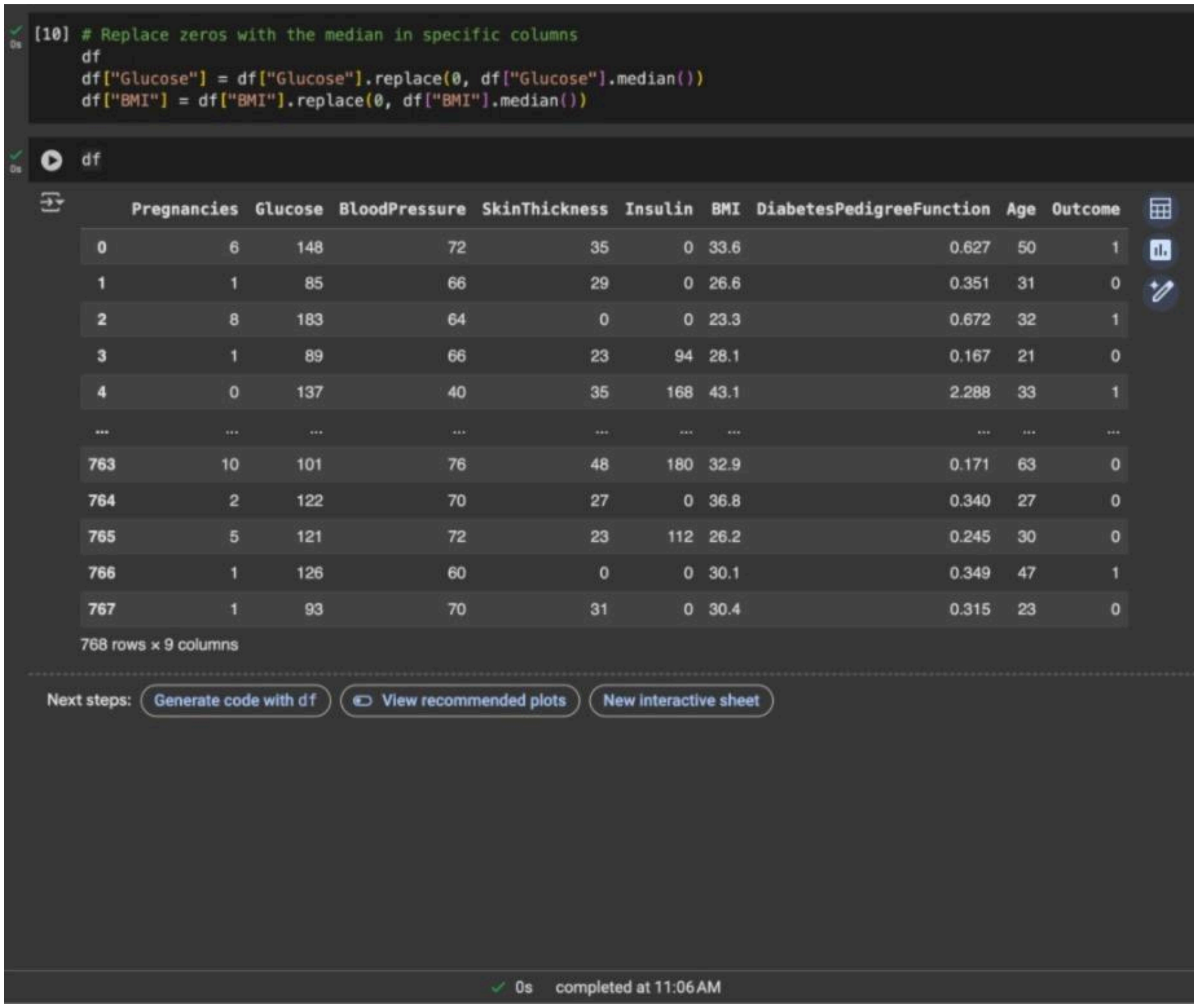
```
df
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0              6      148             72             35        0  33.6                     0.627   50        1
1              1       85             66             29        0  26.6                     0.351   31        0
2              8      183             64              0        0  23.3                     0.672   32        1
3              1       89             66             23       94  28.1                     0.167   21        0
4              0      137             40             35      168  43.1                     2.288   33        1
...          ...      ...            ...            ...      ...   ...                       ...  ...      ...
763           10      101             76             48      180  32.9                     0.171   63        0
764            2      122             70             27        0  36.8                     0.340   27        0
765            5      121             72             23      112  26.2                     0.245   30        0
766            1      126             60              0        0  30.1                     0.349   47        1
767            1       93             70             31        0  30.4                     0.315   23        0
768 rows × 9 columns
```

```
[10] # Replace zeros with the median in specific columns
     df
     df["Glucose"] = df["Glucose"].replace(0, df["Glucose"].median())
     df["BMI"] = df["BMI"].replace(0, df["BMI"].median())
```

```
[11] df
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0              6      148             72             35        0  33.6                     0.627   50        1
1              1       85             66             29        0  26.6                     0.351   31        0
2              8      183             64              0        0  23.3                     0.672   32        1
3              1       89             66             23       94  28.1                     0.167   21        0
```



```
[10] # Replace zeros with the median in specific columns
     df
     df["Glucose"] = df["Glucose"].replace(0, df["Glucose"].median())
     df["BMI"] = df["BMI"].replace(0, df["BMI"].median())
```

```
df
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  DiabetesPedigreeFunction  Age  Outcome
0              6      148             72             35        0  33.6                     0.627   50        1
1              1       85             66             29        0  26.6                     0.351   31        0
2              8      183             64              0        0  23.3                     0.672   32        1
3              1       89             66             23       94  28.1                     0.167   21        0
4              0      137             40             35      168  43.1                     2.288   33        1
...          ...      ...            ...            ...      ...   ...                       ...  ...      ...
763           10      101             76             48      180  32.9                     0.171   63        0
764            2      122             70             27        0  36.8                     0.340   27        0
765            5      121             72             23      112  26.2                     0.245   30        0
766            1      126             60              0        0  30.1                     0.349   47        1
767            1       93             70             31        0  30.4                     0.315   23        0
768 rows × 9 columns
```