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1 practical no.1
2 1. Introduction to Dataset
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6 5. Panda functions for Data Preprocessing
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```

In [3]: 1 import pandas as pd
        2 import seaborn as sns
        3 import numpy as np
        4 import matplotlib.pyplot as plt
        5 import warnings
        6 warnings.filterwarnings("ignore")
        7 from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

```

```

In [8]: 1 df=sns.get_dataset_names()
        2 print(data_set_name)

```

['anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes', 'diamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'glue', 'healthexp', 'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxis', 'tips', 'titanic', 'anagrams', 'anagrams', 'anscombe', 'anscombe', 'attention', 'attention', 'brain_networks', 'brain_networks', 'car_crashes', 'car_crashes', 'diamonds', 'diamonds', 'dots', 'dots', 'dowjones', 'dowjones', 'exercise', 'exercise', 'flights', 'flights', 'fmri', 'fmri', 'geyser', 'geyser', 'glue', 'glue', 'healthexp', 'healthexp', 'iris', 'iris', 'mpg', 'mpg', 'penguins', 'penguins', 'planets', 'planets', 'seaice', 'seaice', 'taxis', 'taxis', 'tips', 'tips', 'titanic', 'titanic', 'anagrams', 'anscombe', 'attention', 'brain_networks', 'car_crashes', 'diamonds', 'dots', 'dowjones', 'exercise', 'flights', 'fmri', 'geyser', 'glue', 'healthexp', 'iris', 'mpg', 'penguins', 'planets', 'seaice', 'taxis', 'tips', 'titanic']

```

In [12]: 1 df=sns.load_dataset('titanic')
        2 df

```

Out[12]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no
...
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	NaN	Southampton	no
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False	B	Southampton	yes
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False	NaN	Southampton	no
889	1	1	male	26.0	0	0	30.0000	C	First	man	True	C	Cherbourg	yes
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	NaN	Queenstown	no

891 rows × 15 columns

```

In [13]: 1 data1=df.head()
        2 data1
        3

```

Out[13]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no

```
In [14]: 1 data2=df.tail()
2 data2
```

```
Out[14]:
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive
886	0	2	male	27.0	0	0	13.00	S	Second	man	True	NaN	Southampton	nc
887	1	1	female	19.0	0	0	30.00	S	First	woman	False	B	Southampton	yes
888	0	3	female	NaN	1	2	23.45	S	Third	woman	False	NaN	Southampton	nc
889	1	1	male	26.0	0	0	30.00	C	First	man	True	C	Cherbourg	yes
890	0	3	male	32.0	0	0	7.75	Q	Third	man	True	NaN	Queenstown	nc

```
In [16]: 1 data3=df.info()
2 data3
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
#   Column          Non-Null Count  Dtype
---  -
0   survived        891 non-null    int64
1   pclass          891 non-null    int64
2   sex             891 non-null    object
3   age            714 non-null    float64
4   sibsp          891 non-null    int64
5   parch          891 non-null    int64
6   fare           891 non-null    float64
7   embarked       889 non-null    object
8   class          891 non-null    category
9   who            891 non-null    object
10  adult_male     891 non-null    bool
11  deck          203 non-null    category
12  embark_town    889 non-null    object
13  alive         891 non-null    object
14  alone         891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

```
In [17]: 1 data4=df['sex'].value_counts(normalize=True)
2 data4
```

```
Out[17]: sex
male      0.647587
female    0.352413
Name: proportion, dtype: float64
```

```
In [18]: 1 data5=df.describe()
2 data5
```

```
Out[18]:
```

	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
In [19]: 1 data6=df["deck"].value_counts(normalize=True)
2 data6
```

```
Out[19]: deck
C    0.290640
B    0.231527
D    0.162562
E    0.157635
A    0.073892
F    0.064039
G    0.019704
Name: proportion, dtype: float64
```

```
In [20]: 1 data7=df.drop(["deck"], axis=1)
2 data7
```

```
Out[20]:
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	embark_town	alive	al
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	Southampton	no	Fi
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	Cherbourg	yes	Fi
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	Southampton	yes	1
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	Southampton	yes	Fi
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	Southampton	no	1
...
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	Southampton	no	1
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False	Southampton	yes	1
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False	Southampton	no	Fi
889	1	1	male	26.0	0	0	30.0000	C	First	man	True	Cherbourg	yes	1
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	Queenstown	no	1

891 rows × 14 columns



```
In [24]: 1 data8=df.drop(["embarked","class","who","adult_male","deck","embark_town","alone"],axis=1)
2 data8
```

```
Out[24]:
```

	survived	pclass	sex	age	sibsp	parch	fare	alive
0	0	3	male	22.0	1	0	7.2500	no
1	1	1	female	38.0	1	0	71.2833	yes
2	1	3	female	26.0	0	0	7.9250	yes
3	1	1	female	35.0	1	0	53.1000	yes
4	0	3	male	35.0	0	0	8.0500	no
...
886	0	2	male	27.0	0	0	13.0000	no
887	1	1	female	19.0	0	0	30.0000	yes
888	0	3	female	NaN	1	2	23.4500	no
889	1	1	male	26.0	0	0	30.0000	yes
890	0	3	male	32.0	0	0	7.7500	no

891 rows × 8 columns

```
In [26]: 1 data9=df['sex'].mode()[0]
2 data9
```

```
Out[26]: 'male'
```

```
In [35]: 1 data10=df['age'].mode
         2 data10
```

```
Out[35]: <bound method Series.mode of 0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
...
886    27.0
887    19.0
888     NaN
889    26.0
890    32.0
Name: age, Length: 891, dtype: float64>
```

```
In [28]: 1 data11=df['age'].mean
         2 data11
```

```
Out[28]: <bound method Series.mean of 0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
...
886    27.0
887    19.0
888     NaN
889    26.0
890    32.0
Name: age, Length: 891, dtype: float64>
```

```
In [29]: 1 data12=df.loc[:, "sex"].mode()
         2 data12
```

```
Out[29]: 0    male
Name: sex, dtype: object
```

```
In [ ]: 1
```

```
In [50]: 1 bool_series = pd.notnull(df["sex"])
         2 bool_series
         3
```

```
Out[50]: 0      True
1      True
2      True
3      True
4      True
...
886    True
887    True
888    True
889    True
890    True
Name: sex, Length: 891, dtype: bool
```

```
In [55]: 1 df['age'].fillna(df['age'].mean(), inplace=True)
         2
```

```
1 data15=df.info()  
2 data15
```

```
1 name- Suhas Nidgundi
2 rollno. - 13249
```

```
1 name- Suhas Nidgundi
2 rollno. - 13249
```