

## Introduction to Pandas Library Function:

### Step-1 Import the pandas Libraries

```
import pandas as pd
```

### Step-2 Import the dataset from this:....

### Step-3 Read csv or excel File

```
df = pd.read_csv('titanic.csv')
```

### Step-4 Print Data from csv or excel File

```
df
```

	PassengerId	Survived	Pclass
0	1	0	3
1	2	1	1
2	3	1	3
3	4	1	1
4	5	0	3
..	...	...	...
886	887	0	2
887	888	1	1
888	889	0	3
889	890	1	1
890	891	0	3

SibSp	Name	Sex	Age
0	Braund, Mr. Owen Harris	male	22.0
1	Cumings, Mrs. John Bradley (Florence Briggs Th... 1	female	38.0
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
...
...
886                  Montvila, Rev. Juozas        male  27.0
0
887                  Graham, Miss. Margaret Edith   female  19.0
0
888      Johnston, Miss. Catherine Helen "Carrie"   female   NaN
1
889                  Behr, Mr. Karl Howell        male  26.0
0
890                  Dooley, Mr. Patrick        male  32.0
0

   Parch      Ticket     Fare Cabin Embarked
0      0          A/5 21171  7.2500   NaN      S
1      0          PC 17599  71.2833  C85      C
2      0      STON/O2. 3101282  7.9250   NaN      S
3      0          113803  53.1000  C123      S
4      0          373450  8.0500   NaN      S
...
...
886      0          211536 13.0000   NaN      S
887      0          112053 30.0000  B42      S
888      2      W./C. 6607  23.4500   NaN      S
889      0          111369 30.0000  C148      C
890      0          370376  7.7500   NaN      Q

```

[891 rows x 12 columns]

## Step-5 See the First 10 Rows

```
df.head(10)
```

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	
5	6	0	3	
6	7	0	1	
7	8	0	3	
8	9	1	3	
9	10	1	2	

SibSp	Name	Sex	Age
0	Braund, Mr. Owen Harris	male	22.0
1	Cumings, Mrs. John Bradley (Florence Briggs Th... 1	female	38.0
2	Heikkinen, Miss. Laina	female	26.0
0	Futrelle, Mrs. Jacques Heath (Lily May Peel) 1	female	35.0
4	Allen, Mr. William Henry	male	35.0
0	Moran, Mr. James 0	male	NaN
6	McCarthy, Mr. Timothy J	male	54.0
0	Palsson, Master. Gosta Leonard 3	male	2.0
8	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg) 0	female	27.0
9	Nasser, Mrs. Nicholas (Adele Achem) 1	female	14.0
Parch	Ticket	Fare	Cabin Embarked
0	A/5 21171	7.2500	Nan S
1	PC 17599	71.2833	C85 C
2	STON/O2. 3101282	7.9250	Nan S
3	113803	53.1000	C123 S
4	373450	8.0500	Nan S
5	330877	8.4583	Nan Q
6	17463	51.8625	E46 S
7	349909	21.0750	Nan S
8	347742	11.1333	Nan S
9	237736	30.0708	Nan C

## Step-6 See the Last 10 Rows

df.tail(10)				
	PassengerId	Survived	Pclass	
Name \ Johann	881	882	0	3
Ulrika	882	883	0	3
James	883	884	0	2
				Markun, Mr.
				Dahlberg, Miss. Gerda
				Banfield, Mr. Frederick

884	885	0	3	Sutehall, Mr.
Henry Jr				
885	886	0	3	Rice, Mrs. William (Margaret
Norton)				
886	887	0	2	Montvila, Rev.
Juozas				
887	888	1	1	Graham, Miss. Margaret
Edith				
888	889	0	3	Johnston, Miss. Catherine Helen
"Carrie"				
889	890	1	1	Behr, Mr. Karl
Howell				
890	891	0	3	Dooley, Mr.
Patrick				

	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
Embarked							
881	male	33.0	0	0	349257	7.8958	NaN
S							
882	female	22.0	0	0	7552	10.5167	NaN
S							
883	male	28.0	0	0	C.A./SOTON 34068	10.5000	NaN
S							
884	male	25.0	0	0	SOTON/OQ 392076	7.0500	NaN
S							
885	female	39.0	0	5	382652	29.1250	NaN
Q							
886	male	27.0	0	0	211536	13.0000	NaN
S							
887	female	19.0	0	0	112053	30.0000	B42
S							
888	female	NaN	1	2	W./C. 6607	23.4500	NaN
S							
889	male	26.0	0	0	111369	30.0000	C148
C							
890	male	32.0	0	0	370376	7.7500	NaN
Q							

## Step-7 Data type of each columns

df.dtypes

PassengerId	int64
Survived	int64
Pclass	int64
Name	object
Sex	object
Age	float64

```

SibSp          int64
Parch          int64
Ticket         object
Fare           float64
Cabin          object
Embarked       object
dtype: object

```

## Step-8 Display Summary Information

```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	\
count	891.000000	891.000000	891.000000	714.000000	891.000000	
mean	446.000000	0.383838	2.308642	29.699118	0.523008	
std	257.353842	0.486592	0.836071	14.526497	1.102743	
min	1.000000	0.000000	1.000000	0.420000	0.000000	
25%	223.500000	0.000000	2.000000	20.125000	0.000000	
50%	446.000000	0.000000	3.000000	28.000000	0.000000	
75%	668.500000	1.000000	3.000000	38.000000	1.000000	
max	891.000000	1.000000	3.000000	80.000000	8.000000	

	Parch	Fare
count	891.000000	891.000000
mean	0.381594	32.204208
std	0.806057	49.693429
min	0.000000	0.000000
25%	0.000000	7.910400
50%	0.000000	14.454200
75%	0.000000	31.000000
max	6.000000	512.329200

```
df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   PassengerId 891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object  
 4   Sex          891 non-null    object  
 5   Age          714 non-null    float64 
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object  

```

```
9    Fare          891 non-null      float64
10   Cabin         204 non-null      object
11   Embarked      889 non-null      object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

## Step-9 Access a specific column

```
df['Age']
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

df.Age
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
```

## Step-10 Access rows by their integer location

```
#accessing from index 25
df.iloc[25]

PassengerId          26
Survived             1
Pclass                3
Name     Asplund, Mrs. Carl Oscar (Selma Augusta Emilia...
```

```

Sex                           female
Age                          38.0
SibSp                         1
Parch                         5
Ticket                      347077
Fare                        31.3875
Cabin                         NaN
Embarked                       S
Name: 25, dtype: object

```

## Step-11 Delete a specific Column

```

df.drop("Age", axis = 1)
#to delete column axis = 1, only delete for particular cell (not
permanently)
#to delete row axis = 0
#to delete permanently set inplace = True

```

	PassengerId	Survived	Pclass
0		1	0
1		2	1
2		3	1
3		4	1
4		5	0
..	..	..	..
886	887	0	2
887	888	1	1
888	889	0	3
889	890	1	1
890	891	0	3

		Name	Sex	SibSp
Parch	\			
0		Braund, Mr. Owen Harris	male	1
0				
1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female		1
0				
2	Heikkinen, Miss. Laina	female		0
0				
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female		1
0				
4	Allen, Mr. William Henry	male		0
0				
..	..	..	..	..
..				
886		Montvila, Rev. Juozas	male	0
0				
887	Graham, Miss. Margaret Edith	female		0

```
0
888      Johnston, Miss. Catherine Helen "Carrie"
2
889      Behr, Mr. Karl Howell
0
890      Dooley, Mr. Patrick
0
```

	Ticket	Fare	Cabin	Embarked
0	A/5 21171	7.2500	NaN	S
1	PC 17599	71.2833	C85	C
2	STON/O2. 3101282	7.9250	NaN	S
3	113803	53.1000	C123	S
4	373450	8.0500	NaN	S
..	...	...	...	...
886	211536	13.0000	NaN	S
887	112053	30.0000	B42	S
888	w./C. 6607	23.4500	NaN	S
889	111369	30.0000	C148	C
890	370376	7.7500	NaN	Q

[891 rows x 11 columns]

```
df.drop("Age", axis = 1, inplace = True)
```

```
df
```

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	
..	...	...	...	
886	887	0	2	
887	888	1	1	
888	889	0	3	
889	890	1	1	
890	891	0	3	

	Parch	Name	Sex	SibSp
0		Braund, Mr. Owen Harris	male	1
0				
1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female		1
0				
2	Heikkinen, Miss. Laina	female		0
0				
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female		1
0				

```

4                               Allen, Mr. William Henry    male     0
0
...
886                               Montvila, Rev. Juozas    male     0
0
887                               Graham, Miss. Margaret Edith female     0
0
888           Johnston, Miss. Catherine Helen "Carrie" female     1
2
889                               Behr, Mr. Karl Howell    male     0
0
890                               Dooley, Mr. Patrick    male     0
0

      Ticket      Fare Cabin Embarked
0        A/5 21171   7.2500   NaN      S
1          PC 17599  71.2833  C85      C
2      STON/O2. 3101282   7.9250   NaN      S
3        113803   53.1000  C123      S
4        373450   8.0500   NaN      S
...
886        211536  13.0000   NaN      S
887        112053  30.0000  B42      S
888      W./C. 6607  23.4500   NaN      S
889        111369  30.0000  C148      C
890        370376   7.7500   NaN      Q

[891 rows x 11 columns]

```

## Step-12 Create a new Column

```

df['Amount'] = df['Fare']*100      #multiply fare to 100 and store value
in amount column
df

  PassengerId  Survived  Pclass \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3
...
886         887         0       2
887         888         1       1
888         889         0       3
889         890         1       1
890         891         0       3

```

```

      Name    Sex  SibSp
Parch \
0          Braund, Mr. Owen Harris    male     1
0
1  Cumings, Mrs. John Bradley (Florence Briggs Th... female     1
0
2          Heikkinen, Miss. Laina  female     0
0
3  Futrelle, Mrs. Jacques Heath (Lily May Peel) female     1
0
4          Allen, Mr. William Henry   male     0
0
..          ...
...
886         Montvila, Rev. Juozas    male     0
0
887         Graham, Miss. Margaret Edith female     0
0
888  Johnston, Miss. Catherine Helen "Carrie" female     1
2
889         Behr, Mr. Karl Howell    male     0
0
890         Dooley, Mr. Patrick    male     0
0

      Ticket   Fare Cabin Embarked  Amount
0        A/5 21171  7.2500   NaN       S  725.00
1           PC 17599  71.2833  C85       C 7128.33
2  STON/O2. 3101282  7.9250   NaN       S  792.50
3        113803  53.1000  C123       S 5310.00
4        373450  8.0500   NaN       S  805.00
..          ...
886        211536 13.0000   NaN       S 1300.00
887        112053 30.0000  B42       S 3000.00
888      W./C. 6607 23.4500   NaN       S 2345.00
889        111369 30.0000  C148       C 3000.00
890        370376  7.7500   NaN       Q  775.00

[891 rows x 12 columns]

```

## Step-13 Perform Condition Selection on DataFrame

```
df[df['Fare'] > 20]
```

Parch	\	Name	Sex	SibSp	
1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female		1	
0					
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female		1	
0					
6	McCarthy, Mr. Timothy J	male		0	
0					
7	Palsson, Master. Gosta Leonard	male		3	
1					
9	Nasser, Mrs. Nicholas (Adele Achem)	female		1	
0					
..		...	...	...	
...					
880	Shelley, Mrs. William (Imanita Parrish Hall)	female		0	
1					
885	Rice, Mrs. William (Margaret Norton)	female		0	
5					
887	Graham, Miss. Margaret Edith	female		0	
0					
888	Johnston, Miss. Catherine Helen "Carrie"	female		1	
2					
889	Behr, Mr. Karl Howell	male		0	
0					
	Ticket	Fare	Cabin	Embarked	Amount
1	PC 17599	71.2833	C85	C	7128.33
3	113803	53.1000	C123	S	5310.00
6	17463	51.8625	E46	S	5186.25
7	349909	21.0750	NaN	S	2107.50
9	237736	30.0708	NaN	C	3007.08
..	...	...	...	...	...
880	230433	26.0000	NaN	S	2600.00
885	382652	29.1250	NaN	Q	2912.50
887	112053	30.0000	B42	S	3000.00
888	W./C. 6607	23.4500	NaN	S	2345.00
889	111369	30.0000	C148	C	3000.00

```
[376 rows x 12 columns]
```

```
df[df['Sex'] == 'female']
```

	PassengerId	Survived	Pclass	\	Name	Sex	SibSp	
Parch	\							
1	2	1	1		Cumings, Mrs. John Bradley (Florence Briggs Th... 0	female	1	
2	3	1	3		Heikkinen, Miss. Laina 0	female	0	
3	4	1	1		Futrelle, Mrs. Jacques Heath (Lily May Peel) 0	female	1	
8	9	1	3		Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg) 2	female	0	
9	10	1	2		Nasser, Mrs. Nicholas (Adele Achem) 0	female	1	
..	...	...	...		...	...	...	
880	881	1	2		Shelley, Mrs. William (Imanita Parrish Hall) 1	female	0	
882	883	0	3		Dahlberg, Miss. Gerda Ulrika 0	female	0	
885	886	0	3		Rice, Mrs. William (Margaret Norton) 5	female	0	
887	888	1	1		Graham, Miss. Margaret Edith 0	female	0	
888	889	0	3		Johnston, Miss. Catherine Helen "Carrie" 2	female	1	
				Ticket	Fare	Cabin	Embarked	Amount
1		PC 17599	71.2833	C85		C	7128.33	
2	STON/O2.	3101282	7.9250	NaN		S	792.50	
3		113803	53.1000	C123		S	5310.00	
8		347742	11.1333	NaN		S	1113.33	
9		237736	30.0708	NaN		C	3007.08	
..		...	...	...	...	...	...	...

880	230433	26.0000	NaN	S	2600.00
882	7552	10.5167	NaN	S	1051.67
885	382652	29.1250	NaN	Q	2912.50
887	112053	30.0000	B42	S	3000.00
888	W./C. 6607	23.4500	NaN	S	2345.00

[314 rows x 12 columns]

```
df[(df['Fare'] > 20) & (df['Fare'] < 50)]
```

	PassengerId	Survived	Pclass	\
7	8	0	3	
9	10	1	2	
11	12	1	1	
13	14	0	3	
16	17	0	3	
..	...	...	...	
880	881	1	2	
885	886	0	3	
887	888	1	1	
888	889	0	3	
889	890	1	1	

		Name	Sex	SibSp	
Parch	\				
7		Palsson, Master. Gosta Leonard	male	3	
1					
9		Nasser, Mrs. Nicholas (Adele Achem)	female	1	
0					
11		Bonnell, Miss. Elizabeth	female	0	
0					
13		Andersson, Mr. Anders Johan	male	1	
5					
16		Rice, Master. Eugene	male	4	
1					
..		...	...	...	
.					
880	Shelley, Mrs. William (Imanita Parrish Hall)	female	0		
1					
885	Rice, Mrs. William (Margaret Norton)	female	0		
5					
887	Graham, Miss. Margaret Edith	female	0		
0					
888	Johnston, Miss. Catherine Helen "Carrie"	female	1		
2					
889	Behr, Mr. Karl Howell	male	0		
0					
	Ticket	Fare	Cabin	Embarked	Amount
7	349909	21.0750	NaN	S	2107.50

```
9          237736  30.0708    NaN      C  3007.08
11         113783  26.5500  C103      S  2655.00
13         347082  31.2750    NaN      S  3127.50
16         382652  29.1250    NaN      Q  2912.50
...
880        230433  26.0000    NaN      S  2600.00
885        382652  29.1250    NaN      Q  2912.50
887        112053  30.0000   B42      S  3000.00
888    W./C. 6607  23.4500    NaN      S  2345.00
889        111369  30.0000  C148      C  3000.00
```

```
[215 rows x 12 columns]
```

## Step-14 Compute the sum of value

```
df.Fare.sum()
```

```
28693.9493
```

## Step-15 Compute the mean of value

```
df.Fare.mean()
```

```
32.204207968574636
```

## Step-16 Count non-null value (column)

```
df.count()
```

```
PassengerId      891
Survived         891
Pclass           891
Name             891
Sex              891
SibSp            891
Parch            891
Ticket           891
Fare             891
Cabin           204
Embarked         889
Amount           891
dtype: int64
```

## Step-17 Find Minimum or Maximum values

```
df.Fare.max()
```

```
512.3292
```

```
df.Fare.min()
```

```
0.0
```

# Numpy & Perform Data Exploration with Pandas

## Numpy

1) NumPy (Numerical Python) is a powerful open-source library in Python used for numerical and scientific computing. 2) It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on them efficiently. 3) NumPy is highly optimized and written in C, making it much faster than using regular Python lists for numerical operations. 4) It serves as the foundation for many other Python libraries in data science and machine learning, like pandas, TensorFlow, and scikit-learn. 5) With features like broadcasting, vectorization, and integration with C/C++ code, NumPy allows for cleaner and faster code in numerical computations.

### Step 1. Import the Numpy library

```
import numpy as np
```

### Step 2. Create a 1D array of numbers

```
#arr = np.arange(20)
#arr = np.arange(5,20)
arr = np.array([1,2,3,4,5])
arr

array([1, 2, 3, 4, 5])
```

### Step 3. Reshape 1D to 2D Array

```
arr1=np.arange(12).reshape(3,4)
#arange(total).reshape(argument1,argument =total)
arr1
#print(type(arr1)) #array type
#arr1.dtype

array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

## Step 4. Create a Linspace array

```
#linspace uses the number of samples (num) as a parameter, whereas
arange uses the step size.
```

```
#linspace includes the endpoint by default, while arange does not.
np.linspace(2,5) #numpy.linspace(start, stop, num=50)
```

```
array([2.          , 2.06122449, 2.12244898, 2.18367347, 2.24489796,
       2.30612245, 2.36734694, 2.42857143, 2.48979592, 2.55102041,
       2.6122449 , 2.67346939, 2.73469388, 2.79591837, 2.85714286,
       2.91836735, 2.97959184, 3.04081633, 3.10204082, 3.16326531,
       3.2244898 , 3.28571429, 3.34693878, 3.40816327, 3.46938776,
       3.53061224, 3.59183673, 3.65306122, 3.71428571, 3.7755102 ,
       3.83673469, 3.89795918, 3.95918367, 4.02040816, 4.08163265,
       4.14285714, 4.20408163, 4.26530612, 4.32653061, 4.3877551 ,
       4.44897959, 4.51020408, 4.57142857, 4.63265306, 4.69387755,
       4.75510204, 4.81632653, 4.87755102, 4.93877551, 5.        ])
```

## Step 5. Create a Random Numbered Array

```
np.random.rand(4,5) #.rand(row,column)
```

```
array([[0.44038032, 0.67471774, 0.44878604, 0.12097114, 0.16000432],
       [0.90871693, 0.89649164, 0.25501194, 0.0460539 , 0.93094023],
       [0.02461087, 0.85730924, 0.95664616, 0.04115632, 0.84472724],
       [0.81159055, 0.86620271, 0.68160496, 0.03558224, 0.47387525]])
```

## Step 6. Create a Random Integer Array

```
np.random.randint(1,100,size=10)

array([ 9,  8,  8, 94, 88, 74,  2, 20, 56, 95])

#2d array
np.random.randint(1,100,size=(4,5))

array([[19, 96, 20, 86, 19],
       [ 9, 67, 22, 23, 64],
       [90, 85, 27, 14, 57],
       [16, 64, 30, 38, 68]])
```

## Step 7. Create a 1D Array and get Max,Min,ArgMax,ArgMin

```
arr=np.random.randint(20,50,size=10)
arr

array([48, 37, 21, 33, 29, 43, 38, 22, 43, 34])

arr.max()
```

```
48  
arr.min()  
21  
#The numpy.argmax() function returns indices of the max element of the array in a particular axis.  
arr.argmax()  
0  
#The numpy.argmin() method returns indices of the min element of the array in a particular axis.  
arr.argmin()  
2
```

## Step 8. Indexing in 1D Array

```
arr[5]  
43
```

## Step 9. Indexing in 2D Array

```
arr2= arr.reshape(2,5)  
arr2  
array([[48, 37, 21, 33, 29],  
       [43, 38, 22, 43, 34]])  
  
arr2[0]  
array([48, 37, 21, 33, 29])  
  
arr2[1][2]  
22
```

## Step 10. Conditional Selection

```
arr3=np.random.randint(1,20,5)  
arr3  
array([13, 5, 19, 3, 3])  
arr3[arr3 > 5]
```

```
array([13, 19])
```

🔥 You did it! 10 exercises down – you're on fire! 🔥

## Pandas

### Step 1. Import the necessary libraries

```
import pandas as pd
```

### Step 2. Import the dataset from this [address](#).

### Step 3. Assign it to a variable called users and use the 'user\_id' as index

```
users=pd.read_csv("https://raw.githubusercontent.com/justmarkham/  
DATA8/master/data/u.user",sep="|",index_col="user_id")  
users
```

	age	gender	occupation	zip_code
user_id				
1	24	M	technician	85711
2	53	F	other	94043
3	23	M	writer	32067
4	24	M	technician	43537
5	33	F	other	15213
...	...	...	...	...
939	26	F	student	33319
940	32	M	administrator	02215
941	20	M	student	97229
942	48	F	librarian	78209
943	22	M	student	77841

```
[943 rows x 4 columns]
```

### Step 4. See the first 25 entries

```
users.head(25)
```

	age	gender	occupation	zip_code
user_id				
1	24	M	technician	85711
2	53	F	other	94043
3	23	M	writer	32067
4	24	M	technician	43537
5	33	F	other	15213
6	42	M	executive	98101
7	57	M	administrator	91344
8	36	M	administrator	05201
9	29	M	student	01002

10	53	M	lawyer	90703
11	39	F	other	30329
12	28	F	other	06405
13	47	M	educator	29206
14	45	M	scientist	55106
15	49	F	educator	97301
16	21	M	entertainment	10309
17	30	M	programmer	06355
18	35	F	other	37212
19	40	M	librarian	02138
20	42	F	homemaker	95660
21	26	M	writer	30068
22	25	M	writer	40206
23	30	F	artist	48197
24	21	F	artist	94533
25	39	M	engineer	55107

## Step 5. See the last 10 entries

```
#default value 5
users.tail(10)

  user_id  age gender occupation zip_code
1  934     61     M   engineer    22902
2  935     42     M     doctor    66221
3  936     24     M     other    32789
4  937     48     M   educator    98072
5  938     38     F technician    55038
6  939     26     F   student    33319
7  940     32     M administrator    02215
8  941     20     M   student    97229
9  942     48     F   librarian    78209
10 943     22     M   student    77841
```

## Step 6. What is the number of observations in the dataset?

```
users.shape[0]
#users.shape -----> ama bai ave row nd col

(943, 4)
```

## Step 7. What is the number of columns in the dataset?

```
users.shape[1]

4
```

## Step 8. Print the name of all the columns.

```
users.columns  
Index(['age', 'gender', 'occupation', 'zip_code'], dtype='object')
```

## Step 9. How is the dataset indexed?

```
users.index  
Index([ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,  
       ...  
       934, 935, 936, 937, 938, 939, 940, 941, 942, 943],  
       dtype='int64', name='user_id', length=943)
```

## Step 10. What is the data type of each column?

```
users.dtypes  
age          int64  
gender       object  
occupation   object  
zip_code     object  
dtype: object
```

## Step 11. Print only the occupation column

```
#users.occupation  
users['occupation']  
  
user_id  
1      technician  
2          other  
3        writer  
4      technician  
5          other  
       ...  
939      student  
940    administrator  
941      student  
942    librarian  
943      student  
Name: occupation, Length: 943, dtype: object
```

## Step 12. How many different occupations are in this dataset?

```
users.occupation.nunique()
```

## Step 13. What is the most frequent occupation?

```
#users.occupation.value_counts()  
users.occupation.value_counts().head(1)  
  
occupation  
student    196  
Name: count, dtype: int64
```

## Step 14. Summarize the DataFrame.

```
users.describe()  
  
          age  
count    943.000000  
mean     34.051962  
std      12.192740  
min      7.000000  
25%     25.000000  
50%     31.000000  
75%     43.000000  
max     73.000000
```

## Step 15. Summarize all the columns

```
users.describe(include='all')  
  
          age   gender occupation zip_code  
count    943.000000      943      943      943  
unique           NaN        2       21      795  
top             NaN        M  student    55414  
freq            NaN       670      196        9  
mean     34.051962      NaN      NaN      NaN  
std      12.192740      NaN      NaN      NaN  
min      7.000000      NaN      NaN      NaN  
25%     25.000000      NaN      NaN      NaN  
50%     31.000000      NaN      NaN      NaN  
75%     43.000000      NaN      NaN      NaN  
max     73.000000      NaN      NaN      NaN
```

## Step 16. Summarize only the occupation column

```
users['occupation'].describe()  
  
count        943  
unique        21  
top    student  
freq        196  
Name: occupation, dtype: object
```

## Step 17. What is the mean age of users?

```
users['age'].mean()
```

```
34.05196182396607
```

## Step 18. What is the age with least occurrence?

```
users.age.value_counts().tail()
```

```
age
7      1
66     1
11     1
10     1
73     1
Name: count, dtype: int64
```

You're not just learning, you're mastering it. Keep aiming higher! 🔥

## 1) First, you need to read the titanic dataset from local disk and display first five records

```
import pandas as pd
df = pd.read_csv('titanic.csv')
-----
FileNotFoundError                         Traceback (most recent call
last)
Cell In[1], line 2
      1 import pandas as pd
----> 2 df = pd.read_csv('titanic.csv')

File ~\anaconda3\Lib\site-packages\pandas\io\parsers\readers.py:1026,
in read_csv(filepath_or_buffer, sep, delimiter, header, names,
index_col, usecols, dtype, engine, converters, true_values,
false_values, skipinitialspace, skiprows, skipfooter, nrows,
na_values, keep_default_na, na_filter, verbose, skip_blank_lines,
parse_dates, infer_datetime_format, keep_date_col, date_parser,
date_format, dayfirst, cache_dates, iterator, chunksize, compression,
thousands, decimal, lineterminator, quotechar, quoting, doublequote,
escapechar, comment, encoding, encoding_errors, dialect, on_bad_lines,
delim_whitespace, low_memory, memory_map, float_precision,
storage_options, dtype_backend)
    1013 kwds_defaults = _refine_defaults_read(
    1014     dialect,
    1015     delimiter,
    (...),
    1022     dtype_backend=dtype_backend,
    1023 )
    1024 kwds.update(kwds_defaults)
-> 1026 return _read(filepath_or_buffer, kwds)

File ~\anaconda3\Lib\site-packages\pandas\io\parsers\readers.py:620,
in _read(filepath_or_buffer, kwds)
    617 validate_names(kwds.get("names", None))
    619 # Create the parser.
--> 620 parser = TextFileReader(filepath_or_buffer, **kwds)
    622 if chunksize or iterator:
    623     return parser

File ~\anaconda3\Lib\site-packages\pandas\io\parsers\readers.py:1620,
in TextFileReader. init (self, f, engine, **kwds)
    1617     self.options["has index names"] = kwds["has_index_names"]
    1619 self.handles: IOHandles | None = None
-> 1620 self._engine = self._make_engine(f, self.engine)
```

```
File ~\anaconda3\Lib\site-packages\pandas\io\parsers\readers.py:1880,
in TextFileReader._make_engine(self, f, engine)
 1878     if "b" not in mode:
 1879         mode += "b"
-> 1880 self.handles = get_handle(
 1881     f,
 1882     mode,
 1883     encoding=self.options.get("encoding", None),
 1884     compression=self.options.get("compression", None),
 1885     memory_map=self.options.get("memory_map", False),
 1886     is_text=is_text,
 1887     errors=self.options.get("encoding_errors", "strict"),
 1888     storage_options=self.options.get("storage_options", None),
 1889 )
1890 assert self.handles is not None
1891 f = self.handles.handle
```

```
File ~\anaconda3\Lib\site-packages\pandas\io\common.py:873, in
get_handle(path_or_buf, mode, encoding, compression, memory_map,
is_text, errors, storage_options)
 868 elif isinstance(handle, str):
 869     # Check whether the filename is to be opened in binary
mode.
 870     # Binary mode does not support 'encoding' and 'newline'.
 871     if ioargs.encoding and "b" not in ioargs.mode:
 872         # Encoding
-> 873         handle = open(
 874             handle,
 875             ioargs.mode,
 876             encoding=ioargs.encoding,
 877             errors=errors,
 878             newline="",
 879         )
 880     else:
 881         # Binary mode
 882         handle = open(handle, ioargs.mode)
```

```
FileNotFoundException: [Errno 2] No such file or directory: 'titanic.csv'
```

```
df
```

---

```
-----
NameError                                                 Traceback (most recent call
last)
Cell In[3], line 1
----> 1 df
```

```
NameError: name 'df' is not defined
```

```
df.head(5)
```

```
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           Bra nd, 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
0            0       A/5 21171  7.2500   NaN      S
1            0       PC 17599  71.2833  C85      C
2            0  STON/O2. 3101282  7.9250   NaN      S
3            0       113803  53.1000  C123      S
4            0       373450  8.0500   NaN      S
```

2) Identify Nominal, Ordinal, Binary and Numeric attributes from data sets and display all values.

3) Identify symmetric and asymmetric binary attributes from data sets and display all values.

4) For each quantitative attribute, calculate its average, standard deviation, minimum, mode, range and maximum values.

```
PassengerId:
Mean = 446.00
Standard deviation = 257.35
Minimum = 1.00
Maximum = 891.00
```

```
Survived:  
    Mean = 0.38  
    Standard deviation = 0.49  
    Minimum = 0.00  
    Maximum = 1.00  
Pclass:  
    Mean = 2.31  
    Standard deviation = 0.84  
    Minimum = 1.00  
    Maximum = 3.00  
Age:  
    Mean = 29.70  
    Standard deviation = 14.53  
    Minimum = 0.42  
    Maximum = 80.00  
SibSp:  
    Mean = 0.52  
    Standard deviation = 1.10  
    Minimum = 0.00  
    Maximum = 8.00  
Parch:  
    Mean = 0.38  
    Standard deviation = 0.81  
    Minimum = 0.00  
    Maximum = 6.00  
Fare:  
    Mean = 32.20  
    Standard deviation = 49.69  
    Minimum = 0.00  
    Maximum = 512.33
```

6) For the qualitative attribute (class), count the frequency for each of its distinct values.

```
3      491  
1      216  
2      184  
Name: Pclass, dtype: int64
```

7) It is also possible to display the summary for all the attributes simultaneously in a table using the `describe()` function. If an attribute is quantitative, it will display its mean, standard deviation and various quantiles (including minimum, median, and maximum) values. If an attribute is qualitative, it will display its number of unique values and the top (most frequent) values.

	PassengerId	Survived	Pclass	Name		
Sex \ count	891.000000	891.000000	891.000000	891		
891 unique	Nan	Nan	Nan	891		
2 top	Nan	Nan	Nan	Braund, Mr. Owen	Harris	
male freq	Nan	Nan	Nan	1		
577 mean	446.000000	0.383838	2.308642	NaN		
Nan std	257.353842	0.486592	0.836071	NaN		
Nan min	1.000000	0.000000	1.000000	NaN		
Nan 25%	223.500000	0.000000	2.000000	NaN		
Nan 50%	446.000000	0.000000	3.000000	NaN		
Nan 75%	668.500000	1.000000	3.000000	NaN		
Nan max	891.000000	1.000000	3.000000	NaN		
Nan						
	Age	SibSp	Parch	Ticket	Fare	
Cabin \ count	714.000000	891.000000	891.000000	891	891.000000	
204 unique	Nan	Nan	Nan	681	NaN	
147 top	Nan	Nan	Nan	347082	NaN B96	
B98 freq	Nan	Nan	Nan	7	NaN	
4 mean	29.699118	0.523008	0.381594	NaN	32.204208	
Nan std	14.526497	1.102743	0.806057	NaN	49.693429	
Nan						

min	0.420000	0.000000	0.000000	NaN	0.000000
NaN					
25%	20.125000	0.000000	0.000000	NaN	7.910400
NaN					
50%	28.000000	0.000000	0.000000	NaN	14.454200
NaN					
75%	38.000000	1.000000	0.000000	NaN	31.000000
NaN					
max	80.000000	8.000000	6.000000	NaN	512.329200
NaN					
Embarked					
count	889				
unique	3				
top	S				
freq	644				
mean	NaN				
std	NaN				
min	NaN				
25%	NaN				
50%	NaN				
75%	NaN				
max	NaN				

## 8) For multivariate statistics, you can compute the covariance and correlation between pairs of attributes.

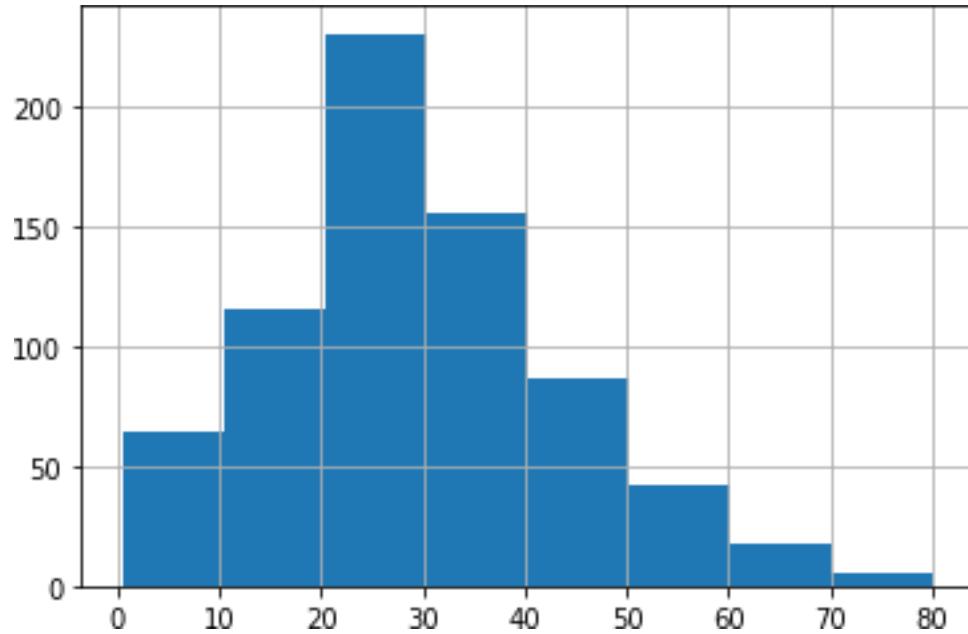
	PassengerId	Survived	Pclass	Age	SibSp
\					
PassengerId	66231.000000	-0.626966	-7.561798	138.696504	-16.325843
Survived		-0.626966	0.236772	-0.137703	-0.551296
Pclass		-7.561798	-0.137703	0.699015	-4.496004
Age		138.696504	-0.551296	-4.496004	211.019125
SibSp		-16.325843	-0.018954	0.076599	-4.163334
Parch		-0.342697	0.032017	0.012429	-2.344191
Fare		161.883369	6.221787	-22.830196	73.849030
Parch					
PassengerId	-0.342697	161.883369			
Survived	0.032017	6.221787			
Pclass	0.012429	-22.830196			

Age	-2.344191	73.849030
SibSp	0.368739	8.748734
Parch	0.649728	8.661052
Fare	8.661052	2469.436846

	PassengerId	Survived	Pclass	Age	SibSp
Parch \					
PassengerId	1.000000	-0.005007	-0.035144	0.036847	-0.057527
0.001652					
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322
0.081629					
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081
0.018443					
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247
0.189119					
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000
0.414838					
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838
1.000000					
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651
0.216225					
					Fare
PassengerId	0.012658				
Survived	0.257307				
Pclass	-0.549500				
Age	0.096067				
SibSp	0.159651				
Parch	0.216225				
Fare	1.000000				

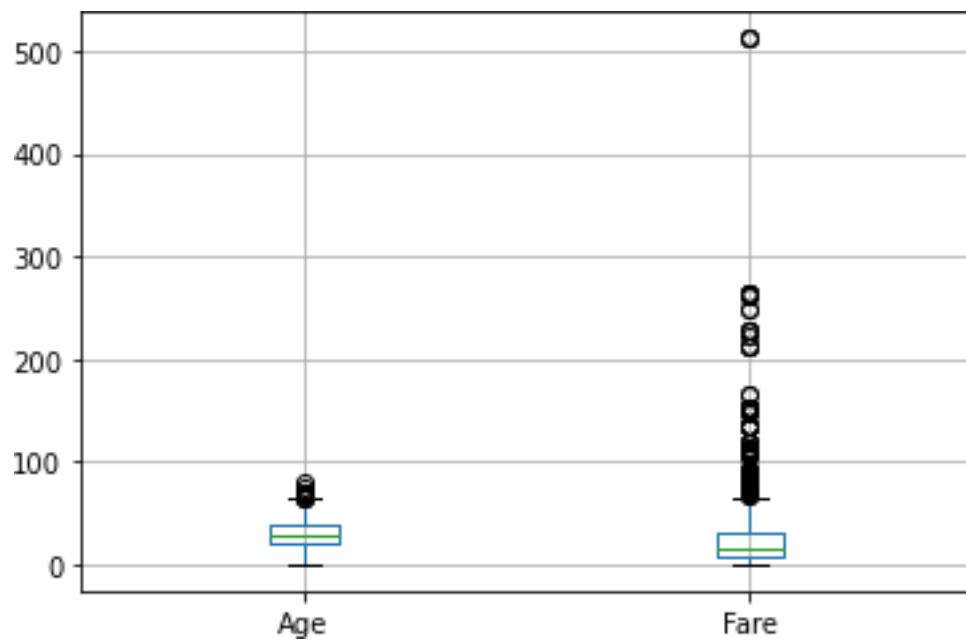
9) Display the histogram for Age attribute by discretizing it into 8 separate bins and counting the frequency for each bin.

```
<AxesSubplot:>
```



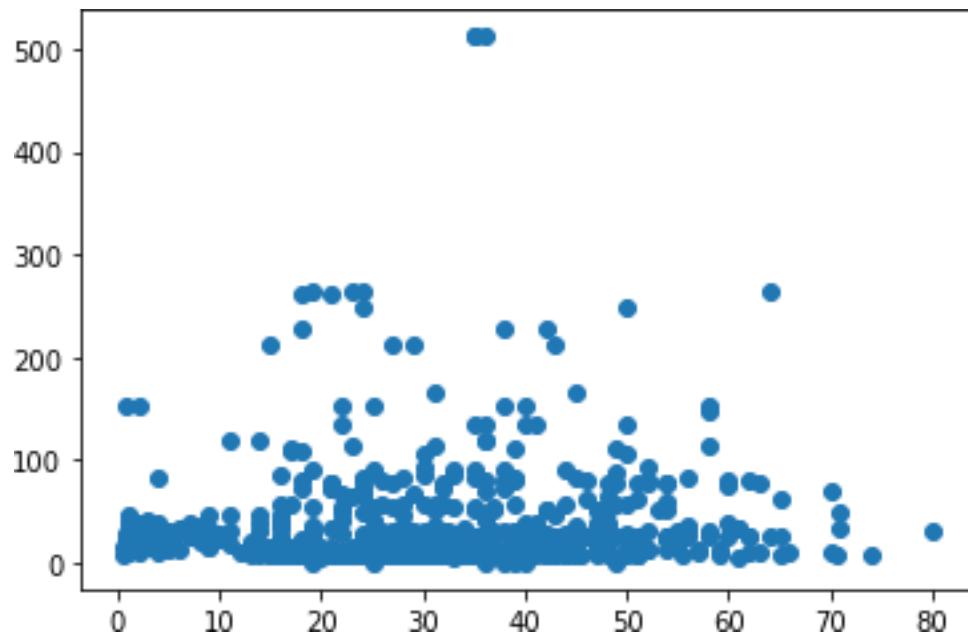
10) A boxplot can also be used to show the distribution of values for each attribute.

```
<AxesSubplot:>
```



11) Display scatter plot for any 5 pair of attributes , we can use a scatter plot to visualize their joint distribution.

```
<matplotlib.collections.PathCollection at 0x7f939a5eadf0>
```



## Step 1. Import the necessary libraries

```
import pandas as pd  
import numpy as np
```

## Step 2. Import the dataset from this [address](https://raw.githubusercontent.com/justmarkham/DAT8/master/data/chipotle.tsv).

## Step 3. Assign it to a variable called chipo.

```
chipo=pd.read_csv("https://raw.githubusercontent.com/justmarkham/  
DAT8/master/data/chipotle.tsv",sep="\t")  
chipo
```

```
order_id  quantity          item_name \
0           1            1    Chips and Fresh Tomato Salsa
1           1            1                  Izze
2           1            1    Nantucket Nectar
3           1            1  Chips and Tomatillo-Green Chili Salsa
4           2            2            Chicken Bowl
...         ...          ...
4617        1833          1            Steak Burrito
4618        1833          1            Steak Burrito
4619        1834          1      Chicken Salad Bowl
4620        1834          1      Chicken Salad Bowl
4621        1834          1      Chicken Salad Bowl

choice_description  item_price
0                      NaN     $2.39
1                [Clementine]     $3.39
2                  [Apple]     $3.39
3                      NaN     $2.39
4  [Tomatillo-Red Chili Salsa (Hot), [Black Beans...     $16.98
...                   ...
4617  [Fresh Tomato Salsa, [Rice, Black Beans, Sour ...     $11.75
4618  [Fresh Tomato Salsa, [Rice, Sour Cream, Cheese...     $11.75
4619  [Fresh Tomato Salsa, [Fajita Vegetables, Pinto...     $11.25
4620  [Fresh Tomato Salsa, [Fajita Vegetables, Lettu...     $8.75
4621  [Fresh Tomato Salsa, [Fajita Vegetables, Pinto...     $8.75

[4622 rows x 5 columns]
```

## Step 4. See the first 10 entries

```
chipo.head(10)
```

```
order_id  quantity          item_name \
0           1            1    Chips and Fresh Tomato Salsa
1           1            1                  Izze
```

```

2      1      1          Nantucket Nectar
3      1      1  Chips and Tomatillo-Green Chili Salsa
4      2      2          Chicken Bowl
5      3      1          Chicken Bowl
6      3      1          Side of Chips
7      4      1          Steak Burrito
8      4      1          Steak Soft Tacos
9      5      1          Steak Burrito

choice  description  item  price
0           NaN     $2.39
1  [Clementine]     $3.39
2      [Apple]     $3.39
3           NaN     $2.39
4  [Tomatillo-Red Chili Salsa (Hot), [Black Beans...     $16.98
5  [Fresh Tomato Salsa (Mild), [Rice, Cheese, Sou...     $10.98
6           NaN     $1.69
7  [Tomatillo Red Chili Salsa, [Fajita Vegetables...     $11.75
8  [Tomatillo Green Chili Salsa, [Pinto Beans, Ch...     $9.25
9  [Fresh Tomato Salsa, [Rice, Black Beans, Pinto...     $9.25

```

## Step 5. What is the number of observations in the dataset?

```
# Solution 1
chipo.shape[0]
```

4622

```
# Solution 2
chipo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4622 entries, 0 to 4621
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   order_id          4622 non-null   int64  
 1   quantity          4622 non-null   int64  
 2   item_name         4622 non-null   object  
 3   choice_description 3376 non-null   object  
 4   item_price        4622 non-null   object  
dtypes: int64(2), object(3)
memory usage: 180.7+ KB
```

## Step 6. What is the number of columns in the dataset?

```
# 1 for columns
# 0 for rows
chipo.shape[1]
```

5

## Step 7. Print the name of all the columns.

```
chipo.columns  
  
Index(['order_id', 'quantity', 'item_name', 'choice_description',  
       'item_price'],  
      dtype='object')
```

## Step 8. How is the dataset indexed?

```
chipo.index  
  
RangeIndex(start=0, stop=4622, step=1)
```

## Step 9. Number of Unique Items ?

```
chipo.item_name.nunique()  
  
50
```

## Step 10. Which was the most-ordered item?

```
c=chipo.groupby('item_name')  
#c.get_group('Chicken Bowl')  
c=c.sum()  
c=c.sort_values(['quantity'], ascending=False)  
c.head(1)  
  
          order_id quantity \  
item_name  
Chicken Bowl    713926      761  
  
                                choice_description \  
item_name  
Chicken Bowl  [Tomatillo-Red Chili Salsa (Hot), [Black Beans...  
  
                                item_price  
item_name  
Chicken Bowl  $16.98 $10.98 $11.25 $8.75 $8.49 $11.25 $8.75 ...
```

## Step 11. How many items were ordered in total?

```
chipo['quantity'].sum()  
  
4972
```

## Step 12. Turn the item price into a float

### Step 12.a. Check the item price type

```
chipo['item_price'].dtypes  
dtype('O')
```

### Step 12.b. Create a lambda function and change the type of item price

```
a="$2.34"  
print(type(a))  
  
<class 'str'>  
  
x=a[1:]  
print(x)  
  
2.34  
  
y=float(x)  
print(y)  
print(type(y))  
  
2.34  
<class 'float'>  
  
m = lambda x: float(x[1:])  
chipo['item_price']=chipo['item_price'].apply(m)
```

### Step 12.c. Check the item price type

```
chipo['item_price'].dtypes  
dtype('float64')
```

## Step 14. How much was the revenue for the period in the dataset?

```
revenue=(chipo['quantity']*chipo['item_price']).sum()  
print("revenue was :$",revenue)  
  
revenue was :$ 39237.02
```

## Step 15. How many orders were made ?

```
chipo['order_id'].nunique()  
1834
```

## Step 17. How many different choice descriptions are there?

```
chipo['choice_description'].nunique()
```

1043

## Step 18. What items have been ordered more than 100 times?

```
chipo.groupby('item_name')['quantity'].sum().loc[lambda x:x>100]

item name
Bottled Water           211
Canned Soda             126
Canned Soft Drink       351
Chicken Bowl            761
Chicken Burrito         591
Chicken Salad Bowl      123
Chicken Soft Tacos      120
Chips                   230
Chips and Fresh Tomato Salsa 130
Chips and Guacamole     506
Side of Chips           110
Steak Bowl               221
Steak Burrito            386
Name: quantity, dtype: int64
```

## Step 19. What is the average revenue amount per order?

```
# Solution 1
chipo['revenue']=chipo['quantity']*chipo['item_price']
c=chipo.groupby('order_id')['revenue'].sum().mean()
c

21.39423118865867
```

```
# Solution 2
```

```
21.394231188658654
```

1) First, you need to read the titanic dataset from local disk and display Last five records

```
import pandas as pd

df = pd.read_csv("titanic.csv")

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   PassengerId 891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object  
 4   Sex          891 non-null    object  
 5   Age          714 non-null    float64 
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object  
 9   Fare          891 non-null    float64 
 10  Cabin        204 non-null    object  
 11  Embarked     889 non-null    object  
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB

df.isnull().sum()

PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin            687
Embarked         2
dtype: int64
```

## 2) Handle Missing Values in data set [use dropna(), fillna(), and interpolate]

```
#je je record ni andar ek pan record missing hse ee record delete
karse
```

```
df.dropna()
```

	PassengerId	Survived	Pclass	\
1	2	1	1	
3	4	1	1	
6	7	0	1	
10	11	1	3	
11	12	1	1	
...	...	...	...	
871	872	1	1	
872	873	0	1	
879	880	1	1	
887	888	1	1	
889	890	1	1	

	SibSp	Name	Sex	Age
1	Cumings, Mrs. John Bradley (Florence Briggs Th... 1		female	38.0
3	Futrelle, Mrs. Jacques Heath (Lily May Peel) 1		female	35.0
6	McCarthy, Mr. Timothy J 0		male	54.0
10	Sandstrom, Miss. Marguerite Rut 1		female	4.0
11	Bonnell, Miss. Elizabeth 0		female	58.0
...	...	...	...	...
871	Beckwith, Mrs. Richard Leonard (Sallie Monypeny) 1		female	47.0
872	Carlsson, Mr. Frans Olof 0		male	33.0
879	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson) 0		female	56.0
887	Graham, Miss. Margaret Edith 0		female	19.0
889	Behr, Mr. Karl Howell 0		male	26.0

	Parch	Ticket	Fare	Cabin	Embarked
1	0	PC 17599	71.2833	C85	C
3	0	113803	53.1000	C123	S
6	0	17463	51.8625	E46	S
10	1	PP 9549	16.7000	G6	S

```

11      0    113783  26.5500          C103      S
..    ...
871     1    11751  52.5542          D35      S
872     0     695  5.0000  B51 B53 B55      S
879     1    11767  83.1583          C50      C
887     0   112053 30.0000          B42      S
889     0   111369 30.0000          C148      C

```

[183 rows x 12 columns]

```
df.dropna(inplace=True)
```

```
df
```

	PassengerId	Survived	Pclass	\
0		1	0	3
1		2	1	1
2		3	1	3
3		4	1	1
4		5	0	3
..	...	...	...	...
886	887	0	2	
887	888	1	1	
888	889	0	3	
889	890	1	1	
890	891	0	3	

SibSp	Name	Sex	Age
0	Braund, Mr. Owen Harris	male	22.0
1	Cumings, Mrs. John Bradley (Florence Briggs Th... 1	female	38.0
2	Heikkinen, Miss. Laina	female	26.0
0	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0
1	Allen, Mr. William Henry	male	35.0
0	...	...	...
..	...	...	...
886	Montvila, Rev. Juozas	male	27.0
0	Graham, Miss. Margaret Edith	female	19.0
0	Johnston, Miss. Catherine Helen "Carrie"	female	NaN
1	Behr, Mr. Karl Howell	male	26.0
0	Dooley, Mr. Patrick	male	32.0

```
0
```

```
Parch      Ticket      Fare Cabin Embarked
0          0    A/5 21171  7.2500   NaN     S
1          0      PC 17599  71.2833  C85     C
2          0  STON/O2. 3101282  7.9250   NaN     S
3          0            113803  53.1000  C123     S
4          0            373450  8.0500   NaN     S
...
886         0            211536 13.0000   NaN     S
887         0            112053 30.0000  B42     S
888         2            W./C. 6607  23.4500   NaN     S
889         0            111369 30.0000  C148     C
890         0            370376  7.7500   NaN     Q
```

```
[891 rows x 12 columns]
```

```
df.dropna(axis=1)
```

```
PassengerId  Survived  Pclass \
1              2         1      1
3              4         1      1
6              7         0      1
10             11        1      3
11             12        1      1
...
871            872        1      1
872            873        0      1
879            880        1      1
887            888        1      1
889            890        1      1
```

```
Name      Sex   Age
SibSp \
1  Cumings, Mrs. John Bradley (Florence Briggs Th... female  38.0
1
3  Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
6  McCarthy, Mr. Timothy J       male  54.0
0
10 Sandstrom, Miss. Marguerite Rut  female  4.0
1
11 Bonnell, Miss. Elizabeth  female  58.0
0
...
...
871 Beckwith, Mrs. Richard Leonard (Sallie Monypeny)  female  47.0
1
872 Carlsson, Mr. Frans Olof       male  33.0
0
```

```

879      Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)   female  56.0
0
887                               Graham, Miss. Margaret Edith   female  19.0
0
889                               Behr, Mr. Karl Howell     male   26.0
0

```

	Parch	Ticket	Fare	Cabin	Embarked
1	0	PC 17599	71.2833	C85	C
3	0	113803	53.1000	C123	S
6	0	17463	51.8625	E46	S
10	1	PP 9549	16.7000	G6	S
11	0	113783	26.5500	C103	S
..	..	..	..	..	..
871	1	11751	52.5542	D35	S
872	0	695	5.0000	B51 B53	B55
879	1	11767	83.1583	C50	C
887	0	112053	30.0000	B42	S
889	0	111369	30.0000	C148	C

[183 rows x 12 columns]

```
df.dropna(how= 'any') #[any|all]
```

	PassengerId	Survived	Pclass	\
1	2	1	1	
3	4	1	1	
6	7	0	1	
10	11	1	3	
11	12	1	1	
..	..	..	..	
871	872	1	1	
872	873	0	1	
879	880	1	1	
887	888	1	1	
889	890	1	1	

	SibSp	Name	Sex	Age
1	Cumings, Mrs. John Bradley (Florence Briggs Th... 1	female	38.0	
3	Futrelle, Mrs. Jacques Heath (Lily May Peel) 1	female	35.0	
6	McCarthy, Mr. Timothy J 0	male	54.0	
10	Sandstrom, Miss. Marguerite Rut 1	female	4.0	
11	Bonnell, Miss. Elizabeth 0	female	58.0	
..	..	..	..	

```

...
871    Beckwith, Mrs. Richard Leonard (Sallie Monypeny)   female  47.0
1
872                               Carlsson, Mr. Frans Olof     male  33.0
0
879    Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)   female  56.0
0
887                               Graham, Miss. Margaret Edith female  19.0
0
889                               Behr, Mr. Karl Howell      male  26.0
0

```

	Parch	Ticket	Fare	Cabin	Embarked
1	0	PC 17599	71.2833	C85	C
3	0	113803	53.1000	C123	S
6	0	17463	51.8625	E46	S
10	1	PP 9549	16.7000	G6	S
11	0	113783	26.5500	C103	S
..	...	...	...	...	...
871	1	11751	52.5542	D35	S
872	0	695	5.0000	B51 B53 B55	S
879	1	11767	83.1583	C50	C
887	0	112053	30.0000	B42	S
889	0	111369	30.0000	C148	C

[183 rows x 12 columns]

```
df.fillna("Darshan")
```

	PassengerId	Survived	Pclass	\
1	2	1	1	
3	4	1	1	
6	7	0	1	
10	11	1	3	
11	12	1	1	
..	...	...	...	
871	872	1	1	
872	873	0	1	
879	880	1	1	
887	888	1	1	
889	890	1	1	

	SibSp	Name	Sex	Age
1	Cumings, Mrs. John Bradley (Florence Briggs Th... female 38.0			
1	Futrelle, Mrs. Jacques Heath (Lily May Peel) female 35.0			
1	McCarthy, Mr. Timothy J male 54.0			
0				

```

10          Sandstrom, Miss. Marguerite Rut female    4.0
1
11          Bonnell, Miss. Elizabeth   female  58.0
0
...
...
871 Beckwith, Mrs. Richard Leonard (Sallie Monypeny) female 47.0
1
872          Carlsson, Mr. Frans Olof     male  33.0
0
879 Potter, Mrs. Thomas Jr (Lily Alexenia Wilson) female 56.0
0
887          Graham, Miss. Margaret Edith female 19.0
0
889          Behr, Mr. Karl Howell     male  26.0
0

      Parch      Ticket      Fare      Cabin Embarked
1        0       PC 17599  71.2833        C85            C
3        0       113803   53.1000        C123            S
6        0       17463   51.8625        E46             S
10       1       PP 9549  16.7000        G6              S
11       0       113783  26.5500        C103            S
...
...
871       1       11751   52.5542        D35            S
872       0       695    5.0000        B51 B53        B55            S
879       1       11767   83.1583        C50             C
887       0       112053  30.0000        B42             S
889       0       111369  30.0000        C148            C

```

[183 rows x 12 columns]

```

#df.fillna({"Age":0,"Cabin":"NA"})
#df.fillna({"Age":(df['Age'].mean()),"Cabin":"NA"}) #float ma value
avse
#df.fillna({"Age":int(df['Age'].mean()),"Cabin":"NA"})
df.fillna({"Age":df.groupby("Sex")['Age'].transform('mean')})

```

	PassengerId	Survived	Pclass	\
1	2	1	1	
3	4	1	1	
6	7	0	1	
10	11	1	3	
11	12	1	1	
...	...	...	...	
871	872	1	1	
872	873	0	1	
879	880	1	1	
887	888	1	1	
889	890	1	1	

SibSp	\	Name	Sex	Age	
1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0		
1					
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0		
1					
6	McCarthy, Mr. Timothy J	male	54.0		
0					
10	Sandstrom, Miss. Marguerite Rut	female	4.0		
1					
11	Bonnell, Miss. Elizabeth	female	58.0		
0					
..		...	...		
...					
871	Beckwith, Mrs. Richard Leonard (Sallie Monypeny)	female	47.0		
1					
872	Carlsson, Mr. Frans Olof	male	33.0		
0					
879	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	female	56.0		
0					
887	Graham, Miss. Margaret Edith	female	19.0		
0					
889	Behr, Mr. Karl Howll	male	26.0		
0					
	Parch	Ticket	Fare	Cabin	Embarked
1	0	PC 17599	71.2833	C85	C
3	0	113803	53.1000	C123	S
6	0	17463	51.8625	E46	S
10	1	PP 9549	16.7000	G6	S
11	0	113783	26.5500	C103	S
..	..	..	..	..	..
871	1	11751	52.5542	D35	S
872	0	695	5.0000	B51 B53 B55	S
879	1	11767	83.1583	C50	C
887	0	112053	30.0000	B42	S
889	0	111369	30.0000	C148	C

[183 rows x 12 columns]

```
df.groupby("Survived") ['Age'].mean()
```

Survived	Age
0	41.350000
1	32.905854
Name:	Age, dtype: float64

```
#group by data free
gdf=
```

```

#df.groupby("Sex") ['Age'].transform('mean')
df.groupby("Sex") ['Age'].transform('median')

1      32.25
3      32.25
6      37.00
10     32.25
11     32.25
...
871    32.25
872    37.00
879    32.25
887    32.25
889    37.00
Name: Age, Length: 183, dtype: float64

#df.interpolate().isnull().sum()
df.interpolate() ['Age'].std()

C:\Users\LENOVO\AppData\Local\Temp\ipykernel_6900\1450143585.py:2:
FutureWarning: DataFrame.interpolate with object dtype is deprecated
and will raise in a future version. Call obj.infer_objects(copy=False)
before interpolating instead.
df.interpolate() ['Age'].std()

15.643865966849717

#method='linear' (default)
#method='time' (used for time series)
#method='polynomial', order=2
#limit_direction='forward' or 'backward' (control fill direction)

```

### 3) Apply Scaling to AGE attribute with min max, decimal scaling and z score.

```

df ['NewAge']=df ["Age"]+5

df

   PassengerId  Survived  Pclass \
1              2         1      1
3              4         1      1
6              7         0      1
10             11        1      3
11             12        1      1
...
871            872        1      1
872            873        0      1
879            880        1      1

```

887	888	1	1	
889	890	1	1	
SibSp	\	Name	Sex	Age
1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	
1				
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	
1				
6	McCarthy, Mr. Timothy J	male	54.0	
0				
10	Sandstrom, Miss. Marguerite Rut	female	4.0	
1				
11	Bonnell, Miss. Elizabeth	female	58.0	
0				
..		...	...	
...				
871	Beckwith, Mrs. Richard Leonard (Sallie Monypeny)	female	47.0	
1				
872	Carlsson, Mr. Frans Olof	male	33.0	
0				
879	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	female	56.0	
0				
887	Graham, Miss. Margaret Edith	female	19.0	
0				
889	Behr, Mr. Karl Howell	male	26.0	
0				

	Parch	Ticket	Fare	Cabin	Embarked	NewAge
1	0	PC 17599	71.2833	C85	C	43.0
3	0	113803	53.1000	C123	S	40.0
6	0	17463	51.8625	E46	S	59.0
10	1	PP 9549	16.7000	G6	S	9.0
11	0	113783	26.5500	C103	S	63.0
..	..	..	..	..	..	..
871	1	11751	52.5542	D35	S	52.0
872	0	695	5.0000	B51 B53 B55	S	38.0
879	1	11767	83.1583	C50	C	61.0
887	0	112053	30.0000	B42	S	24.0
889	0	111369	30.0000	C148	C	31.0

[183 rows x 13 columns]

```
# Min-Max Scaling
df['AGE_MinMax'] = (df['Age'] - df['Age'].min()) / (df['Age'].max() - df['Age'].min())
df
```

PassengerId	Survived	Pclass	\
0	1	0	3

1	2	1	1		
2	3	1	3		
3	4	1	1		
4	5	0	3		
..	...	...	...		
886	887	0	2		
887	888	1	1		
888	889	0	3		
889	890	1	1		
890	891	0	3		
SibSp \					
0	Braund, Mr. Owen Harris				
1	Cumings, Mrs. John Bradley (Florence Briggs Th...)				
1	Heikkinen, Miss. Laina				
0	Futrelle, Mrs. Jacques Heath (Lily May Peel)				
1	Allen, Mr. William Henry				
4	Allen, Mr. William Henry				
0					
..	...				
...	...				
886	Montvila, Rev. Juozas				
0	Graham, Miss. Margaret Edith				
0	Johnston, Miss. Catherine Helen "Carrie"				
1	Behr, Mr. Karl Howell				
889	Behr, Mr. Karl Howell				
0	Dooley, Mr. Patrick				
0	Dooley, Mr. Patrick				
Parch	Ticket	Fare	Cabin	Embarked	AGE_MinMax
0	A/5 21171	7.2500	NaN	S	0.271174
1	PC 17599	71.2833	C85	C	0.472229
2	STON/O2. 3101282	7.9250	NaN	S	0.321438
3	113803	53.1000	C123	S	0.434531
4	373450	8.0500	NaN	S	0.434531
..	...	...	...	...	...
886	211536	13.0000	NaN	S	0.334004
887	112053	30.0000	B42	S	0.233476
888	W./C. 6607	23.4500	NaN	S	NaN
889	111369	30.0000	C148	C	0.321438
890	370376	7.7500	NaN	Q	0.396833

[891 rows x 13 columns]

```
# Decimal Scaling
data_ds=df.copy()
age_ds=data_ds['Age']
max_age=age_ds.max()
temp = len(str(int(max_age)))
print(max_age)
print(temp)
data_ds['DecimalScale']=age_ds/(10 ** temp)
data_ds[['Age', 'DecimalScale']]
```

80.0

2

	Age	DecimalScale
0	22.0	0.22
1	38.0	0.38
2	26.0	0.26
3	35.0	0.35
4	35.0	0.35
..	...	...
886	27.0	0.27
887	19.0	0.19
888	NaN	NaN
889	26.0	0.26
890	32.0	0.32

[891 rows x 2 columns]

```
#using Z-score
data_zs = df.copy()
age_zs = data_zs['Age']
mean_age = age_zs.mean()
std_age = age_zs.std()
data_zs['ZScoreAge'] = (age_zs - mean_age) / std_age
data_zs[['Age', 'ZScoreAge']]
```

	Age	ZScoreAge
0	22.0	-0.530005
1	38.0	0.571430
2	26.0	-0.254646
3	35.0	0.364911
4	35.0	0.364911
..	...	...
886	27.0	-0.185807
887	19.0	-0.736524
888	NaN	NaN
889	26.0	-0.254646
890	32.0	0.158392

```
[891 rows x 2 columns]
```

# Dimensionality Reduction using NumPy

## □ What is Data Reduction?

Data reduction refers to the process of reducing the amount of data that needs to be processed and stored, while preserving the essential patterns in the data.

### Why do we reduce data?

- To reduce computational cost.
- To remove noise and redundant features.
- To improve model performance and training time.
- To visualize high-dimensional data in 2D or 3D.

Common data reduction techniques include:

- Principal Component Analysis (PCA)
- Feature selection
- Sampling

## □ What is Principal Component Analysis (PCA)?

PCA is a **dimensionality reduction technique** that transforms a dataset into a new coordinate system. It identifies the **directions (principal components)** where the variance of the data is maximized.

### Key Concepts:

- **Principal Components:** New features (linear combinations of original features) capturing most variance.
- **Eigenvectors & Eigenvalues:** Used to compute these principal directions.
- **Covariance Matrix:** Measures how features vary with each other.

PCA helps in **visualizing high-dimensional data**, **noise reduction**, and **speeding up algorithms**.

## □ NumPy Functions Summary for PCA

Function	Purpose
<code>np.mean(X, axis=0)</code>	Compute mean of each column (feature-wise mean).
<code>X - np.mean(X, axis=0)</code>	Centering the data (zero mean).
<code>np.cov(X, rowvar=False)</code>	Compute covariance matrix for features.
<code>np.linalg.eigh(cov_mat)</code>	Get eigenvalues and eigenvectors (for symmetric matrices).

Function	Purpose
<code>np.argsort(values) [::-1]</code>	Sort values in descending order.
<code>np.dot(X, eigenvectors)</code>	Project original data onto new axes.

## Step 1: Load the Iris Dataset

```
from sklearn.datasets import load_iris
import numpy as np
import matplotlib.pyplot as plt

iris =load_iris()
X=iris.data
Y=iris.target

print("Original shape :",X.shape)

Original shape : (150, 4)
```

## Step 2: Standardize the data (zero mean)

```
X_meaned = X- np.mean(X, axis=0)
print("Data after centering (first 5 rows): \n",X_meaned[:5])

Data after centering (first 5 rows):
[[ -0.74333333  0.44266667 -2.358     -0.99933333]
 [ -0.94333333 -0.05733333 -2.358     -0.99933333]
 [ -1.14333333  0.14266667 -2.458     -0.99933333]
 [ -1.24333333  0.04266667 -2.258     -0.99933333]
 [ -0.84333333  0.54266667 -2.358     -0.99933333]]
```

## Step 3: Compute the Covariance Matrix

```
cov_mat = np.cov(X_meaned, rowvar=False)
print("Covariance Matrix shape:", cov_mat.shape)
print(cov_mat)

Covariance Matrix shape: (4, 4)
[[ 0.68569351 -0.042434    1.27431544  0.51627069]
 [-0.042434    0.18997942 -0.32965638 -0.12163937]
 [ 1.27431544 -0.32965638  3.11627785  1.2956094 ]
 [ 0.51627069 -0.12163937  1.2956094   0.58100626]]
```

## Step 4: Compute eigenvalues and eigenvectors

```
eigen_values, eigen_vectors = np.linalg.eigh(cov_mat) #linear algebra  
= linag  
print("Eigenvalues:\n", eigen_values)  
print("\nEigenvectors (first 2):\n", eigen_vectors[:, :2])  
  
Eigenvalues:  
[ 0.02383509  0.0782095   0.24267075  4.22824171]  
  
Eigenvectors (first 2):  
[[ 0.31548719  0.58202985]  
[-0.3197231   -0.59791083]  
[-0.47983899 -0.07623608]  
[ 0.75365743 -0.54583143]]
```

## Step 5: Compute eigenvalues and eigenvectors in descending order

```
sorted_index = np.argsort(eigen_values)[::-1]  
sorted_eigenvalues = eigen_values[sorted_index]  
sorted_eigenvectors = eigen_vectors[:, sorted_index]  
print("sort index", sorted_index)  
print("sort eigenvalues", sorted_eigenvalues)  
print("sort eigenvectors", sorted_eigenvectors)  
  
sort index [3 2 1 0]  
sort eigenvalues [4.22824171 0.24267075 0.0782095  0.02383509]  
sort eigenvectors [[-0.36138659  0.65658877  0.58202985  0.31548719]  
[ 0.08452251  0.73016143 -0.59791083 -0.3197231 ]  
[-0.85667061 -0.17337266 -0.07623608 -0.47983899]  
[-0.3582892   -0.07548102 -0.54583143  0.75365743]]
```

## Step 6: Select the top k eigenvectors (top 2)

```
k = 2  
eigenvector_subset = sorted_eigenvectors[:, 0:k] #[row : column]  
print(eigenvector_subset.shape)  
(4, 2)
```

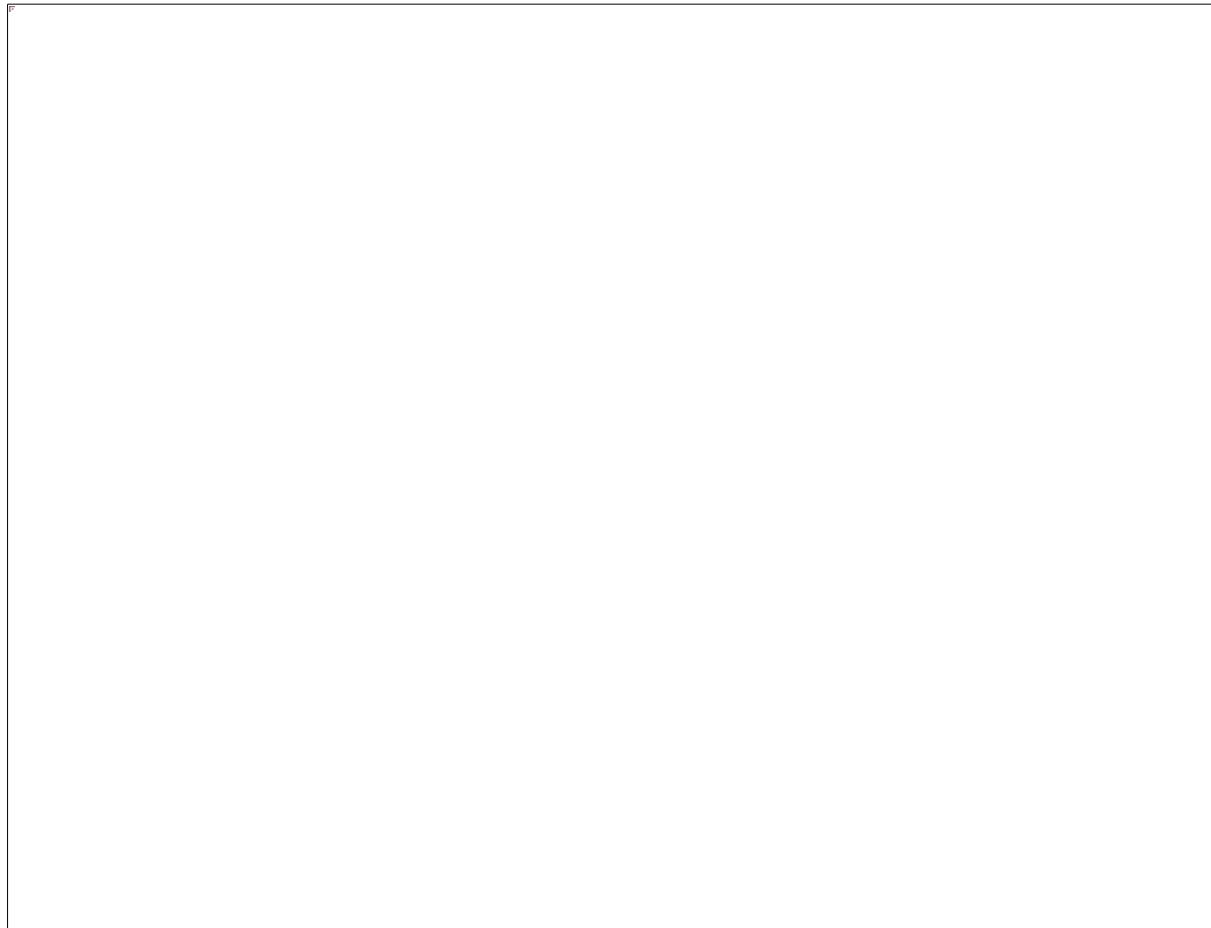
## Step 7: Project the data onto the top k eigenvectors

```
X_reduced = np.dot(X_meaned, eigenvector_subset)
print("Reduced shape:", X_reduced.shape)

Reduced shape: (150, 2)
```

## Step 8: Plot the PCA-Reduced Data

```
plt.figure(figsize=(8,6))
plt.scatter(X_reduced[:,0], X_reduced[:,1], c=Y, cmap='viridis')
plt.xlabel('principle component 1')
plt.ylabel('principle component 2')
plt.title('PCA - IRIS Dataset')
plt.grid(True)
plt.show()
```



## Extra - Bining Method

5,10,11,13,15,35,50,55,72,92,204,215.

Partition them into three bins by each of the following methods:

- (a) equal-frequency (equal-depth) partitioning
- (b) equal-width partitioning

```
Sorted Data: [5, 10, 11, 13, 15, 35, 50, 55, 72, 92, 204, 215]
```

```
(a) Equal-Frequency Bins:  
Bin 1: [5, 10, 11, 13]  
Bin 2: [15, 35, 50, 55]  
Bin 3: [72, 92, 204, 215]
```

```
(b) Equal-Width Bins:  
Bin 1: [5, 10, 11, 13, 15, 35, 50, 55, 72]  
Bin 2: [92]  
Bin 3: [204, 215]
```

## Step 1: Load the Dataset

Load the `Tdata.csv` file and display the first few rows.

```
import pandas as pd

data=pd.read_csv("Tdata.csv")

data.head(5)

   Transaction  bread  butter  coffee  eggs  jam  milk
0            T1      1       1       0      0    0     1
1            T2      1       1       0      0    1     0
2            T3      1       0       0      1    0     1
3            T4      1       1       0      0    0     1
4            T5      1       0       1      0    0     0
```

## Step 2: Drop the 'Transaction' Column

We're only interested in the items (not the transaction IDs).

```
data.drop('Transaction',axis=1,inplace=True)

data

   bread  butter  coffee  eggs  jam  milk
0      1       1       0      0    0     1
1      1       1       0      0    1     0
2      1       0       0      1    0     1
3      1       1       0      0    0     1
4      1       0       1      0    0     0
5      0       0       1      1    1     0
```

## Step 3: Count Single Items

See how many transactions include each item.

```
data.sum()

bread      5
butter     3
coffee     2
eggs      2
jam        2
milk      3
dtype: int64
```

## Step 4: Define Apriori Function

This function finds frequent itemsets of size 1, 2, and 3 with minimum support.

```
from itertools import combinations
def find_frequent_itemsets(df,min_support):
    n=len(df)
    result=[]

    for k in [1,2,3]:
        for items in combinations(df.columns,k):
            mask=df[list(items)].all(axis=1)
            # print("items",items,"mask",mask.sum())
            support=mask.sum()/n
            if support>=min_support:
                result.append((frozenset(items),round(support,2)))
    return result
```

## Step 5: Run Apriori

Set `min_support = 0.6` and display the frequent itemsets.

```
frequent_itemsets=find_frequent_itemsets(data,min_support=0.5)

for itemset, support in frequent_itemsets:
    print(f"{set(itemset)} -> support:{support}")

{'bread'} -> support:0.83
{'butter'} -> support:0.5
{'milk'} -> support:0.5
{'butter', 'bread'} -> support:0.5
{'bread', 'milk'} -> support:0.5
```

## Step 6 Display as a DataFrame

```
result_data=pd.DataFrame(frequent_itemsets,columns=["Itemset","Support"])
result_data

      Itemset  Support
0      (bread)    0.83
1      (butter)    0.50
2      (milk)    0.50
3  (butter, bread)    0.50
4  (bread, milk)    0.50
```

Orange Tool : ->Generate Same Frequent Patterns in Orange tools

Extra : -> Define Apriori Function without itertools

LAB - 7.★ Apriori algo.

<u>TID</u>	<u>Items</u>	$\rightarrow C_1$	<u>ItemSet</u>	<u>Min. Sup.</u>
100	1 3 4		{1 2 3}	2
200	2 3 5		{1 2 3}	3
300	1 2 3 5		{1 3 3}	3
400	2 5		{2 4 3}	1
			{1 5 3}	3

$\rightarrow L^1$	<u>Itemset</u>	<u>Min. Sup.</u>	$\rightarrow C_2$	<u>ItemSet</u>	<u>Min. Sup.</u>
	{1 3}	2		{1 2 3}	1
	{2 3}	3		{1 3 3}	2
	{3 3}	3		{1 5 3}	1
	{5 3}	3		{2 3 3}	2
				{2 5 3}	3
				{3 5 3}	2

$\rightarrow L^2$	<u>Itemset</u>	<u>Min. Sup.</u>	<u>ItemSet</u>	<u>Min. Sup.</u>
	{1 3 3}	2	{1 2 3 3}	1
	{2 3 3}	2	{1 3 5 3}	1
	{2 5 3}	3	{2 3 5 3}	2
	{3 5 3}	2		

+ Rules Generation

<u>Association Rule</u>	<u>Support</u>	<u>Confidence</u>	<u>Confidence (%)</u>
$2 \wedge 3 \rightarrow 5$	2	$\gamma_2 = 1$	100%
$3 \wedge 5 \rightarrow 2$	2	$\gamma_2 = 1$	100%
$2 \wedge 5 \rightarrow 3$	2	$\gamma_3 = 0.66$	66%
$2 \rightarrow 3 \wedge 5$	2	$\gamma_3 = 0.66$	66%
$3 \rightarrow 2 \wedge 5$	2	$\gamma_3 = 0.66$	66%
$5 \rightarrow 2 \wedge 3$	2	$\gamma_3 = 0.66$	66%

$$\frac{A \cup B}{A} = \frac{2^3 \cdot 5}{5} = \frac{2}{3} = 0.66$$

$$\Rightarrow \textcircled{1} \quad 2^3 \rightarrow 5 = \frac{A \rightarrow B}{A} = \frac{2^3 \cdot 5}{2^3} = \frac{2}{2} = 1.$$

- Similarly with others.

\textcircled{2} TIP

Items

1 Bread, Milk

2 Bread, Diaper, Beer, Eggs

3 Milk, Diaper, Beer, Cola

4 Milk, Diaper, Beer, Cola

5 Bread, Milk, Diaper, Cola

	IS	MS
{B, M}	1	3
{M}	4	
{B, E}	2	3
{E}	1	
{D, S}	4	
{C, S}	3	

	IS	MS
{B, S}	1	3
{M}	4	
{B, E}	2	3
{E}	1	
{D, S}	4	
{C, S}	3	

	IS	MS
{B, M, S}	2	
{B, M, E}	1	
{B, M, D}	2	
{B, M, C}	1	
{M, B, E}	2	
{M, D, S}	3	
{M, C, S}	3	

{B, D}	3
{B, C}	2
{D, C}	3

L <sub>2</sub>	{Br, M <sub>3</sub>	2
	{Br, D <sub>3</sub>	2
	{M, Be <sub>3</sub>	2
	{M, D <sub>3</sub>	3
	{M, C <sub>3</sub>	3
	{Be, D <sub>3</sub>	3
	{Be, C <sub>3</sub>	2
	{D, C <sub>3</sub>	3

C <sub>3</sub>	IS	MS
{Br, M, D <sub>3</sub>	1	
{Br, M, Be <sub>3</sub>	0	
{Br, M, C <sub>3</sub>	1	
{Br, Be, D <sub>3</sub>	1	
{Br, D, C <sub>3</sub>	1	
{M, Be, D <sub>3</sub>	2	
{M, Be, C <sub>3</sub>	2	
{M, D, C <sub>3</sub>	3	
{Be, D, C <sub>3</sub>	2	

L<sub>3</sub> →

	IS	MS
{M, Be, D <sub>3</sub>	2	
{M, Be, C <sub>3</sub>	2	
{M, D, C <sub>3</sub>	3	
{Be, D, C <sub>3</sub>	2	

C <sub>4</sub>	IS	MS
{M, Be, D, C <sub>3</sub>	2	

## \* Rules Generation

<u>Association Rule</u>	<u>Support</u>	<u>Confidence</u>	%
$C \wedge B \wedge E \wedge D \rightarrow M$	$\gamma_1 = 1$	$\gamma_1 = 1$	100%
$M \wedge B \wedge E \wedge D \rightarrow C$	$\gamma_2 = 1$	$\gamma_2 = 1$	100%
$M \wedge C \wedge D \rightarrow Be$	$\gamma_3 = 0.66$	$\gamma_3 = 0.66$	66%
$M \wedge Be \wedge C \rightarrow D$	$\gamma_2 = 1$	$\gamma_2 = 1$	100%
$M \wedge Be \rightarrow D \wedge C$	$\gamma_1 = 1$	$\gamma_1 = 1$	100%
$M \wedge D \rightarrow Be \wedge C$	$\gamma_3 = 0.66$	$\gamma_3 = 0.66$	66%
$M \wedge C \rightarrow D \wedge Be$	$\gamma_3 = 0.66$	$\gamma_3 = 0.66$	66%
$M \rightarrow C \wedge Be \wedge D$	$\gamma_4 = 0.5$	<del><math>\frac{0.66}{0.5} = 1.32</math></del>	50%
$C \rightarrow M \wedge Be \wedge D$	$\gamma_3 = 0.66$	<del><math>\frac{0.66}{0.5} = 1.32</math></del>	66%
$Be \rightarrow M \wedge C \wedge D$	$\gamma_3 = 0.66$	$\gamma_3 = 0.66$	66%
$D \rightarrow M \wedge Be \wedge C$	$\gamma_4 = 0.5$	<del><math>\frac{0.66}{0.5} = 1.32</math></del>	50%
$D \wedge C \rightarrow M \wedge Be$	$\gamma_3 = 0.66$	$\gamma_3 = 0.66$	66%
$Be \wedge C \rightarrow M \wedge D$	$\gamma_2 = 1$	$\gamma_2 = 1$	100%
$D \wedge Be \rightarrow M \wedge C$	$\gamma_3 = 0.66$	$\gamma_3 = 0.66$	66%

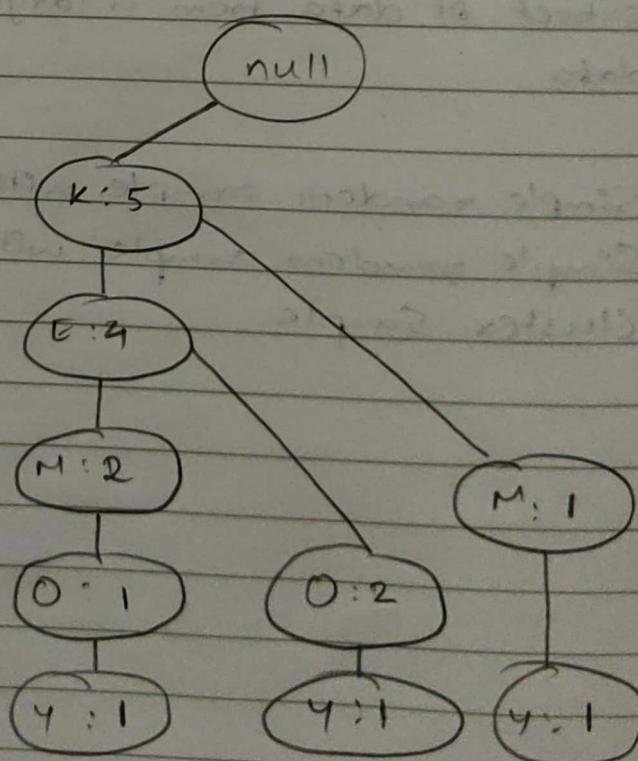
LAB - 2:★ FP Tree

<u>TID</u>	<u>Items</u>	<u>Items</u>	<u>Freq.</u>
1	EKMNOY	A	1
2	DEKNOY	C	2
3	AEKM	D	1
4	CKMUY	E	4
5	CEIKO	K	5
		M	3
		N	2
		O	3
		Y	3
		U	1
		I	1

Frequent Patterns-

K:5, E:4, M:3, O:3, Y:3

- 1 KEMNOY
- 2 KE0Y
- 3 KEM
- 4 KMY
- 5 KEO.



ItemPatterns

Y

{KEMO:13, EKO:13, KM:13}

O

{KEM:13, KE:23}

M

{KE:23, K:13}

E

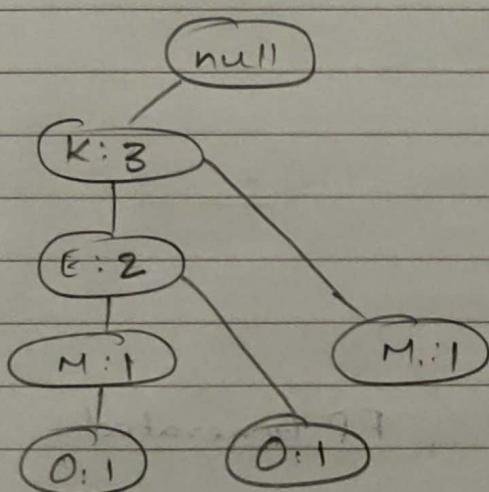
{K:43}

K

-

1. Y

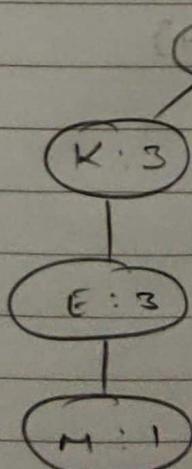
{KEMO:13, EKO:13, KM:13}



{K:3}

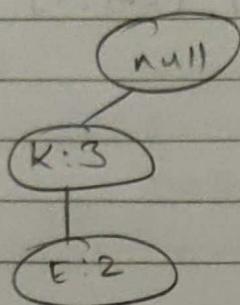
2. O

{KEM:13, KE:23}

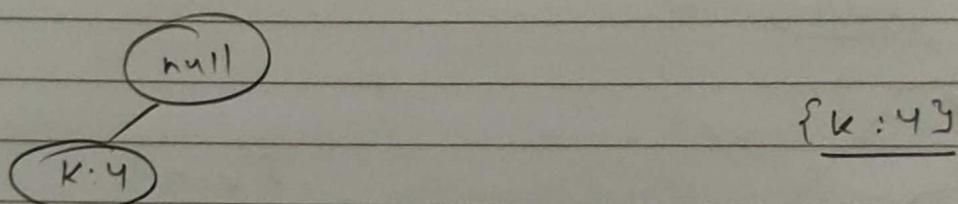


{K, E:3}

3. M  $\{K:E:2\}$   $\{K:1\}$



4. E  $\{K:4\}$



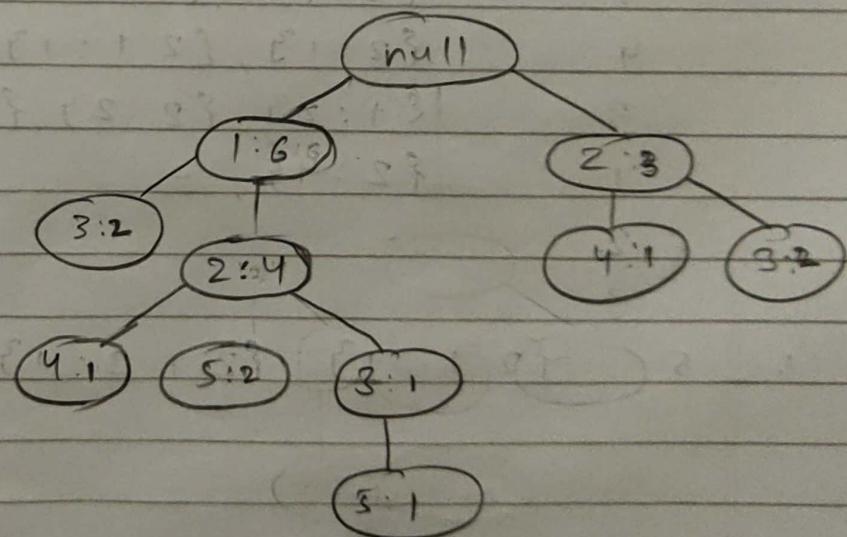
<u>Items.</u>	<u>FP obtained</u>	<u>FP Generated</u>
M	$\{K:3\}$	$\{K, M: 3\}$
O	$\{K, E: 3\}$	$\{K, O: 3\}, \{E, O: 3\}, \{K, E, O: 3\}$
N	$\{K: 3\}$	$\{K, N: 3\}$
E	$\{K: 4\}$	$\{K, E: 4\}$

<u>TID.</u>	<u>Items.</u>	<u>Items</u>	<u>Freq.</u>
1	125	1	6
2	24	2	7
3	23	3	6
4	124	4	2
5	13	5	2
6	23		
7	13		
8	1235		
9	123		

Frequent Patterns-

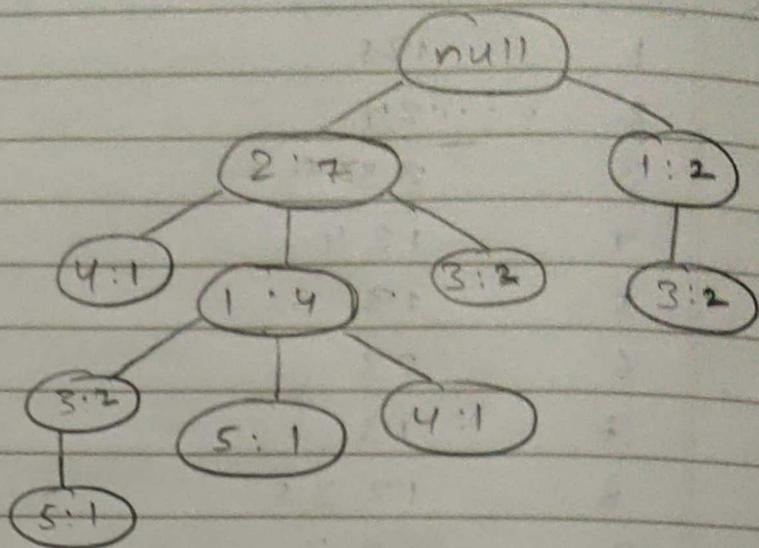
2:7, 1:6, 3:6, 4:2, 5:2

1	125
2	24
3	23
4	124
5	13
6	23
7	13
8	1235
9	123



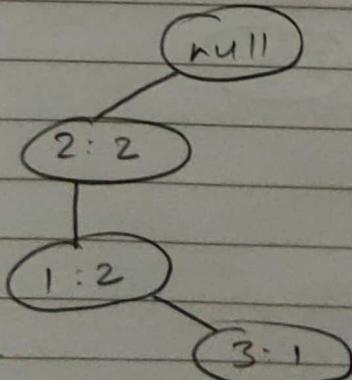
Frequent Patterns:

1	2 1 5
2	2 4
3	2 3
4	2 1 4
5	1 3
6	2 3
7	1 3
8	2 1 3 5
9	2 1 3

Items.      Patterns.

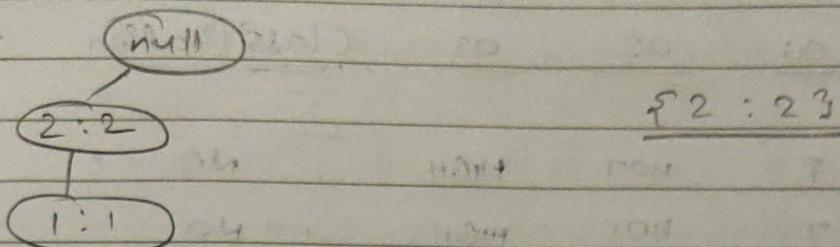
5	{2 1 : 1 3, {2 1 3 : 1 3}
4	{2 : 1 3, {2 1 : 1 3}
3	{1 : 2 3, {2 : 2 3, {2 1 : 2 3}}
1	{2 : 4 3, -}
2	-

1. 5     $\{2 1 : 1 3, \{2 1 3 : 1 3\}$

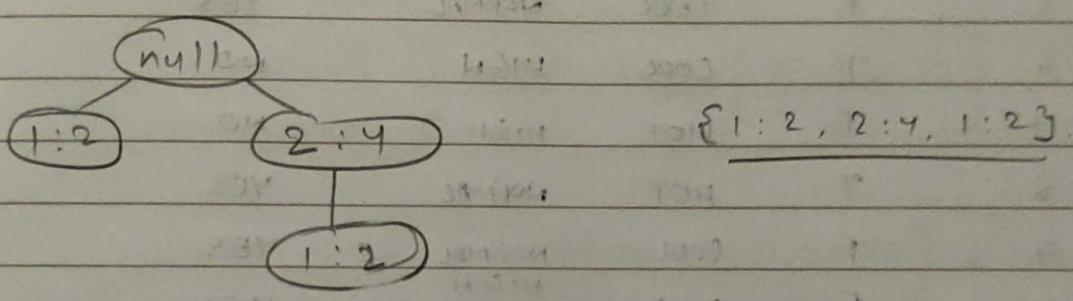


$\{2 : 2, 1 : 2\}$

2. 4  $\{2:13, 2:1:13\}$



3. 3  $\{1:23, 2:23, 2:1:23\}$



4.  $\{2:43\}$

- Items.

FP obtained

FP generated

5	$\{2:2, 1:2\}$	$\{2, 5:23, 1, 5:23\}$
4	$\{2:2\}$	$\{2, 4:23\}$
3	$\{1:2, 2:4, 1:2\}$	$\{1, 3:23, 2, 3:43, 1, 3:23\}$
1	$\{2:43\}$	$\{1, 2:43\}$