



## Data Mining

### Lab - 3

Jeet Bhalodi (23031701006)

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

```
In [2]: import pandas as pd
```

```
In [209... df = pd.read_csv('titanic.csv')
```

```
In [6]: df.head(5)
```

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

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

```
In [24]: numeric=["PassengerId", "Age", "SibSp", "Parch", "Fare"]
         binary = ["Survived", "Sex"]
         ordinal=["Pclass"]
         nominal = ["Name", "Ticket", "Cabin", "Embarked"]
```

```
In [42]: df['PassengerId'].unique()
```

```
Out[42]: array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13,
                14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26,
                27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,
                40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52,
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```

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872, 873, 874, 875, 876, 877, 878, 879, 880, 881, 882, 883, 884,
885, 886, 887, 888, 889, 890, 891], dtype=int64)
```

```
In [62]: df['Survived'].unique()
```

```
Out[62]: array([0, 1], dtype=int64)
```

```
In [20]: df['Pclass'].unique()
```

```
Out[20]: array([3, 1, 2], dtype=int64)
```

```
In [58]: df['Name'].nunique()
```

```
Out[58]: 891
```

```
In [66]: df['Sex'].unique()
```

```
Out[66]: array(['male', 'female'], dtype=object)
```

```
In [48]: df['Age'].unique()
```

```
Out[48]: array([22. , 38. , 26. , 35. , nan, 54. , 2. , 27. , 14. ,
4. , 58. , 20. , 39. , 55. , 31. , 34. , 15. , 28. ,
8. , 19. , 40. , 66. , 42. , 21. , 18. , 3. , 7. ,
49. , 29. , 65. , 28.5 , 5. , 11. , 45. , 17. , 32. ,
16. , 25. , 0.83, 30. , 33. , 23. , 24. , 46. , 59. ,
71. , 37. , 47. , 14.5 , 70.5 , 32.5 , 12. , 9. , 36.5 ,
51. , 55.5 , 40.5 , 44. , 1. , 61. , 56. , 50. , 36. ,
45.5 , 20.5 , 62. , 41. , 52. , 63. , 23.5 , 0.92, 43. ,
60. , 10. , 64. , 13. , 48. , 0.75, 53. , 57. , 80. ,
70. , 24.5 , 6. , 0.67, 30.5 , 0.42, 34.5 , 74. ])
```

```
In [28]: df['SibSp'].unique()
```

```
Out[28]: array([1, 0, 3, 4, 2, 5, 8], dtype=int64)
```

```
In [30]: df['Parch'].unique()
```

```
Out[30]: array([0, 1, 2, 5, 3, 4, 6], dtype=int64)
```

```
In [50]: df['Ticket'].unique()
```

```

Out[50]: array(['A/5 21171', 'PC 17599', 'STON/O2. 3101282', '113803', '373450',
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'349257', '7552', 'C.A./SOTON 34068', 'SOTON/OQ 392076', '211536',
'112053', '111369', '370376'], dtype=object)
```

```
In [52]: df['Fare'].unique()
```

```
Out[52]: array([ 7.25 , 71.2833, 7.925 , 53.1 , 8.05 , 8.4583,
51.8625, 21.075 , 11.1333, 30.0708, 16.7 , 26.55 ,
31.275 , 7.8542, 16. , 29.125 , 13. , 18. ,
7.225 , 26. , 8.0292, 35.5 , 31.3875, 263. ,
7.8792, 7.8958, 27.7208, 146.5208, 7.75 , 10.5 ,
82.1708, 52. , 7.2292, 11.2417, 9.475 , 21. ,
41.5792, 15.5 , 21.6792, 17.8 , 39.6875, 7.8 ,
76.7292, 61.9792, 27.75 , 46.9 , 80. , 83.475 ,
27.9 , 15.2458, 8.1583, 8.6625, 73.5 , 14.4542,
56.4958, 7.65 , 29. , 12.475 , 9. , 9.5 ,
7.7875, 47.1 , 15.85 , 34.375 , 61.175 , 20.575 ,
34.6542, 63.3583, 23. , 77.2875, 8.6542, 7.775 ,
24.15 , 9.825 , 14.4583, 247.5208, 7.1417, 22.3583,
6.975 , 7.05 , 14.5 , 15.0458, 26.2833, 9.2167,
79.2 , 6.75 , 11.5 , 36.75 , 7.7958, 12.525 ,
66.6 , 7.3125, 61.3792, 7.7333, 69.55 , 16.1 ,
15.75 , 20.525 , 55. , 25.925 , 33.5 , 30.6958,
25.4667, 28.7125, 0. , 15.05 , 39. , 22.025 ,
50. , 8.4042, 6.4958, 10.4625, 18.7875, 31. ,
113.275 , 27. , 76.2917, 90. , 9.35 , 13.5 ,
7.55 , 26.25 , 12.275 , 7.125 , 52.5542, 20.2125,
86.5 , 512.3292, 79.65 , 153.4625, 135.6333, 19.5 ,
29.7 , 77.9583, 20.25 , 78.85 , 91.0792, 12.875 ,
8.85 , 151.55 , 30.5 , 23.25 , 12.35 , 110.8833,
108.9 , 24. , 56.9292, 83.1583, 262.375 , 14. ,
164.8667, 134.5 , 6.2375, 57.9792, 28.5 , 133.65 ,
15.9 , 9.225 , 35. , 75.25 , 69.3 , 55.4417,
211.5 , 4.0125, 227.525 , 15.7417, 7.7292, 12. ,
120. , 12.65 , 18.75 , 6.8583, 32.5 , 7.875 ,
14.4 , 55.9 , 8.1125, 81.8583, 19.2583, 19.9667,
89.1042, 38.5 , 7.725 , 13.7917, 9.8375, 7.0458,
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7.6292, 22.525 , 26.2875, 59.4 , 7.4958, 34.0208,
93.5 , 221.7792, 106.425 , 49.5 , 71. , 13.8625,
7.8292, 39.6 , 17.4 , 51.4792, 26.3875, 30. ,
40.125 , 8.7125, 15. , 33. , 42.4 , 15.55 ,
65. , 32.3208, 7.0542, 8.4333, 25.5875, 9.8417,
8.1375, 10.1708, 211.3375, 57. , 13.4167, 7.7417,
9.4833, 7.7375, 8.3625, 23.45 , 25.9292, 8.6833,
8.5167, 7.8875, 37.0042, 6.45 , 6.95 , 8.3 ,
6.4375, 39.4 , 14.1083, 13.8583, 50.4958, 5. ,
9.8458, 10.5167])
```

```
In [54]: df['Cabin'].unique()
```

```
Out[54]: array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
                'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
                'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
                'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
                'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
                'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
                'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
                'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
                'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
                'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
                'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
                'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
                'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
                'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
                'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
                'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
                'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
                'C148'], dtype=object)
```

```
In [56]: df['Embarked'].unique()
```

```
Out[56]: array(['S', 'C', 'Q', nan], dtype=object)
```

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

```
In [ ]: symmetric = ['Sex']
        asymmetric = ['Survived']
```

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

```
In [102... col = ["PassengerId", "Survived", "Pclass", "Age", "SibSp", "Parch", "Fare",]

for i in col:
    print(i, ":-")
    print("    Mean = ", df[i].mean())
    print("    Std Dev. = ", df[i].std())
    print("    MIN = ", df[i].min())
    print("    MAX = ", df[i].max())
    print("    Range = ", df[i].max() - df[i].min())
    print("    Mode = ", df[i].mode().iloc[0])
```



```
PassengerId :-
  Mean = 446.0
  Std Dev. = 257.3538420152301
  MIN = 1
  MAX = 891
  Range = 890
  Mode = 1
Survived :-
  Mean = 0.3838383838383838
  Std Dev. = 0.4865924542648585
  MIN = 0
  MAX = 1
  Range = 1
  Mode = 0
Pclass :-
  Mean = 2.308641975308642
  Std Dev. = 0.8360712409770513
  MIN = 1
  MAX = 3
  Range = 2
  Mode = 3
Age :-
  Mean = 29.69911764705882
  Std Dev. = 14.526497332334044
  MIN = 0.42
  MAX = 80.0
  Range = 79.58
  Mode = 24.0
SibSp :-
  Mean = 0.5230078563411896
  Std Dev. = 1.1027434322934275
  MIN = 0
  MAX = 8
  Range = 8
  Mode = 0
Parch :-
  Mean = 0.38159371492704824
  Std Dev. = 0.8060572211299559
  MIN = 0
  MAX = 6
  Range = 6
  Mode = 0
Fare :-
  Mean = 32.204207968574636
  Std Dev. = 49.693428597180905
  MIN = 0.0
  MAX = 512.3292
  Range = 512.3292
  Mode = 8.05
```

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

In [104...

```
q_atr = df['Pclass'].value_counts()
q_atr
```

```
Out[104... Pclass
3      491
1      216
2      184
Name: count, 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.

```
In [108... df.describe(include='all')
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	F
<b>count</b>	891.000000	891.000000	891.000000	891	891	714.000000	891.000000	891.00
<b>unique</b>	NaN	NaN	NaN	891	2	NaN	NaN	
<b>top</b>	NaN	NaN	NaN	Braund, Mr. Owen Harris	male	NaN	NaN	
<b>freq</b>	NaN	NaN	NaN	1	577	NaN	NaN	
<b>mean</b>	446.000000	0.383838	2.308642	NaN	NaN	29.699118	0.523008	0.38
<b>std</b>	257.353842	0.486592	0.836071	NaN	NaN	14.526497	1.102743	0.80
<b>min</b>	1.000000	0.000000	1.000000	NaN	NaN	0.420000	0.000000	0.00
<b>25%</b>	223.500000	0.000000	2.000000	NaN	NaN	20.125000	0.000000	0.00
<b>50%</b>	446.000000	0.000000	3.000000	NaN	NaN	28.000000	0.000000	0.00
<b>75%</b>	668.500000	1.000000	3.000000	NaN	NaN	38.000000	1.000000	0.00
<b>max</b>	891.000000	1.000000	3.000000	NaN	NaN	80.000000	8.000000	6.00

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

```
In [197... # numeric_df = df.select_dtypes(include=['float64', 'int64'])
# covariance =
# correlation = numeric_df.corr()
```

```
In [211... df.cov(numeric_only=True)
```

Out[211...

	PassengerId	Survived	Pclass	Age	SibSp	Parch	
<b>PassengerId</b>	66231.000000	-0.626966	-7.561798	138.696504	-16.325843	-0.342697	161.8
<b>Survived</b>	-0.626966	0.236772	-0.137703	-0.551296	-0.018954	0.032017	6.2
<b>Pclass</b>	-7.561798	-0.137703	0.699015	-4.496004	0.076599	0.012429	-22.8
<b>Age</b>	138.696504	-0.551296	-4.496004	211.019125	-4.163334	-2.344191	73.8
<b>SibSp</b>	-16.325843	-0.018954	0.076599	-4.163334	1.216043	0.368739	8.7
<b>Parch</b>	-0.342697	0.032017	0.012429	-2.344191	0.368739	0.649728	8.6
<b>Fare</b>	161.883369	6.221787	-22.830196	73.849030	8.748734	8.661052	2469.4



In [213...

```
df.corr(numeric_only=True)
```

Out[213...

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

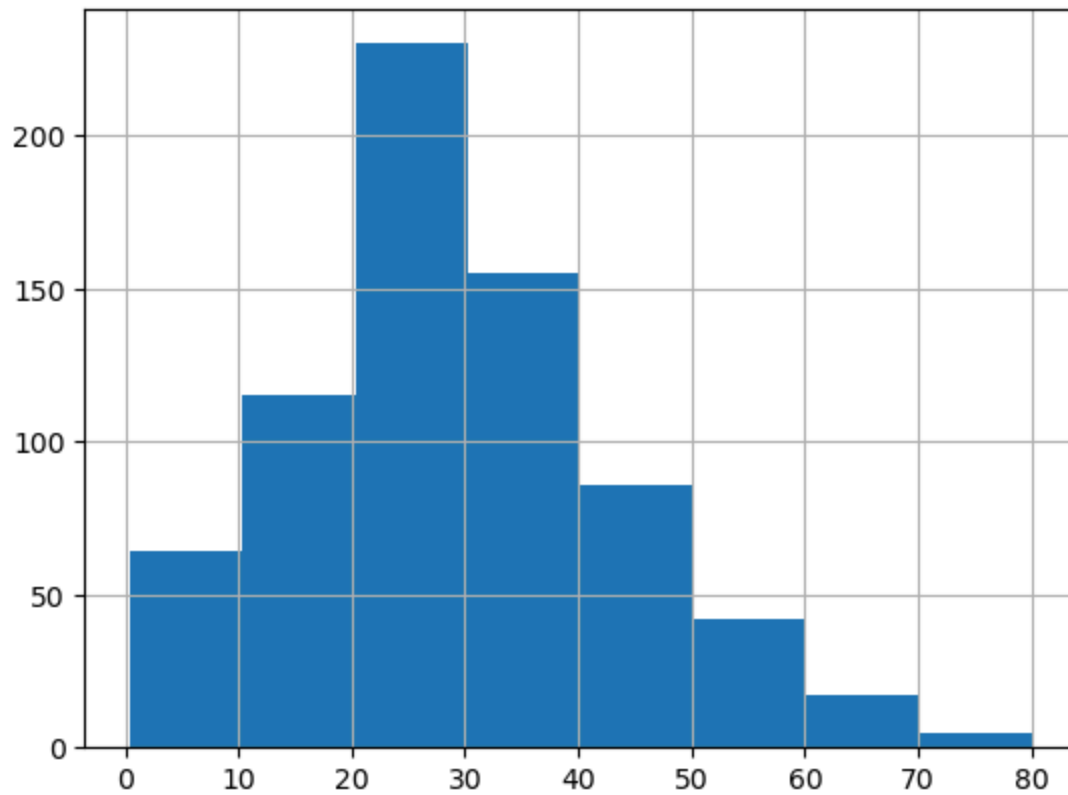
9) Display the histogram for Age attribute by discretizing it into 8 separate bins and counting the frequency for each bin.

In [146...

```
import matplotlib.pyplot as plt
```

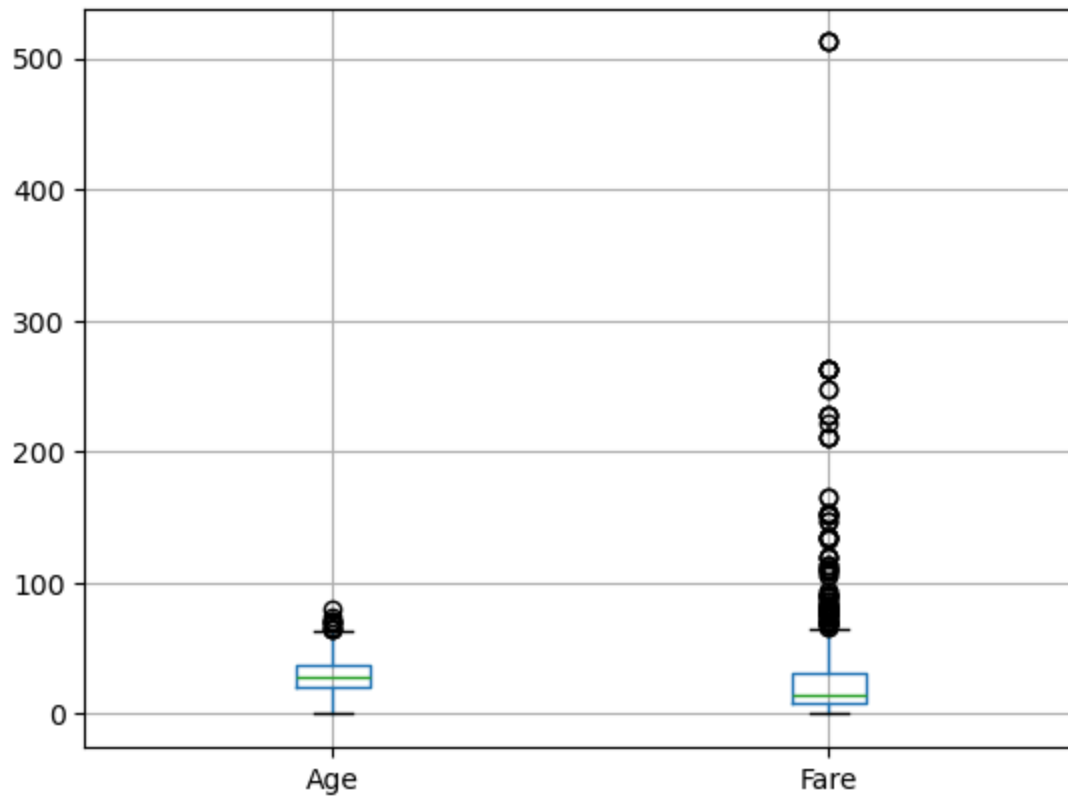
In [223...

```
df['Age'].hist(bins=8)
plt.show()
```



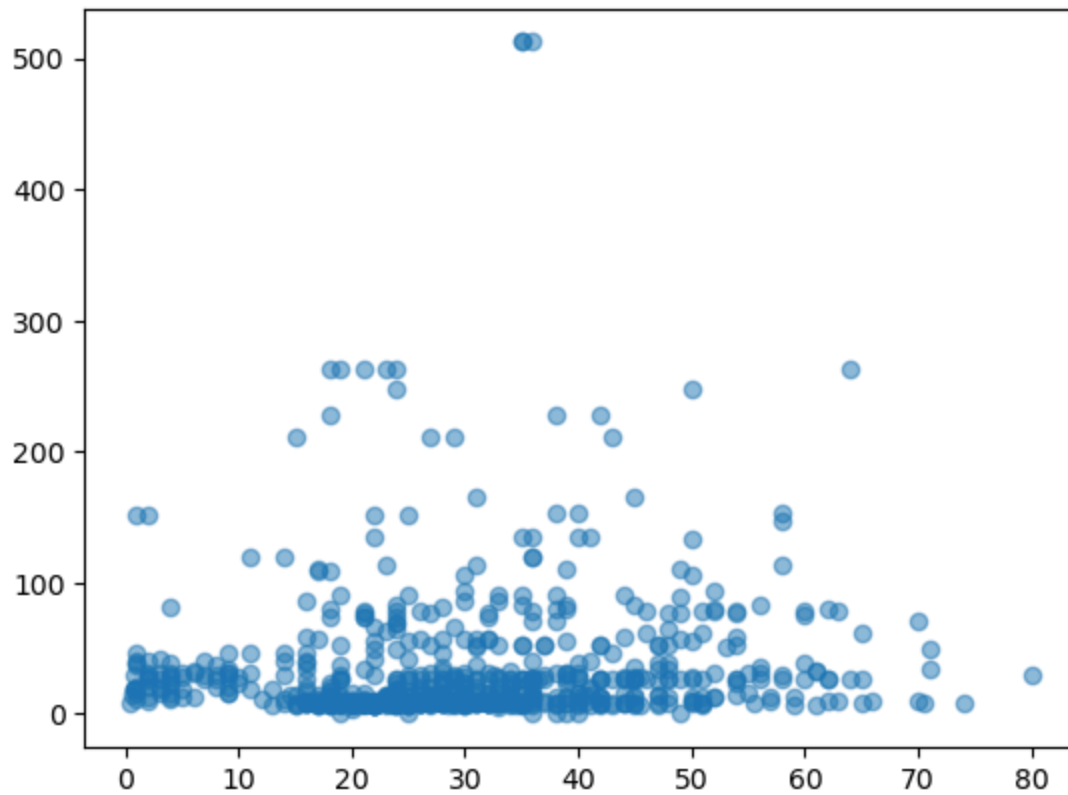
10) A boxplot can also be used to show the distribution of values for each attribute.

```
In [227... df[['Age', 'Fare']].boxplot()  
plt.show()
```

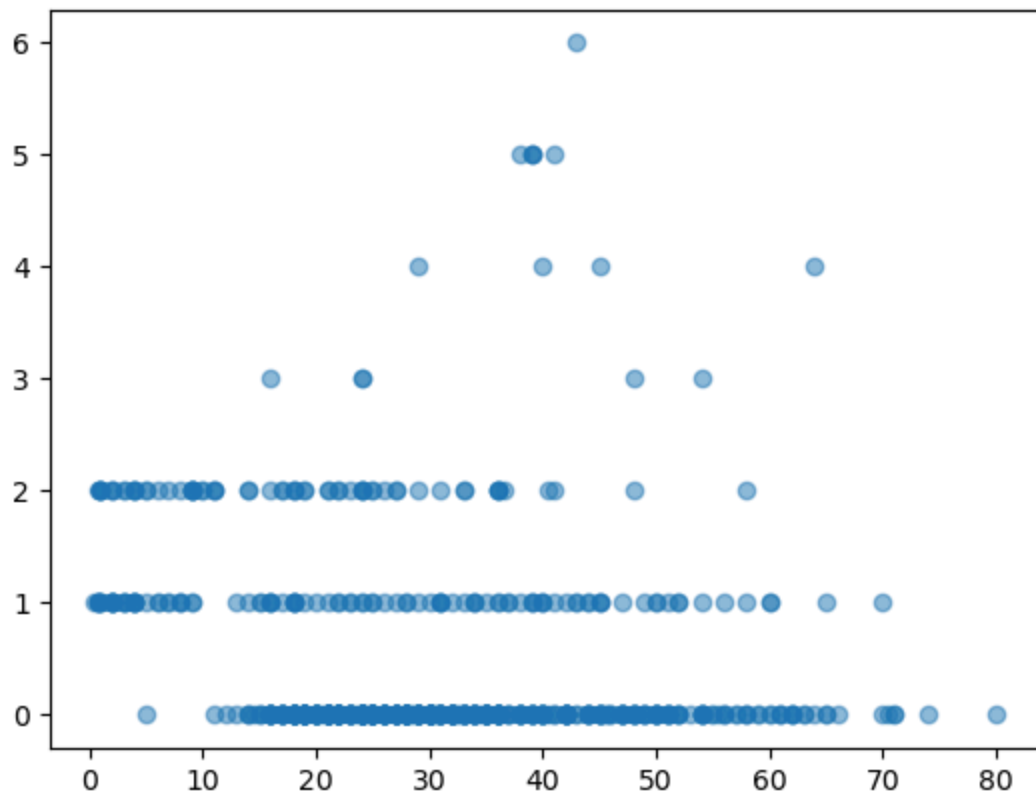


11) Display scatter plot for any 5 pair of attributes , we can use a scatter plot to visualize their joint distribution.

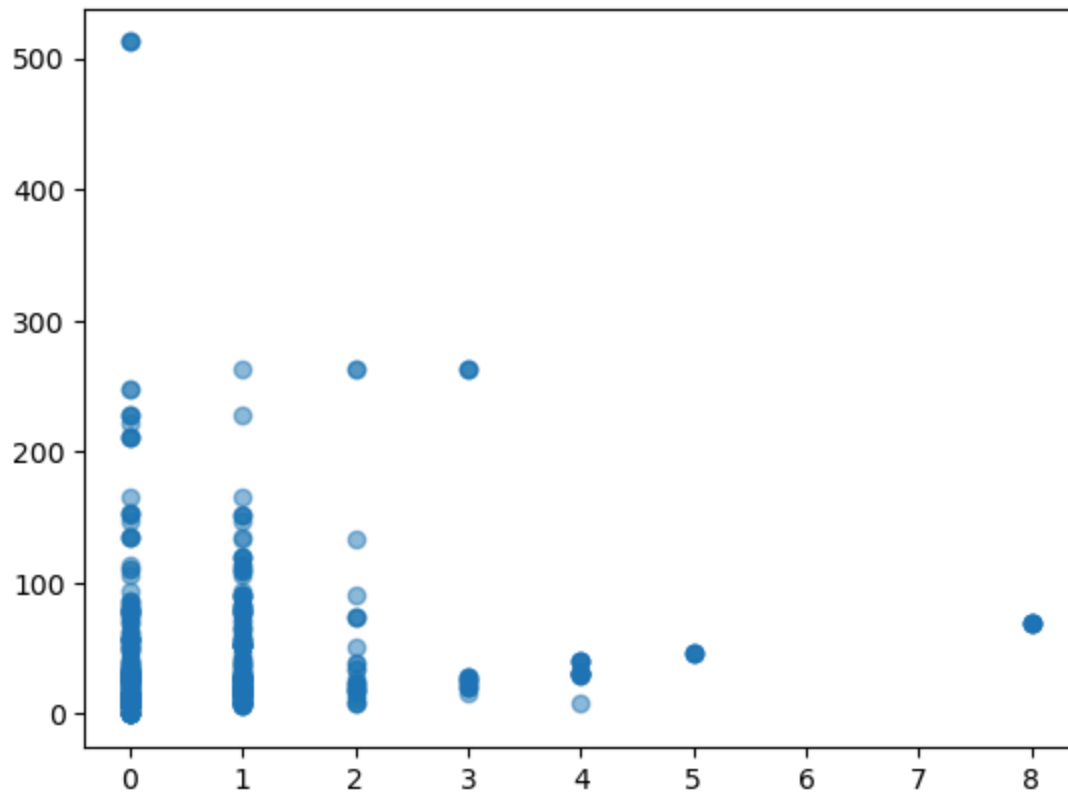
```
In [247... plt.scatter(df['Age'],df['Fare'],alpha=0.5)  
plt.show()
```



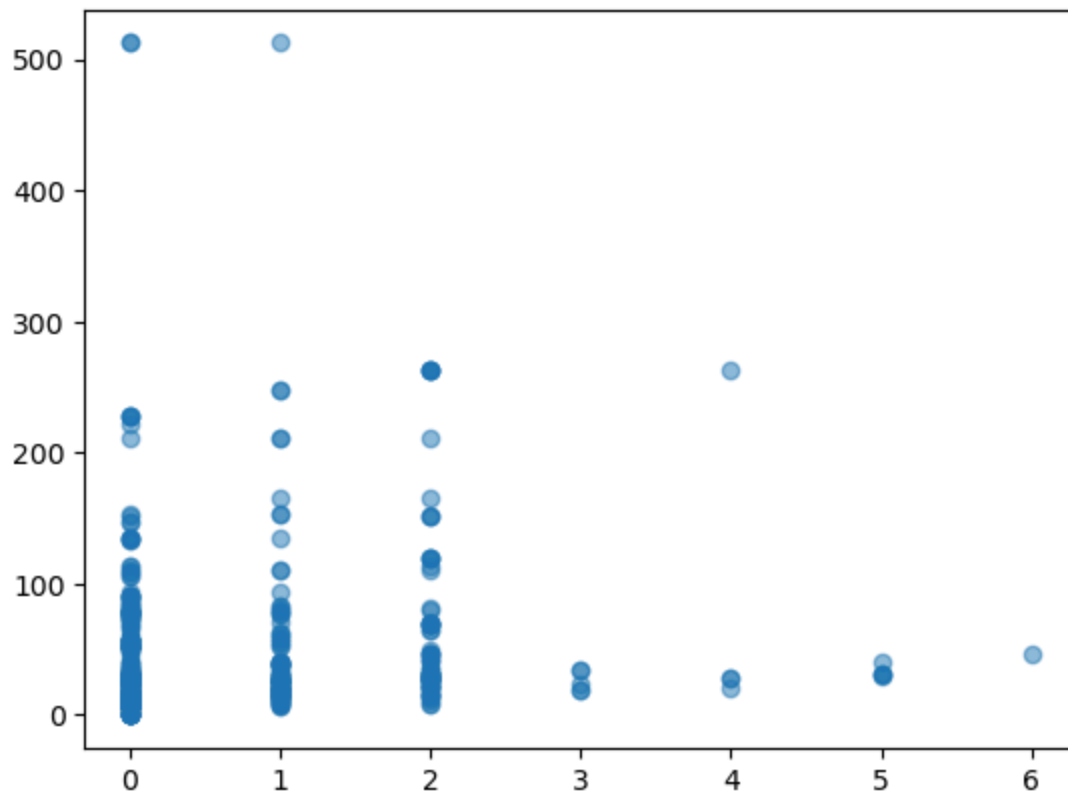
```
In [249... plt.scatter(df['Age'],df['Parch'],alpha=0.5)  
plt.show()
```



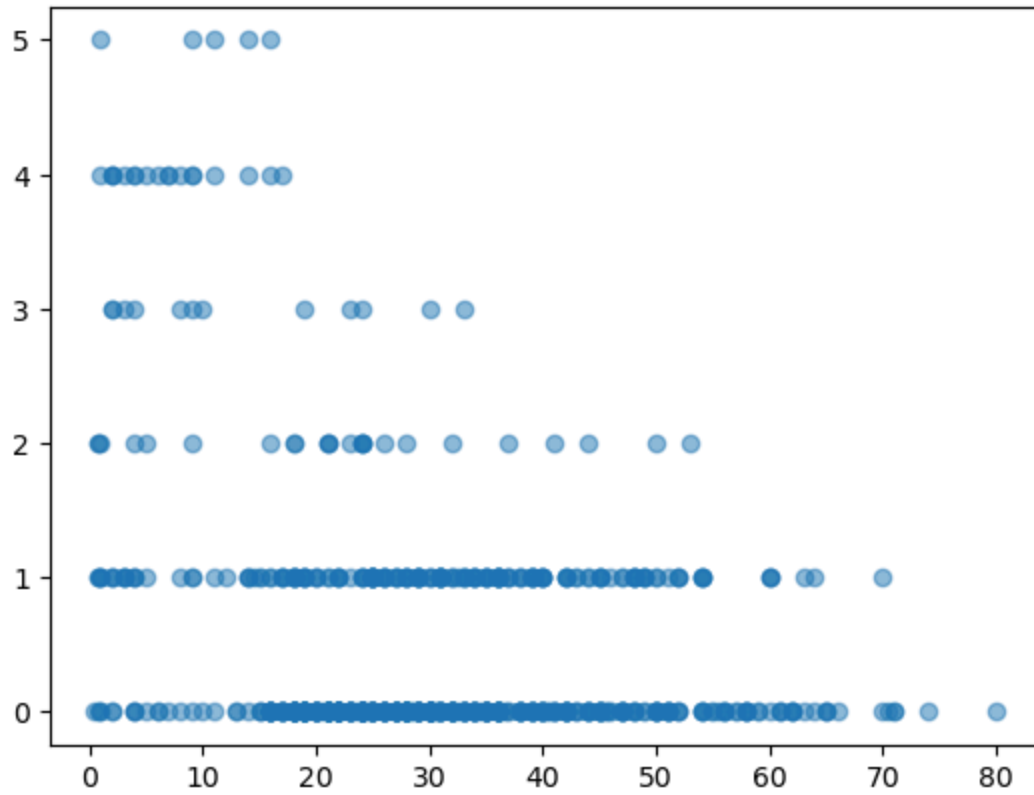
```
In [253... plt.scatter(df['SibSp'],df['Fare'],alpha=0.5)  
plt.show()
```



```
In [255... plt.scatter(df['Parch'],df['Fare'],alpha=0.5)
plt.show()
```



```
In [257... plt.scatter(df['Age'],df['SibSp'],alpha=0.5)
plt.show()
```



In [ ]: