



(<https://www.darshan.ac.in/>)

## Data Mining

### Lab - 3

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

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

```
In [5]: df=pd.read_csv("titanic.csv")
```

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

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

```
In [ ]:
```

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

```
In [ ]: numeric=["PassengerId", "Age", "SibSp", "Parch", "Fare", ]
Nominal=["Name", "Ticket", "Cabin", "Embarked"]
Ordinal=["Pclass"]
Binary=["Survived", "Sex"]
```

```
In [12]: df["PassengerId"].unique()
```

```
Out[12]: 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,
53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65,
66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78,
79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91,
92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104,
105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117,
118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130,
131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143,
144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156,
157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169,
170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182,
183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195,
196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208,
209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221,
222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233, 234,
235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246, 247,
248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259, 260,
261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272, 273,
274, 275, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285, 286,
287, 288, 289, 290, 291, 292, 293, 294, 295, 296, 297, 298, 299,
300, 301, 302, 303, 304, 305, 306, 307, 308, 309, 310, 311, 312,
313, 314, 315, 316, 317, 318, 319, 320, 321, 322, 323, 324, 325,
326, 327, 328, 329, 330, 331, 332, 333, 334, 335, 336, 337, 338,
339, 340, 341, 342, 343, 344, 345, 346, 347, 348, 349, 350, 351,
352, 353, 354, 355, 356, 357, 358, 359, 360, 361, 362, 363, 364,
365, 366, 367, 368, 369, 370, 371, 372, 373, 374, 375, 376, 377,
378, 379, 380, 381, 382, 383, 384, 385, 386, 387, 388, 389, 390,
391, 392, 393, 394, 395, 396, 397, 398, 399, 400, 401, 402, 403,
404, 405, 406, 407, 408, 409, 410, 411, 412, 413, 414, 415, 416,
417, 418, 419, 420, 421, 422, 423, 424, 425, 426, 427, 428, 429,
430, 431, 432, 433, 434, 435, 436, 437, 438, 439, 440, 441, 442,
443, 444, 445, 446, 447, 448, 449, 450, 451, 452, 453, 454, 455,
456, 457, 458, 459, 460, 461, 462, 463, 464, 465, 466, 467, 468,
469, 470, 471, 472, 473, 474, 475, 476, 477, 478, 479, 480, 481,
482, 483, 484, 485, 486, 487, 488, 489, 490, 491, 492, 493, 494,
495, 496, 497, 498, 499, 500, 501, 502, 503, 504, 505, 506, 507,
508, 509, 510, 511, 512, 513, 514, 515, 516, 517, 518, 519, 520,
521, 522, 523, 524, 525, 526, 527, 528, 529, 530, 531, 532, 533,
534, 535, 536, 537, 538, 539, 540, 541, 542, 543, 544, 545, 546,
547, 548, 549, 550, 551, 552, 553, 554, 555, 556, 557, 558, 559,
560, 561, 562, 563, 564, 565, 566, 567, 568, 569, 570, 571, 572,
573, 574, 575, 576, 577, 578, 579, 580, 581, 582, 583, 584, 585,
586, 587, 588, 589, 590, 591, 592, 593, 594, 595, 596, 597, 598,
599, 600, 601, 602, 603, 604, 605, 606, 607, 608, 609, 610, 611,
612, 613, 614, 615, 616, 617, 618, 619, 620, 621, 622, 623, 624,
625, 626, 627, 628, 629, 630, 631, 632, 633, 634, 635, 636, 637,
638, 639, 640, 641, 642, 643, 644, 645, 646, 647, 648, 649, 650,
651, 652, 653, 654, 655, 656, 657, 658, 659, 660, 661, 662, 663,
664, 665, 666, 667, 668, 669, 670, 671, 672, 673, 674, 675, 676,
677, 678, 679, 680, 681, 682, 683, 684, 685, 686, 687, 688, 689,
690, 691, 692, 693, 694, 695, 696, 697, 698, 699, 700, 701, 702,
703, 704, 705, 706, 707, 708, 709, 710, 711, 712, 713, 714, 715,
716, 717, 718, 719, 720, 721, 722, 723, 724, 725, 726, 727, 728,
729, 730, 731, 732, 733, 734, 735, 736, 737, 738, 739, 740, 741,
742, 743, 744, 745, 746, 747, 748, 749, 750, 751, 752, 753, 754,
755, 756, 757, 758, 759, 760, 761, 762, 763, 764, 765, 766, 767,
768, 769, 770, 771, 772, 773, 774, 775, 776, 777, 778, 779, 780,
781, 782, 783, 784, 785, 786, 787, 788, 789, 790, 791, 792, 793,
794, 795, 796, 797, 798, 799, 800, 801, 802, 803, 804, 805, 806,
807, 808, 809, 810, 811, 812, 813, 814, 815, 816, 817, 818, 819,
820, 821, 822, 823, 824, 825, 826, 827, 828, 829, 830, 831, 832,
833, 834, 835, 836, 837, 838, 839, 840, 841, 842, 843, 844, 845,
846, 847, 848, 849, 850, 851, 852, 853, 854, 855, 856, 857, 858,
859, 860, 861, 862, 863, 864, 865, 866, 867, 868, 869, 870, 871,
872, 873, 874, 875, 876, 877, 878, 879, 880, 881, 882, 883, 884,
885, 886, 887, 888, 889, 890, 891], dtype=int64)
```

```
In [15]: df["Survived"].unique()
```

```
Out[15]: array([0, 1], dtype=int64)
```

```
In [16]: df["Pclass"].unique()
```

```
Out[16]: array([3, 1, 2], dtype=int64)
```

```
In [17]: df["Parch"].unique()
```

```
Out[17]: array([0, 1, 2, 5, 3, 4, 6], dtype=int64)
```

```
In [18]: df["Embarked"].unique()
```

```
Out[18]: array(['S', 'C', 'Q', nan], dtype=object)
```

```
In [19]: df["SibSp"].unique()
```

```
Out[19]: array([1, 0, 3, 4, 2, 5, 8], dtype=int64)
```

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

```
In [ ]:
```

```
In [ ]:
```

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

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

```
In [43]: quantitative = ["PassengerId", "Survived", "Pclass", "Age", "SibSp", "Parch", "Fare"]
for i in quantitative :
    print( )
    print(i)

    print("\tmean", df[i].mean())
    print("\tstandard deviation", df[i].std())
    print("\tminimum", df[i].min())
    print("\tmaximum", df[i].max())
    print("\tmode", df[i].mode()[0])
    print("\trange", df[i].max()-df[i].min())
```

#### PassengerId

```
mean 446.0
standard deviation 257.3538420152301
minimum 1
maximum 891
mode 1
range 890
```

#### Survived

```
mean 0.3838383838383838
standard deviation 0.4865924542648585
minimum 0
maximum 1
mode 0
range 1
```

#### Pclass

```
mean 2.308641975308642
standard deviation 0.8360712409770513
minimum 1
maximum 3
mode 3
range 2
```

#### Age

```
mean 29.69911764705882
standard deviation 14.526497332334044
minimum 0.42
maximum 80.0
mode 24.0
range 79.58
```

#### SibSp

```
mean 0.5230078563411896
standard deviation 1.1027434322934275
minimum 0
maximum 8
mode 0
range 8
```

#### Parch

```
mean 0.38159371492704824
standard deviation 0.8060572211299559
minimum 0
maximum 6
mode 0
range 6
```

#### Fare

```
mean 32.204207968574636
standard deviation 49.693428597180905
minimum 0.0
maximum 512.3292
mode 8.05
range 512.3292
```

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

```
In [41]: df["Pclass"].value_counts()
```

```
Out[41]: 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.

```
In [48]: print(df.describe(include="all"))
```

	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

```
In [49]: df.describe()
```

```
Out[49]:
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [50]: `df.describe(include = "object")`

Out[50]:

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	Braund, Mr. Owen Harris	male	347082	B96 B98	S
freq	1	577	7	4	644

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

In [54]: `df.corr()`

C:\Users\student\AppData\Local\Temp\ipykernel\_2196\1134722465.py:1: FutureWarning: The default value of `numeric_only` in `DataFrame.corr` is deprecated. In a future version, it will default to `False`. Select only valid columns or specify the value of `numeric_only` to silence this warning.

`df.corr()`

Out[54]:

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

In [55]: `df.cov()`

C:\Users\student\AppData\Local\Temp\ipykernel\_2196\1545644723.py:1: FutureWarning: The default value of `numeric_only` in `DataFrame.cov` is deprecated. In a future version, it will default to `False`. Select only valid columns or specify the value of `numeric_only` to silence this warning.

`df.cov()`

Out[55]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	66231.000000	-0.626966	-7.561798	138.696504	-16.325843	-0.342697	161.883369
Survived	-0.626966	0.236772	-0.137703	-0.551296	-0.018954	0.032017	6.221787
Pclass	-7.561798	-0.137703	0.699015	-4.496004	0.076599	0.012429	-22.830196
Age	138.696504	-0.551296	-4.496004	211.019125	-4.163334	-2.344191	73.849030
SibSp	-16.325843	-0.018954	0.076599	-4.163334	1.216043	0.368739	8.748734
Parch	-0.342697	0.032017	0.012429	-2.344191	0.368739	0.649728	8.661052
Fare	161.883369	6.221787	-22.830196	73.849030	8.748734	8.661052	2469.436846

In [11]:

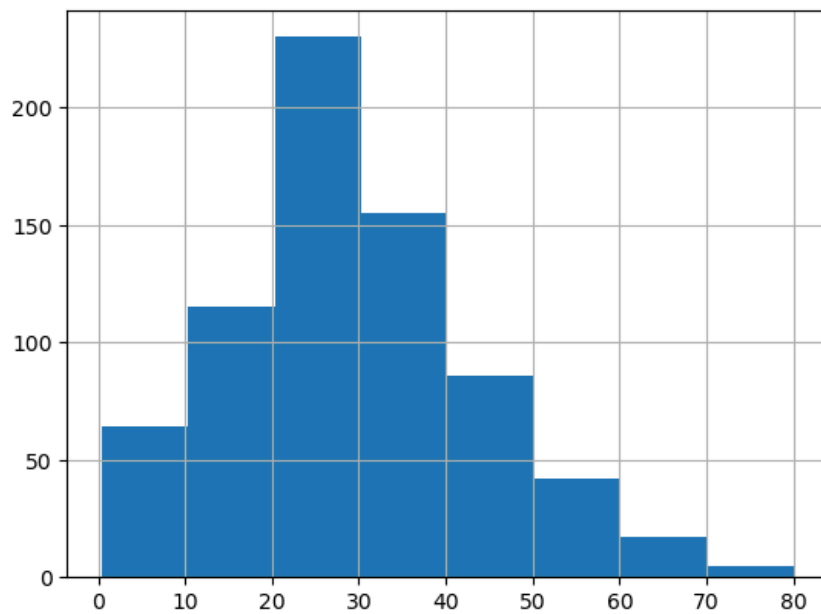
Out[11]:

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

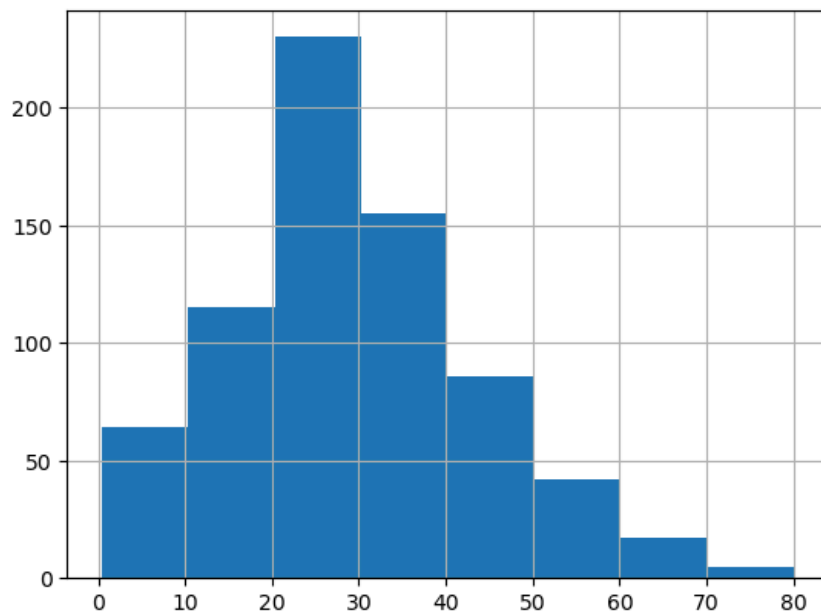
```
In [60]: import matplotlib.pyplot as plt
```

```
In [64]: plt.hist(df["Age"],bins =8)  
plt.grid()
```



```
In [74]: df["Age"].hist(bins=8)
```

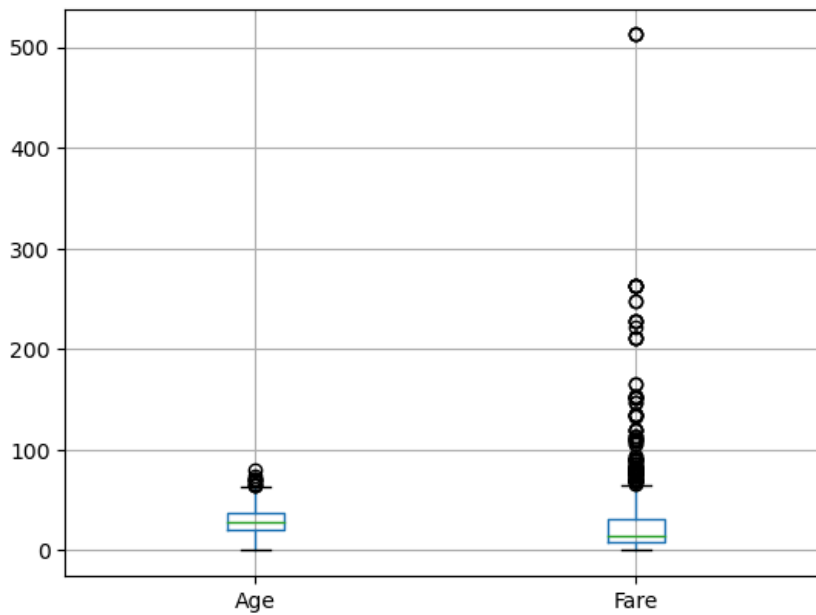
```
Out[74]: <Axes: >
```



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

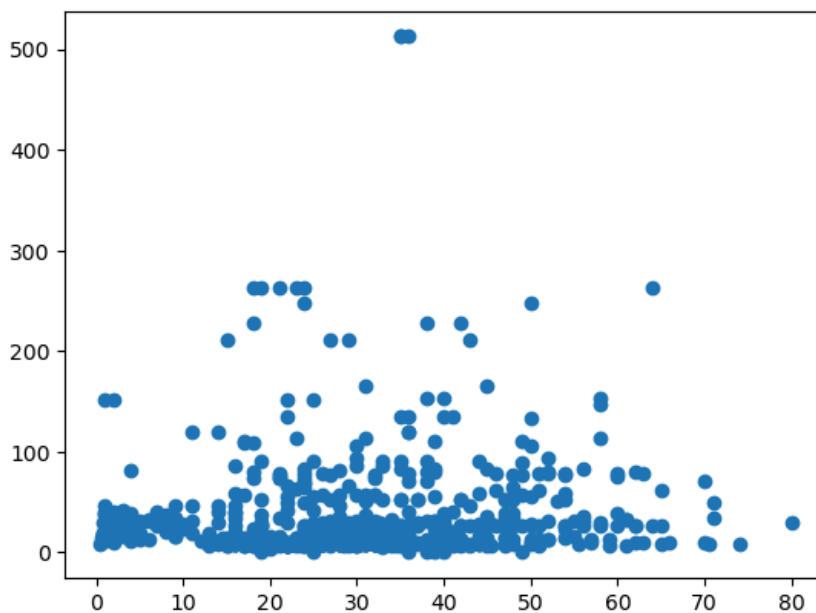
```
In [73]: df.boxplot(["Age", "Fare"])
```

```
Out[73]: <Axes: >
```

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

```
In [75]: #onepare
plt.scatter(df["Age"],df["Fare"])
```

```
Out[75]: <matplotlib.collections.PathCollection at 0x1ae13ad9840>
```



```
In [ ]:
```

```
In [ ]:
```