In [27]:

Out[27]:

In [28]:

Lab Assignment no 3

**Aim**:Perform the following operations on any open source dataset (e.g., data.csv)

1. Provide summary statistics (mean, median, minimum, maximum, standard deviation) for a dataset (age, income etc.) with numeric variables grouped by one of the qualitative (categorical) variable. For example, if your categorical variable is age groups and quantitative variable is income, then provide summary statistics of income grouped by the age groups. Create a list that contains a numeric value for each response to the categorical variable.
2. Write a Python program to display some basic statistical details like percentile, mean, standard deviation etc. of the species of ‘Iris-setosa’, ‘Iris-versicolor’ and ‘Iris- versicolor’ of iris.csv dataset.

Provide the codes with outputs and explain everything that you do in this step.

|  |  |
| --- | --- |
| 1 | **import** pandas **as** pd |
| 2 | file\_path**=**r"C:\Users\shrey\OneDrive\Desktop\MALL\_CUSTOMER.csv" |
| 3 | df**=**pd.read\_csv(file\_path) |
| 4 | df.head() |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **CustomerID** | | **Age** | **Annual Income($)** | **Spending Score** | **Gender** |
| **0** | 1 | 33.0 | 186.0 | 56.0 | male |
| **1** | 2 | 18.0 | 127.0 | 26.0 | male |
| **2** | 3 | 25.0 | 132.0 | 37.0 | male |
| **3** | 4 | 25.0 | 100.0 | 63.0 | male |
| **4** | 5 | 29.0 | 104.0 | 42.0 | male |

Out[28]:

df

1

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **CustomerID** | | **Age** | **Annual Income($)** | **Spending Score** | **Gender** |
| **0** | 1 | 33.0 | 186.0 | 56.0 | male |
| **1** | 2 | 18.0 | 127.0 | 26.0 | male |
| **2** | 3 | 25.0 | 132.0 | 37.0 | male |
| **3** | 4 | 25.0 | 100.0 | 63.0 | male |
| **4** | 5 | 29.0 | 104.0 | 42.0 | male |
| **...** | ... | ... | ... | ... | ... |
| **195** | 196 | 25.0 | 161.0 | 93.0 | male |
| **196** | 197 | 25.0 | 189.0 | 40.0 | male |
| **197** | 198 | 33.0 | 125.0 | 5.0 | male |
| **198** | 199 | 19.0 | 108.0 | 14.0 | male |
| **199** | 200 | 34.0 | 112.0 | 36.0 | male |

200 rows × 5 columns

In [29]:

df.info()

1

<class 'pandas.core.frame.DataFrame'> RangeIndex: 200 entries, 0 to 199

Data columns (total 5 columns):

# Column Non-Null Count Dtype

In [10]:

1. CustomerID 200 non-null
2. Age 184 non-null
3. Annual Income($) 184 non-null
4. Spending Score 185 non-null
5. Gender 200 non-null

int64

float64 float64 float64 object

dtypes: float64(3), int64(1), object(1)

memory usage: 7.9+ KB

(200, 5)

<bound method NDFrame.head of

nding Score Gender

CustomerID Age Annual Income($) Spe

[200 rows x 5 columns]>

df.tail

1

df.head

1

df.shape

1

Out[10]:

In [12]:

Out[12]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 0 | 1 | 33.0 | 186.0 | 56.0 | male |
| 1 | 2 | 18.0 | 127.0 | 26.0 | male |
| 2 | 3 | 25.0 | 132.0 | 37.0 | male |
| 3 | 4 | 25.0 | 100.0 | 63.0 | male |
| 4 | 5 | 29.0 | 104.0 | 42.0 | male |
| .. | ... | ... | ... | ... | ... |
| 195 | 196 | 25.0 | 161.0 | 93.0 | male |
| 196 | 197 | 25.0 | 189.0 | 40.0 | male |
| 197 | 198 | 33.0 | 125.0 | 5.0 | male |
| 198 | 199 | 19.0 | 108.0 | 14.0 | male |
| 199 | 200 | 34.0 | 112.0 | 36.0 | male |

In [13]:

Out[13]: <bound method NDFrame.tail of CustomerID Age Annual Income($) Spe nding Score Gender

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 0 | 1 | 33.0 | 186.0 | 56.0 | male |
| 1 | 2 | 18.0 | 127.0 | 26.0 | male |
| 2 | 3 | 25.0 | 132.0 | 37.0 | male |
| 3 | 4 | 25.0 | 100.0 | 63.0 | male |
| 4 | 5 | 29.0 | 104.0 | 42.0 | male |
| .. | ... | ... | ... | ... | ... |
| 195 | 196 | 25.0 | 161.0 | 93.0 | male |
| 196 | 197 | 25.0 | 189.0 | 40.0 | male |
| 197 | 198 | 33.0 | 125.0 | 5.0 | male |
| 198 | 199 | 19.0 | 108.0 | 14.0 | male |
| 199 | 200 | 34.0 | 112.0 | 36.0 | male |

[200 rows x 5 columns]>

In [14]:

df.describe()

1

Out[14]:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **CustomerID** | **Age** | **Annual Income($)** | **Spending Score** |
| **count** | 200.000000 | 184.000000 | 184.000000 | 185.000000 |
| **mean** | 100.500000 | 26.342391 | 148.244565 | 49.470270 |
| **std** | 57.879185 | 5.133959 | 29.339728 | 28.099985 |
| **min** | 1.000000 | 18.000000 | 100.000000 | 1.000000 |
| **25%** | 50.750000 | 22.000000 | 122.000000 | 26.000000 |
| **50%** | 100.500000 | 26.000000 | 150.000000 | 47.000000 |
| **75%** | 150.250000 | 30.000000 | 170.250000 | 72.000000 |
| **max** | 200.000000 | 35.000000 | 200.000000 | 100.000000 |

In [15]:

26.342391304347824

0

30.0

Name: Age, dtype: float64

df.Age.median()

1

df.Age.mode()

1

df.Age.mean()

1

Out[15]:

In [16]:

Out[16]:

In [17]:

Out[17]: 26.0

In [18]:

df.groupby(['Age']).count()

1

Out[18]:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **CustomerID** | | **Annual Income($)** | **Spending Score** | **Gender** |
| **Age** |  |  |  |  |
| **18.0** | 15 | 14 | 13 | 15 |
| **19.0** | 12 | 11 | 11 | 12 |
| **20.0** | 3 | 3 | 3 | 3 |
| **21.0** | 8 | 8 | 7 | 8 |
| **22.0** | 13 | 12 | 12 | 13 |
| **23.0** | 9 | 7 | 9 | 9 |
| **24.0** | 5 | 5 | 5 | 5 |
| **25.0** | 16 | 15 | 16 | 16 |
| **26.0** | 14 | 14 | 12 | 14 |
| **27.0** | 12 | 9 | 12 | 12 |
| **28.0** | 6 | 5 | 6 | 6 |
| **29.0** | 10 | 10 | 9 | 10 |
| **30.0** | 18 | 17 | 16 | 18 |
| **31.0** | 10 | 7 | 10 | 10 |
| **32.0** | 8 | 7 | 7 | 8 |
| **33.0** | 5 | 5 | 4 | 5 |
| **34.0** | 9 | 9 | 7 | 9 |
| **35.0** | 11 | 10 | 10 | 11 |

In [20]:

df.groupby(['Gender']).count()

1

Out[20]:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **CustomerID** | | **Age** | **Annual Income($)** | **Spending Score** |
| **Gender** |  |  |  |  |
| **female** | 20 | 20 | 8 | 20 |
| **male** | 180 | 164 | 176 | 165 |

In [21]:

5.133959234335101

df[['Age' , 'Annual Income($)', 'Spending Score']].mean()

1

df.Age.std()

1

Out[21]:

In [24]:

|  |  |  |
| --- | --- | --- |
| Out[24]: | Age | 26.342391 |
|  | Annual Income($) | 148.244565 |
|  | Spending Score | 49.470270 |
|  | dtype: float64 |  |

In [30]:

df[['Age' , 'Annual Income($)', 'Spending Score']].mode()

1

Out[30]:

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Age** | **Annual Income($)** | **Spending Score** |
| **0** | 30.0 | 170.0 | 26.0 |

In [32]:

df[['Age' , 'Annual Income($)', 'Spending Score']].median()

1

Out[32]: Age 26.0

Annual Income($) 150.0

Spending Score 47.0

dtype: float64

In [33]:

df[['Age' , 'Annual Income($)', 'Spending Score']].max()

1

Out[33]: Age 35.0

Annual Income($) 200.0

Spending Score 100.0

dtype: float64

In [34]:

df[['Age' , 'Annual Income($)', 'Spending Score']].std()

1

Out[34]: Age 5.133959

Annual Income($) 29.339728

Spending Score 28.099985 dtype: float64

In [35]:

df

1

df2 **=** df.groupby('Gender')

1

In [36]:

Out[36]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **CustomerID** | | **Age** | **Annual Income($)** | **Spending Score** | **Gender** |
| **0** | 1 | 33.0 | 186.0 | 56.0 | male |
| **1** | 2 | 18.0 | 127.0 | 26.0 | male |
| **2** | 3 | 25.0 | 132.0 | 37.0 | male |
| **3** | 4 | 25.0 | 100.0 | 63.0 | male |
| **4** | 5 | 29.0 | 104.0 | 42.0 | male |
| **...** | ... | ... | ... | ... | ... |
| **195** | 196 | 25.0 | 161.0 | 93.0 | male |
| **196** | 197 | 25.0 | 189.0 | 40.0 | male |
| **197** | 198 | 33.0 | 125.0 | 5.0 | male |
| **198** | 199 | 19.0 | 108.0 | 14.0 | male |
| **199** | 200 | 34.0 | 112.0 | 36.0 | male |

200 rows × 5 columns

In [37]:

**for** Gender, Gender\_f **in** df2: print(Gender)

print(Gender\_f)

1

2

3

4

female

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | CustomerID | Age | Annual | Income($) | Spending | Score | Gender |
| 5 | 6 | 35.0 |  | 174.0 |  | 68.0 | female |
| 6 | 7 | 32.0 |  | 114.0 |  | 71.0 | female |
| 7 | 8 | 32.0 |  | 127.0 |  | 49.0 | female |
| 8 | 9 | 28.0 |  | NaN |  | 19.0 | female |
| 9 | 10 | 30.0 |  | NaN |  | 58.0 | female |
| 10 | 11 | 35.0 |  | NaN |  | 34.0 | female |
| 11 | 12 | 32.0 |  | NaN |  | 17.0 | female |
| 12 | 13 | 27.0 |  | NaN |  | 18.0 | female |
| 13 | 14 | 27.0 |  | NaN |  | 26.0 | female |
| 14 | 15 | 31.0 |  | NaN |  | 65.0 | female |
| 15 | 16 | 22.0 |  | NaN |  | 39.0 | female |
| 16 | 17 | 25.0 |  | NaN |  | 65.0 | female |
| 17 | 18 | 19.0 |  | NaN |  | 89.0 | female |
| 18 | 19 | 31.0 |  | NaN |  | 76.0 | female |
| 22 | 23 | 23.0 |  | NaN |  | 93.0 | female |
| 28 | 29 | 29.0 |  | 198.0 |  | 4.0 | female |
| 33 | 34 | 31.0 |  | 176.0 |  | 30.0 | female |
| 56 | 57 | 24.0 |  | 107.0 |  | 74.0 | female |
| 94 | 95 | 28.0 |  | 106.0 |  | 9.0 | female |
| 172 | 173 | 25.0 |  | 152.0 |  | 93.0 | female |
| male |  |  |  |  |  |  |  |
|  | CustomerID | Age | Annual | Income($) | Spending | Score | Gender |
| 0 | 1 | 33.0 |  | 186.0 |  | 56.0 | male |
| 1 | 2 | 18.0 |  | 127.0 |  | 26.0 | male |
| 2 | 3 | 25.0 |  | 132.0 |  | 37.0 | male |
| 3 | 4 | 25.0 |  | 100.0 |  | 63.0 | male |
| 4 | 5 | 29.0 |  | 104.0 |  | 42.0 | male |
| .. | ... | ... |  | ... |  | ... | ... |
| 195 | 196 | 25.0 |  | 161.0 |  | 93.0 | male |
| 196 | 197 | 25.0 |  | 189.0 |  | 40.0 | male |
| 197 | 198 | 33.0 |  | 125.0 |  | 5.0 | male |
| 198 | 199 | 19.0 |  | 108.0 |  | 14.0 | male |
| 199 | 200 | 34.0 |  | 112.0 |  | 36.0 | male |

[180 rows x 5 columns]

In [39]:

df2.get\_group('male')

1

Out[39]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **CustomerID** | | **Age** | **Annual Income($)** | **Spending Score** | **Gender** |
| **0** | 1 | 33.0 | 186.0 | 56.0 | male |
| **1** | 2 | 18.0 | 127.0 | 26.0 | male |
| **2** | 3 | 25.0 | 132.0 | 37.0 | male |
| **3** | 4 | 25.0 | 100.0 | 63.0 | male |
| **4** | 5 | 29.0 | 104.0 | 42.0 | male |
| **...** | ... | ... | ... | ... | ... |
| **195** | 196 | 25.0 | 161.0 | 93.0 | male |
| **196** | 197 | 25.0 | 189.0 | 40.0 | male |
| **197** | 198 | 33.0 | 125.0 | 5.0 | male |
| **198** | 199 | 19.0 | 108.0 | 14.0 | male |
| **199** | 200 | 34.0 | 112.0 | 36.0 | male |

180 rows × 5 columns

In [41]:

df2.get\_group('female')

1

Out[41]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **CustomerID** | | **Age** | **Annual Income($)** | **Spending Score** | **Gender** |
| **5** | 6 | 35.0 | 174.0 | 68.0 | female |
| **6** | 7 | 32.0 | 114.0 | 71.0 | female |
| **7** | 8 | 32.0 | 127.0 | 49.0 | female |
| **8** | 9 | 28.0 | NaN | 19.0 | female |
| **9** | 10 | 30.0 | NaN | 58.0 | female |
| **10** | 11 | 35.0 | NaN | 34.0 | female |
| **11** | 12 | 32.0 | NaN | 17.0 | female |
| **12** | 13 | 27.0 | NaN | 18.0 | female |
| **13** | 14 | 27.0 | NaN | 26.0 | female |
| **14** | 15 | 31.0 | NaN | 65.0 | female |
| **15** | 16 | 22.0 | NaN | 39.0 | female |
| **16** | 17 | 25.0 | NaN | 65.0 | female |
| **17** | 18 | 19.0 | NaN | 89.0 | female |
| **18** | 19 | 31.0 | NaN | 76.0 | female |
| **22** | 23 | 23.0 | NaN | 93.0 | female |
| **28** | 29 | 29.0 | 198.0 | 4.0 | female |
| **33** | 34 | 31.0 | 176.0 | 30.0 | female |
| **56** | 57 | 24.0 | 107.0 | 74.0 | female |
| **94** | 95 | 28.0 | 106.0 | 9.0 | female |
| **172** | 173 | 25.0 | 152.0 | 93.0 | female |

In [43]:

df2[['Age' , 'Annual Income($)', 'Spending Score']].median()

1

Out[43]:

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Age** | **Annual Income($)** | **Spending Score** |
| **Gender** |  |  |  |
| **female** | 28.5 | 139.5 | 53.5 |
| **male** | 26.0 | 150.0 | 47.0 |

In [44]:

df2[['Age' , 'Annual Income($)', 'Spending Score']].mean()

1

Out[44]:

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Age** | **Annual Income($)** | **Spending Score** |
| **Gender** |  |  |  |
| **female** | 28.300000 | 144.250000 | 49.850000 |
| **male** | 26.103659 | 148.426136 | 49.424242 |

In [45]:

df2[['Age' , 'Annual Income($)', 'Spending Score']].max()

1

Out[45]:

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Age** | **Annual Income($)** | **Spending Score** |
| **Gender** |  |  |  |
| **female** | 35.0 | 198.0 | 93.0 |
| **male** | 35.0 | 200.0 | 100.0 |

In [46]:

df2[['Age' , 'Annual Income($)', 'Spending Score']].min()

1

Out[46]:

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Age** | **Annual Income($)** | **Spending Score** |
| **Gender** |  |  |  |
| **female** | 19.0 | 106.0 | 4.0 |
| **male** | 18.0 | 100.0 | 1.0 |

In [47]:

df2[['Age' , 'Annual Income($)', 'Spending Score']].std()

1

Out[47]:

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Age** | **Annual Income($)** | **Spending Score** |
| **Gender** |  |  |  |
| **female** | 4.317650 | 35.668113 | 28.995962 |
| **male** | 5.185656 | 29.129371 | 28.079841 |

In [51]:

df3 **=** pd.read\_csv(url)

1

url **=** "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/

1

In [49]:

In [50]:

df3

1

Out[50]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **5.1** | **3.5** | **1.4** | **0.2** | **Iris-setosa** |
| **0** | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **1** | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **2** | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **3** | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **4** | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... |
| **144** | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **145** | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **146** | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **147** | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **148** | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

149 rows × 5 columns

In [52]:

149 rows × 5 columns

df4

1

df4 **=**df3.groupby("E")

1

df3

1

df3.columns**=**("A" , "B" , " C " , "D" , "E")

1

In [53]:

Out[53]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **A** | **B** | **C** | **D** | **E** |
| **0** | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **1** | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **2** | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **3** | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **4** | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... |
| **144** | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **145** | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **146** | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **147** | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **148** | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

In [54]:

In [55]:

Out[55]: <pandas.core.groupby.generic.DataFrameGroupBy object at 0x000001A686244F10

>

In [56]:

df4.get\_group("Iris-setosa")

1

Out[56]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **A** | **B** | **C** | **D** | **E** |
| **0** | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **1** | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **2** | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **3** | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **4** | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| **5** | 4.6 | 3.4 | 1.4 | 0.3 | Iris-setosa |
| **6** | 5.0 | 3.4 | 1.5 | 0.2 | Iris-setosa |
| **7** | 4.4 | 2.9 | 1.4 | 0.2 | Iris-setosa |
| **8** | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |
| **9** | 5.4 | 3.7 | 1.5 | 0.2 | Iris-setosa |
| **10** | 4.8 | 3.4 | 1.6 | 0.2 | Iris-setosa |
| **11** | 4.8 | 3.0 | 1.4 | 0.1 | Iris-setosa |
| **12** | 4.3 | 3.0 | 1.1 | 0.1 | Iris-setosa |
| **13** | 5.8 | 4.0 | 1.2 | 0.2 | Iris-setosa |
| **14** | 5.7 | 4.4 | 1.5 | 0.4 | Iris-setosa |
| **15** | 5.4 | 3.9 | 1.3 | 0.4 | Iris-setosa |
| **16** | 5.1 | 3.5 | 1.4 | 0.3 | Iris-setosa |
| **17** | 5.7 | 3.8 | 1.7 | 0.3 | Iris-setosa |
| **18** | 5.1 | 3.8 | 1.5 | 0.3 | Iris-setosa |
| **19** | 5.4 | 3.4 | 1.7 | 0.2 | Iris-setosa |
| **20** | 5.1 | 3.7 | 1.5 | 0.4 | Iris-setosa |
| **21** | 4.6 | 3.6 | 1.0 | 0.2 | Iris-setosa |
| **22** | 5.1 | 3.3 | 1.7 | 0.5 | Iris-setosa |
| **23** | 4.8 | 3.4 | 1.9 | 0.2 | Iris-setosa |
| **24** | 5.0 | 3.0 | 1.6 | 0.2 | Iris-setosa |
| **25** | 5.0 | 3.4 | 1.6 | 0.4 | Iris-setosa |
| **26** | 5.2 | 3.5 | 1.5 | 0.2 | Iris-setosa |
| **27** | 5.2 | 3.4 | 1.4 | 0.2 | Iris-setosa |
| **28** | 4.7 | 3.2 | 1.6 | 0.2 | Iris-setosa |
| **29** | 4.8 | 3.1 | 1.6 | 0.2 | Iris-setosa |
| **30** | 5.4 | 3.4 | 1.5 | 0.4 | Iris-setosa |
| **31** | 5.2 | 4.1 | 1.5 | 0.1 | Iris-setosa |
| **32** | 5.5 | 4.2 | 1.4 | 0.2 | Iris-setosa |
| **33** | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |
| **34** | 5.0 | 3.2 | 1.2 | 0.2 | Iris-setosa |
| **35** | 5.5 | 3.5 | 1.3 | 0.2 | Iris-setosa |
| **36** | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |
| **37** | 4.4 | 3.0 | 1.3 | 0.2 | Iris-setosa |
| **38** | 5.1 | 3.4 | 1.5 | 0.2 | Iris-setosa |

**A B C D E**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **39** | 5.0 | 3.5 | 1.3 | 0.3 | Iris-setosa |
| **40** | 4.5 | 2.3 | 1.3 | 0.3 | Iris-setosa |
| **41** | 4.4 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **42** | 5.0 | 3.5 | 1.6 | 0.6 | Iris-setosa |
| **43** | 5.1 | 3.8 | 1.9 | 0.4 | Iris-setosa |
| **44** | 4.8 | 3.0 | 1.4 | 0.3 | Iris-setosa |
| **45** | 5.1 | 3.8 | 1.6 | 0.2 | Iris-setosa |
| **46** | 4.6 | 3.2 | 1.4 | 0.2 | Iris-setosa |
| **47** | 5.3 | 3.7 | 1.5 | 0.2 | Iris-setosa |
| **48** | 5.0 | 3.3 | 1.4 | 0.2 | Iris-setosa |

In [57]:

df4.get\_group("Iris-virginica")

1

Out[57]:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **A** | **B** | **C** | **D** | **E** |
| **99** | 6.3 | 3.3 | 6.0 | 2.5 | Iris-virginica |
| **100** | 5.8 | 2.7 | 5.1 | 1.9 | Iris-virginica |
| **101** | 7.1 | 3.0 | 5.9 | 2.1 | Iris-virginica |
| **102** | 6.3 | 2.9 | 5.6 | 1.8 | Iris-virginica |
| **103** | 6.5 | 3.0 | 5.8 | 2.2 | Iris-virginica |
| **104** | 7.6 | 3.0 | 6.6 | 2.1 | Iris-virginica |
| **105** | 4.9 | 2.5 | 4.5 | 1.7 | Iris-virginica |
| **106** | 7.3 | 2.9 | 6.3 | 1.8 | Iris-virginica |
| **107** | 6.7 | 2.5 | 5.8 | 1.8 | Iris-virginica |
| **108** | 7.2 | 3.6 | 6.1 | 2.5 | Iris-virginica |
| **109** | 6.5 | 3.2 | 5.1 | 2.0 | Iris-virginica |
| **110** | 6.4 | 2.7 | 5.3 | 1.9 | Iris-virginica |
| **111** | 6.8 | 3.0 | 5.5 | 2.1 | Iris-virginica |
| **112** | 5.7 | 2.5 | 5.0 | 2.0 | Iris-virginica |
| **113** | 5.8 | 2.8 | 5.1 | 2.4 | Iris-virginica |
| **114** | 6.4 | 3.2 | 5.3 | 2.3 | Iris-virginica |
| **115** | 6.5 | 3.0 | 5.5 | 1.8 | Iris-virginica |
| **116** | 7.7 | 3.8 | 6.7 | 2.2 | Iris-virginica |
| **117** | 7.7 | 2.6 | 6.9 | 2.3 | Iris-virginica |
| **118** | 6.0 | 2.2 | 5.0 | 1.5 | Iris-virginica |
| **119** | 6.9 | 3.2 | 5.7 | 2.3 | Iris-virginica |
| **120** | 5.6 | 2.8 | 4.9 | 2.0 | Iris-virginica |
| **121** | 7.7 | 2.8 | 6.7 | 2.0 | Iris-virginica |
| **122** | 6.3 | 2.7 | 4.9 | 1.8 | Iris-virginica |
| **123** | 6.7 | 3.3 | 5.7 | 2.1 | Iris-virginica |
| **124** | 7.2 | 3.2 | 6.0 | 1.8 | Iris-virginica |
| **125** | 6.2 | 2.8 | 4.8 | 1.8 | Iris-virginica |
| **126** | 6.1 | 3.0 | 4.9 | 1.8 | Iris-virginica |
| **127** | 6.4 | 2.8 | 5.6 | 2.1 | Iris-virginica |
| **128** | 7.2 | 3.0 | 5.8 | 1.6 | Iris-virginica |
| **129** | 7.4 | 2.8 | 6.1 | 1.9 | Iris-virginica |
| **130** | 7.9 | 3.8 | 6.4 | 2.0 | Iris-virginica |
| **131** | 6.4 | 2.8 | 5.6 | 2.2 | Iris-virginica |
| **132** | 6.3 | 2.8 | 5.1 | 1.5 | Iris-virginica |
| **133** | 6.1 | 2.6 | 5.6 | 1.4 | Iris-virginica |
| **134** | 7.7 | 3.0 | 6.1 | 2.3 | Iris-virginica |
| **135** | 6.3 | 3.4 | 5.6 | 2.4 | Iris-virginica |
| **136** | 6.4 | 3.1 | 5.5 | 1.8 | Iris-virginica |
| **137** | 6.0 | 3.0 | 4.8 | 1.8 | Iris-virginica |

**A B C D E**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **138** | 6.9 | 3.1 | 5.4 | 2.1 | Iris-virginica |
| **139** | 6.7 | 3.1 | 5.6 | 2.4 | Iris-virginica |
| **140** | 6.9 | 3.1 | 5.1 | 2.3 | Iris-virginica |
| **141** | 5.8 | 2.7 | 5.1 | 1.9 | Iris-virginica |
| **142** | 6.8 | 3.2 | 5.9 | 2.3 | Iris-virginica |
| **143** | 6.7 | 3.3 | 5.7 | 2.5 | Iris-virginica |
| **144** | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **145** | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **146** | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **147** | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **148** | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

In [58]:

df4.mean()

1

Out[58]:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **A** | **B** | **C** | **D** |
| **E** |  |  |  |  |
| **Iris-setosa** | 5.004082 | 3.416327 | 1.465306 | 0.244898 |
| **Iris-versicolor** | 5.936000 | 2.770000 | 4.260000 | 1.326000 |
| **Iris-virginica** | 6.588000 | 2.974000 | 5.552000 | 2.026000 |

In [59]:

df4.std()

1

Out[59]:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **A** | **B** | **C** | **D** |
| **E** |  |  |  |  |
| **Iris-setosa** | 0.355879 | 0.384787 | 0.175061 | 0.108130 |
| **Iris-versicolor** | 0.516171 | 0.313798 | 0.469911 | 0.197753 |
| **Iris-virginica** | 0.635880 | 0.322497 | 0.551895 | 0.274650 |

**Name:Sharvari Patil**

**Roll.no:13265**

**Batch:B3**

In [ ]:

1