COMP-1832

Programming Fundamentals for Data Science

Coursework

Author: Sweejalben Nehal Surti

Student ID: 001127898

Course of Study: MSc Data Science

Course Leader:

Dr. Jia Wang

&

Dr. Konstantin Kapinchev

School of Computing and Mathematical Science



COURSEWORK_PYTHON

December 4, 2021

1 Python Programming

```
import numpy as np
import pandas as pd
import calendar
import matplotlib.pyplot as plt
from scipy.stats import norm
import networkx as nx
```

2 Portfolio 1

```
[5]: #1. Download the Dataset.csv file from Moodle, load its content into pandas data

→ frame and visualise the entire content of the data frame

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

print(data.to_string())

print(data.dtypes.value_counts)
```

	longitude	latitude hous	sing_median_age	total_rooms	population
me	dian_income	median_house_v	value ocean_prox	imity	
0	-122.23	37.88	41.0000	880	322
8.	3252	452600	NEAR BAY		
1	-122.23	37.88	41.0000	880	322
8.	3252	452600	NEAR BAY		
2	-122.22	37.86	21.0000	7099	2401
8.	3014	358500	NEAR BAY		
3	-122.25	37.84	52.0001	3104	1157
3.	1200	241400	NEAR BAY		
4	-122.26	37.85	52.0000	3503	1504
3.	2705	241800	NEAR BAY		
5	-121.65	39.32	40.0000	812	374
2.	7891	73500	INLAND		
6	-121.69	39.36	29.0000	2220	1170
2.	3224	56200	INLAND		
7	-121.70	39.37	32.0000	1852	911

1 7005	F7000	TNIAND					
8 -121.70	57000		1010	EOO			
	63900	46.0000	1210	523			
1.9100		INLAND	0220	1505			
	39.36		2330	1505			
2.0474 10 -121.69	56000	INLAND	0.40	COF			
		34.0000	842	635			
1.8355		INLAND	0500	1100			
	39.38	27.0000	2596	1100			
2.3243		NaN	1010	F04			
12 -121.80		30.0000	1019	501			
2.5259	81300		1001	4540			
13 -120.46			4221	1516			
2.3816	116000	INLAND					
14 -120.55		10.0000	1566	785			
2.5000		INLAND					
	38.09	34.0000	2745	1150			
2.3654		INLAND					
	41.75	11.0000	3159	1343			
2.4805		NEAR OCEAN					
	41.77	17.0000	3461	1947			
2.5795	68400	NEAR O					
18 -124.19		15.0000	3140	1645			
	74600						
	41.74		2715	1532			
2.1829		NEAR OCEAN					
20 -124.14		21.0000	2696	1208			
	122400	NEAR OCEAN					
21 -124.16		19.0000	1668	841			
2.1336	75000	NEAR OCEAN					
22 -118.32	33.35	27.0000	1675	744			
2.1579	450000	ISLAND					
23 -118.33	33.34	52.0000	2359	1100			
2.8333	414700	ISLAND					
24 -118.32	33.33	52.0000	2127	733			
3.3906	300000	ISLAND					
25 -118.32	33.34	52.0000	996	341			
2.7361	450000	ISLAND					
26 -118.48	33.43	29.0000	716	422			
2.6042	287500	ISLAND					
27 -118.48	33.43	29.0000	716	422			
2.6042	287500	ISLAND					
<pre><bound indexopsmixin.value_counts="" longitude<="" method="" of="" td=""></bound></pre>							
latitude	float64	1					
housing_median	_age float64	1					
total_rooms int64							
population int64							
median_income	float64	1					
median_house_v	ralue int64	1					

ocean_proximity object

dtype: object>

The above code download the dataset and show all data in dataframe structure i.e. comma separated values with all columns class types

```
[6]: #Check the data frame for the following 'data cleaning' issues and resolve them:
#2. Missing values

data.isnull().sum()

#this code check for missing values in dataset.
```

[6]: longitude 0 latitude 0 housing_median_age 0 total_rooms 0 population 0 median_income 1 median_house_value 0 ocean_proximity 1 dtype: int64

#From above result it can be notice there are misssing values in column 'median_income' and 'ocean_proximity'

```
[7]: #fill missing values

data.fillna(data.mode().iloc[0], inplace=True)
data
```

```
[7]:
         longitude
                     latitude
                                housing_median_age
                                                      total_rooms
                                                                    population \
     0
            -122.23
                         37.88
                                            41.0000
                                                               880
                                                                            322
            -122.23
                         37.88
                                            41.0000
                                                                            322
     1
                                                               880
     2
            -122.22
                         37.86
                                            21.0000
                                                              7099
                                                                           2401
     3
            -122.25
                         37.84
                                            52.0001
                                                              3104
                                                                           1157
     4
            -122.26
                         37.85
                                            52.0000
                                                              3503
                                                                           1504
     5
            -121.65
                         39.32
                                            40.0000
                                                              812
                                                                            374
            -121.69
     6
                         39.36
                                            29.0000
                                                              2220
                                                                           1170
     7
            -121.70
                         39.37
                                            32.0000
                                                              1852
                                                                           911
            -121.70
                         39.36
                                                              1210
                                                                           523
     8
                                            46.0000
     9
            -121.70
                         39.36
                                            37.0000
                                                              2330
                                                                           1505
     10
            -121.69
                         39.36
                                                                           635
                                            34.0000
                                                              842
     11
           -121.74
                         39.38
                                            27.0000
                                                              2596
                                                                           1100
     12
           -121.80
                         39.33
                                            30.0000
                                                              1019
                                                                           501
                         38.15
     13
            -120.46
                                            16.0000
                                                             4221
                                                                           1516
     14
            -120.55
                         38.12
                                            10.0000
                                                              1566
                                                                            785
     15
            -120.56
                         38.09
                                            34.0000
                                                              2745
                                                                           1150
```

16	-124.23	41.75	11.0000	3159	1343
17	-124.21	41.77	17.0000	3461	1947
18	-124.19	41.78	15.0000	3140	1645
19	-124.16	41.74	15.0000	2715	1532
20	-124.14	41.95	21.0000	2696	1208
21	-124.16	41.92	19.0000	1668	841
22	-118.32	33.35	27.0000	1675	744
23	-118.33	33.34	52.0000	2359	1100
24	-118.32	33.33	52.0000	2127	733
25	-118.32	33.34	52.0000	996	341
26	-118.48	33.43	29.0000	716	422
27	-118.48	33.43	29.0000	716	422

		median_house_value	- •
0	8.3252	452600	NEAR BAY
1	8.3252	452600	NEAR BAY
2	8.3014	358500	NEAR BAY
3	3.1200	241400	NEAR BAY
4	3.2705	241800	NEAR BAY
5	2.7891	73500	INLAND
6	2.3224	56200	INLAND
7	1.7885	57000	INLAND
8	1.9100	63900	INLAND
9	2.0474	56000	INLAND
10	1.8355	63000	INLAND
11	2.3243	85500	INLAND
12	2.5259	81300	INLAND
13	2.3816	116000	INLAND
14	2.5000	116100	INLAND
15	2.3654	94900	INLAND
16	2.4805	73200	NEAR OCEAN
17	2.5795	68400	NEAR O
18	1.6654	74600	NEAR O
19	2.1829	69500	NEAR OCEAN
20	2.6042	122400	NEAR OCEAN
21	2.1336	75000	NEAR OCEAN
22	2.1579	450000	ISLAND
23	2.8333	414700	ISLAND
24	3.3906	300000	ISLAND
25	2.7361	450000	ISLAND
26	2.6042	287500	ISLAND
27	2.6042	287500	ISLAND

It can be notice from the dataset that the median_income and ocean_proximity column has one missing value which has been fill by most frequent data of that column.

```
[8]: #3. Unnecessary duplicates
     print(data.duplicated())
     data = data.drop_duplicates().reset_index(drop=True)
     print(data.to_string())
    0
          False
    1
           True
    2
          False
          False
    3
    4
          False
    5
          False
    6
          False
    7
          False
    8
          False
    9
          False
    10
          False
          False
    11
    12
          False
    13
          False
    14
          False
    15
          False
    16
          False
    17
          False
    18
          False
    19
          False
    20
          False
    21
          False
    22
          False
    23
          False
    24
          False
    25
          False
    26
          False
    27
           True
    dtype: bool
        longitude latitude housing_median_age total_rooms population
    median_income median_house_value ocean_proximity
    0
           -122.23
                       37.88
                                          41.0000
                                                            880
                                                                         322
    8.3252
                         452600
                                        NEAR BAY
                                                           7099
                                                                        2401
          -122.22
                       37.86
                                          21.0000
    8.3014
                         358500
                                        NEAR BAY
           -122.25
                       37.84
                                          52.0001
                                                           3104
                                                                        1157
    3.1200
                         241400
                                        NEAR BAY
           -122.26
                       37.85
                                          52.0000
                                                           3503
                                                                        1504
    3.2705
                         241800
                                        NEAR BAY
           -121.65
                       39.32
                                          40.0000
                                                            812
                                                                         374
```

INLAND

73500

2.7891

5 -121.69		29.0000	2220	1170
	56200			
6 -121.70		32.0000	1852	911
1.7885	57000	INLAND		
7 -121.70		46.0000	1210	523
1.9100	63900	INLAND		
8 -121.70		37.0000	2330	1505
2.0474	56000	INLAND		
9 -121.69	39.36	34.0000	842	635
	63000	INLAND		
10 -121.74	39.38	27.0000	2596	1100
2.3243	85500	INLAND		
11 -121.80	39.33	30.0000	1019	501
2.5259	81300	INLAND		
12 -120.46	38.15	16.0000	4221	1516
2.3816	116000	INLAND		
13 -120.55		10.0000	1566	785
2.5000	116100	INLAND		
14 -120.56	38.09	34.0000	2745	1150
2.3654		INLAND		
15 -124.23		11.0000	3159	1343
2.4805		NEAR OCEAN		
16 -124.21		17.0000	3461	1947
2.5795		NEAR O		
17 -124.19			3140	1645
		NEAR O		
18 -124.16		15.0000	2715	1532
2.1829		NEAR OCEAN		
		21.0000	2696	1208
		NEAR OCEAN	2000	1200
20 -124.16		19.0000	1668	841
		NEAR OCEAN	1000	011
21 -118.32			1675	744
2.1579	450000	ISLAND	1010	111
22 -118.33		52.0000	2359	1100
2.8333	414700	ISLAND	2009	1100
23 -118.32	33.33	52.0000	2127	733
3.3906	300000	ISLAND	2121	133
			006	2/1
24 -118.32	33.34	52.0000	996	341
2.7361	450000	ISLAND	74.0	400
25 -118.48	33.43	29.0000	716	422
2.6042	287500	ISLAND		

It can be notice from the dataset that row 1 and 27 has duplicates value which returns TRUE for that row that confirmed this value as duplicates. That 2 row has been dropped by the function duplicates()

[9]: #4. Wrong data types

#housing_median_age has wrong data type which should be integer instead of float

data= data.astype({'housing_median_age': np.int64})
print(data.to_string())

-		sing_median_age		population
		value ocean_prox	-	
0 -122.23	37.88	41	880	322
8.3252	452600	NEAR BAY		
1 -122.22	37.86	21	7099	2401
8.3014	358500	NEAR BAY		
2 -122.25	37.84	52	3104	1157
3.1200	241400	NEAR BAY		
3 -122.26	37.85	52	3503	1504
3.2705	241800	NEAR BAY		
4 -121.65	39.32	40	812	374
2.7891	73500	INLAND		
5 -121.69	39.36	29	2220	1170
2.3224	56200	INLAND		
6 -121.70	39.37	32	1852	911
1.7885	57000	INLAND		
7 -121.70	39.36	46	1210	523
1.9100	63900	INLAND		
8 -121.70	39.36	37	2330	1505
2.0474	56000	INLAND		
9 -121.69	39.36	34	842	635
1.8355	63000	INLAND		
10 -121.74	39.38	27	2596	1100
2.3243	85500	INLAND		
11 -121.80	39.33	30	1019	501
2.5259	81300	INLAND		
12 -120.46	38.15	16	4221	1516
2.3816	116000	INLAND		
13 -120.55	38.12	10	1566	785
2.5000	116100	INLAND		
14 -120.56	38.09	34	2745	1150
2.3654	94900	INLAND		
15 -124.23	41.75	11	3159	1343
2.4805	73200	NEAR OCEAN		
16 -124.21	41.77	17	3461	1947
2.5795	68400	NEAR O		
17 -124.19		15	3140	1645
1.6654	74600	NEAR O		
18 -124.16	41.74	15	2715	1532
2.1829	69500	NEAR OCEAN		
19 -124.14	41.95	21	2696	1208

2.6042	122400	NEAR OCEAN		
20 -124.16	41.92	19	1668	841
2.1336	75000	NEAR OCEAN		
21 -118.32	33.35	27	1675	744
2.1579	450000	ISLAND		
22 -118.33	33.34	52	2359	1100
2.8333	414700	ISLAND		
23 -118.32	33.33	52	2127	733
3.3906	300000	ISLAND		
24 -118.32	33.34	52	996	341
2.7361	450000	ISLAND		
25 -118.48	33.43	29	716	422
2.6042	287500	ISLAND		

We can notice from the dataset that the housing_median_age column type is Float which should be an integer value which has been converted by the function np.int64()

[10]: #5. Wrong values

From above dataset we can notice that column median_income has wrong values. The income should be in large number. Also the ocean_proximity has wrong values in row no. 16,17, which should be as 'NEAR OCEAN' instead of 'NEAR O'.

```
[11]: #6. Save the updated data frame into a new CSV file

data.to_csv("New_Dataset.csv")

# The above code is to save the existing data into new csv file.
```

174730.76923076922

The above code is to calculate the average price of the house..which is 174730.76923076922 as an average price of the house.

```
[13]: #8. Median
print(data['median_house_value'].median())
```

90200.0

The baove code show the median of the house value that is 90200.0

[14]: #9. Range print("The range of the median_house_value is:", data['median_house_value']. →max() - data['median_house_value'].min())

The range of the median_house_value is: 396600

The above code find the range of that data which can be find by its Max value - Min value of that column.

```
[15]: #10. The column 'median_income' contains currency in tens of thousands USD.

#Convert it into USD and visualise the entire updated data frame

data['median_income']=data['median_income'] * 10000

data
```

[15]:	longitude	latitude	housing_median_age	total_rooms	population	\
0	-122.23	37.88	41	880	322	
1	-122.22	37.86	21	7099	2401	
2	-122.25	37.84	52	3104	1157	
3	-122.26	37.85	52	3503	1504	
4	-121.65	39.32	40	812	374	
5	-121.69	39.36	29	2220	1170	
6	-121.70	39.37	32	1852	911	
7	-121.70	39.36	46	1210	523	
8	-121.70	39.36	37	2330	1505	
9	-121.69	39.36	34	842	635	
10	-121.74	39.38	27	2596	1100	
11	-121.80	39.33	30	1019	501	
12	-120.46	38.15	16	4221	1516	
13	-120.55	38.12	10	1566	785	
14	-120.56	38.09	34	2745	1150	
15	-124.23	41.75	11	3159	1343	
16	-124.21	41.77	17	3461	1947	
17	-124.19	41.78	15	3140	1645	
18	-124.16	41.74	15	2715	1532	
19	-124.14	41.95	21	2696	1208	
20	-124.16	41.92	19	1668	841	
21	-118.32	33.35	27	1675	744	
22	-118.33	33.34	52	2359	1100	
23	-118.32	33.33	52	2127	733	
24	-118.32	33.34	52	996	341	
25	-118.48	33.43	29	716	422	

median_income median_house_value ocean_proximity
0 83252.0 452600 NEAR BAY
1 83014.0 358500 NEAR BAY

2	31200.0	241400	NEAR BAY
3	32705.0	241800	NEAR BAY
4	27891.0	73500	INLAND
5	23224.0	56200	INLAND
6	17885.0	57000	INLAND
7	19100.0	63900	INLAND
8	20474.0	56000	INLAND
9	18355.0	63000	INLAND
10	23243.0	85500	INLAND
11	25259.0	81300	INLAND
12	23816.0	116000	INLAND
13	25000.0	116100	INLAND
14	23654.0	94900	INLAND
15	24805.0	73200	NEAR OCEAN
16	25795.0	68400	NEAR O
17	16654.0	74600	NEAR O
18	21829.0	69500	NEAR OCEAN
19	26042.0	122400	NEAR OCEAN
20	21336.0	75000	NEAR OCEAN
21	21579.0	450000	ISLAND
22	28333.0	414700	ISLAND
23	33906.0	300000	ISLAND
24	27361.0	450000	ISLAND
25	26042.0	287500	ISLAND

3 Portfolio 2

3.0.1 Part 1

3.0.2 Initialise a two-dimensional array consisting of 5 rows and 10 columns of uniformly distributed data points of integer values from the interval [0..9]. Consider each row of the two-dimensional array as an independent dataset. Display the values on the screen as a table. Plot the first two rows on a single diagram with different colours.

```
[16]: My_arr = np.empty(shape=(5,10), dtype='int')

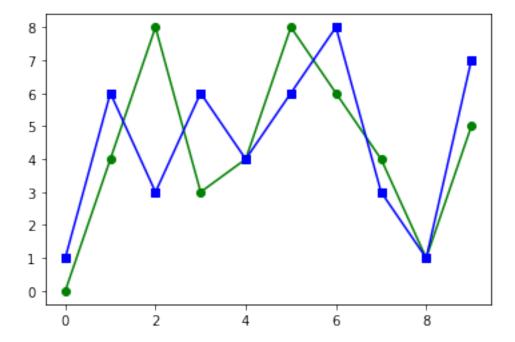
for i in range(0,5):
    for j in range(0,10):
        My_arr[i,j] = int(np.random.randint(0,9))

print(My_arr)

plt.plot(My_arr[0,] , marker = "o", color ="green")
plt.plot(My_arr[1,] , marker = "s", color ="blue")
plt.show()
```

```
[[0 4 8 3 4 8 6 4 1 5]
[1 6 3 6 4 6 8 3 1 7]
```

```
[3 6 7 0 4 2 4 4 1 3]
[3 1 1 8 8 4 8 4 3 6]
[3 6 8 2 7 1 7 3 6 1]]
```



The above code generate the two-dimensional array consisting of 5 rows and 10 columns of uniformly distributed data points of integer values using np.random.randint() function. where plt.plot() function visualize the data as graph.

- 3.0.3 Part 2
- 3.0.4 Provide the following information about each individual row:
- 3.0.5 Mean
- 3.0.6 Median
- 3.0.7 Standard deviation

```
[17]: row_mean = np.mean(My_arr, axis =1)
    print("Mean By its row:", row_mean)

row_median = np.median(My_arr, axis =1)
    print("Median By its row:", row_median)

row_std = np.std(My_arr, axis =1)
    print("Standard Deviation By its row:", row_std)
```

This code find the mean, meadian and Standard Deviation of each individual $_{\mbox{\sc u}}$ -rows.

```
Mean By its row: [4.3 4.5 3.4 4.6 4.4]

Median By its row: [4. 5. 3.5 4. 4.5]

Standard Deviation By its row: [2.49198716 2.33452351 2.00997512 2.61533937 2.53771551]
```

3.0.8 Part 3

3.0.9 Initialise a one-dimensional array representing a normal distribution of 1000 data points with mean value 17 and standard deviation 0.2.

```
[18]: array([17.0871021 , 17.11168963, 16.94467448, 16.4896596 , 16.95476746,
             17.06567924, 17.17335808, 16.7951687, 16.91907479, 17.1643116,
             17.18000543, 17.01106869, 17.0392014, 16.59103135, 17.13666795,
             16.93715652, 16.87004571, 17.02680475, 17.32366372, 17.10914536,
             16.98544317, 16.69948372, 17.29080071, 17.19402319, 17.24797148,
             17.03986578, 17.29477632, 16.66960589, 16.89329687, 17.10539742,
             17.02425186, 17.23456934, 17.01014785, 17.06396743, 17.00411319,
             16.88756041, 17.44352724, 17.11427959, 16.8673481, 17.06808373,
             16.8831875 , 17.20674813 , 17.10504338 , 16.92375556 , 16.91714368 ,
             16.80447175, 16.95268854, 17.15319853, 17.02395346, 16.8188284,
             16.92513867, 17.18699766, 17.02696755, 16.77651585, 16.70020168,
             17.38794735, 17.09354312, 17.09739948, 16.97573832, 17.22058579,
             16.74905093, 16.56631596, 16.83290987, 17.26633769, 16.98950945,
             17.05860926, 16.8204387, 17.14699334, 16.85682185, 17.09290906,
             16.81883683, 17.07050164, 16.86736209, 17.24620704, 17.01713886,
             17.0005637 , 16.7924739 , 16.83954382, 17.07289772, 16.86532834,
             17.31447812, 17.0727732, 17.08231494, 17.02463888, 16.99143152,
             17.08719624, 17.14764329, 17.05833099, 16.89422403, 16.95774643,
             17.26072463, 17.02790852, 17.0969117, 16.97463294, 17.21697948,
             17.11829534, 17.17171107, 16.8231039, 16.90700394, 17.22403978,
             17.08849423, 16.96379442, 17.19300335, 17.53209023, 17.26675625,
             16.63121711, 17.05093245, 17.10449294, 17.01479268, 17.1887665 ,
             17.03844839, 17.06427179, 17.23253528, 16.90747633, 16.85032941,
             16.58846995, 17.03453196, 16.85258579, 17.25193051, 17.1509691,
             16.93583732, 17.18558992, 17.05179778, 17.24642586, 16.87496581,
```

```
17.01876184, 16.76016962, 16.84787505, 16.62248695, 17.08899695,
16.88138056, 17.27993895, 16.79161463, 16.86304199, 16.68506745,
17.06940183, 16.54082787, 17.36471743, 17.1130859, 16.73405412,
17.04836522, 17.09558439, 17.37753412, 16.3047535, 17.25442236,
17.00833729, 17.2813321, 17.02916072, 16.95655001, 16.96556807,
17.12001957, 16.98900228, 17.14103727, 17.19493209, 17.04339813,
16.9682588 , 16.83761681 , 16.80996335 , 16.77112869 , 16.85091437 ,
16.57369657, 16.66997454, 16.76528644, 17.0831637, 16.77015311,
17.06081636, 16.84383629, 17.07054635, 16.89896602, 17.15796042,
17.32121117, 17.07293838, 16.99209081, 17.33826773, 17.16697236,
16.97303699, 16.95737729, 16.89811781, 17.1400396, 17.03198805,
17.4326771 , 17.02159795, 17.26056899, 17.36377224, 16.81623061,
16.63141107, 16.84180498, 17.08166051, 16.85297174, 16.97385609,
17.17690146, 17.39392037, 17.13495342, 17.17263922, 17.095757
16.92279581, 16.57265445, 17.35701406, 16.74115636, 17.28132534,
16.78684841, 16.98123705, 17.18401673, 16.92815912, 16.98921192,
16.88413035, 17.31147289, 16.85391539, 16.99710927, 16.87927108,
16.86867272, 17.00506548, 16.97239156, 16.65560534, 16.85708268,
17.08315371, 16.75007741, 16.92904762, 17.17874049, 16.77178002,
16.73898853, 16.74500984, 17.17072804, 16.91581764, 16.94722422,
16.85015378, 16.84360266, 16.89822629, 17.17538083, 16.91870833,
16.61393145, 16.77649407, 16.91305063, 17.35308936, 17.07171962,
17.0338043 , 17.09277638, 17.19062638, 16.70581859, 16.89875703,
16.65977444, 16.98176876, 16.97479906, 17.09043747, 16.98991103,
17.20978232, 17.02881081, 17.13177579, 16.87954644, 17.03450292,
17.3314627 , 17.32057606 , 16.97832425 , 17.00240832 , 17.48022004 ,
16.85289057, 17.15678176, 16.96308043, 16.97497726, 17.48521196,
17.07623069, 16.91869127, 16.91310712, 17.06349289, 17.05560457,
17.24810957, 16.74589922, 16.96637097, 17.06863117, 17.01676594,
16.97646644, 17.64330057, 16.8809299, 17.21902863, 16.8117574,
16.71010913, 17.31199186, 16.95538194, 17.20559871, 17.12506202,
17.16564741, 17.11614259, 17.06195758, 17.21349204, 16.88671261,
17.126247 , 16.74844092, 16.80362499, 16.7281345 , 17.04168842,
17.39903817, 16.70725687, 17.00519494, 17.23758694, 16.88363217,
16.79862461, 17.10257875, 17.14033806, 17.27011355, 17.08960661,
16.67101228, 17.24553406, 16.96793299, 17.29078326, 17.02023922,
17.07282967, 17.27432187, 17.09803154, 17.30743341, 16.83019166,
17.05633429, 17.06453818, 17.05004635, 17.0286393, 17.14408445,
16.80685992, 16.91366161, 16.7160819, 16.86050876, 16.94289966,
17.27629367, 17.19726841, 16.93227997, 16.84297958, 16.86871134,
16.76381369, 16.47346569, 16.93242973, 16.92818805, 17.11522845,
16.77001698, 16.93497979, 17.27382479, 16.71036307, 16.84721538,
16.48114629, 17.05895385, 16.9285357, 17.03869522, 16.9797574,
16.83449946, 17.06632381, 16.88288106, 16.85442774, 17.27822359,
16.85101851, 16.99124586, 16.89159576, 17.42607425, 16.91302839,
16.99106196, 16.79389608, 17.16649863, 16.97557152, 16.89854355,
17.05486989, 17.03523142, 17.19468506, 17.07287451, 17.1905243,
```

```
16.99944373, 16.80449277, 16.83278781, 16.93020085, 16.92600206,
17.03384304, 17.34032038, 16.73463849, 17.04692571, 17.21833742,
16.85867064, 17.14092235, 16.87981131, 17.01491885, 17.32250173,
17.34566005, 17.10978567, 17.07633421, 16.73286478, 16.96685802,
16.97307978, 16.72769574, 16.7699041 , 16.79484741, 17.17190562,
17.20742087, 17.03335607, 16.99661785, 17.24671431, 17.11688337,
16.99680907, 16.97466717, 17.07169269, 17.21757271, 17.04241237,
16.98532726, 16.96726361, 16.99587737, 16.97597255, 17.027097
17.11240661, 16.93110885, 17.06017294, 17.16639805, 17.00322924,
17.06244733, 17.2397332, 16.81379447, 16.95222193, 17.10775715,
17.2316075 , 16.84793781 , 17.10059813 , 17.21002005 , 17.17674973 ,
17.27232375, 16.68282281, 16.66786976, 17.03270957, 16.7823333 ,
17.17095595, 17.18269907, 16.81570051, 17.25589285, 17.13080517,
16.76238666, 16.94256662, 16.9847868, 16.90372136, 16.8343269,
17.17133821, 17.04579951, 16.83716646, 17.34330914, 16.8920698,
17.24365414, 17.1956349, 16.95577734, 16.95289665, 16.93207337,
16.92225421, 17.12066396, 17.02009611, 16.79014315, 16.90678595,
16.96719557, 16.86034322, 16.95157467, 17.00797235, 17.33032586,
16.95267297, 16.82748735, 17.09759048, 17.05315271, 17.38495279,
16.95664969, 17.13447194, 17.38192329, 16.76829538, 17.1733438
17.40512831, 17.1046592 , 17.07685834, 17.01327833, 16.76704772,
16.9016975 , 16.85377866 , 16.71149575 , 17.4796177 , 17.12941085 ,
16.88313308, 17.05669699, 17.02441329, 16.84429367, 16.84250705,
17.24616495, 16.97781493, 16.54931986, 16.77393326, 17.00415797,
16.98130101, 16.91344251, 17.34416445, 16.93714236, 16.70495567,
17.46928548, 16.88869828, 16.86619906, 17.22901323, 16.89848603,
16.59140242, 16.64258538, 16.74538034, 17.18673442, 16.92062214,
17.2232917 , 16.87954024, 17.09111962, 17.01727635, 16.86461898,
16.98959983, 16.73895912, 17.07663837, 17.081587 , 17.13248722,
17.30011702, 17.74613317, 17.08659209, 16.54060377, 17.00931284,
16.72685796, 17.02672841, 16.96274095, 17.23402272, 16.90336752,
16.80846906, 17.23860891, 17.50852385, 16.96046898, 16.84934625,
16.90266804, 16.65091487, 16.79825849, 17.08337478, 16.960757
16.96315973, 17.20761195, 16.92449528, 16.9726497, 16.99255282,
17.1938683 , 17.05114446, 16.82861775, 16.84630819, 16.8871493 ,
17.19523347, 17.02448867, 16.98378976, 17.00406945, 16.8253051,
16.9483232 , 17.3261083 , 17.42901108, 17.06923059, 17.19164582,
17.37536905, 17.09434624, 17.09362463, 16.79120658, 17.14645801,
16.90114575, 17.12943606, 16.83337851, 16.89426052, 16.95572727,
17.36447407, 16.8737966 , 17.10516326, 16.88881866, 16.96769239,
16.63866217, 16.98759322, 17.16753462, 16.73438146, 17.20365204,
17.23844137, 17.11376551, 16.99169414, 17.1135091, 17.12377164,
17.19181531, 17.34571622, 17.11025025, 16.87899296, 17.1071928,
16.80048074, 17.17027833, 17.20421415, 17.0553907, 17.08924954,
17.10384884, 17.21956301, 17.21478426, 17.27663676, 16.83782446,
16.9170498 , 16.88708824 , 16.96642985 , 17.01484175 , 16.88156577 ,
17.0030851 , 16.95879819, 16.78575395, 17.18875194, 17.02672629,
```

```
16.64194505, 16.97390048, 16.82755559, 16.96058157, 17.12452433,
17.25757005, 16.85967945, 17.10377886, 16.74661992, 17.18839546,
16.98744341, 17.39456792, 16.76598346, 17.02971299, 16.98128241,
16.82868227, 16.782239 , 16.60436532, 16.86966767, 16.93331871,
16.73085275, 16.79516687, 16.85663769, 16.97580048, 17.37473405,
16.81098373, 17.29890242, 16.85797936, 16.90469345, 16.86173778,
16.81550164, 16.91101932, 16.98090993, 16.76381872, 16.86897861,
16.75500041, 16.69082812, 17.22408965, 17.12636543, 16.99472073,
17.34737156, 16.94824706, 17.20846778, 16.82514039, 17.1696851,
17.11981604, 17.09041056, 17.00007794, 17.09997292, 16.91704093,
16.78689802, 17.05875302, 17.04973822, 17.40754813, 16.94701318,
16.8848001 , 17.28777971 , 17.06491415 , 17.0132937 , 17.13262051 ,
17.49059567, 16.85806405, 17.21330979, 16.74457336, 16.96426438,
16.91921888, 16.69834201, 16.78230596, 16.59861587, 17.0603541,
17.24532225, 17.13546265, 16.95791634, 16.84573467, 16.57669411,
17.23505742, 16.93780554, 16.81883459, 16.93600869, 16.8627294,
17.16100369, 16.99353594, 17.32733492, 16.76103006, 17.00904003,
17.29337853, 16.92267024, 16.86567405, 17.04089918, 17.05737348,
16.94032053, 16.88003865, 17.17771863, 17.10731256, 17.00395725,
17.00082153, 17.14393913, 16.89308447, 16.95850986, 16.83129705,
16.6841111 , 16.87650694, 17.19754278, 17.16567435, 17.0044626 ,
17.27958134, 16.94434594, 16.93575396, 16.93549038, 16.84469841,
17.01802707, 16.6425294, 16.81430267, 17.13915078, 16.93349289,
16.75516253, 17.05414939, 17.06148566, 17.28072456, 17.05030592,
16.94289829, 16.96605361, 16.96171429, 16.93183783, 17.06043563,
         , 16.71415556, 17.34401315, 17.02916367, 16.69972944,
16.93445907, 16.8454594 , 16.54754045, 17.02490163, 17.0631384 ,
17.08256759, 16.98198949, 17.00991817, 17.23012272, 17.18708674,
16.86298247, 17.17425369, 17.04430136, 16.79487456, 16.74000569,
16.95717913, 16.6888197, 16.96525916, 17.3445201, 16.82798005,
17.17582521, 17.03053868, 17.21548101, 16.97501587, 16.76272883,
17.07502127, 16.69603914, 17.11770649, 16.54362446, 16.90569892,
17.1964836 , 17.01421042, 17.15853756, 17.10497158, 16.80374771,
17.21172221, 16.55604671, 16.98927839, 17.08279814, 17.11821798,
16.83200999, 17.2289492 , 16.99199146, 17.32612999, 16.51099364,
16.93114227, 16.88046342, 16.83721403, 16.8473788 , 17.20399105,
16.89971402, 16.72703244, 17.07191142, 17.19474086, 17.20692533,
17.19957971, 16.85371874, 16.63790937, 16.85944777, 17.27811408,
16.92783534, 17.04694248, 16.93293716, 17.06517992, 17.00382864,
17.09771436, 16.65670799, 17.10962741, 16.95737722, 17.06685537,
16.9784586 , 17.00109718 , 16.82550141 , 17.27336228 , 16.85342134 ,
17.26332537, 17.12944886, 16.88087533, 16.96850505, 17.01160292,
16.92065022, 17.15109711, 16.90710918, 16.80267196, 17.07506539,
17.02446751, 16.76985395, 16.78416286, 17.12967547, 16.89559053,
17.19361502, 17.27108156, 17.0043217, 16.796008, 16.7974345,
17.17234208, 16.81718383, 17.29691849, 16.79296394, 17.31713979,
16.94227121, 16.97889025, 17.38714219, 17.04971647, 17.17534798,
```

```
17.18242677, 16.87779983, 17.1646998, 16.98367641, 17.0847319,
16.72898733, 16.83396185, 16.97797797, 16.94345655, 16.87616145,
17.04642455, 16.94049581, 16.83857511, 16.43868869, 17.14004766,
16.93586751, 16.82711972, 16.95025948, 17.00493603, 16.92561354,
16.81484952, 16.73457267, 16.92937634, 17.1973348 , 16.77731167,
17.16773373, 17.20536366, 17.12719632, 16.83867001, 16.72455727,
17.47762048, 17.20979336, 17.2102932, 17.4095791, 17.13224638,
17.05135516, 16.62855893, 17.17711174, 16.71069633, 16.93285961,
16.65298256, 16.65576471, 16.8400396, 16.56191472, 16.80629858,
17.12135027, 16.74329593, 17.36098369, 17.20022874, 16.6376544,
16.90673524, 17.21433879, 17.21450323, 17.13379987, 17.02501604,
16.8680352 , 16.95781816, 16.94253805, 17.06658364, 16.67124587,
17.04358793, 17.02347247, 17.0909941 , 17.03970977, 16.9710721 ,
17.10969294, 16.90568685, 17.17004159, 17.06147354, 17.25295724,
16.83005984, 17.00540568, 16.92761069, 16.81518194, 16.86661849,
17.13114053, 17.05908618, 16.73089603, 16.69676875, 16.7536834,
17.24660716, 16.92573589, 17.02117265, 17.00712351, 17.09411461,
17.31279555, 17.25387602, 16.84554709, 16.92005015, 17.15717627,
17.29406874, 17.17870898, 17.32335584, 17.19176775, 16.78917576,
16.5959618 , 17.37509984, 16.9505088 , 17.18634627, 16.75749451,
16.91265389, 16.88205949, 16.81673387, 17.01146871, 16.72569015,
17.00173771, 16.92465372, 16.79806707, 17.10172157, 17.15011894,
16.99575949, 16.88103069, 17.08960643, 17.04211538, 17.02180548,
16.99650496, 16.91095905, 16.99626111, 16.91375668, 16.5431922,
17.17730138, 16.93034734, 17.06799828, 17.18508633, 17.3766111,
17.43597271, 16.88795565, 16.85000319, 16.75325955, 17.08245439,
17.04770094, 16.79470935, 16.93201491, 16.8917455 , 17.05949328,
17.24072714, 16.72237777, 16.85163948, 17.05170608, 16.95802344,
17.03577655, 17.10602765, 17.11049152, 16.67338261, 17.18592262,
16.96741021, 16.93910632, 16.85223359, 16.76595325, 17.16496138,
17.12245535, 16.99069928, 17.05271393, 17.2190864, 16.96177382,
17.16255832, 16.59707838, 16.78837975, 16.96228402, 17.06367125,
16.97194593, 16.7468086, 16.89275522, 16.66783309, 17.08288435,
16.85791867, 17.0622175 , 17.0148367 , 17.23322922, 17.07695526])
```

3.0.10 Part 4

3.0.11 Find the maximum and the minimum values of the dataset and calculate the range.

```
[19]: print("Max:", np.max(norm_array))
    print("Min:", np.min(norm_array))
    print("Range:", round(np.max(norm_array) - np.min(norm_array),2))
# The above code finds the Max, min and range of the data.
```

Max: 17.74613317359515

Min: 16.30475350250239

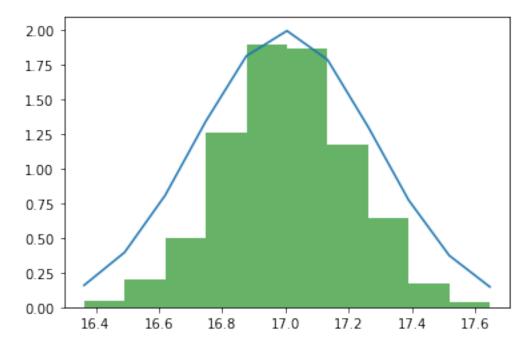
Range: 1.44

- 3.0.12 Part 5 (2 points):
- 3.0.13 Visualise the dataset by using a histogram with 10 bins. Visualise the probability density function.
- 3.0.14 Probability density function f:
- 3.0.15 $f=1/(2) e^{(((x-)^2)/2^2)}$
- 3.0.16 Where X represents the data points, is the mean value and is the standard deviation.

```
[18]: A,X,C = plt.hist(norm_array, bins=10, density=True, alpha=0.6, color='g')
# plt.show()

f = (1/(std*np.sqrt(2*np.pi)))*np.exp(-((X-mean)/(2*std))**2)
#f = (1/(std*np.sqrt(2*np.pi)))*np.exp(-(X-mean)**2/(2*std)**2)

plt.plot(X,f)
plt.show()
```



The above code plots the data on histogram and shows the normally distibuted data with its density. The density of that data has been found using Probability density function of math function.

4 Portfolio 3

- 4.0.1 Task 1:
- 4.0.2 Initialize the following matrix
- 4.0.3 A: {[2,5,1],[4,3,7],[1,3,2]}
- 4.0.4 Find the determinant, the trace and the inverse of matrix A

```
[21]: # Initialise a matrix M with 3 by 3 elements
      M = np.array([[2,5,1],[4,3,7],[1,3,2]])
      # Display the matrix
      print(M)
      # Calculate the determinant of M
      D = np.linalg.det(M)
      # Display the determinant
      print('Determinant:', D)
      # Calculate the trace of M
      T = np.trace(M)
      #Display the trace
      print('Trace:', T)
      # Calculate the inverse of M
      I = np.linalg.inv(M)
      print('Matrix:',M)
      print('Inverse of Matrix:', I)
     [[2 5 1]
      [4 3 7]
      [1 3 2]]
     Determinant: -26.00000000000014
     Trace: 7
     Matrix: [[2 5 1]
      [4 \ 3 \ 7]
      [1 3 2]]
     Inverse of Matrix: [[ 0.57692308  0.26923077 -1.23076923]
      [ 0.03846154 -0.11538462  0.38461538]
      [-0.34615385 0.03846154 0.53846154]]
```

The above code find the determinant of the matrix using algebric function of python det(). Display the Trace of the matrix and the inverse of the matrix using fuction trace() and inv() respectively.

- 4.0.5 Task 2:
- 4.0.6 Initialise the following square matrices B and C:
- 4.0.7 B ={[4,7,2],[3,2,5],[6,4,3]}
- 4.0.8 $C = \{[3,1,9],[7,5,8],[2,1,1]\}$
- 4.0.9 Find the product P of the matrices B and C by using the Python function for matrix
- 4.0.10 multiplication. Display the result on the screen.

```
[23]: # Initialise a matrix B with 3x3 elements
B = np.array([[4,7,2],[3,2,5],[6,4,3]], dtype='int')

# Initialise a matrix C with 3x3 elements
C = np.array([[3,1,9],[7,5,8],[2,1,1]], dtype='int')

# Calculate p = B*C
p = np.matmul(B,C)

#print Product p
print('p:', p)

# The above code multiply the two matrix and generate the new matrix using
function np.matmul().
```

```
p: [[65 41 94]
[33 18 48]
[52 29 89]]
```

- 4.0.11 Task 3:
- 4.0.12 Consider the following system of linear equations:
- $4.0.13 \quad 3x + 2y z = 25$
- 4.0.14 2x y + 4z = 19
- $4.0.15 \quad 4x 2y + 3z = 18$
- 4.0.16 Represent the system of linear equations by using matrices.
- **4.0.17** Solution:

Representation the system of linear equations by matrices:

$$(3,2,-1)$$
 (x) (25)
 $(2,-1,4)$ (y) = (19)
 $(4,-2,3)$ (z) (18)

And by following notation:

$$MX = C$$
, where $(3,2,-1)(x)(25)M = (2,-1,4), X = (y), C = (19)(4,-2,3)(z)(18)$

- 4.0.18 Task 4:
- 4.0.19 Provide the algebraic steps for solving the system of linear equations from Task 3 by
- 4.0.20 using matrix notation.
- 4.0.21 Solution:

Step 1: MX = c find the Matrix M, X and C as below for Task 3

The matrix has 3 rows and 1 column

$$(3,2,-1)$$
 (x) (25)
 $M = (2,-1,4)$, $X = (y)$, $C = (19)$
 $(4,-2,3)$ (z) (18)

Step 2: $M^-1 MX = M^-1 C$

Step 3: Find the Inverse of matrix M

$$IX = M^-1 C$$

Step 4: Calculate $X = M^-1 * C$ which solve the linear equation system and gives values for X,Y,Z.

- 4.0.22 Task 5:
- 4.0.23 Solve the system of linear equations from Task 3 by using Python script utilising matrix
- 4.0.24 multiplication and inverse matrix

```
[21]: # Initialise a matrix M with 3x3 elements
M = np.array([[3,2,-1],[2,-1,4],[4,-2,3]])

#Initialise a matrix c
C = np.array([25,19,18])

# Calculate the inverse of Matrix M
I = np.linalg.inv(M)

#Calculate X = I*C
X = np.matmul(I,C)

#Display Matrix X
print('X:', X)
```

X: [5. 7. 4.]

The above code solved the linear equation from the task 3 and give the values of X,Y,Z which we put in the eqution to solved the linear equation.

5 Portfolio 4

5.0.1 Task 1 (5 points)

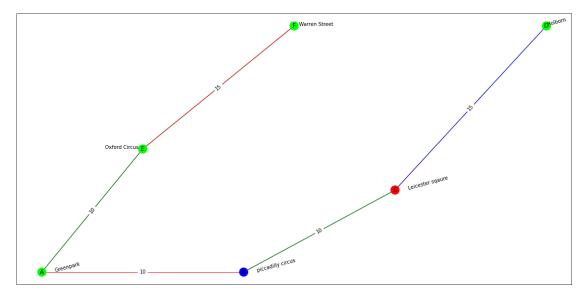
Develop a graph which represents the public transport network of a city of your choice. Some cities have extensive public transport networks. In such case, represent minimum 3 lines with minimum 4 stations on each line. When visualising the network, use different colours for the different lines and their corresponding stations. Provide attributes to the edges which correspond to the distances between stations and visualise them. If the actual distances between the stations are not available, approximate them by using online map services. Visualise the names of the stations.

```
[66]: # Create a graph object
      G= nx.Graph()
      # Add $ station to the graph
      G.add_node('A',npos=(10,20),color_node='#00FF00')
      G.add_node('B',npos=(18,20),color_node='#0000FF')
      G.add_node('C',npos=(24,21),color_node='#FF0000')
      G.add_node('D',npos=(30,23),color_node='#00FF00')
      G.add_node('E',npos=(14,21.5),color_node='#00FF00')
      G.add_node('F',npos=(20,23),color_node='#00FF00')
      # Connect nodes
      G.add_edge('A', 'B', color='r', distance=10)
      G.add_edge('B', 'C', color='g',distance=10)
      G.add_edge('C', 'D', color='b',distance=15)
      G.add_edge('A', 'E', color='g',distance=10)
      G.add_edge('E', 'F', color='r',distance=15)
      # Extract attributes from the graph to dictionaries
      pos = nx.get_node_attributes(G, 'npos')
      node_colour = nx.get_node_attributes(G, 'color_node')
      edge_colour = nx.get_edge_attributes(G, 'color')
      distance = nx.get_edge_attributes(G, 'distance')
      # Place the dictionary values in lists
      NodeList = list(node_colour.values())
      EdgeList = list(edge_colour.values())
      # Set the size of the figure
      plt.figure(figsize=(20, 10))
      # Display the names of the stations
      plt.text(10.5,20,s='Greenpark', rotation=15)
```

```
plt.text(18.5,20, s='piccadilly circus', rotation=15)
plt.text(24.5,21, s='Leicester sqaure', rotation=15)
plt.text(30,23, s='Holborn', rotation=15)
plt.text(12.5,21.5, s='Oxford Circus', rotation=0)
plt.text(20.2,23, s='Warren Street', rotation=0)

# Draw the nodes and the edges
nx.draw_networkx(G, pos, node_color=NodeList)
nx.draw_networkx_edges(G, pos, edge_color=EdgeList)
nx.draw_networkx_edge_labels(G, pos, edge_labels=distance)

# Visualise the graph
plt.show()
```



The below graph shows the public transport network of london city which describes some DLR station of the city using NetworkX library The round shapes describes the node as station and the lines as edges which connects the stations and each edges has its attributes and the number between the edges describes the distance between two stations.

5.0.2 Task 2 (5 points)

Find the average monthly temperatures of three cities of your choice. Represent the data by using a heat map. Provide a colour scale for guidance. Allow the user to specify a threshold for the heat map. Based on this threshold value, use different base colours when representing the data points.

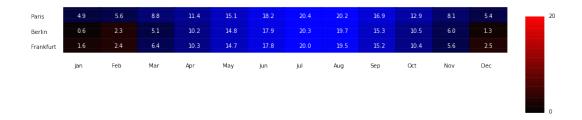
```
[24]: def DrawBox(x, y, size, r, g, b):
    if r < 0:
        r = int(0)
    if g < 0:</pre>
```

```
g = int(0)
           if b < 0:
                     b = int(0)
           if r > 255:
                     r = int(255)
           if g > 255:
                       g = int(255)
           if b > 255:
                      b = int(255)
           for i in range(0, int(size)):
                       plt.plot([x, x + size], [y + i, y + i], '#{:02x}{:02x}'.format(r, | y + i], '#{:02x}'.format(r, | y 
   \rightarrowg, b))
# Store the dataset into a data frame
df = pd.read_csv('HeatMap.csv')
# Print the content on the screen
print(df.head(7))
# Set the plot
plt.figure(figsize=(18, 5))
plt.axis([0, 600, 0, 400])
plt.xticks([])
plt.yticks([])
plt.axis('off')
Min = int(min(df.min(numeric_only=True)))
Max = int(max(df.max(numeric_only=True)))
BoxSize = int(40)
OffsetX = int(15)
OffsetY = int(12)
thresold = int(input("Specify Thresold Value:"))
# Generate the heat map
for i in range(0, df.shape[0]):
           for j in range(1, df.shape[1]):
                       ColourCode = int(((df.values[i, j]-Min)/(Max-Min))*255)
                       if df.values[i, j] > thresold:
                                  DrawBox(20+BoxSize*j, 300-BoxSize*i, BoxSize, 0, 0, ColourCode)
                       if df.values[i, j] <= thresold:</pre>
                                  DrawBox(20+BoxSize*j, 300-BoxSize*i, BoxSize, ColourCode, 0, 0)
                       plt.text(OffsetX+20+BoxSize*j, OffsetY+300-BoxSize*i, str(df.values[i,__
```

```
# Generate the scale
for i in range(0, 256):
    plt.plot([560, 580], [i + 60, i + 60], \#\{:02x\}\{:02x\}\{:02x\}\}.format(int(i),
 \rightarrow 0, 0)
plt.text(585, 58, Min)
plt.text(585, 312, Max)
plt.text(72, 180, 'Jan')
plt.text(112, 180, 'Feb')
plt.text(152, 180, 'Mar')
plt.text(192, 180, 'Apr')
plt.text(232, 180, 'May')
plt.text(272, 180, 'Jun')
plt.text(312, 180, 'Jul')
plt.text(352, 180, 'Aug')
plt.text(392, 180, 'Sep')
plt.text(432, 180, 'Oct')
plt.text(472, 180, 'Nov')
plt.text(512, 180, 'Dec')
plt.text(25, 310, str(df.values[0, 0]))
plt.text(25, 270, str(df.values[1, 0]))
plt.text(25, 230, str(df.values[2, 0]))
plt.show()
        City
                1
                     2
                          3
                                4
                                      5
                                            6
                                                  7
                                                        8
                                                                   10
                                                                        11
0
             4.9 5.6 8.8 11.4 15.1 18.2 20.4
                                                     20.2
       Paris
                                                           16.9
                                                                 12.9
                                                                       8.1
      Berlin 0.6
                  2.3
                        5.1
                             10.2
                                  14.8
                                        17.9
                                               20.3
                                                     19.7
                                                           15.3
                                                                 10.5
                                                                       6.0
2 Frankfurt 1.6 2.4
                        6.4 10.3 14.7 17.8 20.0
                                                     19.5 15.2 10.4
```

2 Frankfurt 1.6 2.4 6.4 10.3

12
0 5.4
1 1.3
2 2.5
Specify Thresold Value:3



The above code creat the heat map for the data from csv file HatMap.csv. Also user can specify the thresold value if thresold value is greater than data points then it shows the balck and orange color either blue and black. The below graph shows the heat map for the 3 city's monthly average temperature for the year. The Dark black color shows the lower temperature of the month and the dark orange color shows the highest temperature of the month July and August and it also represents the strong correlation between the 3 city's temperature for the same months.

5.0.3 Task 3 (5 points)

Represent the data from Task 2 by using parallel coordinates. Use different colours for each city's average monthly temperatures.

```
[26]: # Print dimension of dataset
    print('Number of Rows: ', Tempdata.shape[0])
    print('Number of Columns: ', Tempdata.shape[1])

# Find the maximum values per column
Maximum = np.amax(Tempdata, axis=0)

# Normalise to interval 0 .. 100
for i in range(0, Tempdata.shape[0]):
    for j in range(0, Tempdata.shape[1]-1):
        Tempdata[i, j] = float(Tempdata[i, j]*(100.0/Maximum[j]))

# Spine names
Name = ['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']

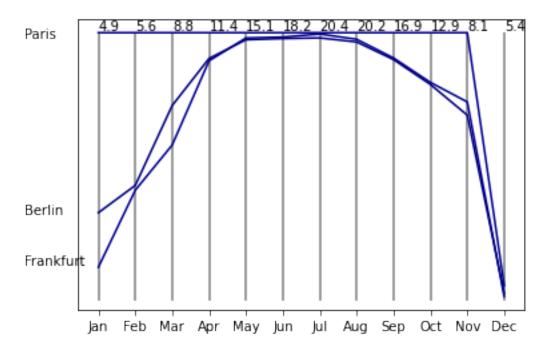
# Test for random RGB in hex
k = ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9', 'A', 'B', 'C', 'D', 'E', ''F']

MyC = '#'
for i in range(0, 6):
    s = np.random.choice(k)
    MyC = MyC + s
```

```
plt.yticks([])
# Spines
for i in range(0, Tempdata.shape[1]):
    plt.vlines(i, 0, 100, '#808080')
# Generate the parallel coordinates
for i in range(0, Tempdata.shape[0]):
    if Tempdata[i, 4] < float(40.0):</pre>
        MyC = '#'
        for j in range(0, 6):
            s1 = np.random.choice(k)
            s2 = np.random.choice(k)
            MyC = '#' + s1 + s2 + '0000'
        plt.plot(Name, Tempdata[i], MyC)
for i in range(0, Tempdata.shape[0]):
    if float(40.0) < Tempdata[i, 4] < float(60.0):</pre>
        MvC = '#'
        for j in range(0, 6):
            s1 = np.random.choice(k)
            s2 = np.random.choice(k)
            MyC = '#' + '00' + s1 + s2 + '00'
        plt.plot(Name, Tempdata[i], MyC)
for i in range(0, Tempdata.shape[0]):
    if float(60.0) < Tempdata[i, 4]:</pre>
        MyC = '#'
        for j in range(0, 6):
            s1 = np.random.choice(k)
            s2 = np.random.choice(k)
            MyC = '#' + '0000' + s1 + s2
        plt.plot(Name, Tempdata[i], MyC)
plt.text(0, 101, round(Maximum[0], 2))
plt.text(1, 101, round(Maximum[1], 2))
plt.text(2, 101, round(Maximum[2], 2))
plt.text(3, 101, round(Maximum[3], 2))
plt.text(4, 101, round(Maximum[4], 2))
plt.text(5, 101, round(Maximum[5], 2))
plt.text(6, 101, round(Maximum[6], 2))
plt.text(7, 101, round(Maximum[7], 2))
plt.text(8, 101, round(Maximum[8], 2))
plt.text(9, 101, round(Maximum[9], 2))
plt.text(10, 101, round(Maximum[10], 2))
plt.text(11, 101, round(Maximum[11], 2))
```

```
plt.text(-2, 13, 'Frankfurt')
plt.text(-2, 32, 'Berlin')
plt.text(-2, 98, 'Paris')
plt.show()
```

Number of Rows: 3 Number of Columns: 12



Parallel Coordinates Plots are ideal for comparing many variables together and seeing the relationships between them. The above parallel coordinates graph shows the data of the three different cities temperature data, Paris, Berlin, Frankfurt. We can notice fro the above graph that the Paris city has highest temperature compare to two other cities. We can also notice from the graph that berlin and frankfurt has almost the same temperature over the year. for the month April-october both berlin and franfurt have almost the same temperature.

COURSEWORK_R-Final

December 4, 2021

1 R Programming

2 Portfolio 1

```
[21]: install.packages("tidyverse")
      install.packages("data.table")
      install.packages("modeest")
      library(tidyr)
      library(ggplot2)
      library(dplyr)
      library(stringr)
      library(data.table)
      library(modeest)
     Installing package into 'C:/Users/khala/OneDrive/Documents/R/win-library/4.1'
     (as 'lib' is unspecified)
     package 'tidyverse' successfully unpacked and MD5 sums checked
     The downloaded binary packages are in
             C:\Users\khala\AppData\Local\Temp\Rtmp4gu1tR\downloaded_packages
     Warning message:
     "package 'data.table' is in use and will not be installed"
     Warning message:
     "package 'modeest' is in use and will not be installed"
```

2.0.1 The tidyr::who dataset contains tuberculosis (TB) cases broken down by year, country, age, gender, and diagnosis method. The data comes from the 2014 World Health Organization Global Tuberculosis Report

```
[22]: tidyr::who #Shows the who dataset
```

	country	iso2	iso3	year	new_sp_m014	new_sp_m1524	new_sp_m2534
	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>	<int></int>	<int></int>	<int></int>
-	Afghanistan	AF	AFG	1980	NA	NA	NA
	Afghanistan	AF	AFG	1981	NA	NA	NA
	Afghanistan	AF	AFG	1982	NA	NA	NA
	Afghanistan	AF	AFG	1983	NA	NA	NA
	Afghanistan	AF	AFG	1984	NA	NA	NA :
	Afghanistan	AF	AFG	1985	NA	NA	NA :
	Afghanistan	AF	AFG	1986	NA	NA	NA :
	Afghanistan	AF	AFG	1987	NA	NA	NA :
	Afghanistan	AF	AFG	1988	NA	NA	NA :
	Afghanistan	AF	AFG	1989	NA	NA	NA :
	Afghanistan	AF	AFG	1990	NA	NA	NA :
	Afghanistan	AF	AFG	1991	NA	NA	NA :
	Afghanistan	AF	AFG	1992	NA	NA	NA :
	Afghanistan	AF	AFG	1993	NA	NA	NA :
	Afghanistan	AF	AFG	1994	NA	NA	NA :
	Afghanistan	AF	AFG	1995	NA	NA	NA
	Afghanistan	AF	AFG	1996	NA	NA	NA
	Afghanistan	AF	AFG	1997	0	10	6
	Afghanistan	AF	AFG	1998	30	129	128
	Afghanistan	AF	AFG	1999	8	55	55
	Afghanistan	AF	AFG	2000	52	228	183
	Afghanistan	AF	AFG	2001	129	379	349
	Afghanistan	AF	AFG	2002	90	476	481
	Afghanistan	AF	AFG	2003	127	511	436
	Afghanistan	AF	AFG	2004	139	537	568
	Afghanistan	AF	AFG	2005	151	606	560
	Afghanistan	AF	AFG	2006	193	837	791
	Afghanistan	AF	AFG	2007	186	856	840
	Afghanistan	AF	AFG	2008	187	941	773
A tibble: 7240×60	Afghanistan	AF	AFG	2009	200	906	705
	Zimbabwe	ZW	ZWE	1984	NA	NA	NA
	Zimbabwe	ZW	ZWE	1985	NA	NA	NA
	Zimbabwe	ZW	ZWE	1986	NA	NA	NA
	Zimbabwe	ZW	ZWE	1987	NA	NA	NA
	Zimbabwe	ZW	ZWE	1988	NA	NA	NA
	Zimbabwe	ZW	ZWE	1989	NA	NA	NA
	Zimbabwe	ZW	ZWE	1990	NA	NA	NA
	Zimbabwe	ZW	ZWE	1991	NA	NA	NA
	Zimbabwe	ZW	ZWE	1992	NA	NA	NA
	Zimbabwe	ZW	ZWE	1993	NA	NA	NA
	Zimbabwe	ZW	ZWE	1994	NA	NA	NA
	Zimbabwe	ZW	ZWE	1995	NA	NA	NA
	Zimbabwe	ZW	ZWE	1996	NA	NA	NA
	Zimbabwe	ZW	ZWE	1997	NA	NA	NA
	Zimbabwe	ZW	ZWE	1998	NA	NA	NA
	Zimbabwe	ZW	ZWE	1999	NA	NA	NA
	Zimbabwe	ZW	ZWE_2	2000	NA	NA	NA
	Zimbabwe	ZW	ZWE	2001	NA	NA	NA
	Zimbabwe	ZW	ZWE	2002	191	600	2548
	Zimbabwe	ZW	ZWE	2003	133	874	3048

***There are 7240 rows and 60 columns in the above dataset of who.

2.0.2 1.Gather together all the columns from _new_spm014 to _newrelf65

```
[23]: who1 <- who %>%
    pivot_longer(
        cols = starts_with("new"), #Columns starts with new
        names_to = "Key", #new column name for all that columns gathers
        values_to = "Cases", # columns name for all values
        values_drop_na = TRUE # Drops rows that correspond to missing values
    )
```

The above code gathers all columns start with "new" prefix into new column as "Key" and its value as column "Cases" and drops rows that correspond to missing values

```
[24]: who1 #The new Dataset agthers all the columns as new key column "Key" with its \_ \_ values as "Cases"
```

	country	iso2	iso3	year	Key	Cases
	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>	<chr></chr>	<int></int>
-	Afghanistan	AF	AFG	1997	new_sp_m014	0
	Afghanistan	AF	AFG	1997	new_sp_m1524	10
	Afghanistan	AF	AFG	1997	new_sp_m2534	6
	Afghanistan	AF	AFG	1997	new_sp_m3544	3
	Afghanistan	AF	AFG	1997	new_sp_m4554	5
	Afghanistan	AF	AFG	1997	new_sp_m5564	2
	Afghanistan	AF	AFG	1997	new_sp_m65	0
	Afghanistan	AF	AFG	1997	new_sp_f014	5
	Afghanistan	AF	AFG	1997	new_sp_f1524	38
	Afghanistan	AF	AFG	1997	new_sp_f2534	36
	Afghanistan	AF	AFG	1997	new_sp_f3544	14
	Afghanistan	AF	AFG	1997	new_sp_f4554	8
	Afghanistan	AF	AFG	1997	new_sp_f5564	0
	Afghanistan	AF	AFG	1997	new_sp_f65	1
	Afghanistan	AF	AFG	1998	new_sp_m014	30
	Afghanistan	AF	AFG	1998	new_sp_m1524	129
	Afghanistan	AF	AFG	1998	new_sp_m2534	128
	Afghanistan	AF	AFG	1998	new_sp_m3544	90
	Afghanistan	AF	AFG	1998	new_sp_m4554	89
	Afghanistan	AF	AFG	1998	new_sp_m5564	64
	Afghanistan	AF	AFG	1998	new_sp_m65	41
	Afghanistan	AF	AFG	1998	new_sp_f014	45
	Afghanistan	AF	AFG	1998	new_sp_f1524	350
	Afghanistan	AF	AFG	1998	new_sp_f2534	419
	Afghanistan	AF	AFG	1998	new_sp_f3544	194
	Afghanistan	AF	AFG	1998	new_sp_f4554	118
	Afghanistan	AF	AFG	1998	new_sp_f5564	61
	Afghanistan	AF	AFG	1998	new_sp_f65	20
	Afghanistan	AF	AFG	1999	new_sp_m014	8
A tibble: 76046 × 6	Afghanistan	AF	AFG	1999	new_sp_m1524	55
					- 1 -	
	Zimbabwe	ZW	ZWE	2012	new_sn_f5564	516
	Zimbabwe	ZW	ZWE	2012	new_sn_f65	432
	Zimbabwe	ZW	ZWE	2012	new_ep_m014	233
	Zimbabwe	ZW	ZWE	2012	new_ep_m1524	214
	Zimbabwe	ZW	ZWE	2012	new_ep_m2534	658
	Zimbabwe	ZW	ZWE	2012	new_ep_m3544	789
	Zimbabwe	ZW	ZWE	2012	new_ep_m4554	331
	Zimbabwe	ZW	ZWE	2012	new_ep_m5564	178
	Zimbabwe	ZW	ZWE	2012	new_ep_m65	182
	Zimbabwe	ZW	ZWE	2012	new_ep_f014	208
	Zimbabwe	ZW	ZWE	2012	new_ep_f1524	319
	Zimbabwe	ZW	ZWE	2012	new_ep_f2534	710
	Zimbabwe	ZW	ZWE	2012	new_ep_f3544	579
	Zimbabwe	ZW	ZWE	2012	new_ep_f4554	228
	Zimbabwe	ZW	ZWE	2012	new_ep_f5564	140
	Zimbabwe	ZW	ZWE	2012	new_ep_f65	143
	Zimbabwe	ZW	$ZWE_{\!\!\!\!\!4}$	2013	newrel_m014	1315
	Zimbabwe	ZW	ZWE	2013	newrel_m1524	1642
	Zimbabwe	ZW	ZWE	2013	newrel_m2534	5331
	Zimbabwe	ZW	ZWE	2013	newrel_m3544	5363
	•• •				= r1 <u>—</u>	

After gathering columns into one column key the dimension of data is 76046 (rows) \times 6 (columns).

2.0.3 2.Make variable names consistent Instead of _newrel we have newrel. It is hard to spot this here but if you do not fix it,we will get errors in subsequent steps.

```
[25]: who1$Key <- str_replace(who1$Key,'newrel','new_rel') # Replace String "newrel"

→with "new_rel"

[26]: who2 <- who1
```

who2

	country	iso2	iso3	year	Key	Cases
	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>	<chr></chr>	<int></int>
	Afghanistan	AF	AFG	1997	new_sp_m014	0
	Afghanistan	AF	AFG	1997	new_sp_m1524	10
	Afghanistan	AF	AFG	1997	new_sp_m2534	6
	Afghanistan	AF	AFG	1997	new_sp_m3544	3
	Afghanistan	AF	AFG	1997	new_sp_m4554	5
	Afghanistan	AF	AFG	1997	new_sp_m5564	2
	Afghanistan	AF	AFG	1997	new_sp_m65	0
	Afghanistan	AF	AFG	1997	new_sp_f014	5
	Afghanistan	AF	AFG	1997	new_sp_f1524	38
	Afghanistan	AF	AFG	1997	new_sp_f2534	36
	Afghanistan	AF	AFG	1997	new_sp_f3544	14
	Afghanistan	AF	AFG	1997	new_sp_f4554	8
	Afghanistan	AF	AFG	1997	new_sp_f5564	0
	Afghanistan	AF	AFG	1997	new_sp_f65	1
	Afghanistan	AF	AFG	1998	new_sp_m014	30
	Afghanistan	AF	AFG	1998	new_sp_m1524	129
	Afghanistan	AF	AFG	1998	new_sp_m2534	128
	Afghanistan	AF	AFG	1998	new_sp_m3544	90
	Afghanistan	AF	AFG	1998	new_sp_m4554	89
	Afghanistan	AF	AFG	1998	new_sp_m5564	64
	Afghanistan	AF	AFG	1998	new_sp_m65	41
	Afghanistan	AF	AFG	1998	new_sp_f014	45
	Afghanistan	AF	AFG	1998	new_sp_f1524	350
	Afghanistan	AF	AFG	1998	new_sp_f2534	419
	Afghanistan	AF	AFG	1998	new_sp_f3544	194
	Afghanistan	AF	AFG	1998	new_sp_f4554	118
	Afghanistan	AF	AFG	1998	new_sp_f5564	61
	Afghanistan	AF	AFG	1998	new_sp_f65	20
	Afghanistan	AF	AFG	1999	new_sp_m014	8
A tibble: 76046 × 6	Afghanistan	AF	AFG	1999	new_sp_m1524	55
71 tibble. 70040 × 0	7 Hghamstan				11cw_5p_1111524	
	 Zimbabwe	 ZW	 ZWE	 2012	 new_sn_f5564	 516
	Zimbabwe	ZW	ZWE	2012	new_sn_f65	432
	Zimbabwe	ZW	ZWE	2012	new_ep_m014	233
	Zimbabwe	ZW	ZWE	2012	new_ep_m1524	214
	Zimbabwe	ZW	ZWE	2012	new_ep_m2534	658
	Zimbabwe	ZW	ZWE	2012	new_ep_m3544	789
	Zimbabwe	ZW	ZWE	2012	new_ep_m4554	331
	Zimbabwe	ZW	ZWE	2012	new_ep_m5564	178
	Zimbabwe	ZW	ZWE	2012	new_ep_m65	182
	Zimbabwe	ZW	ZWE	2012	new_ep_f014	208
	Zimbabwe	ZW	ZWE	2012	new_ep_f1524	319
	Zimbabwe	ZW	ZWE	2012	new_ep_f2534	710
	Zimbabwe	ZW	ZWE	2012	new_ep_f3544	579
	Zimbabwe	ZW	ZWE	2012	new_ep_f4554	228
	Zimbabwe	ZW	ZWE	2012	new_ep_f5564	140
	Zimbabwe	ZW	ZWE	2012	new_ep_f65	143
	Zimbabwe	ZW	ZWE	2013	new_rel_m014	1315
	Zimbabwe	ZW	ZWE	2013	new_rel_m1524	1642
	Zimbabwe	ZW	ZWE	2013	new_rel_m2534	5331
	Zimbabwe	ZW	ZWE	2013	new_rel_m3544	5363
	ZIIIDabwe	Z V V	Z 7 7 L	2010	116 W_161_1110044	5505

The who2 is new dataset afeter replacing the sring String "newrel" with "new_rel" of column Key

- 2.0.4 3. Run the following code
- 2.0.5 wh3 <- who2 %>%
- 2.0.6 separate(key, c("new", "type", "sexage"), sep = "_")
- 2.0.7 Now you get a dataset who3. Comment these two lines of code. What is the purpose of using %>%.

```
[27]: who3 <- who2 %>% separate(Key, c("new", "type", "sexage"), sep = "_")
```

The above code separate the one column into three column by "_" using separate function. The purpose of the %>% is that its work as a pipe for the data. it passes the left hand side of the operator to the first argument of the right hand side of the operator. In the above code, the data frame who2 gets passed to separate().

[28]: who3

	country	iso2	iso3	year	new	type	sexage	Cases
	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>
•	Afghanistan	AF	AFG	1997	new	sp	m014	0
	Afghanistan	AF	AFG	1997	new	sp	m1524	10
	Afghanistan	AF	AFG	1997	new	sp	m2534	6
	Afghanistan	AF	AFG	1997	new	sp	m3544	3
	Afghanistan	AF	AFG	1997	new	sp	m4554	5
	Afghanistan	AF	AFG	1997	new	sp	m5564	2
	Afghanistan	AF	AFG	1997	new	sp	m65	0
	Afghanistan	AF	AFG	1997	new	sp	f014	5
	Afghanistan	AF	AFG	1997	new	sp	f1524	38
	Afghanistan	AF	AFG	1997	new	sp	f2534	36
	Afghanistan	AF	AFG	1997	new	sp	f3544	14
	Afghanistan	AF	AFG	1997	new	sp	f4554	8
	Afghanistan	AF	AFG	1997	new	sp	f5564	0
	Afghanistan	AF	AFG	1997	new	sp	f65	1
	Afghanistan	AF	AFG	1998	new	sp	m014	30
	Afghanistan	AF	AFG	1998	new	sp	m1524	129
	Afghanistan	AF	AFG	1998	new	sp	m2534	128
	Afghanistan	AF	AFG	1998	new	sp	m3544	90
	Afghanistan	AF	AFG	1998	new	sp	m4554	89
	Afghanistan	AF	AFG	1998	new	sp	m5564	64
	Afghanistan	AF	AFG	1998	new	sp	m65	41
	Afghanistan	AF	AFG	1998	new	sp	f014	45
	Afghanistan	AF	AFG	1998	new	sp	f1524	350
	Afghanistan	AF	AFG	1998	new	sp	f2534	419
	Afghanistan	AF	AFG	1998	new	sp	f3544	194
	Afghanistan	AF	AFG	1998	new	sp	f4554	118
	Afghanistan	AF	AFG	1998	new	sp	f5564	61
	Afghanistan	AF	AFG	1998	new	sp	f65	20
	Afghanistan	AF	AFG	1999	new	sp	m014	8
A tibble: 76046×8	Afghanistan	AF	AFG	1999	new	sp	m1524	55
					•••	•••		
	Zimbabwe	ZW	ZWE	2012	new	sn	f5564	516
	Zimbabwe	ZW	ZWE	2012	new	sn	f65	432
	Zimbabwe	ZW	ZWE	2012	new	ер	m014	233
	Zimbabwe	ZW	ZWE	2012	new	ep	m1524	214
	Zimbabwe	ZW	ZWE	2012	new	ep	m2534	658
	Zimbabwe	ZW	ZWE	2012	new	ep	m3544	789
	Zimbabwe	ZW	ZWE	2012	new	ep	m4554	331
	Zimbabwe	ZW	ZWE	2012	new	ep	m5564	178
	Zimbabwe	ZW	ZWE	2012	new	ep	m65	182
	Zimbabwe	ZW	ZWE	2012	new	ep	f014	208
	Zimbabwe	ZW	ZWE	2012	new	ep	f1524	319
	Zimbabwe	ZW	ZWE	2012	new	ep	f2534	710
	Zimbabwe	ZW	ZWE	2012	new	ep	f3544	579
	Zimbabwe	ZW	ZWE	2012	new	ep	f4554	228
	Zimbabwe	ZW	ZWE	2012	new	ep	f5564	140
	Zimbabwe	ZW	ZWE	2012	new	ep	f65	143
	Zimbabwe	ZW	ZWE ₈	2013	new	rel	m014	1315
	Zimbabwe	ZW	ZWE	2013	new	rel	m1524	1642
	Zimbabwe	ZW	ZWE	2013	new	rel	m2534	5331
	Zimbabwe	ZW	ZWE	2013	new	rel	m3544	5363

2.0.8 4.Separate sexage into sex and age: Use the function separate(). Name the dataset who4

```
[29]: who4 <- (separate(who3, col=sexage, into=c("sex", "age"), sep='(?<=[a-zA-Z])(? \hookrightarrow=[0-9])'))
```

The above code separate the sexage column into two column sex and age by numeric and alpha regular expression using separate function.

2.0.9 5.Print the first 5 rows and the last 5 rows of the dataset who4 to the screen.

[30]:	head(who4)	#shows	the	first	6	data	from	the	datafarme	e who4
	tail(who4)	#shows	the	last	6	data .	from	the	data farme	who4

	country	iso2	iso3	year	new	type	sex	age	Cases
	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>	<chr></chr>	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>
	Afghanistan	AF	AFG	1997	new	sp	m	014	0
A tibble: 6×9	Afghanistan	AF	AFG	1997	new	sp	m	1524	10
A tibble. 0 x 9	Afghanistan	AF	AFG	1997	new	sp	m	2534	6
	Afghanistan	AF	AFG	1997	new	sp	m	3544	3
	Afghanistan	AF	AFG	1997	new	sp	m	4554	5
	Afghanistan	AF	AFG	1997	new	sp	m	5564	2
	country	iso2	iso3	year	new	type	sex	age	Cases
	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>	<chr></chr>	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>
	Zimbabwe	ZW	ZWE	2013	new	rel	f	1524	2069
A tibble: 6×9	Zimbabwe	ZW	ZWE	2013	new	rel	f	2534	4649
A tibble. 6 x 9	Zimbabwe	ZW	ZWE	2013	new	rel	f	3544	3526
	Zimbabwe	ZW	ZWE	2013	new	rel	f	4554	1453
	Zimbabwe	ZW	ZWE	2013	new	rel	f	5564	811
	Zimbabwe	ZW	ZWE	2013	new	rel	f	65	725

2.0.10 6.Export who4 as an csv file and save it in your local directory.

```
[31]: fwrite(who4, "C:/Users/khala/OneDrive/Desktop/who.csv") #saved file in my local_ \rightarrow directory
```

The above fwrite function id much better and faster then read_csv and other function

3 Portfolio 2

```
[49]: # Print the first 6 rows
head(iris)
```

		Sepal.Length <dbl></dbl>	Sepal.Width <dbl></dbl>	Petal.Length <dbl></dbl>	Petal.Width <dbl></dbl>	Species <fct></fct>
•	1	5.1	3.5	1.4	0.2	setosa
A data.frame: 6×5	2	4.9	3.0	1.4	0.2	setosa
A data.frame. 0 x 3	3	4.7	3.2	1.3	0.2	setosa
	4	4.6	3.1	1.5	0.2	setosa
	5	5.0	3.6	1.4	0.2	setosa
	6	5.4	3.9	1.7	0.4	setosa

[50]: df_iris=iris df_iris # Iris Dataset

5.1 3.5 1.4 0.2 setosa 4.9 3.0 1.4 0.2 setosa 4.9 3.0 1.4 0.2 setosa 4.7 3.2 1.3 0.2 setosa 5.0 3.6 1.4 0.2 setosa 5.0 3.6 1.4 0.2 setosa 5.0 3.6 1.4 0.3 setosa 5.0 3.4 1.4 0.3 setosa 5.0 3.4 1.4 0.3 setosa 5.0 3.4 1.5 0.2 setosa 6.0 3.1 1.5 0.1 setosa 6.0 3.1 1.5 0.1 setosa 6.0 3.0 1.1 5.0 0.2 setosa 6.0 3.0 1.1 0.1 0.2 setosa 6.0 3.0 1.1 0.0 0.2 setosa 6.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	-	1012 17	1012 17	1012 17	1012 17	
47 32 1.3 0.2 setosa 46 3.1 1.5 0.2 setosa 50 3.6 1.4 0.2 setosa 4.6 3.4 1.4 0.3 setosa 4.6 3.4 1.4 0.3 setosa 5.0 3.4 1.5 0.2 setosa 4.6 3.4 1.4 0.3 setosa 4.7 1.5 0.2 setosa 4.8 1.5 0.1 setosa 4.8 3.4 1.6 0.2 setosa 4.8 3.4 1.6 0.2 setosa 4.8 3.0 1.4 0.1 setosa 4.8 3.0 1.4 0.1 setosa 4.8 3.0 1.1 0.1 setosa 4.8 3.0 1.4 0.1 setosa 4.8 3.0 1.4 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.5 1.4 0.2 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.8 1.5 0.2 setosa 5.1 3.8 1.7 0.2 setosa 5.1 3.8 1.7 0.2 setosa 5.1 3.3 1.7 0.5 setosa 5.2 3.5 1.5 0.2 setosa 5.0 3.4 1.4 1.5 1.5 0.2 1.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1		5.1	3.5	1.4	0.2	setosa
4.6		4.9	3.0	1.4		setosa
5.0		4.7	3.2	1.3	0.2	setosa
5.4 3.9 1.7 0.4 setosa 4.6 3.4 1.4 0.3 setosa 5.0 3.4 1.5 0.2 setosa 4.4 2.9 1.4 0.2 setosa 4.9 3.1 1.5 0.1 setosa 5.4 3.7 1.5 0.2 setosa 4.8 3.4 1.6 0.2 setosa 4.8 3.0 1.4 0.1 setosa 4.8 3.0 1.1 0.1 setosa 4.8 3.0 1.1 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.1 3.5 1.4 0.3 setosa 5.1 3.8 1.7 0.3 setosa 5.1 3.7 1.5 0.4 setosa		4.6	3.1	1.5		setosa
4.6 3.4 1.4 0.3 setosa setosa 4.4 2.9 1.4 0.2 setosa 4.9 3.1 1.5 0.2 setosa 4.9 3.1 1.5 0.2 setosa 4.8 3.7 1.5 0.2 setosa 4.8 3.4 1.6 0.2 setosa 4.8 3.0 1.4 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.5 1.4 0.3 setosa 5.1 3.8 1.7 0.2 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.3 1.7 0.2 setosa 5.1 3.3 1.7 0.2 setosa 5.1 3.3 1.7 0.5 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 5.2 3.5 1.5 0.2 setosa 6.3 3.4 1.4 0.2 setosa 6.3 2.7 4.9 1.8 virginica 7.7 2.8 6.7 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.3 2.7 4.9 1.8 virginica 6.3 2.7 4.9 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.2 3.0 5.8 1.6 virginica 7.2 3.0 5.8 1.6 virginica 7.7 3.0 6.1 2.3 virginica 6.3 2.8 5.1 1.5 virginica 7.9 3.8 6.4 2.0 virginica 6.3 2.8 5.6 2.2 virginica 6.3 3.4 1.5 5.5 1.8 virginica 6.4 2.8 5.6 2.2 virginica 6.3 3.4 1.5 5.5 1.8 virginica 6.4 3.1 5.5 1.8 virginica 6.4 3.1 5.5 1.8 virginica 6.4 3.1 5.5 1.8 virginica 6.4 4.8 3.1 5.5 1.8 virginica 6.4 4.8 5.5 1.1 5.5 1.8 virginica 6.4 4.8 5.5		5.0	3.6	1.4	0.2	setosa
5.0 3.4 1.5 0.2 setosa 4.4 2.9 1.4 0.2 setosa 4.9 3.1 1.5 0.1 setosa 5.4 3.7 1.5 0.2 setosa 4.8 3.4 1.6 0.2 setosa 4.8 3.0 1.4 0.1 setosa 4.8 3.0 1.1 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.1 3.5 1.4 0.3 setosa 5.1 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.3 1.7 0.5 setosa		5.4	3.9	1.7	0.4	setosa
4.4 2.9		4.6	3.4	1.4	0.3	setosa
4.9 3.1 1.5 0.1 setosa setosa 4.8 3.4 1.6 0.2 setosa 4.8 3.0 1.4 0.1 setosa 4.8 3.0 1.1 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.7 4.4 1.5 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.5 1.4 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.4 1.7 0.2 setosa 4.6 3.6 1.0 0.2 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.4 1.6 0.2 setosa 5.0 3.4 1.6 0.2 setosa 5.2		5.0	3.4	1.5	0.2	setosa
5.4 3.7 1.5 0.2 setosa 4.8 3.4 1.6 0.2 setosa 4.8 3.0 1.4 0.1 setosa 4.3 3.0 1.1 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.4 3.9 1.3 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa		4.4	2.9	1.4	0.2	setosa
4.8 3.4 1.6 0.2 setosa 4.8 3.0 1.4 0.1 setosa 4.8 3.0 1.4 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.4 3.9 1.3 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 5.2 3.4 1.6 0.2 setosa 5.2 3.4 1.4 1.4 1.5 3.4 1.4 1.4 1.5 1.4 1.4 1.4 1.4 1.4 1.4 1.4 1.4 1.4 1.4		4.9	3.1	1.5	0.1	setosa
4.8		5.4	3.7	1.5	0.2	setosa
4.3 3.0 1.1 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.4 3.9 1.3 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.3 1.7 0.5 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.4 1.4 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.9 3.2 <td></td> <td>4.8</td> <td>3.4</td> <td>1.6</td> <td>0.2</td> <td>setosa</td>		4.8	3.4	1.6	0.2	setosa
4.3 3.0 1.1 0.1 setosa 5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.4 3.9 1.3 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.7 1.5 0.4 setosa 5.1 3.3 1.7 0.5 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.4 1.4 0.2 setosa 6.2 3.4 1.4 0.2 setosa 8.1 1.5 <td></td> <td>4.8</td> <td>3.0</td> <td>1.4</td> <td>0.1</td> <td>setosa</td>		4.8	3.0	1.4	0.1	setosa
5.8 4.0 1.2 0.2 setosa 5.7 4.4 1.5 0.4 setosa 5.4 3.9 1.3 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.2 3.2 5.7 2.3 virginica			3.0			
5.7 4.4 1.5 0.4 setosa 5.4 3.9 1.3 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.4 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.9 3.2 5.7 2.3 virginica 6.9 3.2 5.7 2.3 virginica <t< td=""><td></td><td>5.8</td><td>4.0</td><td></td><td></td><td>setosa</td></t<>		5.8	4.0			setosa
5.4 3.9 1.3 0.4 setosa 5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.4 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 5.1 3.3 1.7 0.5 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.4 1.4 0.2 setosa 6.9 3.2 5.7 2.3 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica			4.4	1.5	0.4	setosa
5.1 3.5 1.4 0.3 setosa 5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.4 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.9 3.2 5.7 2.3 virginica 7.7 2.8 6.7 2.0 virginica 6.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.7 3.3 5.7 2.1 virginica 6.2						
5.7 3.8 1.7 0.3 setosa 5.1 3.8 1.5 0.3 setosa 5.4 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 5.1 3.3 1.7 0.5 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.2 3.5 1.5 0.2 setosa 8 4.9 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 virginica 7.7 2.8 <						
5.1 3.8 1.5 0.3 setosa 5.4 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.2 3.2 3.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa 8 4.9 2.0 virginica 9 3.2 5.7 2.3 virginica 7.7 2.8 6.7 2.0 virginica 6.7 3.3 5.7 2.1 virginica						
5.4 3.4 1.7 0.2 setosa 5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa 6.9 3.2 5.7 2.3 virginica 6.9 3.2 5.7 2.3 virginica 7.7 2.8 6.7 2.0 virginica 6.7 3.3 5.7 2.1 virginica 6.7 3.3 5.7 2.1 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>						
5.1 3.7 1.5 0.4 setosa 4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.9 3.2 5.7 2.3 virginica 6.9 3.2 5.7 2.3 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.						
4.6 3.6 1.0 0.2 setosa 5.1 3.3 1.7 0.5 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa 6.2 3.2 3.6 0.2 setosa 8 1.6 0.2 setosa 9 3.2 5.7 2.3 virginica 10 1.6 0.2 setosa 10 1.8 1.9 virginica 10 1.8 1.8 virginica <						
5.1 3.3 1.7 0.5 setosa 4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa 6.9 3.2 5.7 2.3 virginica 5.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.1 3.0 5.8 1.6 virginica 7.4 2.8 6.1						
4.8 3.4 1.9 0.2 setosa 5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.5 1.5 0.2 setosa 6.2 3.4 1.4 0.2 setosa 6.9 3.2 1.6 0.2 setosa 6.9 3.2 5.7 2.3 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.9 3.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 7.9 3.8 6.4 2.0 virginica 6.3 2.8 5.6 2.1 virginica 6.4 2.8 5.6 2.1 virginica 6.4 2.8 5.6 2.1 virginica 7.9 3.8 6.4 2.0 virginica 7.9 3.8 6.4 2.0 virginica 6.3 2.8 5.6 2.2 virginica 6.3 3.4 11 5.5 1.5 virginica 6.3 3.4 11 5.5 1.8 virginica 6.4 3.1 5.5 1.8 virginica 6.4 3.1 5.5 1.8 virginica 6.4 virginica 6.3 3.4 11 5.5 1.8 virginica 6.4 virginica 6.3 3.4 virginica 6.4 3.1 5.5 1.8 virginica 6.4 virginica 6.4 3.1 5.5 1.8 virginica 6.4 virgi						
5.0 3.0 1.6 0.2 setosa 5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 virginica 7.7 2.8 6.7 2.0 virginica 7.7 3.3 5.7 2.1 virginica 6.2 2.8 4.8 1.8						
5.0 3.4 1.6 0.4 setosa 5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa 6.9 3.2 5.7 2.3 virginica 5.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 6.7 3.3 5.7 2.1 virginica 6.2 2.8 4.8 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.9 3.8						
5.2 3.5 1.5 0.2 setosa 5.2 3.4 1.4 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa 6.9 3.2 5.7 2.3 virginica 5.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 6.7 3.3 5.7 2.1 virginica 7.2 3.2 6.0 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.2 3.0 5.8 1.6 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.4 2.8 5.6 2.2 virginica 6.3 3.4 11 5.6 2.4 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica						
5.2 3.4 1.4 0.2 setosa A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa						
A data.frame: 150 × 5 4.7 3.2 1.6 0.2 setosa 6.9 3.2 5.7 2.3 virginica 5.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 7.2 3.2 6.0 1.8 virginica 7.2 3.2 6.0 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 7.9 3.8 6.4 2.0 virginica 6.1 2.6 5.6 1.4 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 6.1 2.6 5.6 1.4 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.4 3.1 5.5 1.8 virginica						
6.9 3.2 5.7 2.3 virginica 5.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 7.2 3.2 6.0 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 6.4 3.1 5.5 1.8 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.4 0.0 3.0 4.8 1.8 virginica	A data framo: 150 v 5					
6.9 3.2 5.7 2.3 virginica 5.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 6.7 3.2 6.0 1.8 virginica 7.2 3.2 6.0 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.3 2.8 5.6 2.2 virginica 6.1 2.6 5.6 1.4 virginica 6.1 2.6 5.6 1.4 virginica 6.3 3.4 11 5.5 1.8 v	A data.iraine. 150 x 5					
5.6 2.8 4.9 2.0 virginica 7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 7.2 3.2 6.0 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.4 3.1 5.5 1.8 v						
7.7 2.8 6.7 2.0 virginica 6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 7.2 3.2 6.0 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 6.1 2.6 5.6 1.4 virginica 6.3 3.4 11 5.6 2.4 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.						
6.3 2.7 4.9 1.8 virginica 6.7 3.3 5.7 2.1 virginica 7.2 3.2 6.0 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.3 2.8 5.1 2.3 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						virginica
6.7 3.3 5.7 2.1 virginica 7.2 3.2 6.0 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 7.9 3.8 6.4 2.0 virginica 6.3 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						-
7.2 3.2 6.0 1.8 virginica 6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.3 3.4 11 5.5 1.8 virginica 6.3 3.4 15.5 1.8 virginica 6.3 3.4 11 5.5 1.8 virginica						
6.2 2.8 4.8 1.8 virginica 6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
6.1 3.0 4.9 1.8 virginica 6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.5 3.0 4.8 1.8 virginica						
6.4 2.8 5.6 2.1 virginica 7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						~
7.2 3.0 5.8 1.6 virginica 7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
7.4 2.8 6.1 1.9 virginica 7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
7.9 3.8 6.4 2.0 virginica 6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
6.4 2.8 5.6 2.2 virginica 6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						-
6.3 2.8 5.1 1.5 virginica 6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
6.1 2.6 5.6 1.4 virginica 7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
7.7 3.0 6.1 2.3 virginica 6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
6.3 3.4 11 5.6 2.4 virginica 6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica						
6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica		7.7	3.0	6.1	2.3	virginica
6.4 3.1 5.5 1.8 virginica 6.0 3.0 4.8 1.8 virginica			3.4	5.6	2.4	virginica
6.0 3.0 4.8 1.8 virginica			3.1	5.5	1.8	virginica
		6.0	3.0	4.8	1.8	
		6.9	3.1	5.4	2.1	virginica

Sepal.Length Sepal.Width Petal.Length Petal.Width Species <dbl> <dbl> <dbl> <fct>

The above dataset is for Iris which show the different species by its different attributes such as Sepal.Length,Sepal.Width,Petal.Length and Petal.Width.

```
[51]: new_df_iris <- na.omit(df_iris) #remove NA values new_df_iris
```

		Sepal.Length <dbl></dbl>	Sepal.Width <dbl></dbl>	Petal.Length <dbl></dbl>	Petal.Width <dbl></dbl>	Species <fct></fct>
	1	5.1	3.5	1.4	0.2	setosa
	2	4.9	3.0	1.4	0.2	setosa
	3	4.7	3.2	1.3	0.2	setosa
	4	4.6	3.1	1.5	0.2	setosa
	5	5.0	3.6	1.4	0.2	setosa
	6	5.4	3.9	1.7	0.4	setosa
	7	4.6	3.4	1.4	0.3	setosa
	8	5.0	3.4	1.5	0.2	setosa
	9	4.4	2.9	1.4	0.2	setosa
	10	4.9	3.1	1.5	0.1	setosa
	11	5.4	3.7	1.5	0.2	setosa
	12	4.8	3.4	1.6	0.2	setosa
	13	4.8	3.0	1.4	0.1	setosa
	14	4.3	3.0	1.1	0.1	setosa
	15	5.8	4.0	1.2	0.2	setosa
	16	5.7	4.4	1.5	0.4	setosa
	17	5.4	3.9	1.3	0.4	setosa
	18	5.1	3.5	1.4	0.3	setosa
	19	5.7	3.8	1.7	0.3	setosa
	20	5.1	3.8	1.5	0.3	
						setosa
	21	5.4	3.4	1.7	0.2	setosa
	22	5.1	3.7	1.5	0.4	setosa
	23	4.6	3.6	1.0	0.2	setosa
	24	5.1	3.3	1.7	0.5	setosa
	25	4.8	3.4	1.9	0.2	setosa
	26	5.0	3.0	1.6	0.2	setosa
	27	5.0	3.4	1.6	0.4	setosa
	28	5.2	3.5	1.5	0.2	setosa
	29	5.2	3.4	1.4	0.2	setosa
A data.frame: 150×5	30	4.7	3.2	1.6	0.2	setosa
		•••	•••	•••	•••	•••
	121	6.9	3.2	5.7	2.3	virginica
	122	5.6	2.8	4.9	2.0	virginica
	123	7.7	2.8	6.7	2.0	virginica
	124	6.3	2.7	4.9	1.8	virginica
	125	6.7	3.3	5.7	2.1	virginica
	126	7.2	3.2	6.0	1.8	virginica
	127	6.2	2.8	4.8	1.8	virginica
	128	6.1	3.0	4.9	1.8	virginica
	129	6.4	2.8	5.6	2.1	virginica
	130	7.2	3.0	5.8	1.6	virginica
	131	7.4	2.8	6.1	1.9	virginica
	132	7.9	3.8	6.4	2.0	virginica
	133	6.4	2.8	5.6	2.2	virginica
	134	6.3	2.8	5.1	1.5	virginica
	135	6.1	2.6	5.6	1.4	virginica
	136	7.7	3.0	6.1	2.3	virginica
	137	6.3		5.6	2.4	virginica
	138	6.4	3.4 ₁₃ 3.1	5.5	1.8	virginica
	139	6.0	3.0	4.8	1.8	virginica
	140	6.9	3.1	5.4	2.1	•
	140	0.7	J.1	J . 4	۷.1	virginica

From above dataset we can notice that this dataset does not contain NA values

3.0.1 Q1. Compute the mean, median and mode of sepal length

```
[52]: paste("mean of speal.Length is:", mean(new_df_iris$Sepal.Length)) #the function_\( \to mean() find mean of the column \)

paste("median of speal.Length is:",median(new_df_iris$Sepal.Length)) #the_\( \to function median() find median value of the column \)

paste("mode of speal.Length is:",mfv(new_df_iris$Sepal.Length)) #the function_\( \to mfv() find mode of the column \)
```

'mean of speal.Length is: 5.8433333333333333

'median of speal.Length is: 5.8'

'mode of speal.Length is: 5'

3.0.2 Q2. Compute how "spread out" the data are. Here you need to calculate the minimum, maximum and range of sepal length

```
[53]: paste("Minimum value of speal.Length is:",min(new_df_iris$Sepal.Length))_\(\text{\text{\text{\text{\text{Minimum}}}} value of the column}\)

paste("Maximum value of speal.Length is:",max(new_df_iris$Sepal.Length))_\(\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{
```

'Minimum value of speal.Length is: 4.3'

'Maximum value of speal.Length is: 7.9'

- 1. 'The range of speal.Length is: 4.3' 2. 'The range of speal.Length is: 7.9'
- 3.0.3 Q3. Calculate the interquartile (IQR) range of sepal length. Use the function quantile() to measure quantiles for the same variable, sepal length, and comment what is the difference and relation of these two functions regarding the results shown on your screen?

```
[54]: summary(new_df_iris$Sepal.Length)
paste("The interquartile(IQR) of speal.Length is:",IQR(new_df_iris$Sepal.Length))
paste("The quantile of speal.Length is:",quantile(new_df_iris$Sepal.Length))
```

```
Min. 1st Qu. Median Mean 3rd Qu. Max. 4.300 5.100 5.800 5.843 6.400 7.900
```

'The interquartile(IQR) of speal.Length is: 1.3'

1. 'The quantile of speal.Length is: 4.3' 2. 'The quantile of speal.Length is: 5.1' 3. 'The quantile of speal.Length is: 5.8' 4. 'The quantile of speal.Length is: 7.9'

Quantiles are points in a distribution that relate to the rank order of values in that distribution. The middle value(middle quantile, 50th quartile) is known as the median. The first and last values is

limit, the minimum and maximum values. the second and 4th values are lower quartile(25th quartile) and upper quartile((75th quartile) of the data.

However the interquartile(IQR) is the upper quartile((75th quartile) - lower quartile(25th quartile) of the data.

3.0.4 Q4. Compute the variance and standard deviation of sepal length

```
[55]: paste("The variance of speal.Length is:",var(new_df_iris$Sepal.Length)) # the_\(\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\te}
```

'The variance of speal.Length is: 0.685693512304251'

'The standard variance of speal.Length is: 0.828066127977863'

3.0.5 Q5. Choose the right function to show min, max, mean, median, 1st and 3rd quantiles all at once of the variable sepal length

```
[56]: summary(new_df_iris$Sepal.Length) #This function summary() gives descriptiv⊔

→ statistics of the column sepal.length.

Min. 1st Qu. Median Mean 3rd Qu. Max.

4.300 5.100 5.800 5.843 6.400 7.900
```

3.0.6 Q6. Use sapply() to compute the mean and quantiles of each column in the dataset iris.

```
[57]: colMeans(new_df_iris[sapply(new_df_iris, is.numeric)]) #the function clsMeans()

→Use to find mean of all columns

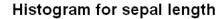
sapply(new_df_iris[,1:4],quantile) #The below table shows the all columns

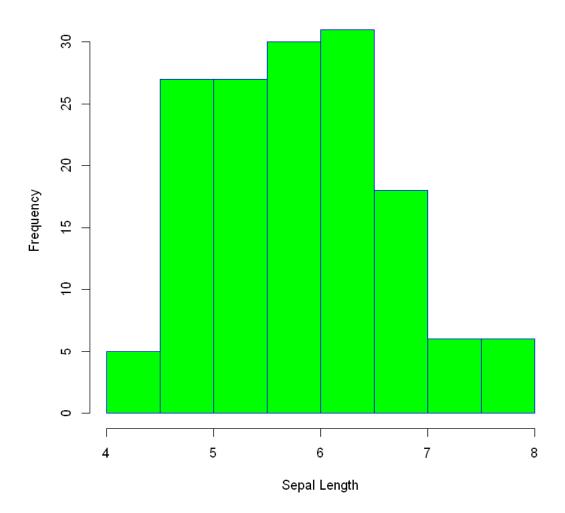
→quantile
```

Sepal.Length 5.84333333333333**Sepal.Width** 3.057333333333**Petal.Length** 3.758 **Petal.Width** 1.1993333333333

```
Sepal.Width
                                                                  Petal.Length
                                                                                  Petal.Width
                                    Sepal.Length
                                                    2.0
                              0%
                                    4.3
                                                                   1.00
                                                                                  0.1
                             25%
                                    5.1
                                                    2.8
                                                                   1.60
                                                                                  0.3
A matrix: 5 \times 4 of type dbl
                             50%
                                    5.8
                                                    3.0
                                                                   4.35
                                                                                  1.3
                             75%
                                    6.4
                                                    3.3
                                                                   5.10
                                                                                  1.8
                            100%
                                    7.9
                                                    4.4
                                                                   6.90
                                                                                  2.5
```

3.0.7 Q7. Use the in-built R basic functions (no need to import any library) to create a histogram for sepal length. Make sure you add the following arguments:

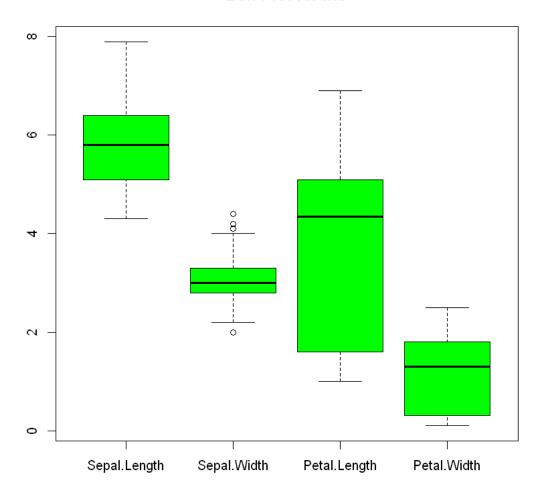




The histogram is used to evaluate the distribution of the data. The above histogram gram graph we can notice that the graph is for sepal Length of the species. The green vertical line indicates the bin, y-axis shows the frequency of the sepal legth data and x-axis shows the values of the sepal Length. We can notice from the above histogram that the maximum sepal.length is between 5.5 to 6.5.

3.0.8 Q8. Use the in-built R basic function to create one boxplot for sepal length, sepal width, petal length and petal width

Box-Plot for Iris



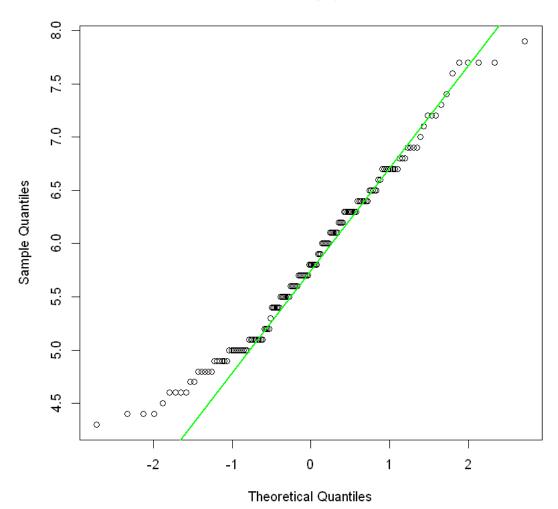
Box plots can be used to compare variables, particularly for illustrating median/spread between different groups of data. The above graph shows the Box-plot graph for the sepal length, sepal width, petal length and petal width of the Iris data. The box shows the Interquartile of the data. The middle line between box represents the median of the data, the portion of the box beside the median it shows the upper quartile and lower quartile of the data, the two vertical line shows the

range of the data, the bubble outside the range shows the outliers. It can be seen from the graph that the Sepal.Width has the outliers in its data.

- 3.0.9 Q9. The R base functions qqnorm() and qqplot() are used to produce quantile-quantile plots:
- 3.0.10 qqnorm(): produces a normal QQ plot of the variable
- 3.0.11 qqline(): adds a reference lineUse these two functions to create a QQ plot for sepal length.
- 3.0.12 You will need to set the reference line colour as green, and its width as 2)

```
[43]: qqnorm(new_df_iris$Sepal.Length)
qqline(new_df_iris$Sepal.Length,col='green', lwd=2)
```





From the above plot It can be notice that the QQplot is not following the straight QQline, indicating that the sepal Length is not distribted normally.

4 R Programming Portfolio 3

 $ggplot2::ggplot() \ // \ use \ a \ function \ defined \ in \ ggplot2::mpg \ // load \ a \ dataset \ from \ package \ ggplot2$

```
[63]: mpg=ggplot2::mpg mpg
```

	manufacturer	model	displ	year	cyl	trans	drv	cty
	<chr></chr>	<chr></chr>	<dbl></dbl>	<int></int>	<int></int>	<chr></chr>	<chr></chr>	<int></int>
-	audi	a4	1.8	1999	4	auto(l5)	f	18
	audi	a4	1.8	1999	4	manual(m5)	f	21
	audi	a4	2.0	2008	4	manual(m6)	f	20
	audi	a4	2.0	2008	4	auto(av)	f	21
	audi	a4	2.8	1999	6	auto(15)	f	16
	audi	a4	2.8	1999	6	manual(m5)	f	18
	audi	a4	3.1	2008	6	auto(av)	f	18
	audi	a4 quattro	1.8	1999	4	manual(m5)	4	18
	audi	a4 quattro	1.8	1999	4	auto(l5)	4	16
	audi	a4 quattro	2.0	2008	4	manual(m6)	4	20
	audi	a4 quattro	2.0	2008	4	auto(s6)	4	19
	audi	a4 quattro	2.8	1999	6	auto(l5)	4	15
	audi	a4 quattro	2.8	1999	6	manual(m5)	4	17
	audi	a4 quattro	3.1	2008	6	auto(s6)	4	17
	audi	a4 quattro	3.1	2008	6	manual(m6)	4	15
	audi	a6 quattro	2.8	1999	6	auto(l5)	4	15
	audi	a6 quattro	3.1	2008	6	auto(s6)	4	17
	audi	a6 quattro	4.2	2008	8	auto(s6)	4	16
	chevrolet	c1500 suburban 2wd	5.3	2008	8	auto(l4)	r	14
	chevrolet	c1500 suburban 2wd	5.3	2008	8	auto(l4)	r	11
	chevrolet	c1500 suburban 2wd	5.3	2008	8	auto(l4)	r	14
	chevrolet	c1500 suburban 2wd	5.7	1999	8	auto(l4)	r	13
	chevrolet	c1500 suburban 2wd	6.0	2008	8	auto(l4)	r	12
	chevrolet	corvette	5.7	1999	8	manual(m6)	r	16
	chevrolet	corvette	5.7	1999	8	auto(l4)	r	15
	chevrolet	corvette	6.2	2008	8	manual(m6)	r	16
	chevrolet	corvette	6.2	2008	8	auto(s6)	r	15
	chevrolet	corvette	7.0	2008	8	manual(m6)	r	15
	chevrolet	k1500 tahoe 4wd	5.3	2008	8	auto(l4)	4	14
A tibble: 234 × 11		k1500 tahoe 4wd	5.3	2008	8	auto(l4)	$\overline{4}$	11
	•••	•••						
	toyota	toyota tacoma 4wd	3.4	1999	6	auto(l4)	4	15
	toyota	toyota tacoma 4wd	4.0	2008	6	manual(m6)	4	15
	toyota	toyota tacoma 4wd	4.0	2008	6	auto(l5)	4	16
	volkswagen	gti	2.0	1999	4	manual(m5)	f	21
	volkswagen	gti	2.0	1999	4	auto(l4)	f	19
	volkswagen	gti	2.0	2008	4	manual(m6)	f	21
	volkswagen	gti	2.0	2008	4	auto(s6)	f	22
	volkswagen	gti	2.8	1999	6	manual(m5)	f	17
	volkswagen	jetta	1.9	1999	4	manual(m5)	f	33
	volkswagen	jetta	2.0	1999	4	manual(m5)	f	21
	volkswagen	jetta	2.0	1999	4	auto(l4)	f	19
	volkswagen	jetta	2.0	2008	4	auto(s6)	f	22
	volkswagen	jetta	2.0	2008	4	manual(m6)	f	21
	volkswagen	jetta	2.5	2008	5	auto(s6)	f	21
	volkswagen	jetta	2.5	2008	5	manual(m5)	f	21
	volkswagen	jetta	2.8	1999	6	auto(l4)	f	16
	volkswagen	jetta 20	2.8	1999	6	manual(m5)	f	17
	volkswagen	new beetle	1.9	1999	4	manual(m5)	f	35
	volkswagen	new beetle	1.9	1999	4	auto(l4)	f	29
	volkswagen	new beetle	2.0	1999	4	manual(m5)	f	21
	9					` /		

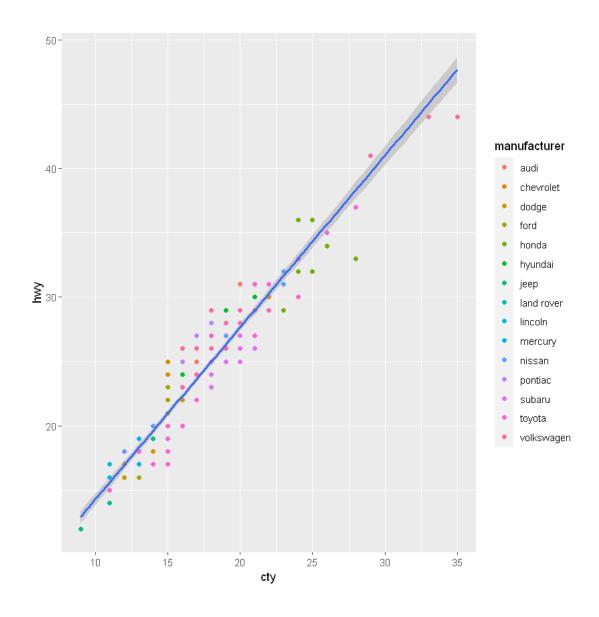
[45]: summary(mpg)

```
manufacturer
                      model
                                            displ
                                                             year
                   Length: 234
Length: 234
                                       Min.
                                               :1.600
                                                        Min.
                                                               :1999
Class :character
                   Class :character
                                       1st Qu.:2.400
                                                        1st Qu.:1999
Mode :character
                                       Median :3.300
                                                        Median:2004
                   Mode :character
                                       Mean
                                               :3.472
                                                        Mean
                                                                :2004
                                       3rd Qu.:4.600
                                                        3rd Qu.:2008
                                               :7.000
                                       Max.
                                                        Max.
                                                                :2008
                                        drv
     cyl
                   trans
                                                             cty
Min.
       :4.000
                Length: 234
                                    Length: 234
                                                        Min.
                                                               : 9.00
1st Qu.:4.000
                                                        1st Qu.:14.00
                Class : character
                                    Class : character
Median :6.000
                Mode :character
                                    Mode :character
                                                        Median :17.00
Mean
       :5.889
                                                        Mean
                                                                :16.86
3rd Qu.:8.000
                                                        3rd Qu.:19.00
       :8.000
                                                                :35.00
Max.
                                                        Max.
     hwy
                                       class
                      fl
       :12.00
                Length:234
                                    Length: 234
Min.
1st Qu.:18.00
                Class :character
                                    Class : character
Median :24.00
                Mode :character
                                    Mode :character
Mean
       :23.44
3rd Qu.:27.00
Max.
       :44.00
```

4.0.1 Q1. Plot and explain: Which vehicle brand (or manufacturer), offers the best mpg in both city and in the highway?

```
[46]: mpg_cityHwy <- ggplot(mpg, aes(cty, hwy))
mpg_cityHwy + geom_point(aes(colour = manufacturer))+
    stat_smooth(method = "lm")</pre>
```

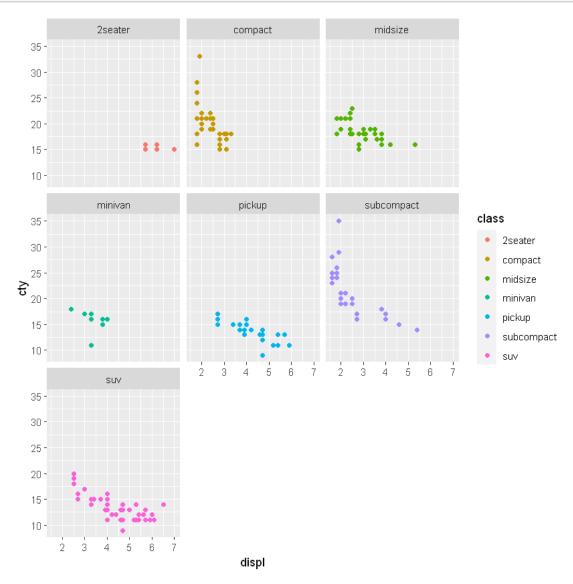
[`]geom_smooth()` using formula 'y ~ x'



The above scatter plots give a great view of best mpg offers by both city and highway. The x-axis shows the city mpg(Miles per gallon) and y-axis shows the highway mpg where mapping vehicle manufacturing company as a color aesthetic with regression line. It can be notice from the above scatter plots that the Vehicle company *Volkswagen* has the highest mpg performance in both city is 35 and highway is 44 compares to other vehicle brands.

4.0.2 Q2. Plot and explain: Which type of car, regarding their displ range (size of engine) has the lowest mpg in the city categorised by the vehicle type (e.g., compact, suv or 2seaters defined in the variable class)?

```
[47]: mpg_displ <- ggplot(mpg, aes(displ,cty,color=class))
mpg_displ + facet_wrap(~ class)+ geom_point()</pre>
```



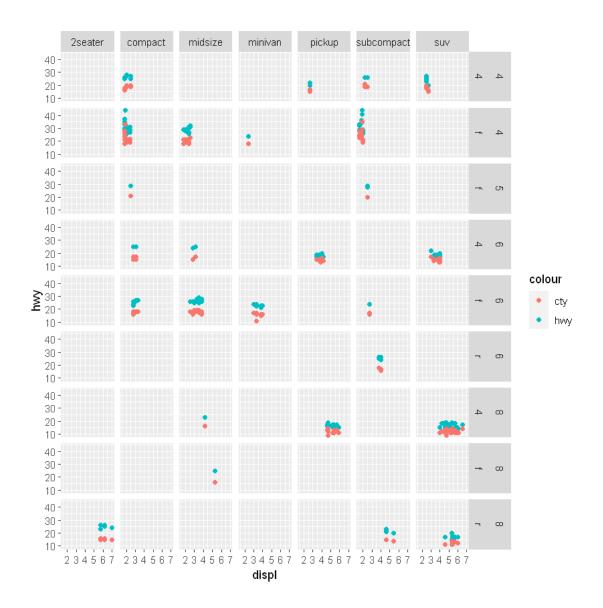
The above scatter plots give a great view of how mpg decrease with high dispacement range of vehicles(size of engine)in city. The x-axis shows the displacement range and y-axis shows the city mpg however the data is categorised by vehicle types using facet_wrap() function. Facets split our plot into facets(subplots) that each displays one subset of the data.here we have used single variable so we have used facet_wrap(). from above chart, we can clearly notice that the *SUV and pickup* has the lowest mpg which is 9 in city with its size of the engine which is 4.7.

4.0.3 Q3.Plot and explain: Which type of car, regarding their displ range (size of engine) has the best mpg performance in both city and highway? Display the resulting plot categorised by the number of cylinders and the drive type (the type of drive train, where f = front-wheel drive, r = f rear wheel drive, f = f and drives mostly in the highway, which type of car would you choose?

```
[48]: ggplot(data=mpg)+
    geom_point(aes(x = displ , y = hwy,color = "hwy"))+
    geom_point( aes(x = displ, y = cty,color = "cty"))+
    facet_grid(cyl ~ drv~ class)

#scatterplot_class <-ggplot(mpg, aes(x = cty , y = hwy))

#scatterplot_class + geom_point( aes(color = class))+
#facet_grid(cyl ~ drv ~ displ )</pre>
```



Above scatter plot describes the mpg performance of both city and highway and with thier displacement range and it is categorised by cylinder size of the vehicle and vehicle types. The x-axis show the displacement range and y -axis shows the highway mpg and city mpg performance blue color, orange color, respectively.

From above plot It can be notice that Compact, subcompact and midsize vehicle has the highest mpg in both city and highway but with 4 wheel-drive and front-wheel drive and 4 cylinder which is vehicle types of Volkswagen brand but the low dispalcement range. From above plot It can be notice that in respect to the higher litter engine and good performance on highway, it is recommended to choose the *2seater* which has 7 diplacement range and 8 cylinder and rear-wheel drive with highway performance around 25-30 mpg.