

Experiment 1

logistic-regression

September 30, 2024

1 importing Dependence

```
[1]: import numpy as np
import pandas as pd
```

2 importing dataset

```
[3]: dataset = pd.read_csv(r'dataset.csv')
dataset.head()
```

```
[3]:
```

	temp_c	condition	wind_kph	pressure_mb	humidity	feelslike_c	heatindex_c
0	24.5	Clear	4.7	1004.0	41.0	25.1	25.1
1	24.2	Clear	4.7	1004.0	41.0	24.9	24.9
2	23.8	Clear	4.7	1004.0	41.0	24.8	24.8
3	23.5	Clear	4.7	1004.0	42.0	24.6	24.6
4	23.2	Clear	4.3	1004.0	43.0	24.6	24.6

3 Train Test Split

```
[5]: x = dataset.drop('condition' , axis = 1)
y = dataset['condition']
```

4 Over-Sampling the data

```
[7]: from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=20 , k_neighbors = 2)
x , y = sm.fit_resample(x , y)
```

5 Encoding our output variable

```
[9]: from sklearn.preprocessing import LabelEncoder
condition_encoder = LabelEncoder()
dataset['condition'] = condition_encoder.fit_transform(dataset['condition'])
dataset.head()
```

```
[9]:   temp_c  condition  wind_kph  pressure_mb  humidity  feelslike_c  \
0    24.5         0      4.7      1004.0      41.0        25.1
1    24.2         0      4.7      1004.0      41.0        24.9
2    23.8         0      4.7      1004.0      41.0        24.8
3    23.5         0      4.7      1004.0      42.0        24.6
4    23.2         0      4.3      1004.0      43.0        24.6

   heatindex_c
0          25.1
1          24.9
2          24.8
3          24.6
4          24.6
```

```
[11]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x , y , test_size=.3 ,
random_state=42)
```

6 model training

```
[13]: from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(X_train,y_train)
```

```
C:\Users\ayush\anaconda3\Lib\site-
packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

```
n_iter_i = _check_optimize_result(
```

```
[13]: LogisticRegression()
```

7 model evaluation

```
[15]: from sklearn.metrics import accuracy_score, classification_report
y_pred = model.predict(X_test)
report = classification_report(y_test , y_pred)
score = accuracy_score(y_test , y_pred)
```

```
[17]: print(report)
print("Score : ", score)
```

	precision	recall	f1-score	support
Clear	0.76	0.73	0.75	104
Cloudy	0.53	0.50	0.52	101
Fog	0.84	0.87	0.85	107
Light drizzle	0.57	0.65	0.61	96
Light rain	0.63	0.66	0.64	103
Light rain shower	0.18	0.06	0.09	107
Mist	0.42	0.77	0.55	90
Moderate or heavy rain shower	0.19	0.21	0.20	89
Moderate rain	0.34	0.35	0.35	92
Overcast	0.56	0.34	0.42	109
Partly cloudy	0.39	0.36	0.38	96
Patchy light rain with thunder	0.55	1.00	0.71	88
Patchy rain possible	0.25	0.32	0.28	101
Sunny	0.72	0.63	0.68	115
Thundery outbreaks possible	0.77	0.31	0.45	105
accuracy			0.51	1503
macro avg	0.51	0.52	0.50	1503
weighted avg	0.52	0.51	0.50	1503

Score : 0.5149700598802395

Experiment 2

decision-tree

October 4, 2024

1 Importing Dependencies and Dataset

```
[2]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
dataset = pd.read_csv(r'dataset.csv')
dataset.head()
```

```
[2]:
```

	temp_c	condition	wind_kph	pressure_mb	humidity	feelslike_c	heatindex_c
0	24.5	Clear	4.7	1004.0	41.0	25.1	25.1
1	24.2	Clear	4.7	1004.0	41.0	24.9	24.9
2	23.8	Clear	4.7	1004.0	41.0	24.8	24.8
3	23.5	Clear	4.7	1004.0	42.0	24.6	24.6
4	23.2	Clear	4.3	1004.0	43.0	24.6	24.6

```
[3]: x = dataset.drop('condition' , axis = 1)
y = dataset['condition']
```

2 Over-Sampling the data

```
[5]: from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=20 , k_neighbors = 2)
x , y = sm.fit_resample(x , y)
```

3 Encoding our output variable

```
[7]: from sklearn.preprocessing import LabelEncoder
condition_encoder = LabelEncoder()
dataset['condition'] = condition_encoder.fit_transform(dataset['condition'])
dataset.head()
```

```
[7]:
```

	temp_c	condition	wind_kph	pressure_mb	humidity	feelslike_c	\
0	24.5	0	4.7	1004.0	41.0	25.1	
1	24.2	0	4.7	1004.0	41.0	24.9	
2	23.8	0	4.7	1004.0	41.0	24.8	

3	23.5	0	4.7	1004.0	42.0	24.6
4	23.2	0	4.3	1004.0	43.0	24.6

	heatindex_c
0	25.1
1	24.9
2	24.8
3	24.6
4	24.6

4 Train Test Split

```
[9]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x , y , test_size=.3 ,
random_state=42)
```

5 model training

```
[11]: from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model.fit(X_train,y_train)
```

```
[11]: DecisionTreeClassifier()
```

6 model evaluation

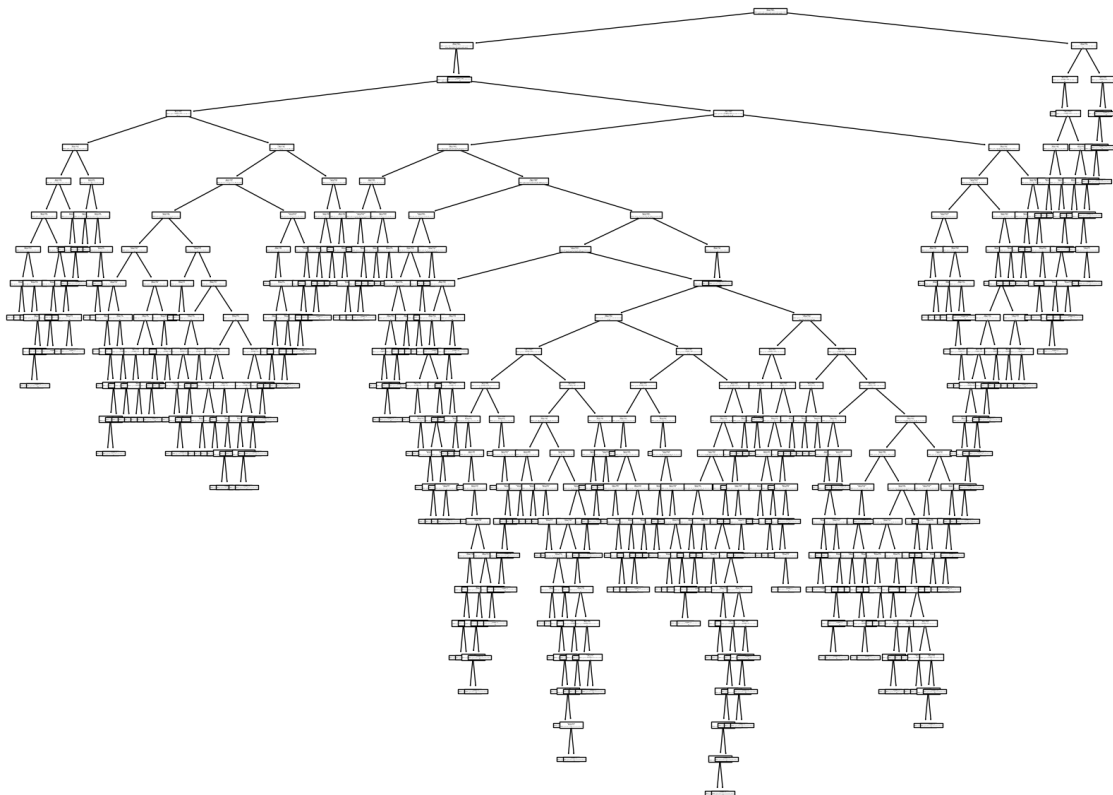
```
[13]: from sklearn.metrics import accuracy_score,classification_report
y_pred = model.predict(X_test)
report = classification_report(y_test , y_pred)
score = accuracy_score(y_test , y_pred)
print(report)
print("Score : ",score)
```

	precision	recall	f1-score	support
Clear	0.86	0.84	0.85	104
Cloudy	0.95	0.91	0.93	101
Fog	0.95	0.96	0.96	107
Light drizzle	0.98	1.00	0.99	96
Light rain	1.00	1.00	1.00	103
Light rain shower	0.89	0.80	0.84	107
Mist	0.96	0.98	0.97	90
Moderate or heavy rain shower	0.98	0.94	0.96	89
Moderate rain	1.00	1.00	1.00	92

Overcast	0.83	0.96	0.89	109
Partly cloudy	0.80	0.81	0.81	96
Patchy light rain with thunder	0.99	1.00	0.99	88
Patchy rain possible	0.85	0.86	0.86	101
Sunny	0.90	0.80	0.85	115
Thundery outbreaks possible	0.92	0.99	0.95	105
accuracy			0.92	1503
macro avg	0.92	0.92	0.92	1503
weighted avg	0.92	0.92	0.92	1503

Score : 0.9214903526280772

```
[26]: from sklearn import tree
plt.figure(figsize=(20 , 15))
tree.plot_tree(model)
plt.show()
```



Experiment – 04

Aim –

- (A) Write a program to perform addition of two 8-bit numbers in 8085.
- (B) Write a program to perform subtraction of two 8-bit numbers in 8085.

Software Used – Jubin Simulator 8085.

Program for Addition –

The screenshot shows the 8085 Simulator interface. The main window is titled "8085 Simulator" and has a menu bar with File, Edit, Tools, Settings, Simulation, Subroutine, View, Load Sample Program, and Help. Below the menu bar are tabs for Editor, Assembler, and Disassembler. The Assembler window is active, showing the "8085 Assembly Language Editor" with the following code:

```
MVI A,04;  
MVI B,03;  
ADD B;  
STA 2504;  
HLT;
```

At the bottom of the Assembler window are buttons for "Autocorrect" and "Assemble". To the right of the Assembler window is a "Registers" panel. It contains a table of registers and their values, a table of flags, and a table of system variables.

Register	Value	7	6	5	4	3	2	1	0
Accumulator	00	0	0	0	0	0	0	0	0
Register B	00	0	0	0	0	0	0	0	0
Register C	00	0	0	0	0	0	0	0	0
Register D	00	0	0	0	0	0	0	0	0
Register E	00	0	0	0	0	0	0	0	0
Register H	00	0	0	0	0	0	0	0	0
Register L	00	0	0	0	0	0	0	0	0
Memory(M)	00	0	0	0	0	0	0	0	0

Register	Value	S	Z	*	AC	*	P	*	CY
Flag Register	00	0	0	0	0	0	0	0	0

Type	Value
Stack Pointer(SP)	0000
Memory Pointer (HL)	0000
Program Status Word(PSW)	0000
Program Counter(PC)	0000
Clock Cycle Counter	0
Instruction Counter	0

SOD	SID	INTR	TRAP	R7.5	R6.5	R5.5
0	0	0	0	0	0	0

For SIM instruction

SOD	SDE	*	R7.5	MSE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

For RIM instruction

SID	I7.5	I6.5	I5.5	IE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

No. Converter Tool :

Hexadecimal	Decimal	Binary
0		0

Created by : Jubin Mitra

Output –

The screenshot displays the 8085 Simulator interface. The main window is divided into several sections:

- Assembler Window:** Contains a table of assembly instructions.

* Address	Label	Mnemonics	Hexcode	Bytes	M-Cycles	T-States
✓ 0000		MVI A,04	3E	2	2	7
0001			04			
✓ 0002		MVI B,03	06	2	2	7
0003			03			
✓ 0004		ADD B	80	1	1	4
✓ 0005		STA 2504	32	3	4	13
0006			04			
0007			25			
✓ 0008		HLT	76	1	2	5
- Registers Window:** Displays the status of various registers and system variables.

Register	Value	7	6	5	4	3	2	1	0
Accumulator	07	0	0	0	0	0	1	1	1
Register B	03	0	0	0	0	0	0	1	1
Register C	00	0	0	0	0	0	0	0	0
Register D	00	0	0	0	0	0	0	0	0
Register E	00	0	0	0	0	0	0	0	0
Register H	00	0	0	0	0	0	0	0	0
Register L	00	0	0	0	0	0	0	0	0
Memory(M)	3E	0	0	1	1	1	1	1	0

Register	Value	S	Z	*	AC	*	P	*	CY
Flag Register	00	0	0	0	0	0	0	0	0

Type	Value
Stack Pointer(SP)	0000
Memory Pointer (HL)	0000
Program Status Word(PSW)	0700
Program Counter(PC)	0008
Clock Cycle Counter	41
Instruction Counter	6

SOD	SID	INTR	TRAP	R7.5	R6.5	R5.5
0	0	0	0	0	0	0

For SIM instruction							
SOD	SDE	*	R7.5	MSE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

For RIM instruction							
SID	I7.5	I6.5	I5.5	IE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

No. Converter Tool :

Hexadecimal	Decimal	Binary
0		0
- Simulate Window:** Includes a 'Start From' field set to 0000 and two buttons: 'Run all At a Time' and 'Step By Step'.

Created by : Jubin Mitra

Result :- Hence, the Addition of two 8-bit numbers is completed.

Program for Subtraction –

8085 Simulator

File Edit Tools Settings Simulation Subroutine View Load Sample Program Help

Editor Assembler

8085 Assembly Language Editor

Assembler Disassembler

MVI A,04;
MVI B,03;
SUB B;
STA 2504;
HLT;

Autocorrect Assemble

Registers Memory Devices

Registers :

Register	Value	7	6	5	4	3	2	1	0
Accumulator	00	0	0	0	0	0	0	0	0
Register B	00	0	0	0	0	0	0	0	0
Register C	00	0	0	0	0	0	0	0	0
Register D	00	0	0	0	0	0	0	0	0
Register E	00	0	0	0	0	0	0	0	0
Register H	00	0	0	0	0	0	0	0	0
Register L	00	0	0	0	0	0	0	0	0
Memory(M)	00	0	0	0	0	0	0	0	0

Register	Value	S	Z	*	AC	*	P	*	CY
Flag Register	00	0	0	0	0	0	0	0	0

Type	Value
Stack Pointer(SP)	0000
Memory Pointer (HL)	0000
Program Status Word(PSW)	0000
Program Counter(PC)	0000
Clock Cycle Counter	0
Instruction Counter	0

SOD	SID	INTR	TRAP	R7.5	R6.5	R5.5
0	0	0	0	0	0	0

For SIM instruction

SOD	SDE	*	R7.5	MSE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

For RIM instruction

SID	I7.5	I6.5	I5.5	IE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

No. Converter Tool :

Hexadecimal	Decimal	Binary
0	0	0

Created by : Jubin Mitra

Output –

8085 Simulator

File Edit Tools Settings Simulation Subroutine View Load Sample Program Help

Editor Assembler

Assembler

* Address	Label	Mnemonics	Hexcode	Bytes	M-Cycles	T-States
✓ 0000		MVI A,04	3E	2	2	7
0001			04			
✓ 0002		MVI B,03	06	2	2	7
0003			03			
✓ 0004		SUB B	90	1	1	4
✓ 0005		STA 2504	32	3	4	13
0006			04			
0007			25			
✓ 0008		HLT	76	1	2	5

Simulate

Start From → 0000

Run all At a Time Step By Step

Registers Memory Devices

Registers :

Register	Value	7	6	5	4	3	2	1	0
Accumulator	01	0	0	0	0	0	0	0	1
Register B	03	0	0	0	0	0	0	1	1
Register C	00	0	0	0	0	0	0	0	0
Register D	00	0	0	0	0	0	0	0	0
Register E	00	0	0	0	0	0	0	0	0
Register H	00	0	0	0	0	0	0	0	0
Register L	00	0	0	0	0	0	0	0	0
Memory(M)	3E	0	0	1	1	1	1	1	0

Register	Value	S	Z	*	AC	*	P	*	CY
Flag Register	10	0	0	0	1	0	0	0	0

Type	Value
Stack Pointer(SP)	0000
Memory Pointer (HL)	0000
Program Status Word(PSW)	0110
Program Counter(PC)	0008
Clock Cycle Counter	41
Instruction Counter	6

SOD	SID	INTR	TRAP	R7.5	R6.5	R5.5
0	0	0	0	0	0	0

For SIM instruction

SOD	SDE	*	R7.5	MSE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

For RIM instruction

SID	I7.5	I6.5	I5.5	IE	M7.5	M6.5	M5.5
0	0	0	0	0	0	0	0

No. Converter Tool :

Hexadecimal	Decimal	Binary
0		0

Created by : .Jubini Mitra

Result :- Hence, the Subtraction of two 8-bit numbers is completed.

practical-2

October 2, 2024

1 0176CD221037

2 Data Preprocessing

3 importing libraries

```
[1]: import numpy as np
import pandas as pd
```

4 set data display limit

```
[2]: pd.set_option('display.max_rows' , 60)
pd.set_option('display.max_columns' , 60)
```

5 load data and preprocessed

```
[3]: dataset = pd.read_csv(r'Uttar Pradesh.csv')
```

```
[4]: drop = [ 'will_it_snow' , 'chance_of_snow' , 'vis_km' , 'vis_miles' , 'gust_mph'
            , 'gust_kph' , 'chance_of_rain' , 'state' , 'city']
dataset.drop(drop , axis = 'columns' , inplace = True)
```

```
[5]: dataset
```

```
[5]:      temp_c      condition  wind_kph  \
0      24.5  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  4.7
1      24.2  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  4.7
2      23.8  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  4.7
3      23.5  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  4.7
4      23.2  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  4.3
...      ...      ...      ...      ...
1147    26.0  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  11.5
1148    25.1  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  11.5
1149    24.1  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  11.5
1150    23.7  {'text': 'Clear', 'icon': '//cdn.weatherapi.co...  9.7
```

```
1151      23.3 {'text': 'Clear', 'icon': '//cdn.weatherapi.co...      7.9
```

	pressure_mb	humidity	feelslike_c	windchill_c	heatindex_c
0	1004.0	41.0	25.1	24.5	25.1
1	1004.0	41.0	24.9	24.2	24.9
2	1004.0	41.0	24.8	23.8	24.8
3	1004.0	42.0	24.6	23.5	24.6
4	1004.0	43.0	24.6	23.2	24.6
...
1147	1010.0	57.0	27.2	26.0	27.2
1148	1010.0	59.0	26.3	25.1	26.3
1149	1011.0	60.0	25.5	24.1	25.5
1150	1011.0	61.0	25.3	23.7	25.3
1151	1011.0	62.0	25.1	23.3	25.1

```
[1152 rows x 8 columns]
```

```
[6]: cond = dataset['condition']
cond.dtype
```

```
[6]: dtype('O')
```

```
[7]: # to convert string dictionary to dictionary
type(eval(cond[0]))
```

```
[7]: dict
```

```
[8]: # this functions convert all the string dictionary values to dictionary value
# and only get the relevant value that we need
def string_to_dict(condition):
    new_cond = []
    for i in range(len(condition)):
        data = condition[i]
        data = eval(data)
        text = data['text']
        new_cond.append(text)
    return new_cond
```

```
[9]: new_cond = string_to_dict(cond)
```

```
[10]: dataset['condition'] = new_cond
```

```
[11]: dataset
```

	temp_c	condition	wind_kph	pressure_mb	humidity	feelslike_c	\
0	24.5	Clear	4.7	1004.0	41.0	25.1	
1	24.2	Clear	4.7	1004.0	41.0	24.9	

2	23.8	Clear	4.7	1004.0	41.0	24.8
3	23.5	Clear	4.7	1004.0	42.0	24.6
4	23.2	Clear	4.3	1004.0	43.0	24.6
...
1147	26.0	Clear	11.5	1010.0	57.0	27.2
1148	25.1	Clear	11.5	1010.0	59.0	26.3
1149	24.1	Clear	11.5	1011.0	60.0	25.5
1150	23.7	Clear	9.7	1011.0	61.0	25.3
1151	23.3	Clear	7.9	1011.0	62.0	25.1

	windchill_c	heatindex_c
0	24.5	25.1
1	24.2	24.9
2	23.8	24.8
3	23.5	24.6
4	23.2	24.6
...
1147	26.0	27.2
1148	25.1	26.3
1149	24.1	25.5
1150	23.7	25.3
1151	23.3	25.1

[1152 rows x 8 columns]

6 data visualization

```
[13]: data_visualize = dataset.drop('condition' , axis= 'columns')
```

```
[14]: data_visualize
```

```
[14]:
```

	temp_c	wind_kph	pressure_mb	humidity	feelslike_c	windchill_c	\
0	24.5	4.7	1004.0	41.0	25.1	24.5	
1	24.2	4.7	1004.0	41.0	24.9	24.2	
2	23.8	4.7	1004.0	41.0	24.8	23.8	
3	23.5	4.7	1004.0	42.0	24.6	23.5	
4	23.2	4.3	1004.0	43.0	24.6	23.2	
...	
1147	26.0	11.5	1010.0	57.0	27.2	26.0	
1148	25.1	11.5	1010.0	59.0	26.3	25.1	
1149	24.1	11.5	1011.0	60.0	25.5	24.1	
1150	23.7	9.7	1011.0	61.0	25.3	23.7	
1151	23.3	7.9	1011.0	62.0	25.1	23.3	

	heatindex_c
0	25.1

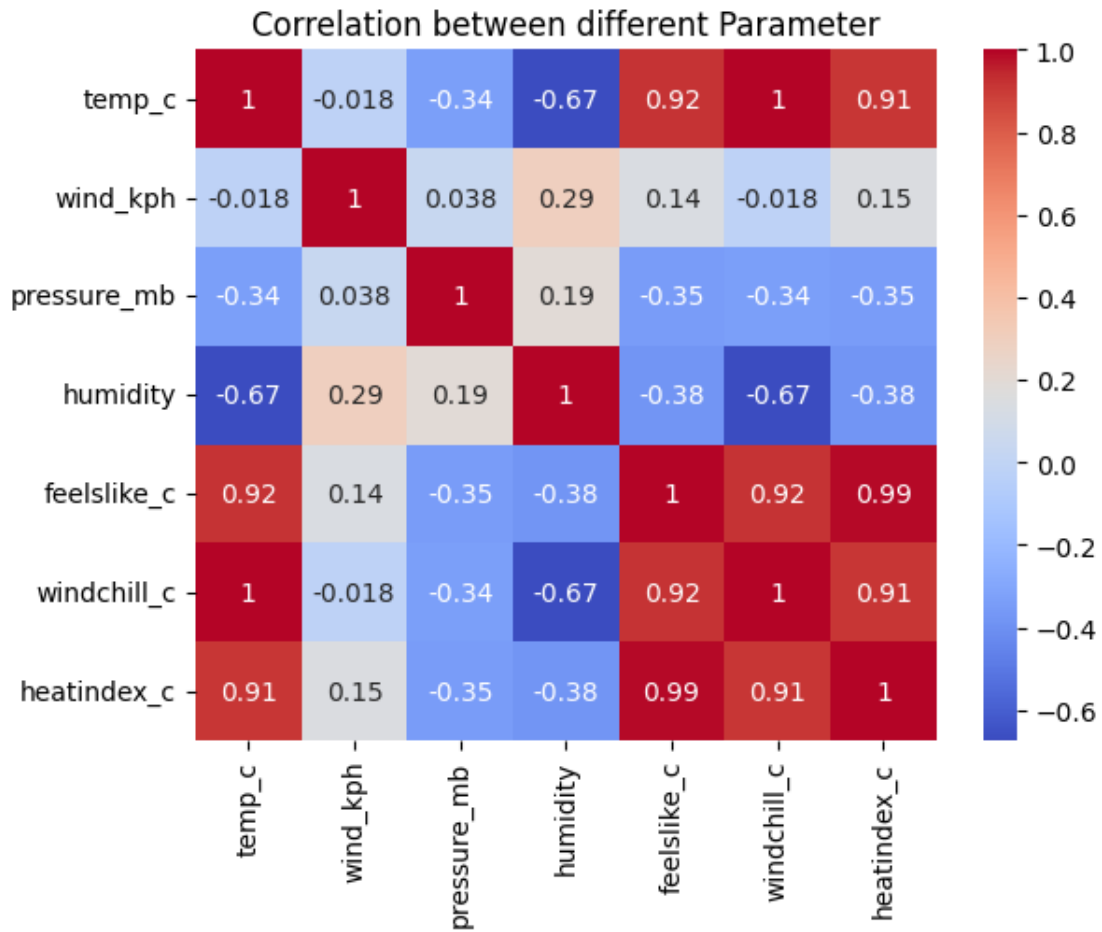
1	24.9
2	24.8
3	24.6
4	24.6
...	...
1147	27.2
1148	26.3
1149	25.5
1150	25.3
1151	25.1

[1152 rows x 7 columns]

```
[15]: # to find correlation between different parameters
corr = data_visualize.corr()
```

```
[16]: import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```
[17]: sns.heatmap(corr , annot=True ,cmap = 'coolwarm')
plt.title('Correlation between different Parameter')
# save this figure so that we can visualize it
plt.savefig('CorrelationHeatMap.jpg')
plt.show()
```



```
[19]: dataset.drop('windchill_c' , axis = 'columns' , inplace= True)
```

```
[20]: # we save our pre processed dataset for further use in machine learning
      ↪ algorithm deployment
dataset.to_csv('dataset.csv' , index = False)
```

practical-4

October 2, 2024

1 0176CD221037

2 Kmeans and Kmedoids clustering

```
[2]: # importing dependencies
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
import pandas as pd
import numpy as np
%matplotlib inline
```

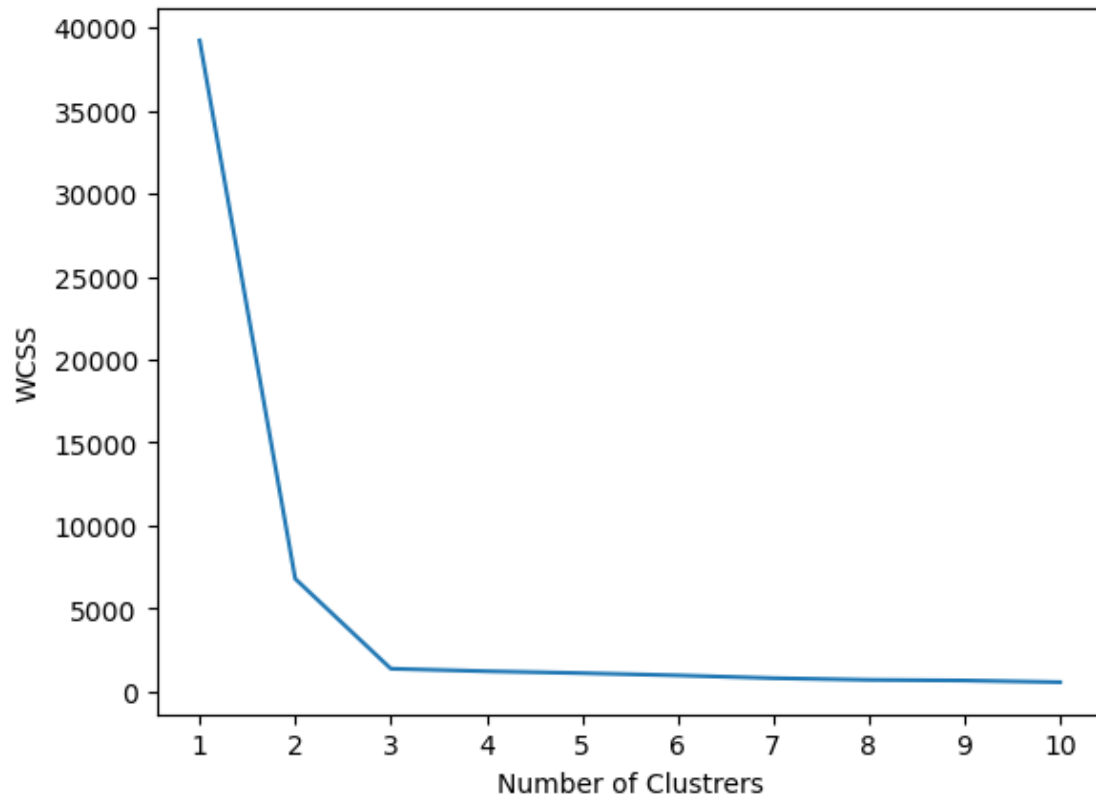
Kmeans clustering

```
[4]: X,y=make_blobs(n_samples=1000,centers=3,n_features=2)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,
    ↪random_state=42)

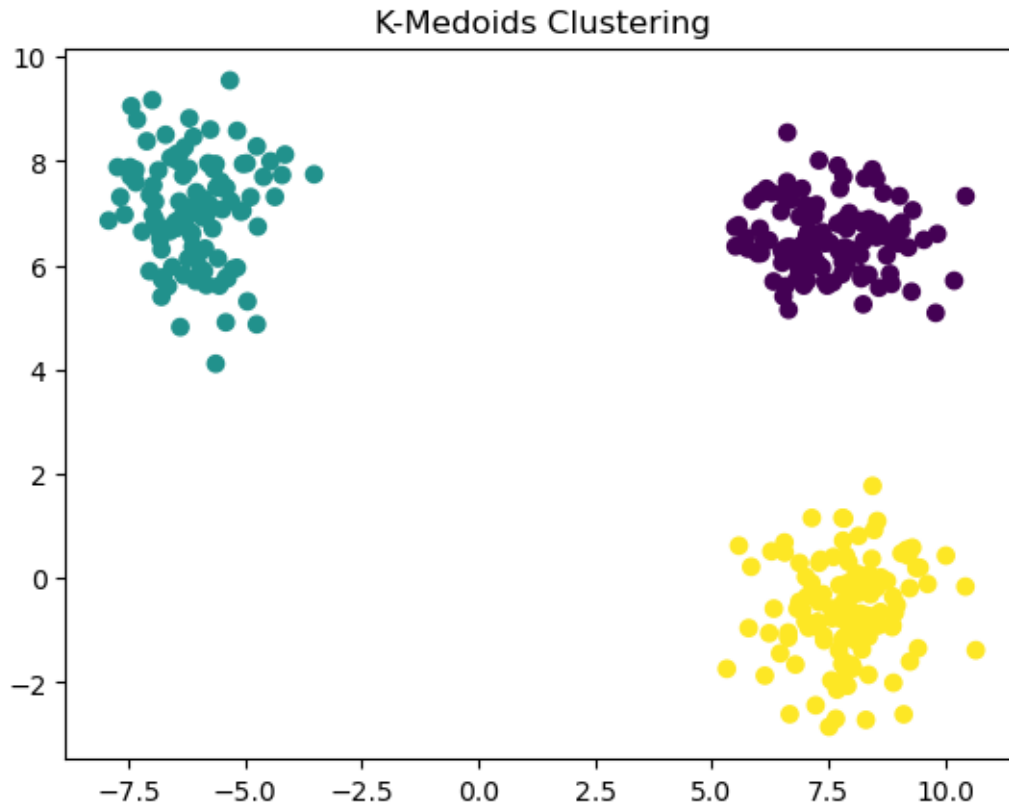
import warnings
warnings.filterwarnings("ignore")

from sklearn.cluster import KMeans
## Elbow method To select K Value
wcss=[]
for k in range(1,11):
    kmeans=KMeans(n_clusters=k,init="k-means++")
    kmeans.fit(X_train)
    wcss.append(kmeans.inertia_)
## plot elbow curve
plt.plot(range(1,11),wcss)
plt.xticks(range(1,11))
plt.xlabel("Number of Clustrers")
plt.ylabel("WCSS")
plt.show()
```

```
[5]: # Here we take k value as 3
kmeans=KMeans(n_clusters=3,init="k-means++")
kmeans.fit_predict(X_train)
y_pred=kmeans.predict(X_test)

plt.scatter(X_test[:,0],X_test[:,1],c=y_pred)
plt.title('K-Medoids Clustering')
plt.show()
```



```
[6]: ## the output we get is right as we select 3 centers and here we get 3 clusters
```

Kmedoids Clustering

```
[8]: import numpy as np
from sklearn.metrics import pairwise_distances
from random import sample

# Function to compute total cost (sum of distances) for a set of medoids
def compute_cost(X, medoids, clusters):
    cost = 0
    for medoid, cluster in zip(medoids, clusters):
        cost += np.sum(pairwise_distances(X[cluster], X[medoid].reshape(1, -1)))
    return cost

# K-medoids clustering using Partitioning Around Medoids (PAM)
def k_medoids(X, k, max_iter=300):
    m, n = X.shape
    # Randomly initialize medoids
    medoids = sample(range(m), k)
    for iteration in range(max_iter):
```

```

clusters = [[] for _ in range(k)]

# Assign each point to the nearest medoid
for idx, point in enumerate(X):
    distances = [np.linalg.norm(point - X[medoid]) for medoid in
↪medoids]

    closest_medoid = np.argmin(distances)
    clusters[closest_medoid].append(idx)

new_medoids = []
# Update medoids for each cluster
for cluster in clusters:
    if len(cluster) == 0:
        continue
    distances_sum = np.sum(pairwise_distances(X[cluster], X[cluster]),
↪axis=1)

    new_medoid = cluster[np.argmin(distances_sum)]
    new_medoids.append(new_medoid)

# Check for convergence
if set(medoids) == set(new_medoids):
    break

medoids = new_medoids

# Final cluster assignment
final_clusters = [[] for _ in range(k)]
for idx, point in enumerate(X):
    distances = [np.linalg.norm(point - X[medoid]) for medoid in medoids]
    closest_medoid = np.argmin(distances)
    final_clusters[closest_medoid].append(idx)

# Compute final cost
final_cost = compute_cost(X, medoids, final_clusters)
return medoids, final_clusters, final_cost

# Example usage:
if __name__ == "__main__":
    from sklearn.datasets import make_blobs
    import matplotlib.pyplot as plt
    # Create sample data
    X, y = make_blobs(n_samples=300, centers=4, random_state=42)
    # Perform K-medoids clustering
    k = 4
    medoids, clusters, cost = k_medoids(X, k)
    # Plot the clusters and medoids
    for i, cluster in enumerate(clusters):
        plt.scatter(X[cluster, 0], X[cluster, 1], label=f'Cluster {i+1}')
    plt.scatter(X[medoids, 0], X[medoids, 1], s=200, c='red', label='Medoids',
↪marker='x')
    plt.legend()

```

```
plt.title('K-Medoids Clustering')  
plt.show()
```

