```
#importing the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#reading the dataset by calling pandas
data = pd.read_csv("rna seq .csv")

#gives the shape of the data i.e how many rows and columns it contains
data.shape

(653, 24)

#gives the head part of the data
```

data.head()

→▼		Target seq	Start	End	Sequence	G	U	bi	uni	duplex	Pos1	 Pos18	Dif_5- 3	Content+	Content-	Cons+	Cons-
	0	M60857	195	213	AUUAUCCACUGUUUUUGGA	3	9	-7.0	-1.9	-28.1	-1.1	 -2.4	-1.3	2	6	2	6
	1	M60857	197	215	AAAUUAUCCACUGUUUUUG	2	9	-0.7	0.0	-24.2	-0.9	 -2.1	-1.2	1	6	1	5
	2	M60857	199	217	CAAAAUUAUCCACUGUUUU	1	8	-1.5	0.0	-24.2	-2.1	 -0.9	1.2	2	5	3	2
	3	M60857	201	219	CACAAAAUUAUCCACUGUU	1	6	-0.6	0.0	-26.7	-2.1	 -0.9	1.2	3	3	3	3
	4	M60857	203	221	GCCACAAAAUUAUCCACUG	2	4	-0.1	0.0	-30.3	-3.4	 -2.1	1.3	4	2	2	3
5	ō ro	ws × 24 co	olumns														

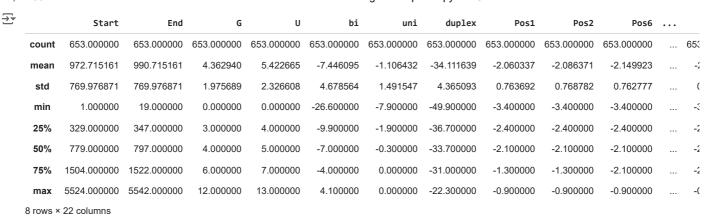
#returns the information of the data
data.info()

<</pre>
<<class 'pandas.core.frame.DataFrame'>
RangeIndex: 653 entries, 0 to 652
Data columns (total 24 columns):

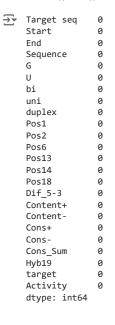
рата	` ,							
#	Column	Non	-Null Count	, ,				
0	Tangat sag							
	Target seq		non-null	object				
1	Start		non-null	int64				
2	End		non-null	int64				
3	Sequence		non-null	object				
4	G	653		int64				
5	U	653	non-null	int64				
6	bi	653	non-null	float64				
7	uni	653	non-null	float64				
8	duplex	653	non-null	float64				
9	Pos1	653	non-null	float64				
10	Pos2	653	non-null	float64				
11	Pos6	653	non-null	float64				
12	Pos13	653	non-null	float64				
13	Pos14	653	non-null	float64				
14	Pos18	653	non-null	float64				
15	Dif_5-3	653	non-null	float64				
16	Content+	653	non-null	int64				
17	Content-	653	non-null	int64				
18	Cons+	653	non-null	int64				
19	Cons-	653	non-null	int64				
20	Cons_Sum	653	non-null	int64				
21	Hyb19	653	non-null	float64				
22	target	653	non-null	float64				
23	Activity	653	non-null	float64				
dtype	es: float64(int64(9),	object(2)					
memoi	ry usage: 12	KB	- ',					

#describes the statistical measures of the data data.describe()

4



#checking the presence of missing values
data.isnull().sum()



#the column named TARGET SEQ is dropped because it contains text and assigned to the variable rna rna = data.drop('Target seq', axis = 1)

#the column named sequence is dropped because it contains text and assigned to the variable rna_seq
rna_seq = rna.drop('Sequence', axis = 1)

#collecting the informaton of the dataset after dropping the 2 columns $ma_{eq}.info()$

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 653 entries, 0 to 652
Data columns (total 22 columns):
Column Non-Null Count Dtype

Data	COTUMNIS (coca.	L ZZ COTUMNIS	, .
#	Column	Non-	-Null Count	Dtype
0	Start	653	non-null	int64
1	End	653	non-null	int64
2	G	653	non-null	int64
3	U	653	non-null	int64
4	bi	653	non-null	float64
5	uni	653	non-null	float64
6	duplex	653	non-null	float64
7	Pos1	653	non-null	float64
8	Pos2	653	non-null	float64
9	Pos6	653	non-null	float64
10	Pos13	653	non-null	float64
11	Pos14	653	non-null	float64
12	Pos18	653	non-null	float64
13	Dif_5-3	653	non-null	float64
14	Content+	653	non-null	int64
15	Content-	653	non-null	int64
16	Cons+	653	non-null	int64
17	Cons-	653	non-null	int64
18	Cons_Sum	653	non-null	int64
19	Hyb19	653	non-null	float64
20	target	653	non-null	float64
21	Activity	653	non-null	float64

```
dtypes: float64(13), int64(9)
memory usage: 112.4 KB
```

```
# scaling the data with the StandardScalar function of sklearn library
# to make mean as 0 and std. deviation as 1
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
# fitting the data to standardscaler and storing the scaled data in the variable data_scaled
data_scaled = scaler.fit_transform(rna_seq)
#importing the kmeans from sklearn
from sklearn.cluster import KMeans
#this line creates a sequence of integers from 1 to 9 , representing the possible values for the number of clusters (k) to evaluate.
k_meansclus = range(1,10)
#This line initializes an empty list named wcss to store the Within-Cluster Sum of Squares (WCSS) for each k value.
#WCSS is a measure of how well data points are grouped within their assigned clusters in K-Means clustering.
wcss = []
#intializing the for loop
for k in k_meansclus:
#this line creates a new KMeans model, specifying the number of clusters (n clusters) to be k
   km = KMeans(n_clusters = k)
#This line fits the KMeans model to the data
   km.fit(data_scaled)
```

#km.inertia_: After fitting the KMeans model for a specific k, this line accesses the model's inertia_ attribute. This attribute stores

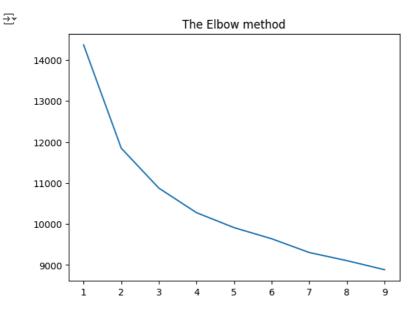
#The WCSS value is then appended to the wcss list, effectively storing the WCSS for each evaluated k (number of clusters).

Within-Cluster Sum of Squares (WCSS)

wcss.append(km.inertia)

```
[14366.0000000000004,
11848.386915668325,
10874.064452966397,
10275.626986045678,
9910.629300270894,
9639.140221903133,
9303.259613419987,
9105.283643636888,
8884.604690950462]
```

#visualising the elbow plot
plt.title('The Elbow method')
#plotting the eblow method by clusters on x axis and wcss on y axis
plt.plot(k_meansclus, wcss)
plt.show()



#this line creates a new instance of the KMeans class
#n_clusters parameter specifies the number of clusters we want the model to identify in the data.
#max_iter parameter sets the maximum number of iterations the K-Means algorithm will perform. During each iteration, the algorithm refir
km1 = KMeans(n_clusters = 3, max_iter = 100, random_state = 0)
#this line fits the KMeans model (km1) to the data stored in the data_scaled variable.
km1.fit(data_scaled)

```
KMeans (1)?
KMeans(max_iter=100, n_clusters=3, random_state=0)
```

#The fit part ensures the KMeans model is properly fitted to data (data_scaled) in case it wasn't fitted before. #The predict part predicts the cluster labels for the data points in data_scaled $Y = km1.fit_predict(data_scaled)$

```
array([1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 2, 2, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1]
        1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0,
        2, 2, 2, 2, 1, 2, 2, 2, 2, 1, 1, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1,
          1, 1, 0, 2, 2, 2, 2, 2, 2, 2, 1, 2, 0, 1, 1, 1, 1, 1, 0, 0,
        0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1,
        0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0,
        1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 2, 2,
        2, 2, 2, 2, 2, 0, 2, 0, 2, 2, 0, 0, 2, 1, 1, 2, 0, 1, 0, 2, 2,
        2, 1, 2, 0, 1, 0, 0, 2, 2, 2, 2, 2, 0, 0, 0, 0, 2, 0, 0, 2, 2,
        2, 2, 2, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
          0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       1, 1, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 1, 2, 0, 2, 2, 2, 2,
        2, 1, 0, 1, 1, 0, 0, 0, 1, 2, 0, 1, 1, 0, 1, 2, 0, 1, 1, 1, 1, 0,
        0, 1, 0, 1, 0, 1, 0, 2, 2, 0, 2, 0, 0, 2, 1, 2, 1, 1, 1, 1, 1, 1,
        0, 0, 1, 1, 0, 2, 2, 1, 0, 1, 2, 1, 1, 0, 2, 0, 1, 2, 2, 2, 2, 2,
          1, 2, 0, 0, 1, 0, 0, 1, 2, 1, 0, 0, 2, 0, 0, 0, 1, 1, 1, 2, 0,
        0, 0, 0, 0, 0, 1, 0, 1, 0, 2, 2, 2, 1, 2, 2, 2, 0, 0, 1, 1, 1, 1,
          1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 2, 1, 2, 2, 0, 2,
        2, 2, 2, 0, 0, 1, 0, 0, 0, 0, 2, 0, 0, 2, 0, 1, 1, 0, 0, 0, 0,
          0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
          1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1,
        0, 0, 0, 0, 0, 1, 0, 2, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1,
        2, 0, 2, 2, 0, 0, 2, 0, 2, 0, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
          1, 1, 0, 2, 2, 0, 0, 2, 2, 2, 0, 1, 0, 1, 0, 0, 1, 2, 0, 2, 1,
        2, 0, 2, 2, 0, 0, 2, 2, 1, 1, 2, 0, 0, 2, 2, 2, 0, 2, 2, 2, 2,
        2, 2, 2, 0, 2, 2, 0, 2, 2, 2, 2, 0, 1, 1, 1, 2, 2, 1, 0, 0,
        0, 2, 1, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 0, 1, 2, 2, 2, 0,
        2, 2, 2, 1, 0, 0, 0, 2, 2, 2, 0, 0, 1, 1], dtype=int32)
```

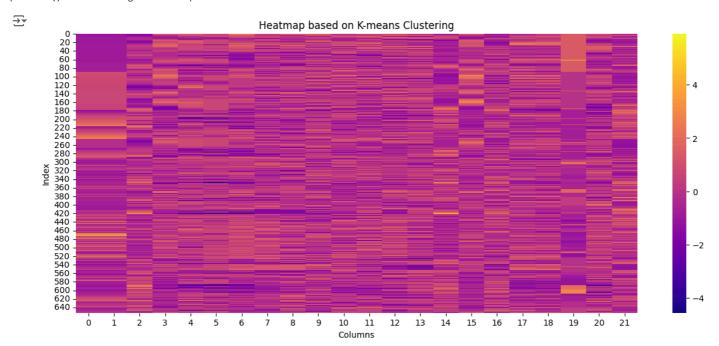
#this returns the centers of each clusters
km1.cluster_centers_

```
⇒ array([[ 3.34668680e-01, 3.34668680e-01, -1.13260426e-01,
              7.55738438e-02, 1.71252733e-01, 1.53631314e-01,
             3.21667281e-01, -2.56059590e-01, -6.25567155e-02,
             4.37246791e-04, -7.90155827e-02, 1.15562704e-02,
             5.70557530e-01, 6.09717948e-01, -1.55826387e-01,
             -9.11274595e-02, 3.32271278e-01, -4.13545952e-01,
             -4.31326995e-01, -2.16103639e-01, 2.03586862e-01,
             4.54658789e-01],
            [-1.22803536e-01, -1.22803536e-01, -5.03005599e-01,
             5.43837383e-01, 4.31060781e-01, 4.17255122e-01,
4.88040834e-01, 5.34522711e-01, 2.88646792e-01,
             3.00167094e-01, 3.98958033e-01, 3.36162075e-01,
             -2.69396782e-01, -5.90521273e-01, -5.35600049e-01,
             6.12870023e-01, -7.69908183e-01, 8.13315686e-01,
             9.18081560e-01, 9.58812182e-02, 3.02960883e-01,
             -6.68513059e-01],
            [-3.15641031e-01, -3.15641031e-01, 9.28680499e-01,
             -9.33889657e-01, -9.06911772e-01, -8.59698163e-01,
             -1.21806664e+00, -4.23399061e-01, -3.41983265e-01,
             -4.53667443e-01, -4.83827447e-01, -5.24635585e-01,
             -4.47511834e-01, -2.14904668e-02, 1.04159049e+00,
             -7.88533285e-01, 6.64559638e-01, -6.08407647e-01,
             -7.39903540e-01, 1.78788394e-01, -7.61985101e-01,
             3.28328024e-01]])
```

#he using np.array which likely converts the variable data_scaled into a NumPy array, assuming data_scaled is currently not a NumPy array data_imp = np.array(data_scaled)

data_imp

plt.figure(figsize = (15,6))#defining the size of the plot
#creates a heatmap visualization using the Seaborn library (sns) to represent the data in data_imp.
sns.heatmap(data_imp, cmap='plasma')
plt.title('Heatmap based on K-means Clustering') # title of the plot
plt.xlabel('Columns') # label on x axis
plt.ylabel('Index') # label on y axis
plt.show() # visualizing the heatmap



Start coding or $\underline{\text{generate}}$ with AI.