Practical- 9 ML
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[30]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[31]:
```
df = pd.read_csv('sales_data_sample.csv',encoding='unicode_escape')
df.head()
```

[31]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	\
0	10107	30	95.70	2	2871.00	
1	10121	34	81.35	5	2765.90	
2	10134	41	94.74	2	3884.34	
3	10145	45	83.26	6	3746.70	
4	10159	49	100.00	14	5205.27	

	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID	…	\
0	2/24/2003 0:00	Shipped	1	2	2003	…	
1	5/7/2003 0:00	Shipped	2	5	2003	…	
2	7/1/2003 0:00	Shipped	3	7	2003	…	
3	8/25/2003 0:00	Shipped	3	8	2003	…	
4	10/10/2003 0:00	Shipped	4	10	2003	…	

	ADDRESSLINE1	ADDRESSLINE2	CITY	STATE	\
0	897 Long Airport Avenue	NaN	NYC	NY	
1	59 rue de l'Abbaye	NaN	Reims	NaN	
2	27 rue du Colonel Pierre Avia	NaN	Paris	NaN	
3	78934 Hillside Dr.	NaN	Pasadena	CA	
4	7734 Strong St.	NaN	San Francisco	CA	

	POSTALCODE	COUNTRY	TERRITORY	CONTACTLASTNAME	CONTACTFIRSTNAME	DEALSIZE
0	10022	USA	NaN	Yu	Kwai	Small
1	51100	France	EMEA	Henriot	Paul	Small
2	75508	France	EMEA	Da Cunha	Daniel	Medium
3	90003	USA	NaN	Young	Julie	Medium
4	NaN	USA	NaN	Brown	Julie	Medium

[5 rows x 25 columns]

[32]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   ORDERNUMBER       2823 non-null   int64
 1   QUANTITYORDERED   2823 non-null   int64
 2   PRICEEACH         2823 non-null   float64
 3   ORDERLINENUMBER   2823 non-null   int64
 4   SALES             2823 non-null   float64
 5   ORDERDATE         2823 non-null   object
 6   STATUS            2823 non-null   object
 7   QTR_ID            2823 non-null   int64
 8   MONTH_ID          2823 non-null   int64
 9   YEAR_ID           2823 non-null   int64
 10  PRODUCTLINE       2823 non-null   object
 11  MSRP              2823 non-null   int64
 12  PRODUCTCODE       2823 non-null   object
 13  CUSTOMERNAME      2823 non-null   object
 14  PHONE             2823 non-null   object
 15  ADDRESSLINE1      2823 non-null   object
 16  ADDRESSLINE2      302 non-null    object
 17  CITY              2823 non-null   object
 18  STATE             1337 non-null   object
 19  POSTALCODE        2747 non-null   object
 20  COUNTRY           2823 non-null   object
 21  TERRITORY         1749 non-null   object
 22  CONTACTLASTNAME   2823 non-null   object
 23  CONTACTFIRSTNAME  2823 non-null   object
 24  DEALSIZE          2823 non-null   object
dtypes: float64(2), int64(7), object(16)
memory usage: 551.5+ KB
```

[33]:
```
df_drop  = ['ADDRESSLINE1', 'ADDRESSLINE2', 'POSTALCODE', 'CITY', 'TERRITORY',␣
 ↪'PHONE', 'STATE', 'CONTACTFIRSTNAME', 'CONTACTLASTNAME', 'CUSTOMERNAME',␣
 ↪'ORDERNUMBER']
df = df.drop(df_drop, axis=1)
```

[34]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   QUANTITYORDERED  2823 non-null   int64
```

```
 1   PRICEEACH         2823 non-null   float64
 2   ORDERLINENUMBER   2823 non-null   int64
 3   SALES             2823 non-null   float64
 4   ORDERDATE         2823 non-null   object
 5   STATUS            2823 non-null   object
 6   QTR_ID            2823 non-null   int64
 7   MONTH_ID          2823 non-null   int64
 8   YEAR_ID           2823 non-null   int64
 9   PRODUCTLINE       2823 non-null   object
 10  MSRP              2823 non-null   int64
 11  PRODUCTCODE       2823 non-null   object
 12  COUNTRY           2823 non-null   object
 13  DEALSIZE          2823 non-null   object
dtypes: float64(2), int64(6), object(6)
memory usage: 308.9+ KB
```

[35]:
```
for col in df.columns.values:
    print(df[col].value_counts())
```

```
34    112
21    103
46    101
27    100
31     97
41     97
45     97
26     96
29     94
48     94
25     94
20     93
33     92
22     92
32     91
24     91
38     91
49     91
36     89
44     89
37     87
43     85
39     84
28     82
40     78
42     76
30     75
23     73
35     71
```

```
47     70
50     65
55     16
66      5
15      4
51      4
61      3
18      3
60      3
76      3
59      3
56      3
19      3
64      3
10      2
6       2
11      2
54      2
70      2
97      1
85      1
62      1
52      1
16      1
13      1
58      1
65      1
12      1
77      1
Name: QUANTITYORDERED, dtype: int64
100.00    1304
59.87        6
96.34        6
57.73        5
80.55        5
          …
48.30        1
87.96        1
36.21        1
98.48        1
62.24        1
Name: PRICEEACH, Length: 1016, dtype: int64
1     307
2     291
3     270
4     256
5     239
6     221
```

```
7     197
8     187
9     165
10    141
11    128
12    110
13     97
14     81
15     56
16     42
17     25
18     10
Name: ORDERLINENUMBER, dtype: int64
3003.00    3
5464.69    2
2257.92    2
5004.80    2
2172.48    2
          ..
2312.24    1
2793.71    1
1908.28    1
3441.37    1
2116.16    1
Name: SALES, Length: 2763, dtype: int64
11/14/2003 0:00    38
11/24/2004 0:00    35
11/12/2003 0:00    34
11/17/2004 0:00    32
11/4/2004 0:00     29
                   ..
4/20/2004 0:00      1
8/4/2004 0:00       1
2/2/2004 0:00       1
8/28/2004 0:00      1
4/21/2003 0:00      1
Name: ORDERDATE, Length: 252, dtype: int64
Shipped       2617
Cancelled       60
Resolved        47
On Hold         44
In Process      41
Disputed        14
Name: STATUS, dtype: int64
4    1094
1     665
2     561
3     503
```

```
Name: QTR_ID, dtype: int64
11    597
10    317
5     252
1     229
2     224
3     212
8     191
12    180
4     178
9     171
7     141
6     131
Name: MONTH_ID, dtype: int64
2004    1345
2003    1000
2005     478
Name: YEAR_ID, dtype: int64
Classic Cars        967
Vintage Cars        607
Motorcycles         331
Planes              306
Trucks and Buses    301
Ships               234
Trains               77
Name: PRODUCTLINE, dtype: int64
118    104
99     103
136     80
62      78
68      77
      …
73      23
41      22
170     22
71      22
92      22
Name: MSRP, Length: 80, dtype: int64
S18_3232    52
S10_1949    28
S24_1444    28
S10_4962    28
S24_2840    28
            ..
S18_1749    22
S24_2887    22
S24_3969    22
S18_4409    22
```

```
S18_4933    22
Name: PRODUCTCODE, Length: 109, dtype: int64
USA            1004
Spain           342
France          314
Australia       185
UK              144
Italy           113
Finland          92
Norway           85
Singapore        79
Canada           70
Denmark          63
Germany          62
Sweden           57
Austria          55
Japan            52
Belgium          33
Switzerland      31
Philippines      26
Ireland          16
Name: COUNTRY, dtype: int64
Medium    1384
Small     1282
Large      157
Name: DEALSIZE, dtype: int64
```

[36]:
```
df.
  ↪drop(columns=['ORDERDATE','STATUS','MONTH_ID','QTR_ID','YEAR_ID'],inplace=True)
df.head()
```

[36]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	PRODUCTLINE	MSRP	\
0	30	95.70	2	2871.00	Motorcycles	95	
1	34	81.35	5	2765.90	Motorcycles	95	
2	41	94.74	2	3884.34	Motorcycles	95	
3	45	83.26	6	3746.70	Motorcycles	95	
4	49	100.00	14	5205.27	Motorcycles	95	

	PRODUCTCODE	COUNTRY	DEALSIZE
0	S10_1678	USA	Small
1	S10_1678	France	Small
2	S10_1678	France	Medium
3	S10_1678	USA	Medium
4	S10_1678	USA	Medium

[37]:
```
from sklearn.preprocessing import LabelEncoder
def convert_categories(col):
```

```
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col].values)
```

[38]:
```
categories = ['PRODUCTLINE','PRODUCTCODE','COUNTRY','DEALSIZE']
for col in categories:
    convert_categories(col)
```

[41]:
```
df.head()
```

[41]:

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	PRODUCTLINE	MSRP	\
0	30	95.70	2	2871.00	1	95	
1	34	81.35	5	2765.90	1	95	
2	41	94.74	2	3884.34	1	95	
3	45	83.26	6	3746.70	1	95	
4	49	100.00	14	5205.27	1	95	

	PRODUCTCODE	COUNTRY	DEALSIZE
0	0	18	2
1	0	6	2
2	0	6	1
3	0	18	1
4	0	18	1

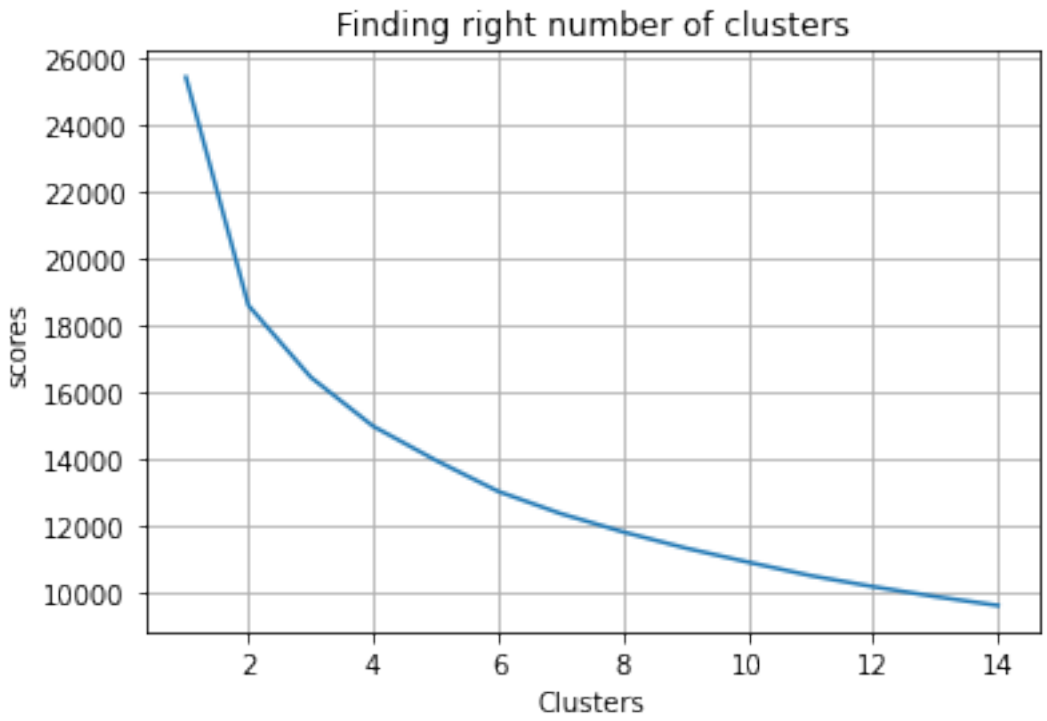
[42]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
data = sc.fit_transform(df)
```

0.0.1 Elbow Method

Finding optimal numbers of clusters is elbow method For each value of K, we are calculating WCSS (Within-Cluster Sum of Square). WCSS is the sum of squared distance between each point and the centroid in a cluster.When we plot the WCSS with the K value, the plot looks like an Elbow

[44]:
```
from sklearn.cluster import KMeans
wcss = []
for k in range(1,15):
    kmeans = KMeans(n_clusters=k,init='k-means++',random_state=15)
    kmeans.fit(data)
    wcss.append(kmeans.inertia_)
```

[49]:
```
k = list(range(1,15))
plt.plot(k,wcss)
plt.xlabel('Clusters')
plt.ylabel('scores')
plt.title('Finding right number of clusters')
plt.grid()
plt.show()
```



At k=4, the graph starts to move almost parallel to the X-axis. The K value corresponding to this point is the optimal K value or an optimal number of clusters.

[ ]: