Business Report

Clustering Analysis

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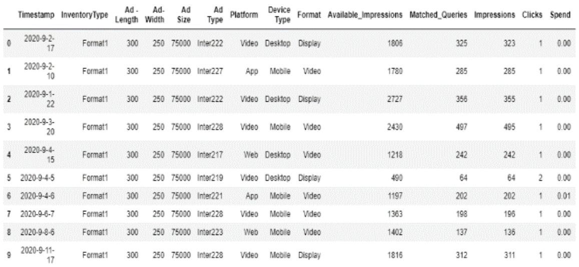
A. Read the data and perform basic analysis such as printing a few rows (head and tail), info, data summary, null values duplicate values, etc.

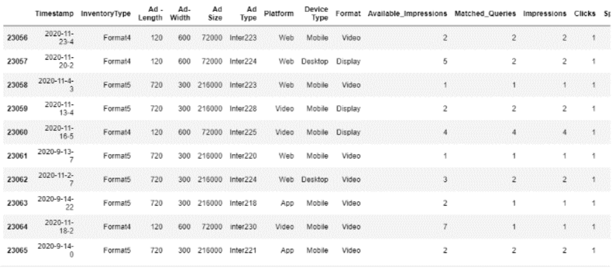
Ans:

Data Head



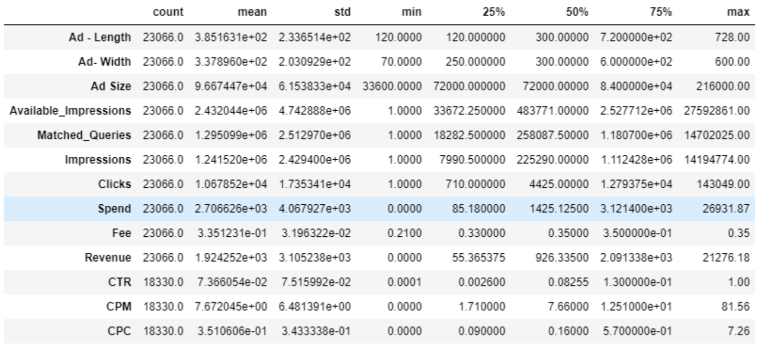
	Timestamp	InventoryType	Ad - Length	Ad- Width	Ad Size	Ad Type	Platform	Device Type	Format	Available_Impressions	Matched_Queries	Impressions	Clicks	Spend
0	2020-9-2-17	Format1	300	250	75000	Inter222	Video	Desktop	Display	1806	325	323	1	0.00
1	2020-9-2-10	Format1	300	250	75000	Inter227	App	Mobile	Video	1780	285	285	1	0.00
2	2020-9-1-22	Format1	300	250	75000	Inter222	Video	Desktop	Display	2727	356	355	1	0.00
3	2020-9-3-20	Format1	300	250	75000	Inter228	Video	Mobile	Video	2430	497	495	1	0.00
4	2020-9-4-15	Format1	300	250	75000	Inter217	Web	Desktop	Video	1218	242	242	1	0.00
5	2020-9-4-5	Format1	300	250	75000	Inter219	Video	Desktop	Display	490	64	64	2	0.00
6	2020-9-4-6	Format1	300	250	75000	Inter221	App	Mobile	Video	1197	202	202	1	0.01
7	2020-9-6-7	Format1	300	250	75000	Inter228	Video	Mobile	Video	1363	198	196	1	0.00
8	2020-9-8-6	Format1	300	250	75000	Inter223	Web	Mobile	Video	1402	137	136	1	0.00
9	2020-9-11-17	Format1	300	250	75000	Inter228	Video	Mobile	Display	1816	312	311	1	0.00

Data Tail



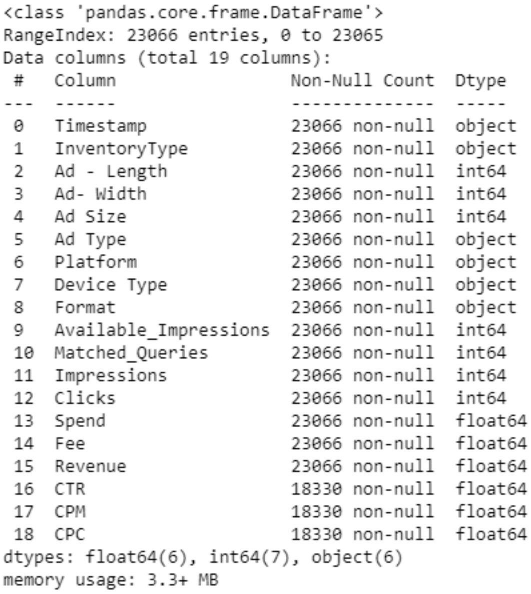
	Timestamp	InventoryType	Ad - Length	Ad- Width	Ad Size	Ad Type	Platform	Device Type	Format	Available_Impressions	Matched_Queries	Impressions	Clicks	Sp
23056	2020-11-23-4	Format4	120	600	72000	Inter223	Web	Mobile	Video	2	2	2	1	
23057	2020-11-20-2	Format4	120	600	72000	Inter224	Web	Desktop	Display	5	2	2	1	
23058	2020-11-4-3	Format5	720	300	216000	Inter223	Web	Mobile	Video	1	1	1	1	
23059	2020-11-13-4	Format5	720	300	216000	Inter228	Video	Mobile	Display	2	2	2	1	
23060	2020-11-16-5	Format4	120	600	72000	Inter225	Video	Mobile	Display	4	4	4	1	
23061	2020-9-13-7	Format5	720	300	216000	Inter220	Web	Mobile	Video	1	1	1	1	
23062	2020-11-2-7	Format5	720	300	216000	Inter224	Web	Desktop	Video	3	2	2	1	
23063	2020-9-14-22	Format5	720	300	216000	Inter218	App	Mobile	Video	2	1	1	1	
23064	2020-11-18-2	Format4	120	600	72000	inter230	Video	Mobile	Video	7	1	1	1	
23065	2020-9-14-0	Format5	720	300	216000	Inter221	App	Mobile	Video	2	2	2	1	

Data Summary



	count	mean	std	min	25%	50%	75%	max
Ad - Length	23066.0	3.851631e+02	2.336514e+02	120.0000	120.000000	300.00000	7.200000e+02	728.00
Ad- Width	23066.0	3.378960e+02	2.030929e+02	70.0000	250.000000	300.00000	6.000000e+02	600.00
Ad Size	23066.0	9.667447e+04	6.153833e+04	33600.0000	72000.000000	72000.00000	8.400000e+04	216000.00
Available_Impressions	23066.0	2.432044e+06	4.742888e+06	1.0000	33672.250000	483771.00000	2.527712e+06	27592861.00
Matched_Queries	23066.0	1.295099e+06	2.512970e+06	1.0000	18282.500000	258087.50000	1.180700e+06	14702025.00
Impressions	23066.0	1.241520e+06	2.429400e+06	1.0000	7990.500000	225290.00000	1.112428e+06	14194774.00
Clicks	23066.0	1.067852e+04	1.735341e+04	1.0000	710.000000	4425.00000	1.279375e+04	143049.00
Spend	23066.0	2.706626e+03	4.067927e+03	0.0000	85.180000	1425.12500	3.121400e+03	26931.87
Fee	23066.0	3.351231e-01	3.196322e-02	0.2100	0.330000	0.35000	3.500000e-01	0.35
Revenue	23066.0	1.924252e+03	3.105238e+03	0.0000	55.365375	926.33500	2.091338e+03	21276.18
CTR	18330.0	7.366054e-02	7.515992e-02	0.0001	0.002600	0.08255	1.300000e-01	1.00
CPM	18330.0	7.672045e+00	6.481391e+00	0.0000	1.710000	7.66000	1.251000e+01	81.56
CPC	18330.0	3.510606e-01	3.433338e-01	0.0000	0.090000	0.16000	5.700000e-01	7.26

Data Info

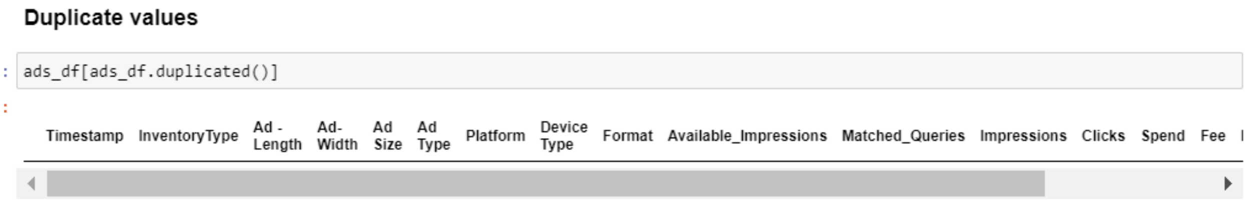


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23066 entries, 0 to 23065
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Timestamp              23066 non-null  object
 1   InventoryType          23066 non-null  object
 2   Ad - Length            23066 non-null  int64
 3   Ad- Width              23066 non-null  int64
 4   Ad Size                23066 non-null  int64
 5   Ad Type                23066 non-null  object
 6   Platform               23066 non-null  object
 7   Device Type            23066 non-null  object
 8   Format                 23066 non-null  object
 9   Available_Impressions  23066 non-null  int64
 10  Matched_Queries        23066 non-null  int64
 11  Impressions            23066 non-null  int64
 12  Clicks                 23066 non-null  int64
 13  Spend                  23066 non-null  float64
 14  Fee                    23066 non-null  float64
 15  Revenue                23066 non-null  float64
 16  CTR                    18330 non-null  float64
 17  CPM                    18330 non-null  float64
 18  CPC                    18330 non-null  float64
dtypes: float64(6), int64(7), object(6)
memory usage: 3.3+ MB
```

- The data consists of **23,066 rows** and **19 columns**
- There is a total of **13 numeric columns** and **6 categoric columns**
- It can be observed from the data info that null values exist in the **CTR, CPM and CPC columns** of the dataset

B. Treat missing values in CPC, CTR and CPM using the formula given.

Ans:



Duplicate values

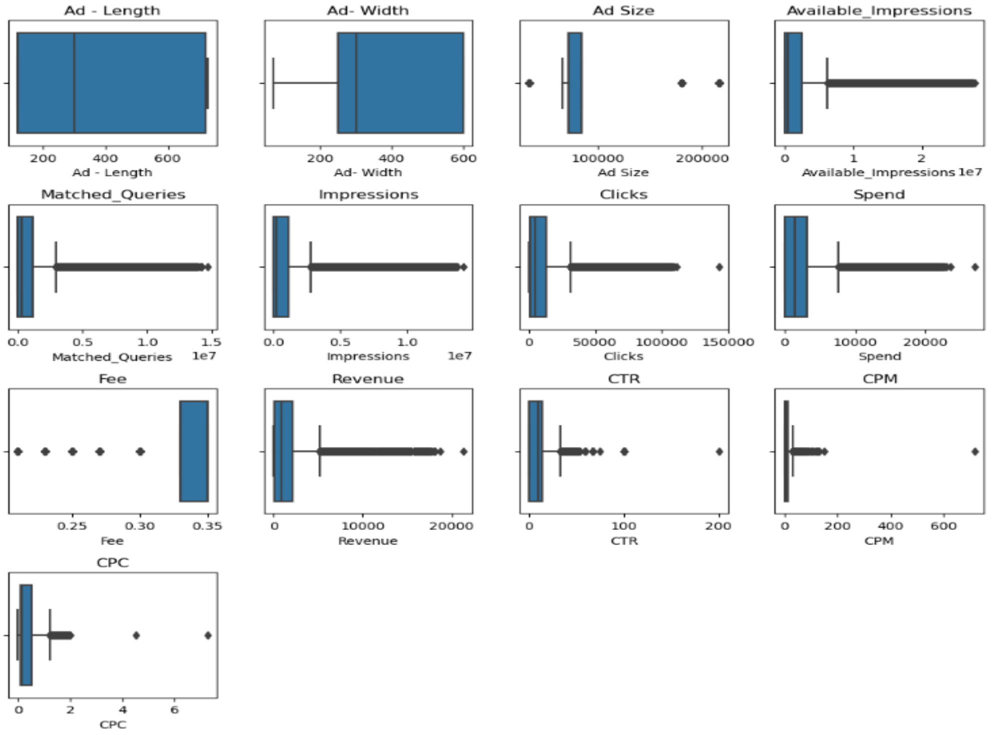
```
ads_df[ads_df.duplicated()]
```

	Timestamp	InventoryType	Ad - Length	Ad- Width	Ad Size	Ad Type	Platform	Device Type	Format	Available_Impressions	Matched_Queries	Impressions	Clicks	Spend	Fee

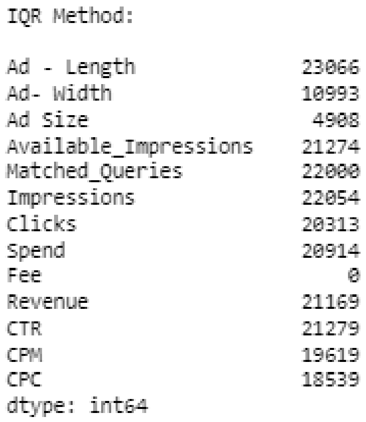
- There are **no duplicate entries** in the dataset.
- The missing values for CPC, CTR and CPM can be treated by using the formulae provided.

C. Check if there are any outliers. Do you think treating outliers is necessary for K-Means clustering? Based on your judgement decide whether to treat outliers and if yes, which method to employ.

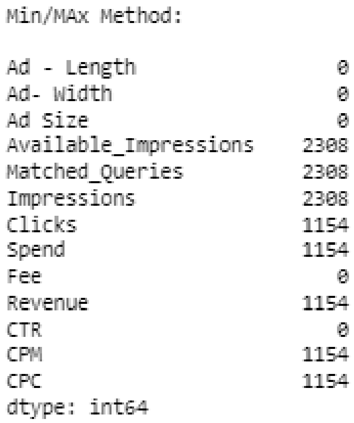
Ans:



- It can be observed that there are various outliers in the columns.
- K-Means clustering is sensitive to outliers as they can significantly affect the centroids and hence distort the clusters.
- Outliers tend to pull the cluster centres towards them which causes the clusters to be improperly defined.
- Hence, it becomes important for us to treat such outliers before proceeding with K-Means clustering.

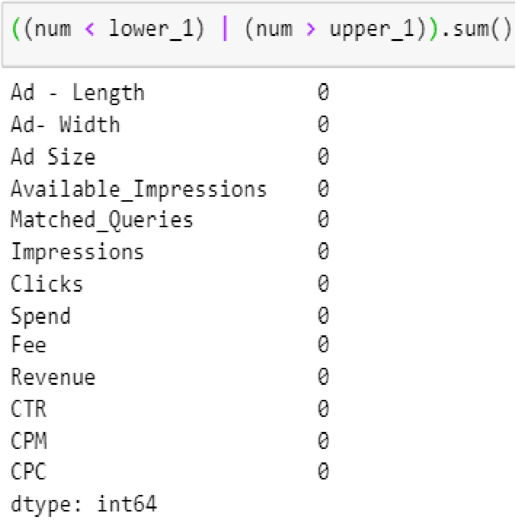


```
IQR Method:

Ad - Length               23066
Ad- Width                 10993
Ad Size                    4908
Available_Impressions     21274
Matched_Queries           22000
Impressions               22054
Clicks                    20313
Spend                     20914
Fee                           0
Revenue                   21169
CTR                       21279
CPM                       19619
CPC                       18539
dtype: int64
```



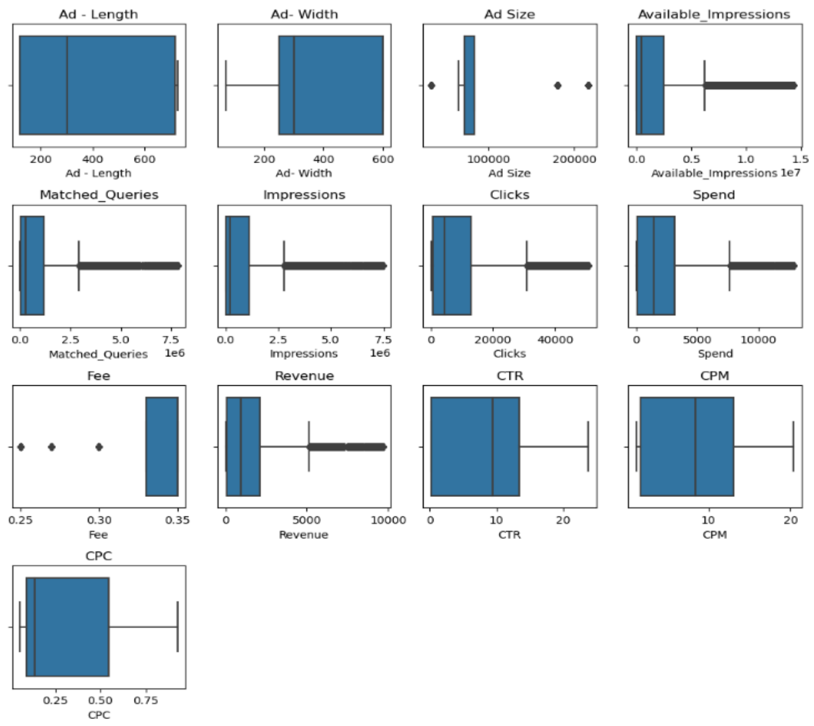
```
Min/MAx Method:

Ad - Length                 0
Ad- Width                   0
Ad Size                     0
Available_Impressions    2308
Matched_Queries          2308
Impressions              2308
Clicks                   1154
Spend                    1154
Fee                         0
Revenue                  1154
CTR                         0
CPM                      1154
CPC                      1154
dtype: int64
```

- It can be observed that the **number of outliers is comparatively higher when employing the IQR method over the Min/Max method** for the outlier calculation.
- Treating a greater number of outliers also results into decreasing the data variability which might not produce accurate results.
- Hence, we can proceed by treating the outliers using the Min/Max method



```
((num < lower_1) | (num > upper_1)).sum()
```

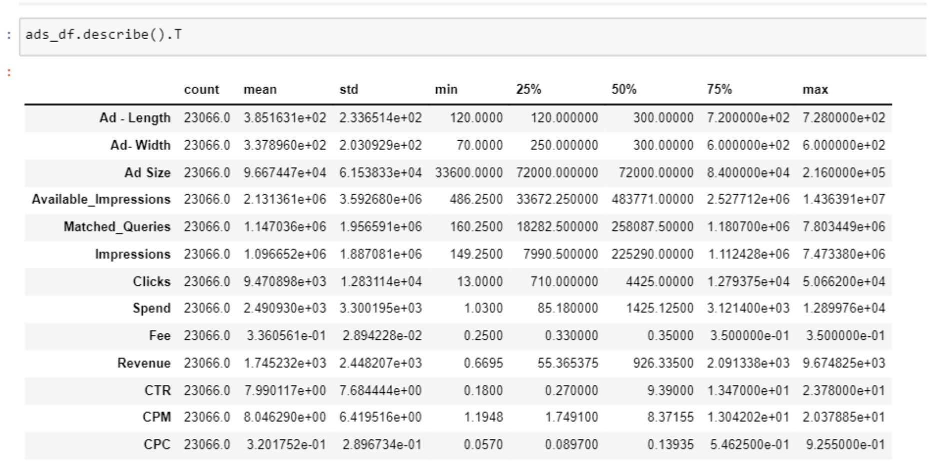
```
Ad - Length              0
Ad- Width                0
Ad Size                  0
Available_Impressions    0
Matched_Queries          0
Impressions              0
Clicks                   0
Spend                    0
Fee                      0
Revenue                  0
CTR                      0
CPM                      0
CPC                      0
dtype: int64
```



From the boxplots it can be visualized that the outliers have now been treated for the numeric variables.

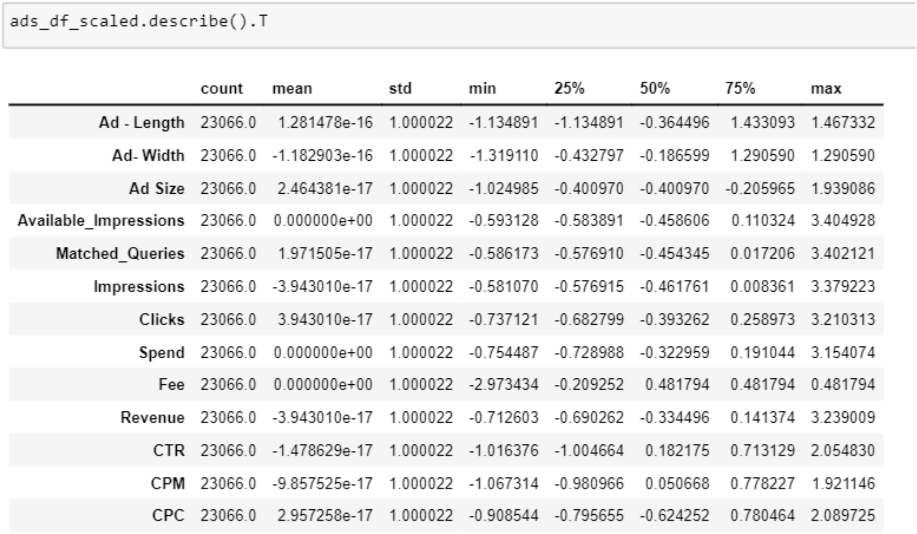
D. Perform z-score scaling and discuss how it affects the speed of the algorithm.

Ans:



```
ads_df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Ad - Length	23066.0	3.851631e+02	2.336514e+02	120.0000	120.000000	300.00000	7.200000e+02	7.280000e+02
Ad- Width	23066.0	3.378960e+02	2.030929e+02	70.0000	250.000000	300.00000	6.000000e+02	6.000000e+02
Ad Size	23066.0	9.667447e+04	6.153833e+04	33600.0000	72000.000000	72000.00000	8.400000e+04	2.160000e+05
Available_Impressions	23066.0	2.131361e+06	3.592680e+06	486.2500	33672.250000	483771.00000	2.527712e+06	1.436391e+07
Matched_Queries	23066.0	1.147036e+06	1.956591e+06	160.2500	18282.500000	258087.50000	1.180700e+06	7.803449e+06
Impressions	23066.0	1.096652e+06	1.887081e+06	149.2500	7990.500000	225290.00000	1.112428e+06	7.473380e+06
Clicks	23066.0	9.470898e+03	1.283114e+04	13.0000	710.000000	4425.00000	1.279375e+04	5.066200e+04
Spend	23066.0	2.490930e+03	3.300195e+03	1.0300	85.180000	1425.12500	3.121400e+03	1.289976e+04
Fee	23066.0	3.360561e-01	2.894228e-02	0.2500	0.330000	0.35000	3.500000e-01	3.500000e-01
Revenue	23066.0	1.745232e+03	2.448207e+03	0.6695	55.365375	926.33500	2.091338e+03	9.674825e+03
CTR	23066.0	7.990117e+00	7.684444e+00	0.1800	0.270000	9.39000	1.347000e+01	2.378000e+01
CPM	23066.0	8.046290e+00	6.419516e+00	1.1948	1.749100	8.37155	1.304202e+01	2.037885e+01
CPC	23066.0	3.201752e-01	2.896734e-01	0.0570	0.089700	0.13935	5.462500e-01	9.255000e-01



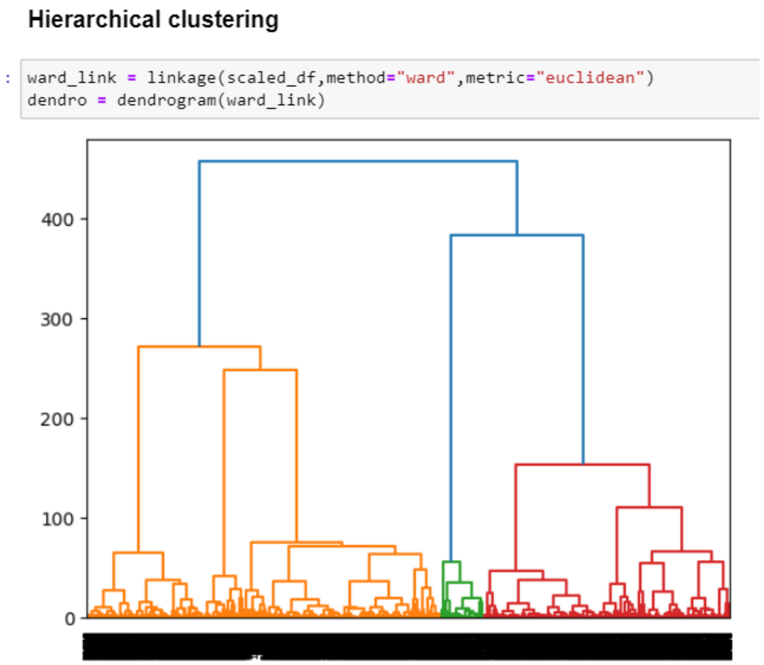
```
ads_df_scaled.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Ad - Length	23066.0	1.281478e-16	1.000022	-1.134891	-1.134891	-0.364496	1.433093	1.467332
Ad- Width	23066.0	-1.182903e-16	1.000022	-1.319110	-0.432797	-0.186599	1.290590	1.290590
Ad Size	23066.0	2.464381e-17	1.000022	-1.024985	-0.400970	-0.400970	-0.205965	1.939086
Available_Impressions	23066.0	0.000000e+00	1.000022	-0.593128	-0.583891	-0.458606	0.110324	3.404928
Matched_Queries	23066.0	1.971505e-17	1.000022	-0.586173	-0.576910	-0.454345	0.017206	3.402121
Impressions	23066.0	-3.943010e-17	1.000022	-0.581070	-0.576915	-0.461761	0.008361	3.379223
Clicks	23066.0	3.943010e-17	1.000022	-0.737121	-0.682799	-0.393262	0.258973	3.210313
Spend	23066.0	0.000000e+00	1.000022	-0.754487	-0.728988	-0.322959	0.191044	3.154074
Fee	23066.0	0.000000e+00	1.000022	-2.973434	-0.209252	0.481794	0.481794	0.481794
Revenue	23066.0	-3.943010e-17	1.000022	-0.712603	-0.690262	-0.334496	0.141374	3.239009
CTR	23066.0	-1.478629e-17	1.000022	-1.016376	-1.004664	0.182175	0.713129	2.054830
CPM	23066.0	-9.857525e-17	1.000022	-1.067314	-0.980966	0.050668	0.778227	1.921146
CPC	23066.0	2.957258e-17	1.000022	-0.908544	-0.795655	-0.624252	0.780464	2.089725

- Scaling the data by converting it into its respective Z-scores **helps in standardization** and is an important aspect of data pre-processing.
- It ensures that **each feature contributes equally to the distance calculation** and hence helps in the smooth functioning of the algorithms.
- It can be observed from the above summary of the data that **prior to scaling, the data ranges were very varied** however **after it has been scaled, the data has become standardized with similar data ranges**.

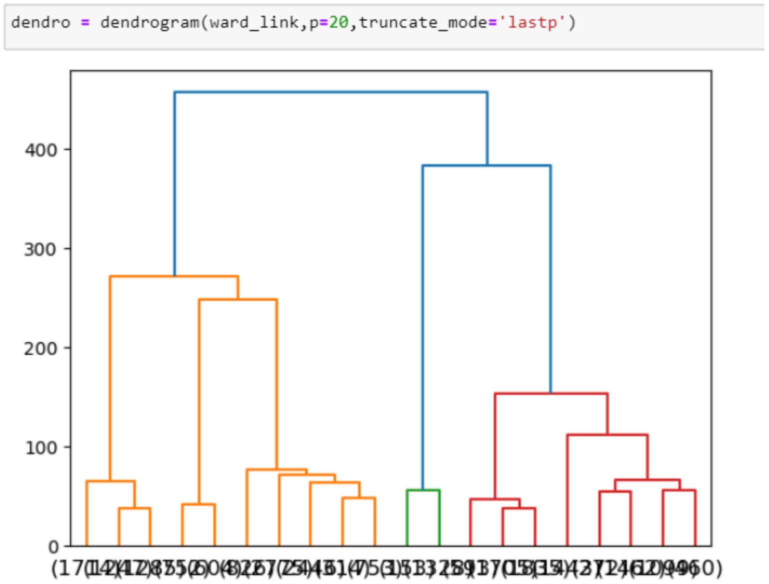
E. **Perform Hierarchical by constructing a Dendrogram using WARD and Euclidean distance.**

Ans:



Hierarchical clustering

```
ward_link = linkage(scaled_df,method="ward",metric="euclidean")
dendro = dendrogram(ward_link)
```

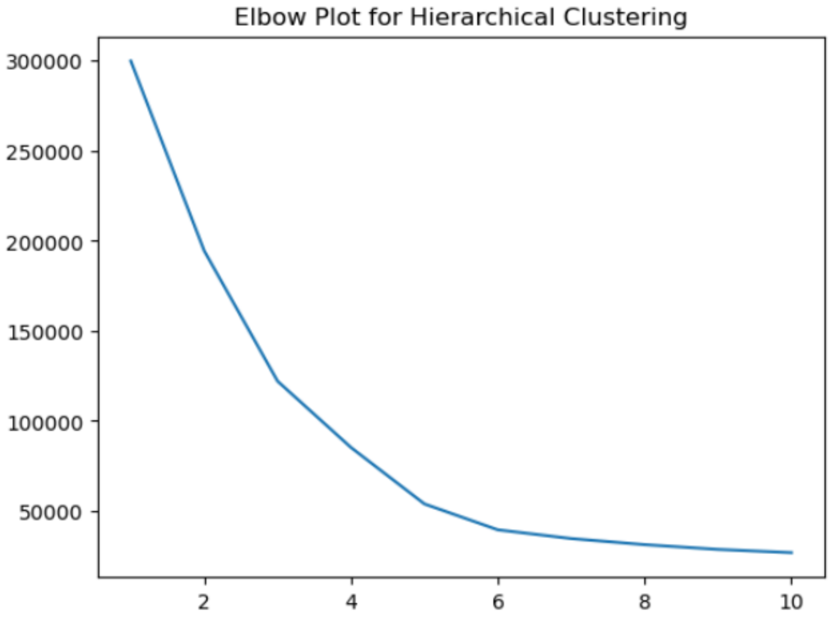


```
dendro = dendrogram(ward_link,p=20,truncate_mode='lastp')
```

As per the dendrogram, it can be observed that the ideal number of clusters should be 3.

F. **Make Elbow plot (up to n=10) and identify optimum number of clusters for k-means algorithm.**

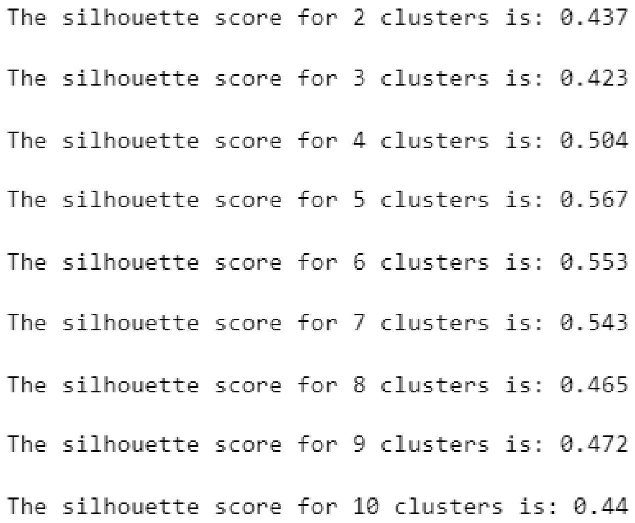
Ans:



As per the elbow plot and the WSS for different numbers of clusters, it seems like **5 clusters are ideal for the K-Means algorithm** as the drop in the WSS values after n=5 isn't as steep as it was for the previous values of n.

G. Print silhouette scores for up to 10 clusters and identify optimum number of clusters.

Ans:



```
The silhouette score for 2 clusters is: 0.437

The silhouette score for 3 clusters is: 0.423

The silhouette score for 4 clusters is: 0.504

The silhouette score for 5 clusters is: 0.567

The silhouette score for 6 clusters is: 0.553

The silhouette score for 7 clusters is: 0.543

The silhouette score for 8 clusters is: 0.465

The silhouette score for 9 clusters is: 0.472

The silhouette score for 10 clusters is: 0.44
```

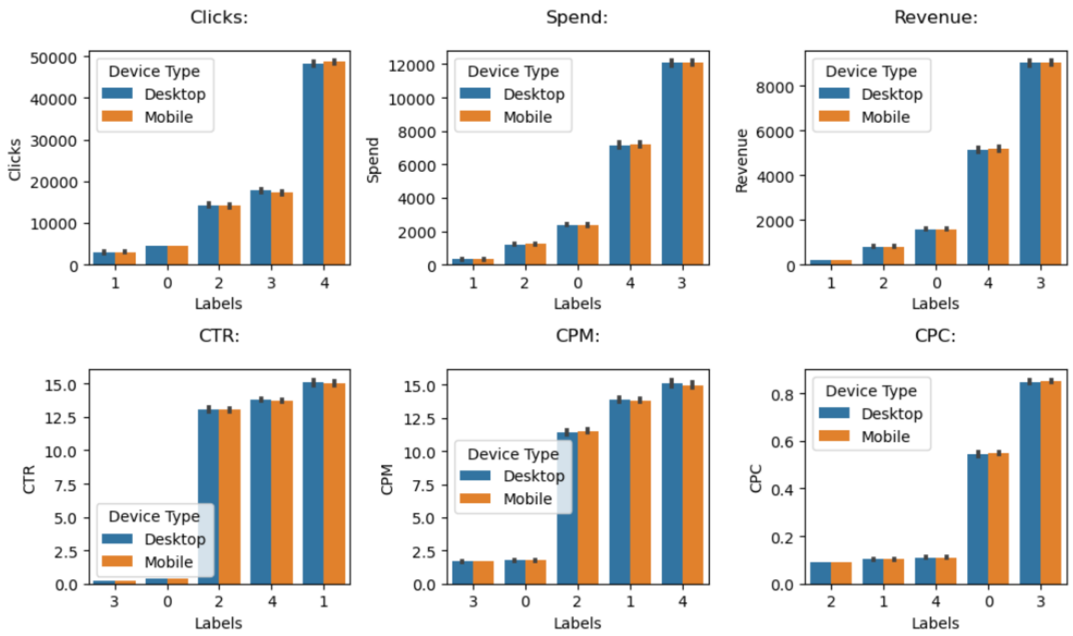
Similar to our previous conclusion derived from the elbow plot and WSS values, it can be observed that **5 clusters are ideal for the K-Means algorithm** as per the silhouette scores.

H. Profile the ads based on optimum number of clusters using silhouette score and your domain understanding.

Ans: As per the conclusions drawn from the scree plot, WSS values and silhouette scores, we can proceed by creating 5 clusters for the dataset. We will input the value of n as 5 and thereafter assign the corresponding cluster labels to our original dataset.

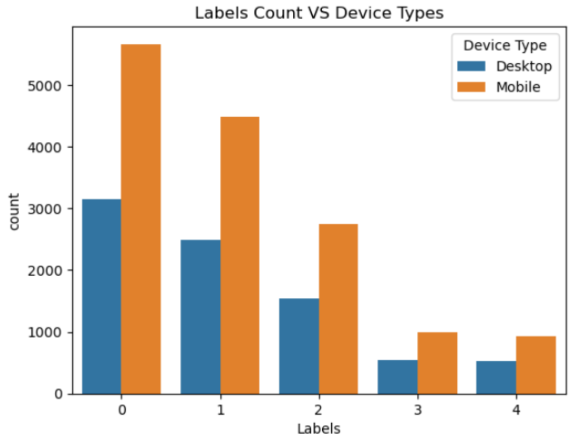
Following inferences can be derived from the silhouette sample scores:

- A negative silhouette width indicates that an observation has been placed incorrectly in a cluster as it is closer to another cluster.
- A total of **33 silhouette width values** out of **approximately 23,000 data entries** have negative values.
- This is a very negligible number which indicates that **our observations have been correctly allocated within the clusters**.



- Cluster 0: The ads category generating **average number of Clicks, Spend and Revenue values with low values of CTR, CPM and CPC** for both desktop and mobile devices.
- Cluster 1: The ads category generating **the lowest number of Clicks, Spend and Revenue values however consisting of the highest values of CTR and high values of CPM.**
- Cluster 2: The ads category generating **lowest values of CPC and average values for Spend, Revenue, Clicks and CPM.**
- Cluster 3: The ads category **generating highest Spend, Revenue and CPC values however consisting of lowest values of CTR and CPM.**
- Cluster 4: The ads category **generating highest values of Clicks, CTR and CPM and high values of Spend and Revenue**.

- Mobiles dominate desktops in all the categories
- The ads category with the 0th label has the most count for both the devices
- The ads category with the 4th label has the least count for both the devices



I. Conclude the project by providing summary of your learnings.

Ans: The following summary can be drawn from the clustering analysis:

- The ads pertaining to clusters 0 and 2 lie in the low to average range when compared to the rest of the clusters. They lie in the middle of almost all the metrics and the ad agency can device new strategies and planning to increase the promotion of such ads.
- The ads pertaining to cluster 1 lie in the low yielding range with the lowest values for Clicks, Spend and Revenue. The CTR values are the highest for this cluster which means that despite of being viewed, the revenue generation for such ads is low. The ad agency can either undertake certain drastic measures to promote or upsell this category of ads to ensure greater revenue generation or it can replace it with more featuring ads.
- The ads pertaining to cluster 3 are responsible for the most revenue generation along with the Spend and CPC costs. The CTR values however are the lowest for such ads and the ads agency can resort to new lucrative strategies in order to promote them.
- The ads pertaining to cluster 4 have high values of Clicks, CTR and CPM. The revenue generation for such ads can be increased by investing more resources in such ad categories.