DS203_Customer_Segmentation

November 13, 2021

[5]:
```
import numpy as np
import pandas as pd
```

[6]:
```
np.random.seed(42)
```

[7]:
```
df = pd.read_csv('/content/Train.csv')
dataset = df.copy()
display(dataset)
```

```
          ID  Gender Ever_Married  ...  Family_Size  Var_1 Segmentation
0     462809    Male           No  ...          4.0  Cat_4            D
1     462643  Female          Yes  ...          3.0  Cat_4            A
2     466315  Female          Yes  ...          1.0  Cat_6            B
3     461735    Male          Yes  ...          2.0  Cat_6            B
4     462669  Female          Yes  ...          6.0  Cat_6            A
...      ...     ...          ...  ...          ...    ...          ...
8063  464018    Male           No  ...          7.0  Cat_1            D
8064  464685    Male           No  ...          4.0  Cat_4            D
8065  465406  Female           No  ...          1.0  Cat_6            D
8066  467299  Female           No  ...          4.0  Cat_6            B
8067  461879    Male          Yes  ...          3.0  Cat_4            B

[8068 rows x 11 columns]
```

Performing basic data cleaning

[8]:
```
dataset = dataset.drop(columns = ['ID'])
dataset = dataset[dataset['Profession'].notna()]
dataset = dataset.fillna(0)
dataset = dataset.loc[(dataset[['Graduated', 'Gender', 'Ever_Married',␣
↪'Var_1']] != 0).all(axis=1)]


display(dataset)
```

```
     Gender Ever_Married  Age  ... Family_Size  Var_1  Segmentation
0      Male           No   22  ...         4.0  Cat_4             D
```

```
1     Female          Yes   38   ...         3.0  Cat_4                A
2     Female          Yes   67   ...         1.0  Cat_6                B
3       Male          Yes   67   ...         2.0  Cat_6                B
4     Female          Yes   40   ...         6.0  Cat_6                A
...      ...          ...  ...   ...         ...    ...              ...
8062    Male          Yes   41   ...         5.0  Cat_6                B
8064    Male           No   35   ...         4.0  Cat_4                D
8065  Female           No   33   ...         1.0  Cat_6                D
8066  Female           No   27   ...         4.0  Cat_6                B
8067    Male          Yes   37   ...         3.0  Cat_4                B

[7669 rows x 10 columns]
```

[9]:
```
dataset_expanded = dataset.drop(columns = ['Segmentation'])
dataset_expanded = pd.get_dummies(dataset_expanded, sparse = True)
display(dataset_expanded)
```

```
      Age  Work_Experience  Family_Size  ...  Var_1_Cat_5  Var_1_Cat_6  Var_1_Cat_7
0      22              1.0          4.0  ...            0            0            0
1      38              0.0          3.0  ...            0            0            0
2      67              1.0          1.0  ...            0            1            0
3      67              0.0          2.0  ...            0            1            0
4      40              0.0          6.0  ...            0            1            0
...   ...              ...          ...  ...          ...          ...          ...
8062   41              0.0          5.0  ...            0            1            0
8064   35              3.0          4.0  ...            0            0            0
8065   33              1.0          1.0  ...            0            1            0
8066   27              1.0          4.0  ...            0            1            0
8067   37              0.0          3.0  ...            0            0            0

[7669 rows x 28 columns]
```

We can see that we have around 28 features now

[10]:
```
from sklearn.preprocessing import StandardScaler
```

[11]:
```
copy = dataset_expanded.copy()

scaler = StandardScaler()
scaler.fit(copy)
X_scale = scaler.transform(copy)
df_scale = pd.DataFrame(X_scale, columns=copy.columns)
display(df_scale)
```

```
           Age  Work_Experience  ...  Var_1_Cat_6  Var_1_Cat_7
0    -1.288844        -0.412541  ...     -1.40404    -0.160246
1    -0.330085        -0.712880  ...     -1.40404    -0.160246
```

```
2     1.407665        -0.412541  ...      0.71223   -0.160246
3     1.407665        -0.712880  ...      0.71223   -0.160246
4    -0.210240        -0.712880  ...      0.71223   -0.160246
...        ...              ...  ...          ...         ...
7664 -0.150318        -0.712880  ...      0.71223   -0.160246
7665 -0.509852         0.188138  ...     -1.40404   -0.160246
7666 -0.629697        -0.412541  ...      0.71223   -0.160246
7667 -0.989232        -0.412541  ...      0.71223   -0.160246
7668 -0.390008        -0.712880  ...     -1.40404   -0.160246

[7669 rows x 28 columns]
```

[12]:
```python
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

[13]:
```python
df_scale2 = df_scale.copy()
kmeans_scale = KMeans(n_clusters=4, n_init=100, max_iter=400, init='k-means++',␣
 ↪random_state=42).fit(df_scale2)
print('KMeans Scaled Silhouette Score: {}'.format(silhouette_score(df_scale2,␣
 ↪kmeans_scale.labels_, metric='euclidean')))
labels_scale = kmeans_scale.labels_
clusters_scale = pd.concat([df_scale2, pd.DataFrame({'cluster_scaled':
 ↪labels_scale})], axis=1)
```

```
KMeans Scaled Silhouette Score: 0.1287897501946912
```

We can see that our Silhouette Score is extremely bad at 0.13 which suggests that there are too many features for KMeans

To solve this problem, we will be plotting a heatmap and see for what features the segmentation does not have a appreciable correlation so we can drop these features

[14]:
```python
dataset_heatmap = df.drop(columns = ['ID'])
dataset_heatmap = dataset_heatmap[dataset_heatmap['Profession'].notna()]
dataset_heatmap = dataset_heatmap.fillna(0)
dataset_heatmap = dataset_heatmap.loc[(dataset_heatmap[['Graduated', 'Gender',␣
 ↪'Ever_Married', 'Var_1']] != 0).all(axis=1)]

dataset_heatmap = pd.get_dummies(dataset_heatmap, sparse = True)
display(dataset_heatmap)
```

```
      Age  Work_Experience  ...  Segmentation_C  Segmentation_D
0      22              1.0  ...               0               1
1      38              0.0  ...               0               0
2      67              1.0  ...               0               0
3      67              0.0  ...               0               0
4      40              0.0  ...               0               0
...   ...              ...  ...             ...             ...
```

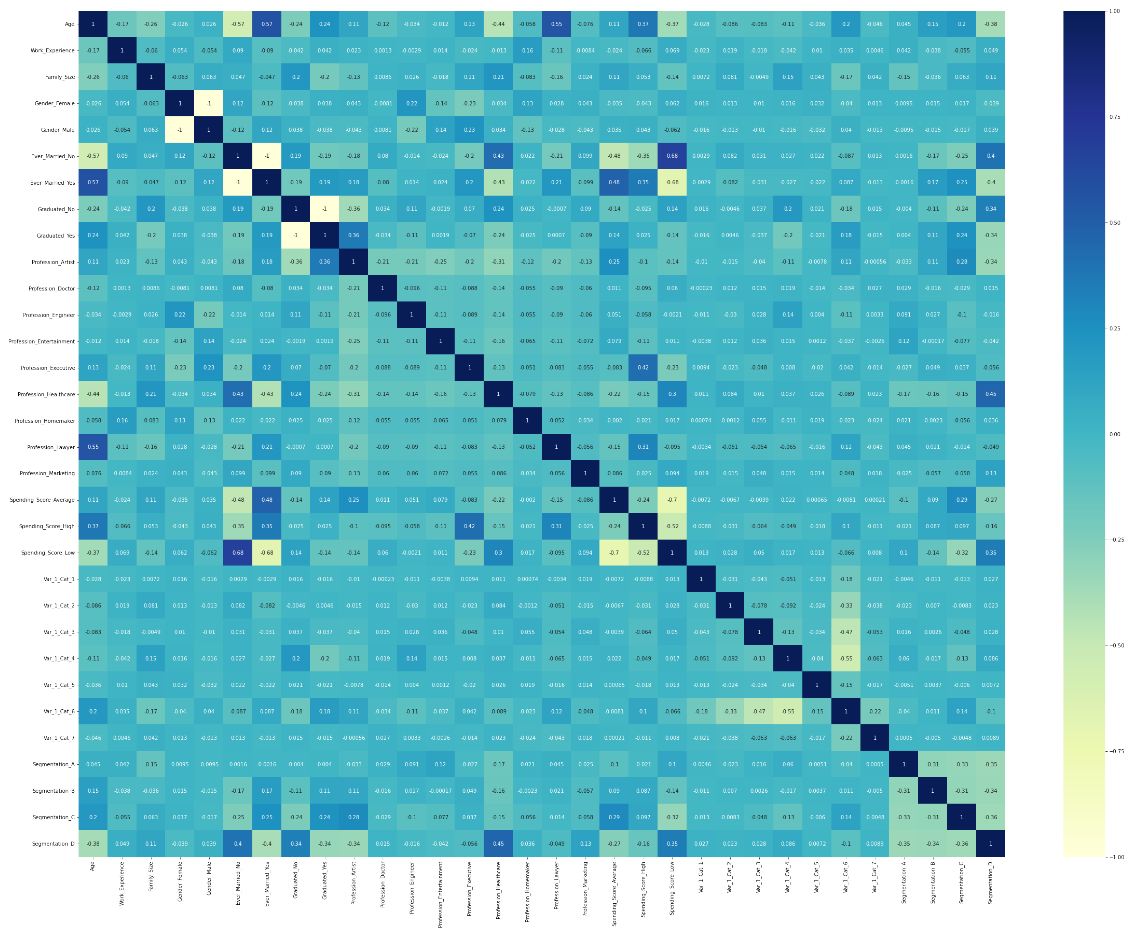
```
8062   41               0.0  ...            0               0
8064   35               3.0  ...            0               1
8065   33               1.0  ...            0               1
8066   27               1.0  ...            0               0
8067   37               0.0  ...            0               0

[7669 rows x 32 columns]
```

[15]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(40, 30))

# plotting correlation heatmap
dataplot = sns.heatmap(dataset_heatmap.corr(), cmap="YlGnBu", annot=True)

# displaying heatmap
plt.show()
```



We can see that the segmentation does not really depend on factors like Gender and Work Experience and the Var_1 column. That means we can drop these columns for further analysis

[16]:
```
dataset_cleaned = df.drop(columns = ['ID','Gender', 'Work_Experience', 'Var_1',␣
↪'Segmentation'])
dataset_cleaned = dataset_cleaned[dataset_cleaned['Profession'].notna()]
dataset_cleaned = dataset_cleaned.loc[(dataset_cleaned[['Graduated',␣
↪'Ever_Married']] != 0).all(axis=1)]
dataset_cleaned.Graduated.replace(('Yes', 'No'), (1, 0), inplace=True)
dataset_cleaned.Ever_Married.replace(('Yes', 'No'), (1, 0), inplace=True)
dataset_cleaned = dataset_cleaned.dropna()
display(dataset_cleaned)
```

```
      Ever_Married  Age  Graduated     Profession Spending_Score  Family_Size
0              0.0   22        0.0     Healthcare            Low          4.0
1              1.0   38        1.0       Engineer        Average          3.0
2              1.0   67        1.0       Engineer            Low          1.0
3              1.0   67        1.0         Lawyer           High          2.0
4              1.0   40        1.0  Entertainment           High          6.0
...            ...  ...        ...            ...            ...          ...
8062           1.0   41        1.0         Artist           High          5.0
8064           0.0   35        0.0      Executive            Low          4.0
8065           0.0   33        1.0     Healthcare            Low          1.0
8066           0.0   27        1.0     Healthcare            Low          4.0
8067           1.0   37        1.0      Executive        Average          3.0

[7434 rows x 6 columns]
```

[17]:
```
dataset_cleaned = pd.get_dummies(dataset_cleaned, sparse = True)
```

[18]:
```
display(dataset_cleaned)
```

```
      Ever_Married  Age  ...  Spending_Score_High  Spending_Score_Low
0              0.0   22  ...                    0                   1
1              1.0   38  ...                    0                   0
2              1.0   67  ...                    0                   1
3              1.0   67  ...                    1                   0
4              1.0   40  ...                    1                   0
...            ...  ...  ...                  ...                 ...
8062           1.0   41  ...                    1                   0
8064           0.0   35  ...                    0                   1
8065           0.0   33  ...                    0                   1
8066           0.0   27  ...                    0                   1
8067           1.0   37  ...                    0                   0

[7434 rows x 16 columns]
```

We've successfully managed to reduce the dataset to 16 features from 28

[19]:
```
copy2 = dataset_cleaned.copy()

scaler2 = StandardScaler()
scaler2.fit(copy2)
X_scale2 = scaler2.transform(copy2)
df_scale3 = pd.DataFrame(X_scale2, columns=copy2.columns)
display(df_scale3)
```

```
      Ever_Married       Age  ...  Spending_Score_High  Spending_Score_Low
0        -1.205933 -1.295875  ...            -0.425367            0.822321
1         0.829233 -0.332744  ...            -0.425367           -1.216070
2         0.829233  1.412930  ...            -0.425367            0.822321
3         0.829233  1.412930  ...             2.350910           -1.216070
4         0.829233 -0.212353  ...             2.350910           -1.216070
...            ...       ...  ...                  ...                 ...
7429      0.829233 -0.152157  ...             2.350910           -1.216070
7430     -1.205933 -0.513331  ...            -0.425367            0.822321
7431     -1.205933 -0.633723  ...            -0.425367            0.822321
7432     -1.205933 -0.994897  ...            -0.425367            0.822321
7433      0.829233 -0.392940  ...            -0.425367           -1.216070

[7434 rows x 16 columns]
```

[20]:
```
df_scale4 = df_scale3.copy()
kmeans_scale = KMeans(n_clusters=4, n_init=100, max_iter=400, init='k-means++',
 ↪random_state=42).fit(df_scale4)
print('KMeans Scaled Silhouette Score: {}'.format(silhouette_score(df_scale4,
 ↪kmeans_scale.labels_, metric='euclidean')))
labels_scale = kmeans_scale.labels_
clusters_scale = pd.concat([df_scale4, pd.DataFrame({'cluster_scaled':
 ↪labels_scale})], axis=1)
```

```
KMeans Scaled Silhouette Score: 0.23238024254207695
```

We can see a clear increase in our silhouette score to 0.23 from 0.13

[21]:
```
display(clusters_scale)
```

```
      Ever_Married       Age  ...  Spending_Score_Low  cluster_scaled
0        -1.205933 -1.295875  ...            0.822321               3
1         0.829233 -0.332744  ...           -1.216070               2
2         0.829233  1.412930  ...            0.822321               1
3         0.829233  1.412930  ...           -1.216070               0
4         0.829233 -0.212353  ...           -1.216070               0
...            ...       ...  ...                 ...             ...
7429      0.829233 -0.152157  ...           -1.216070               0
```

```
7430     -1.205933 -0.513331  ...           0.822321             1
7431     -1.205933 -0.633723  ...           0.822321             3
7432     -1.205933 -0.994897  ...           0.822321             3
7433      0.829233 -0.392940  ...          -1.216070             2

[7434 rows x 17 columns]
```

Try to perfrom elbow, other methods to find suitable clusters

1 PCA optional section

[22]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components = 0.95)
pca.fit(df_scale4)
reduced = pca.transform(df_scale4)
```

[27]:
```
print(reduced.shape)
```

```
(7434, 12)
```

2 T-SNE

[28]:
```
from sklearn.manifold import TSNE
import timeit
```

3 Two Dimensional Plot

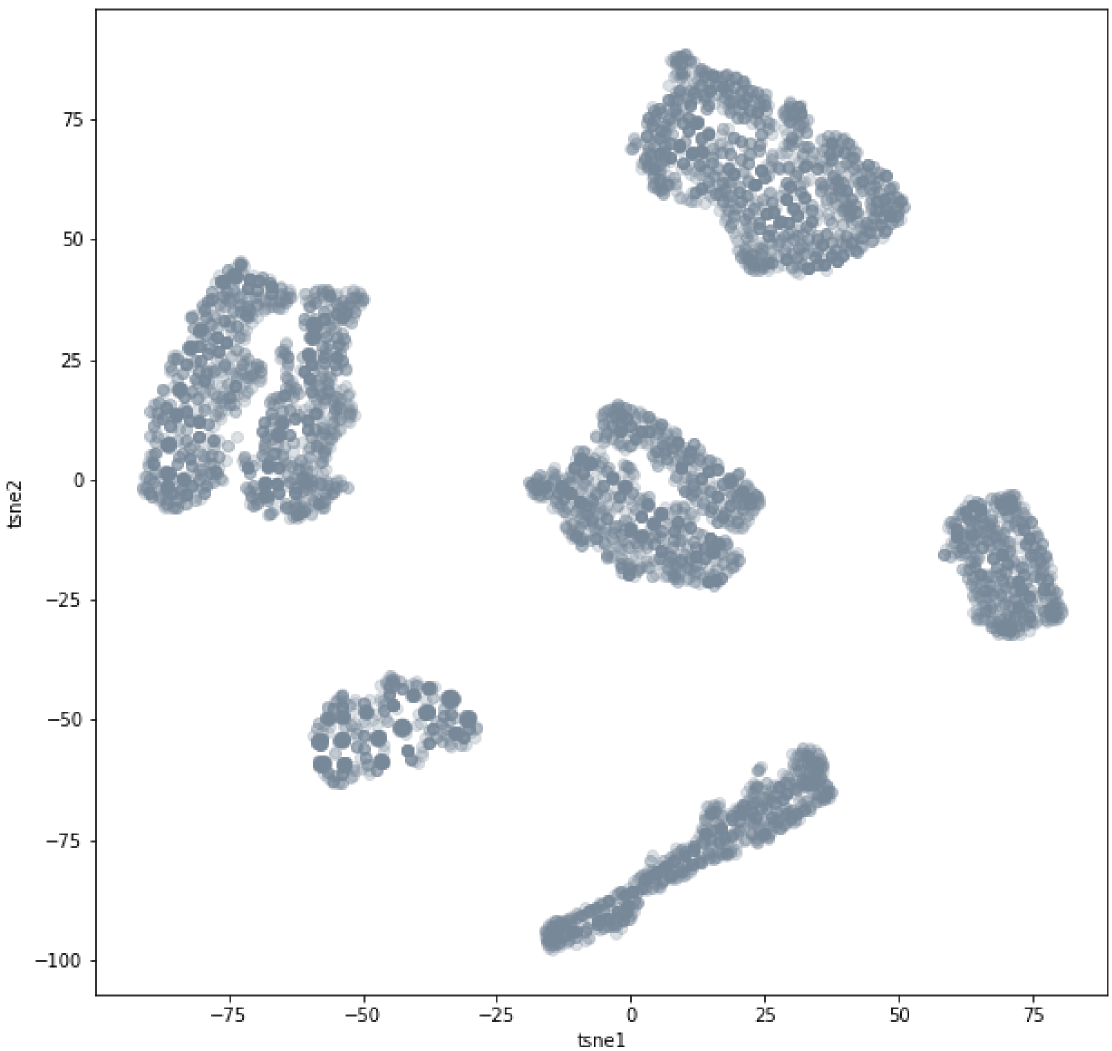
[29]:
```
start = timeit.default_timer()
tsne = TSNE(n_components=2, verbose=1, perplexity=80, n_iter=5000,␣
 ↪learning_rate=200, random_state = 42)

tsne_scale_results = tsne.fit_transform(copy2)
end = timeit.default_timer()
tsne_df_scale = pd.DataFrame(tsne_scale_results, columns=['tsne1', 'tsne2'])
print('t-SNE done! Time elapsed: {} seconds'.format(end-start))
```

```
[t-SNE] Computing 241 nearest neighbors...
[t-SNE] Indexed 7434 samples in 0.018s...
[t-SNE] Computed neighbors for 7434 samples in 0.582s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7434
[t-SNE] Computed conditional probabilities for sample 2000 / 7434
[t-SNE] Computed conditional probabilities for sample 3000 / 7434
[t-SNE] Computed conditional probabilities for sample 4000 / 7434
[t-SNE] Computed conditional probabilities for sample 5000 / 7434
```

```
[t-SNE] Computed conditional probabilities for sample 6000 / 7434
[t-SNE] Computed conditional probabilities for sample 7000 / 7434
[t-SNE] Computed conditional probabilities for sample 7434 / 7434
[t-SNE] Mean sigma: 0.967803
[t-SNE] KL divergence after 250 iterations with early exaggeration: 61.149101
[t-SNE] KL divergence after 5000 iterations: 0.692845
t-SNE done! Time elapsed: 368.51054587999994 seconds
```

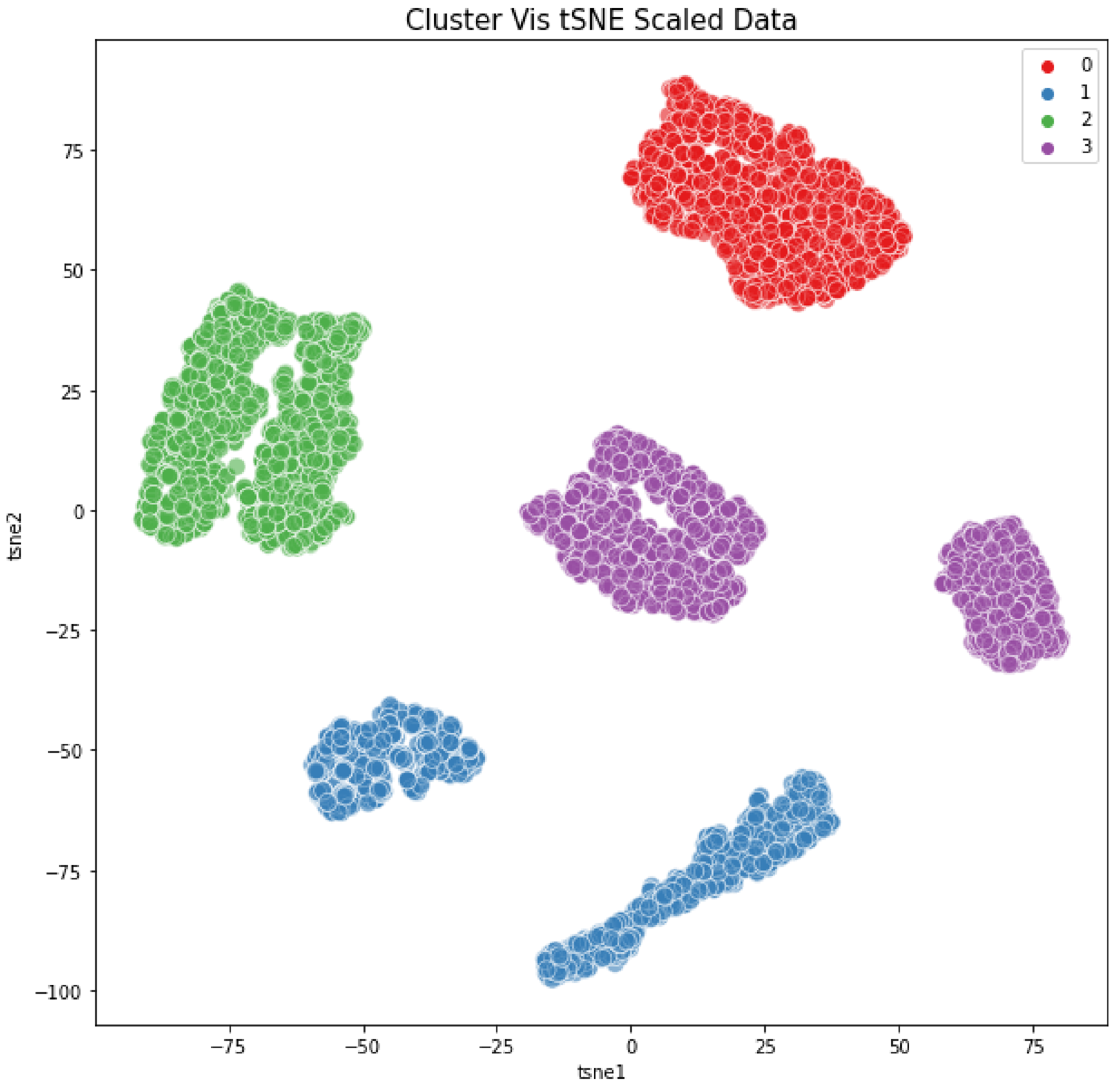
[30]:
```
plt.figure(figsize = (10,10))
plt.scatter(tsne_df_scale.iloc[:,0],tsne_df_scale.iloc[:,1],alpha=0.25,␣
 ↪facecolor='lightslategray')
plt.xlabel('tsne1')
plt.ylabel('tsne2')
plt.show()
```



[31]:
```
kmeans_tsne_scale = KMeans(n_clusters=4, n_init=100, max_iter=800,␣
↪init='k-means++', random_state=42).fit(tsne_df_scale)
print('KMeans tSNE Scaled Silhouette Score: {}'.
↪format(silhouette_score(tsne_df_scale, kmeans_tsne_scale.labels_,␣
↪metric='euclidean')))
labels_tsne_scale = kmeans_tsne_scale.labels_
clusters_tsne_scale = pd.concat([tsne_df_scale, pd.DataFrame({'tsne_clusters':
↪labels_tsne_scale})], axis=1)
```

```
KMeans tSNE Scaled Silhouette Score: 0.5922470688819885
```

[32]:
```
plt.figure(figsize = (10,10))
sns.scatterplot(x = clusters_tsne_scale.iloc[:,0],y = clusters_tsne_scale.iloc[:
↪,1],hue=labels_tsne_scale, palette='Set1', s=100, alpha=0.6).
↪set_title('Cluster Vis tSNE Scaled Data', fontsize=15)
plt.legend()
plt.show()
```



[41]:
```python
from sklearn.decomposition import PCA
```

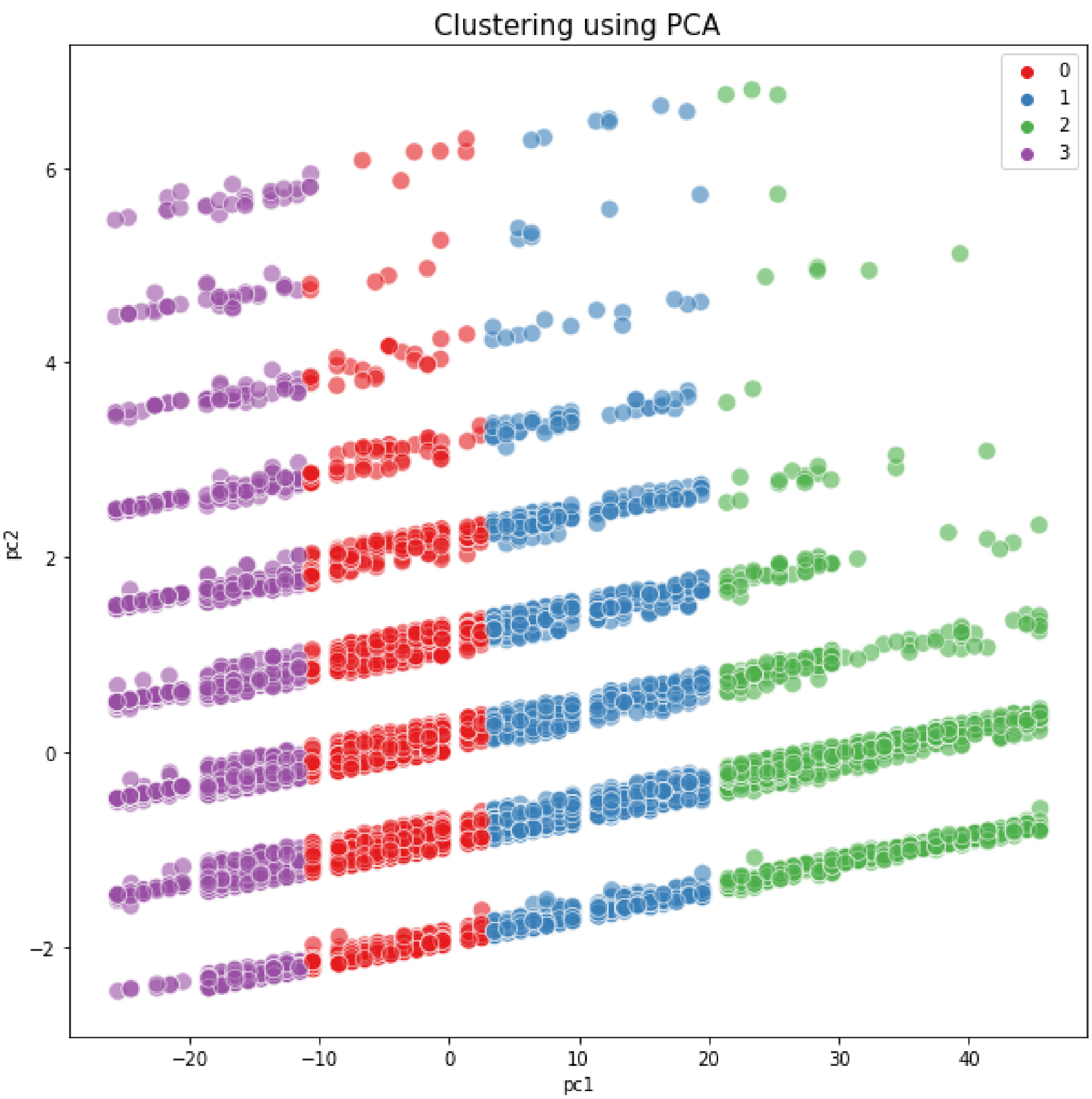
[46]:
```python
start = timeit.default_timer()
pca = PCA(n_components = 2, random_state = 42)
pca_scale_results = pca.fit_transform(copy2)
end = timeit.default_timer()
pca_df_scale = pd.DataFrame(pca_scale_results, columns=['pc1', 'pc2'])
print('t-SNE done! Time elapsed: {} seconds'.format(end-start))
print(pca.explained_variance_ratio_)
```

```
t-SNE done! Time elapsed: 0.03451279799992335 seconds
[0.98642641 0.00779754]
```

[43]:
```
kmeans_pca_scale = KMeans(n_clusters=4, n_init=100, max_iter=800,␣
↪init='k-means++', random_state=42).fit(pca_df_scale)
print('KMeans PCA Scaled Silhouette Score: {}'.
↪format(silhouette_score(pca_df_scale, kmeans_pca_scale.labels_,␣
↪metric='euclidean')))
labels_pca_scale = kmeans_pca_scale.labels_
clusters_pca_scale = pd.concat([pca_df_scale, pd.DataFrame({'pca_clusters':
↪labels_pca_scale})], axis=1)
```

```
KMeans PCA Scaled Silhouette Score: 0.5286711782004786
```

[44]:
```
plt.figure(figsize = (10,10))
sns.scatterplot(x = clusters_pca_scale.iloc[:,0],y = clusters_pca_scale.iloc[:
↪,1],hue=labels_pca_scale, palette='Set1', s=100, alpha=0.6).
↪set_title('Clustering using PCA', fontsize=15)
plt.legend()
plt.show()
```



4 3 Dimensional Plot

[33]:
```
start = timeit.default_timer()
tsne = TSNE(n_components=3, verbose=1, perplexity=80, n_iter=5000,␣
 ↪learning_rate=200, random_state = 42)

tsne_scale_results = tsne.fit_transform(copy2)
end = timeit.default_timer()
tsne_df_scale = pd.DataFrame(tsne_scale_results, columns=['tsne1', 'tsne2',␣
 ↪'tsne3'])
print('t-SNE done! Time elapsed: {} seconds'.format(end-start))
```

```
[t-SNE] Computing 241 nearest neighbors...
[t-SNE] Indexed 7434 samples in 0.018s...
[t-SNE] Computed neighbors for 7434 samples in 0.618s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7434
[t-SNE] Computed conditional probabilities for sample 2000 / 7434
[t-SNE] Computed conditional probabilities for sample 3000 / 7434
[t-SNE] Computed conditional probabilities for sample 4000 / 7434
[t-SNE] Computed conditional probabilities for sample 5000 / 7434
[t-SNE] Computed conditional probabilities for sample 6000 / 7434
[t-SNE] Computed conditional probabilities for sample 7000 / 7434
[t-SNE] Computed conditional probabilities for sample 7434 / 7434
[t-SNE] Mean sigma: 0.967803
[t-SNE] KL divergence after 250 iterations with early exaggeration: 60.717396
[t-SNE] KL divergence after 5000 iterations: 0.559766
t-SNE done! Time elapsed: 1293.319928696 seconds
```

[34]:
```
kmeans_tsne_scale = KMeans(n_clusters=4, n_init=100, max_iter=800,␣
↪init='k-means++', random_state=42).fit(tsne_df_scale)
print('KMeans tSNE Scaled Silhouette Score: {}'.
↪format(silhouette_score(tsne_df_scale, kmeans_tsne_scale.labels_,␣
↪metric='euclidean')))
labels_tsne_scale = kmeans_tsne_scale.labels_
clusters_tsne_scale = pd.concat([tsne_df_scale, pd.DataFrame({'tsne_clusters':
↪labels_tsne_scale})], axis=1)
```

```
KMeans tSNE Scaled Silhouette Score: 0.44695645570755005
```

[35]:
```
import plotly.graph_objs as go
```

[36]:
```
Scene = dict(xaxis = dict(title  = 'tsne1'),yaxis = dict(title  =␣
↪'tsne2'),zaxis = dict(title  = 'tsne3'))
labels = labels_tsne_scale
trace = go.Scatter3d(x=clusters_tsne_scale.iloc[:,0], y=clusters_tsne_scale.
↪iloc[:,1], z=clusters_tsne_scale.iloc[:,2], mode='markers',marker=dict(color␣
↪= labels, colorscale='Viridis', size = 10, line = dict(color =␣
↪'yellow',width = 5)))
layout = go.Layout(margin=dict(l=0,r=0),scene = Scene, height = 1000,width =␣
↪1000)
data = [trace]
fig = go.Figure(data = data, layout = layout)
fig.show()
```

[48]:
```
start = timeit.default_timer()
pca = PCA(n_components = 3, random_state = 42)
pca_scale_results = pca.fit_transform(copy2)
end = timeit.default_timer()
pca_df_scale = pd.DataFrame(pca_scale_results, columns=['pc1', 'pc2', 'pc3'])
print('PCA done! Time elapsed: {} seconds'.format(end-start))
```

```
print(pca.explained_variance_ratio_)
```

```
PCA done! Time elapsed: 0.04889983300017775 seconds
[0.98642641 0.00779754 0.00162805]
```

[49]:
```
kmeans_pca_scale = KMeans(n_clusters=4, n_init=100, max_iter=800,␣
 ↪init='k-means++', random_state=42).fit(pca_df_scale)
print('KMeans PCA Scaled Silhouette Score: {}'.
 ↪format(silhouette_score(pca_df_scale, kmeans_pca_scale.labels_,␣
 ↪metric='euclidean')))
labels_pca_scale = kmeans_pca_scale.labels_
clusters_pca_scale = pd.concat([pca_df_scale, pd.DataFrame({'pca_clusters':
 ↪labels_pca_scale})], axis=1)
```

```
KMeans PCA Scaled Silhouette Score: 0.5225822486130006
```

[50]:
```
Scene = dict(xaxis = dict(title  = 'pc1'),yaxis = dict(title  = 'pc2'),zaxis =␣
 ↪dict(title  = 'pc3'))
labels = labels_pca_scale
trace = go.Scatter3d(x=clusters_pca_scale.iloc[:,0], y=clusters_pca_scale.iloc[:
 ↪,1], z=clusters_pca_scale.iloc[:,2], mode='markers',marker=dict(color =␣
 ↪labels, colorscale='Viridis', size = 10, line = dict(color = 'yellow',width␣
 ↪= 5)))
layout = go.Layout(margin=dict(l=0,r=0),scene = Scene, height = 1000,width =␣
 ↪1000)
data = [trace]
fig = go.Figure(data = data, layout = layout)
fig.show()
```

[ ]: