Wonderful Wines of the World

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pandas_profiling import ProfileReport
import requests
from math import ceil

from sklearn.feature_selection import VarianceThreshold
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler, StandardScaler
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.cluster import DBSCAN, KMeans, AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram
from sklearn.base import clone
from sklearn.neighbors import NearestNeighbors
from yellowbrick.cluster import KElbowVisualizer
```

Project Plan

Phase	Deliverable
Business Understanding	Background
	Business Objectives and Success Criteria
	Assumptions and Constrains
	Data Mining Goals and Success Criteria
	Data Mining Success Criteria
Data Understanding	Data Description
	Exploratory Analysis
Data Preparation	Select Data
	Clean Data
	Construct Data
Modeling	Select Modeling Techniques
	Build Model
	Assess Models
Evaluation	Evaluate Results
	Cluster Analysis
Deployment	Marketing Strategies

1. Import Dataset

In [2]:

```
# load dataset
df = pd.read_excel("WonderfulWinesoftheWorld.xlsx")
df.head()
```

Out[2]:

	Custid	Dayswus	Age	Edu	Income	Kidhome	Teenhome	Freq	Recency	Monetary	...	SMRack	LGRack	Humid	Spcork
0	5325.0	653.0	55.0	20.0	78473.0	0.0	0.0	20.0	18.0	826.0	...	0	0	0	0
1	3956.0	1041.0	75.0	18.0	105087.0	0.0	0.0	36.0	33.0	1852.0	...	0	0	0	1
2	3681.0	666.0	18.0	12.0	27984.0	1.0	0.0	4.0	56.0	39.0	...	0	0	0	0
3	2829.0	1049.0	42.0	16.0	61748.0	1.0	1.0	2.0	46.0	37.0	...	0	0	0	0
4	8788.0	837.0	47.0	16.0	65789.0	0.0	1.0	2.0	3.0	36.0	...	0	0	0	0

5 rows × 30 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10001 entries, 0 to 10000
Data columns (total 30 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Custid        10001 non-null  float64
 1   Dayswus       10001 non-null  float64
 2   Age           10001 non-null  float64
 3   Edu           10001 non-null  float64
 4   Income        10001 non-null  float64
 5   Kidhome       10001 non-null  float64
 6   Teenhome      10001 non-null  float64
 7   Freq          10001 non-null  float64
 8   Recency       10001 non-null  float64
 9   Monetary      10001 non-null  float64
 10  LTV           10001 non-null  float64
 11  Perdeal       10001 non-null  float64
 12  Dryred        10001 non-null  float64
 13  Sweetred      10001 non-null  float64
 14  Drywh         10001 non-null  float64
 15  Sweetwh       10001 non-null  float64
 16  Dessert       10001 non-null  float64
 17  Exotic        10001 non-null  float64
 18  WebPurchase   10001 non-null  float64
 19  WebVisit      10001 non-null  float64
 20  SMRack        10001 non-null  int64
 21  LGRack        10001 non-null  int64
 22  Humid         10001 non-null  int64
 23  Spcork        10001 non-null  int64
 24  Bucket        10001 non-null  int64
 25  Access        10001 non-null  int64
 26  Complain      10001 non-null  int64
 27  Mailfriend    10001 non-null  int64
 28  Emailfriend   10001 non-null  int64
 29  Rand          10000 non-null  float64
dtypes: float64(21), int64(9)
memory usage: 2.3 MB
```

In [4]:

```
#ProfileReport(df)
```

2. Data Preprocessing

In [5]:

```
# remove last row since it represents average values for each column
df.drop(df.tail(1).index, inplace = True)
df
```

Out[5]:

	Custid	Dayswus	Age	Edu	Income	Kidhome	Teenhome	Freq	Recency	Monetary	...	SMRack	LGRack	Humid	Spcork
0	5325.0	653.0	55.0	20.0	78473.0	0.0	0.0	20.0	18.0	826.0	...	0	0	0	0
1	3956.0	1041.0	75.0	18.0	105087.0	0.0	0.0	36.0	33.0	1852.0	...	0	0	0	1
2	3681.0	666.0	18.0	12.0	27984.0	1.0	0.0	4.0	56.0	39.0	...	0	0	0	0
3	2829.0	1049.0	42.0	16.0	61748.0	1.0	1.0	2.0	46.0	37.0	...	0	0	0	0
4	8788.0	837.0	47.0	16.0	65789.0	0.0	1.0	2.0	3.0	36.0	...	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	1383.0	1132.0	57.0	20.0	81033.0	0.0	1.0	19.0	59.0	776.0	...	1	0	0	0
9996	4070.0	596.0	66.0	15.0	84714.0	0.0	0.0	18.0	45.0	720.0	...	0	0	0	0
9997	7909.0	619.0	18.0	12.0	40466.0	0.0	0.0	3.0	65.0	47.0	...	0	0	0	0
9998	4158.0	1107.0	33.0	16.0	53661.0	1.0	0.0	1.0	368.0	15.0	...	0	0	0	0
9999	4914.0	979.0	55.0	16.0	94926.0	0.0	1.0	25.0	28.0	1148.0	...	0	0	0	0

10000 rows × 30 columns

In [6]:

```
conv_cols = ['Kidhome', 'Teenhome']
df[conv_cols] = df[conv_cols].applymap(np.int64)
```

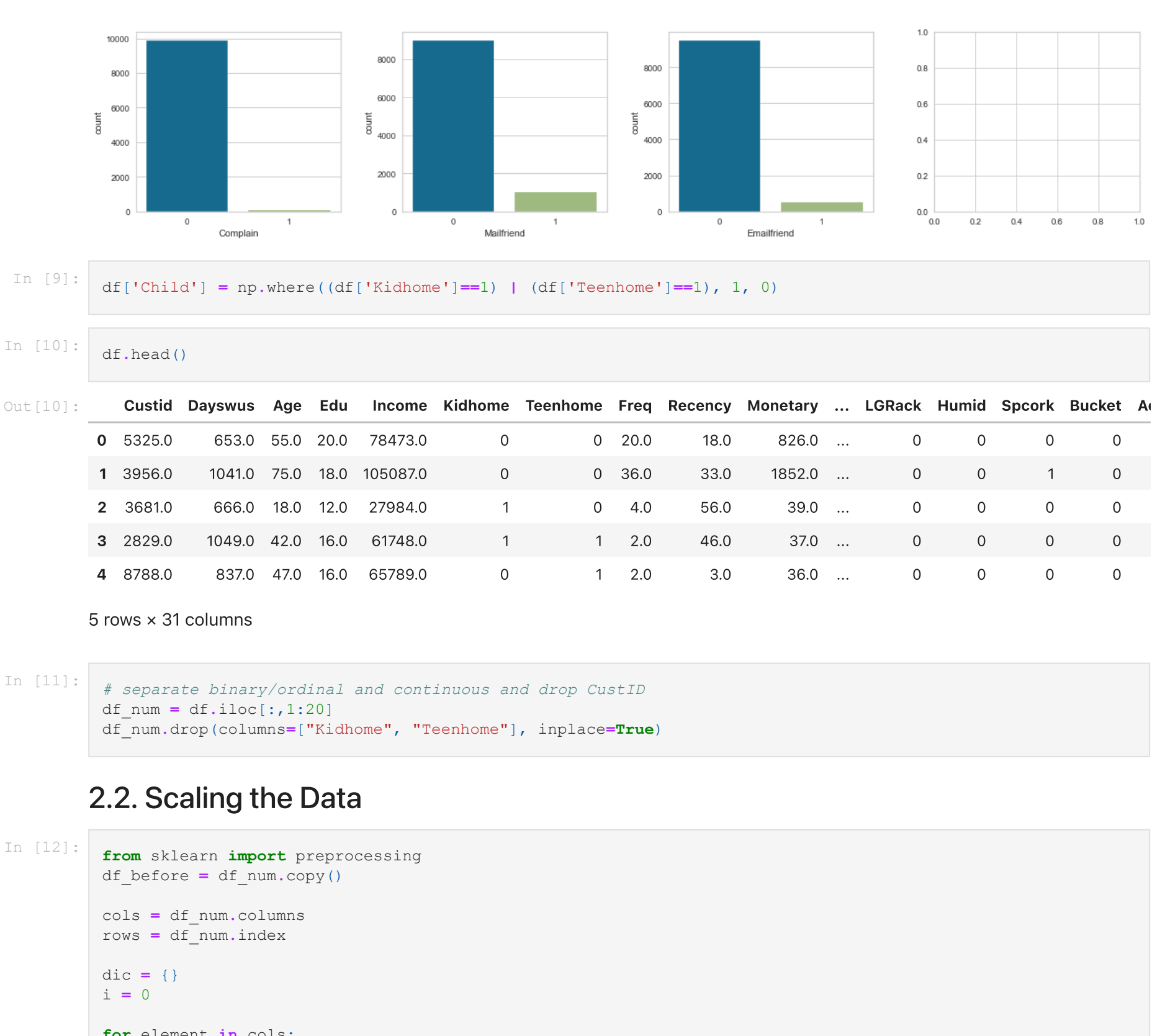
2.1. Non Metric Visualisation

In [7]:

```
non_metric_features = df.select_dtypes(exclude=['float64']).columns.to_list()
```

In [8]:

```
# All Non-Metric/ Low Cardinality Variables' Absolute Frequencies
sns.set_style("whitegrid")

features = non_metric_features
# Prepare figure. Create individual axes where each bar plot will be placed
fig, axes = plt.subplots(3, ceil(len(features) / 3), figsize=(21, 17))

# Plot data
# Iterate across axes objects and associate each bar plot:
for ax, feat in zip(axes.flatten(), features):
    sns.countplot(x=df[feat], ax=ax)

title = "Categorical/Low Cardinality Variables' Absolute Frequencies"
plt.suptitle(title)
# Rotating X-axis labels
axes.flatten()[0].tick_params(axis='x', labelrotation = 90)
axes.flatten()[2].tick_params(axis='x', labelrotation = 90)
plt.subplots_adjust(wspace=0.3, hspace=0.7)

plt.show()
```



In [9]:

```
df["Child"] = np.where((df['Kidhome']==1) | (df['Teenhome']==1), 1, 0)
```

In [10]:

```
df.head()
```

Out[10]:

	Custid	Dayswus	Age	Edu	Income	Kidhome	Teenhome	Freq	Recency	Monetary	...	LGRack	Humid	Spcork	Bucket
0	5325.0	653.0	55.0	20.0	78473.0	0	0	20.0	18.0	826.0	...	0	0	0	0
1	3956.0	1041.0	75.0	18.0	105087.0	0	0	36.0	33.0	1852.0	...	0	0	1	0
2	3681.0	666.0	18.0	12.0	27984.0	1	0	4.0	56.0	39.0	...	0	0	0	0
3	2829.0	1049.0	42.0	16.0	61748.0	1	1	2.0	46.0	37.0	...	0	0	0	0
4	8788.0	837.0	47.0	16.0	65789.0	0	1	2.0	3.0	36.0	...	0	0	0	0

5 rows × 31 columns

In [11]:

```
# separate binary/ordinal and continuous and drop CustID
df_num = df.iloc[:,1:20]
df_num.drop(columns=["Kidhome", "Teenhome"], inplace=True)
```

2.2. Scaling the Data

In [12]:

```
from sklearn import preprocessing
df_before = df_num.copy()

cols = df_num.columns
rows = df_num.index

dic = {}
i = 0

for element in cols:
    dic[i]=element
    i = i + 1

x = df_num.values #returns a numpy array
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
df_scaled = pd.DataFrame(x_scaled)
df_scaled = df_scaled.rename(columns=dic)
df_scaled.head()
```

Out[12]:

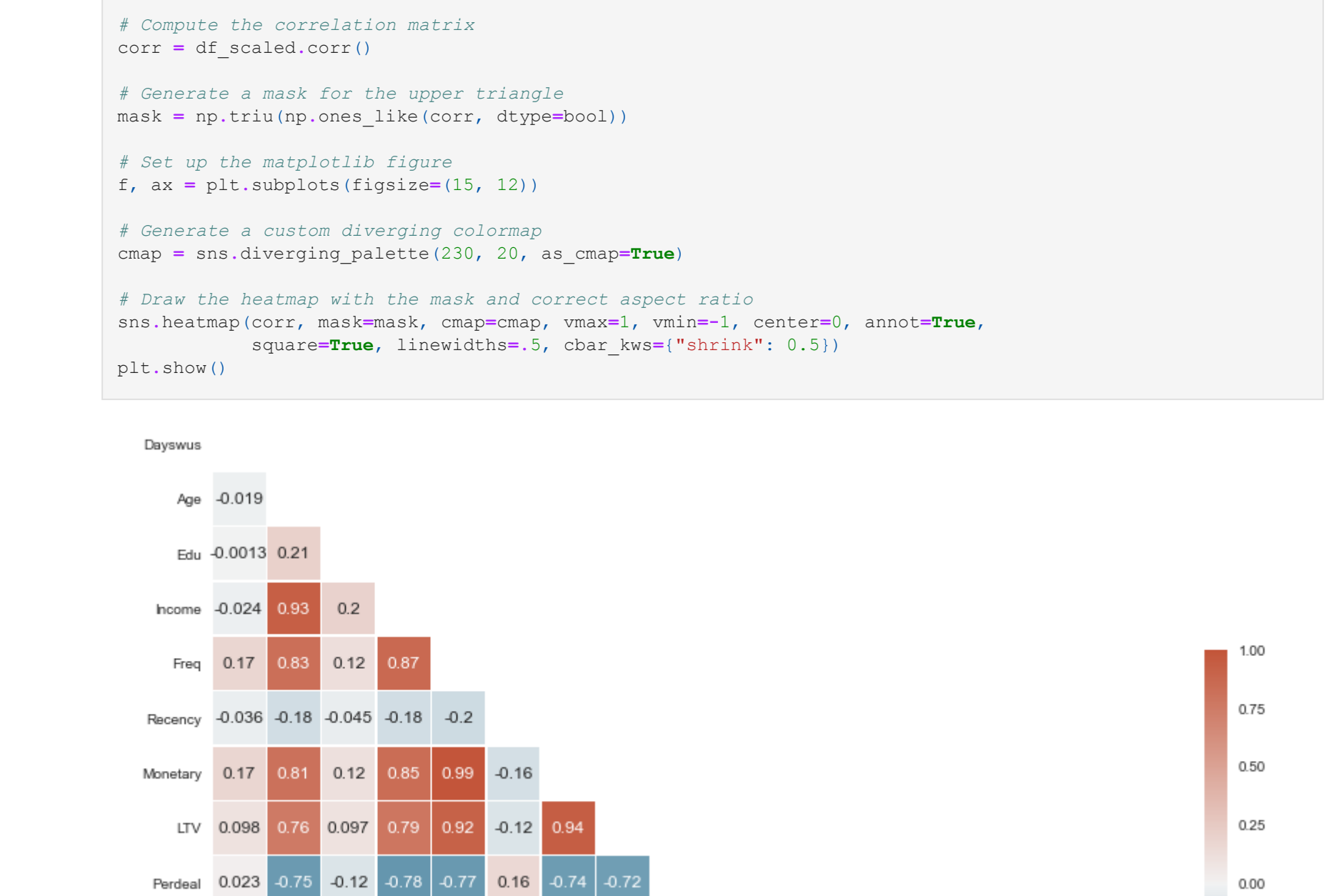
	Dayswus	Age	Edu	Income	Freq	Recency	Monetary	LTV	Perdeal	Dryred	Sweetred	Drywh
0	0.147143	0.616667	1.00	0.524183	0.345455	0.032787	0.269206	0.316404	0.072165	0.673469	0.053333	0.342466
1	0.701429	0.950000	0.75	0.727922	0.636364	0.060109	0.606041	0.364144	0.020619	0.489796	0.000000	0.616438
2	0.165714	0.000000	0.00	0.137673	0.054545	0.102004	0.010834	0.086846	0.907216	0.030612	0.386667	0.178082
3	0.712857	0.400000	0.50	0.396148	0.018182	0.083789	0.010177	0.087354	0.721649	0.867347	0.013333	0.136986
4	0.410000	0.483333	0.50	0.427083	0.018182	0.005464	0.009849	0.092433	0.360825	0.857143	0.000000	0.150685

2.3. Metric Visualization

In [13]:

```
fig, ax = plt.subplots(figsize=(16,8))
sns.boxplot(x="variable", y="value", data=pd.melt(df_scaled), ax=ax)
```

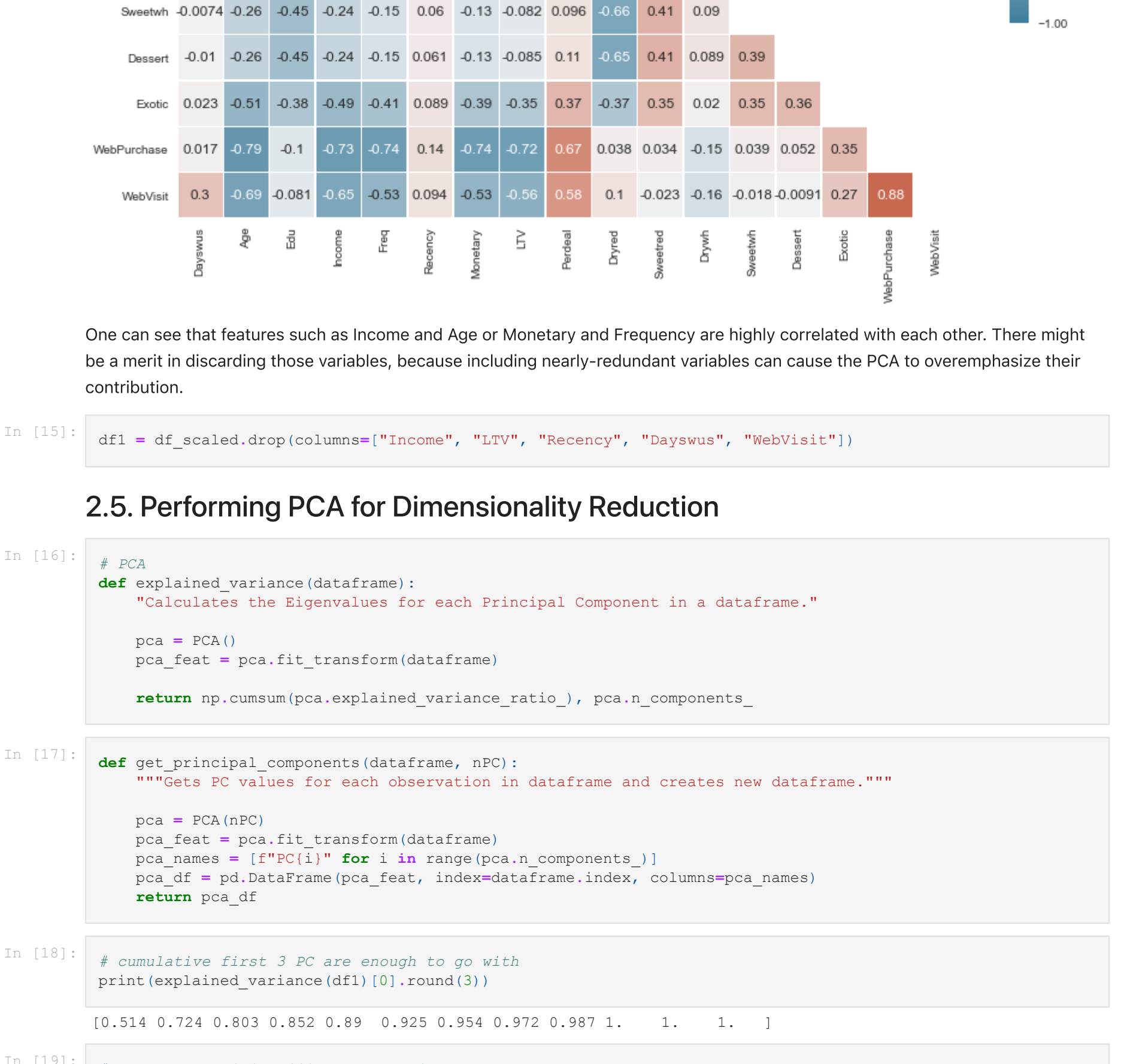
Out[13]: <AxesSubplot:xlabel='variable', ylabel='value'>



2.4. Checking Redundancy

In [14]:

```
# Correlation Matrix

# Compute the correlation matrix
corr = df_scaled.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(15, 12))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, vmin=-1, center=0, annot=True,
            square=True, linewidths=.5, cbar_kws={"shrink": 0.5})

plt.show()
```



One can see that features such as Income and Age or Monetary and Frequency are highly correlated with each other. There might be a merit in discarding those variables, because including nearly-redundant variables can cause the PCA to overemphasize their contribution.

In [15]:

```
df1 = df_scaled.drop(columns=["Income", "LTV", "Recency", "Dayswus", "WebVisit"])
```

2.5. Performing PCA for Dimensionality Reduction

In [16]:

```
# PCA
def explained_variance(dataframe):
    "Calculates the Eigenvalues for each Principal Component in a dataframe."

    pca = PCA()
    pca_feat = pca.fit_transform(dataframe)

    return np.cumsum(pca.explained_variance_ratio_), pca.components_
```

In [17]:

```
def get_principal_components(dataframe, nPC):
    """Gets PC values for each observation in dataframe and creates new dataframe."""
    pca = PCA(nPC)
    pca_feat = pca.fit_transform(dataframe)
    pca_names = [f"PC{i}" for i in range(pca.n_components_)]
    pca_df = pd.DataFrame(pca_feat, index=dataframe.index, columns=pca_names)
    return pca_df
```

In [18]:

```
# cumulative first 3 PC are enough to go with
print(explained_variance(df1)[0].round(3))
```

```
[0.514 0.724 0.803 0.852 0.89  0.925 0.954 0.972 0.987 1.    1.    1.    1.   ]
```

In [19]:

```
# get pc explaining 80% of the variance
pca_num = get_principal_components(df1, 3)
pca_num.head()
```

Out[19]:

	PC0	PC1	PC2
0	0.389565	-0.332765	0.176738
1	0.852400	0.082875	0.230937
2	-1.002513	0.658097	-0.327440
3	-0.505874	-0.367367	-0.335385
4	-0.251796	-0.370861	-0.344171

2.6. Visualizing the preprocessed dataset with TSNE

In [20]:

```
# TSNE
tsne_data = TSNE(random_state=10).fit_transform(pca_num)

x = tsne_data[:,0]
y = tsne_data[:,1]
```

In [21]:

```
plt.figure(figsize=(10,10))
sns.scatterplot(x,y)
```

```
/opt/anaconda3/envs/Business_Cases/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

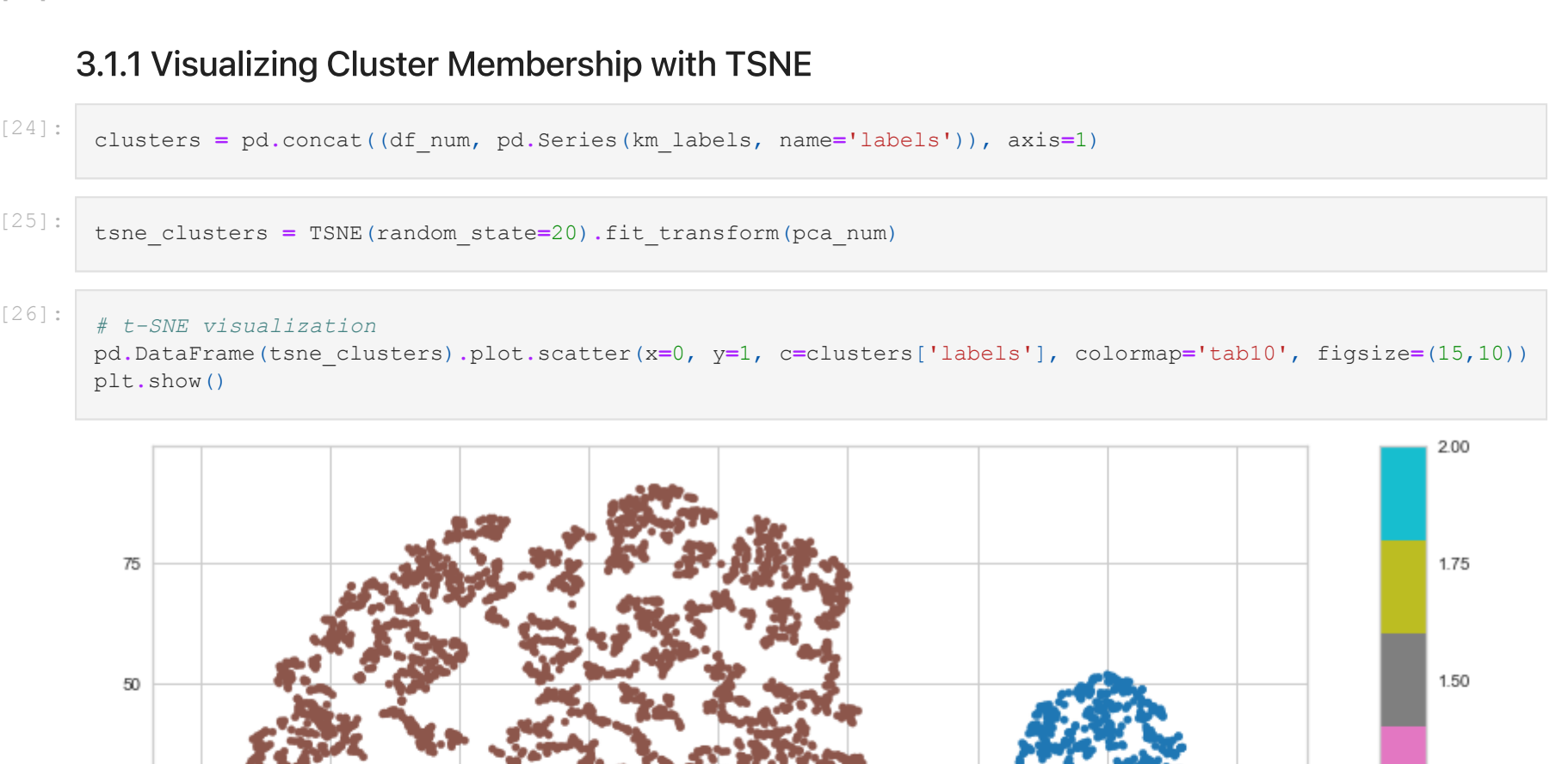
Out[21]: <AxesSubplot:>

3. Clustering

3.1. K-Means

In [22]:

```
# KMeans Elbow
model = KMeans(pca_num)
visualizer = KElbowVisualizer(model, k=(1,10))

visualizer.fit(pca_num)
visualizer.show()           # Finalize and render the figure
```



Out[22]: <AxesSubplot:title={'center':'Distortion Score Elbow for KMeans Clustering'}, xlabel='k', ylabel='distortion score'>

In [23]:

```
number_clusters = 3
kmclust = KMeans(
    n_clusters=number_clusters,
    init='k-means++',
    n_init=10,
    random_state=27,
    tol= 1e-4)
km_labels = kmclust.fit_predict(pca_num)
km_labels
```

Out[23]: array([2, 1, 0, ..., 0, 0, 1], dtype=int32)

3.1.1 Visualizing Cluster Membership with TSNE

In [24]:

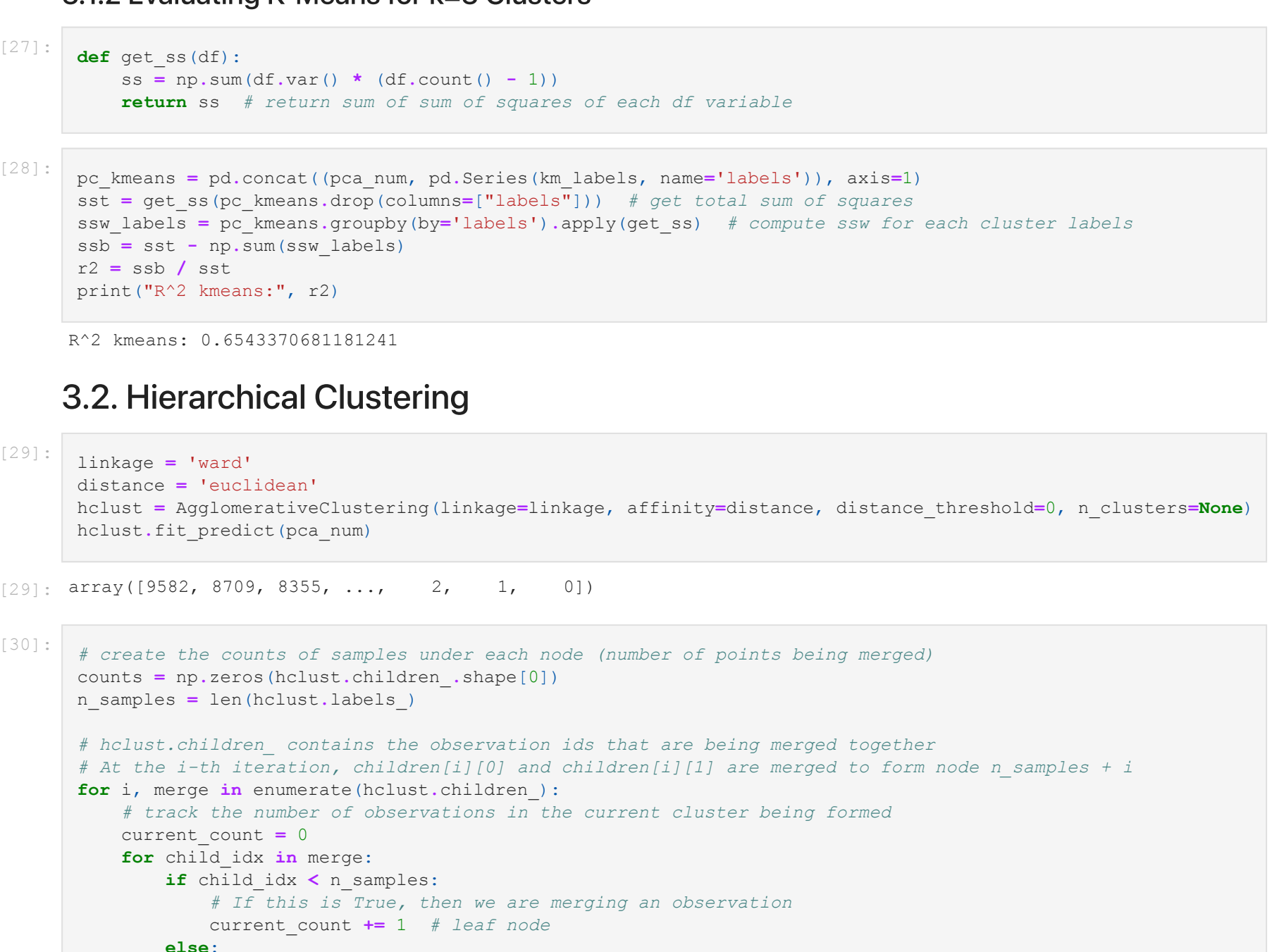
```
clusters = pd.concat([df_num, pd.Series(km_labels, name='labels')], axis=1)
```

In [25]:

```
tsne_clusters = TSNE(random_state=20).fit_transform(pca_num)
```

In [26]:

```
# t-SNE visualization
pd.DataFrame(tsne_clusters).plot.scatter(x=0, y=1, c=clusters['labels'], colormap='tab10', figsize=(15,10))
plt.show()
```



3.1.2 Evaluating K-Means for k=3 Clusters

In [27]:

```
def get_ss(df):
    ss = np.sum(df.var() * (df.count() - 1))
    return ss  # return sum of sum of squares of each df variable
```

In [28]:

```
pc_kmeans = pd.concat((pca_num, pd.Series(km_labels, name='labels')), axis=1)
sst = get_ss(pc_kmeans.drop(columns=["labels"]))  # get total sum of squares
ssw_labels = pc_kmeans.groupby(by="labels").apply(get_ss)  # compute ssw for each cluster labels
ssb = sst - np.sum(ssw_labels)
r2 = ssb / sst
print("R^2 kmeans:", r2)
```

```
R^2 kmeans: 0.6543370681181241
```

3.2. Hierarchical Clustering

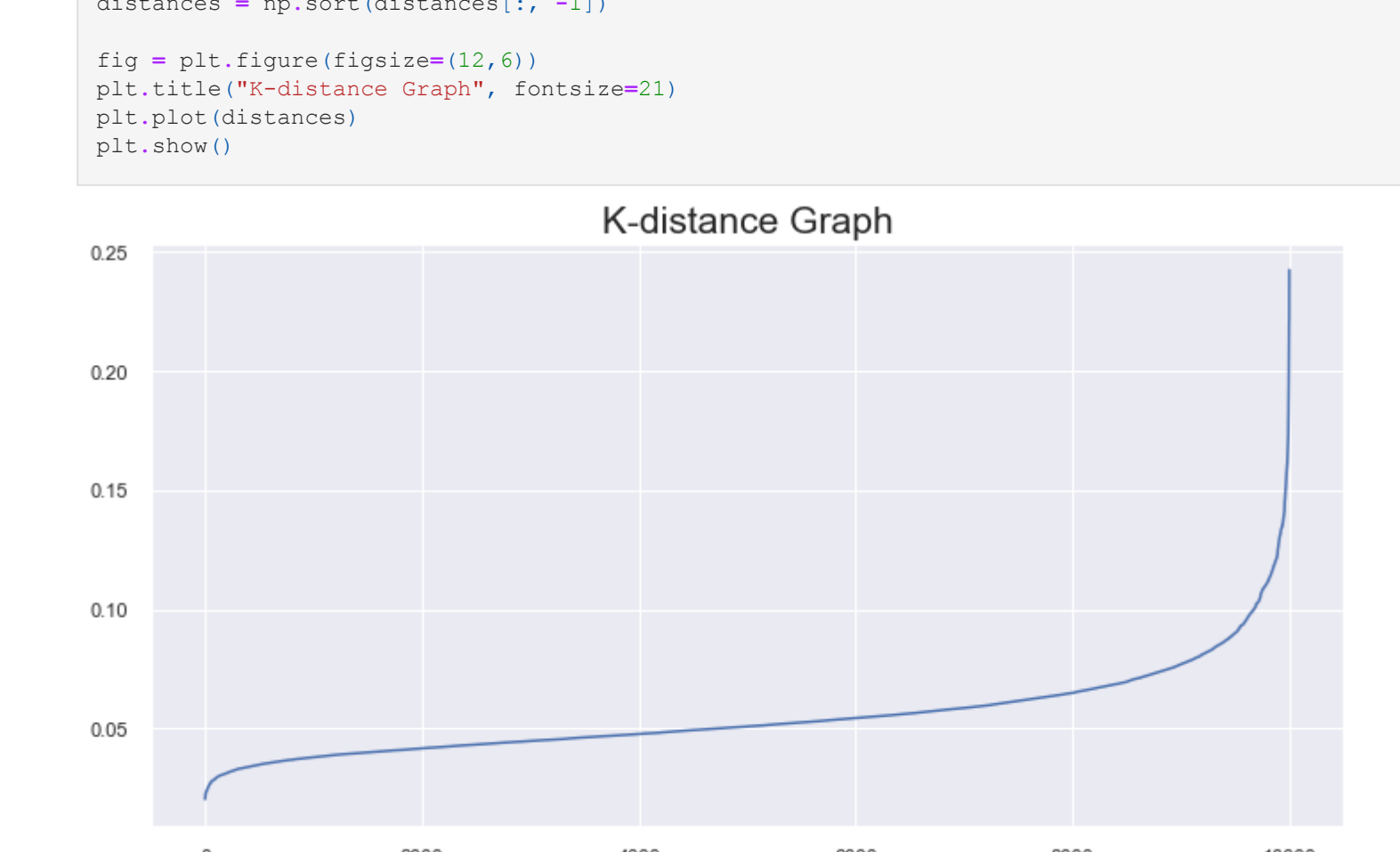
In [29]:

```
linkage = 'ward'
distance = 'euclidean'
hclust = AgglomerativeClustering(linkage=linkage, affinity=distance, distance_threshold=0, n_clusters=None)
hclust.fit_predict(pca_num)
```

Out[29]: array([9582, 6709, 9355, ...,   2,   1,   0])

In [30]:

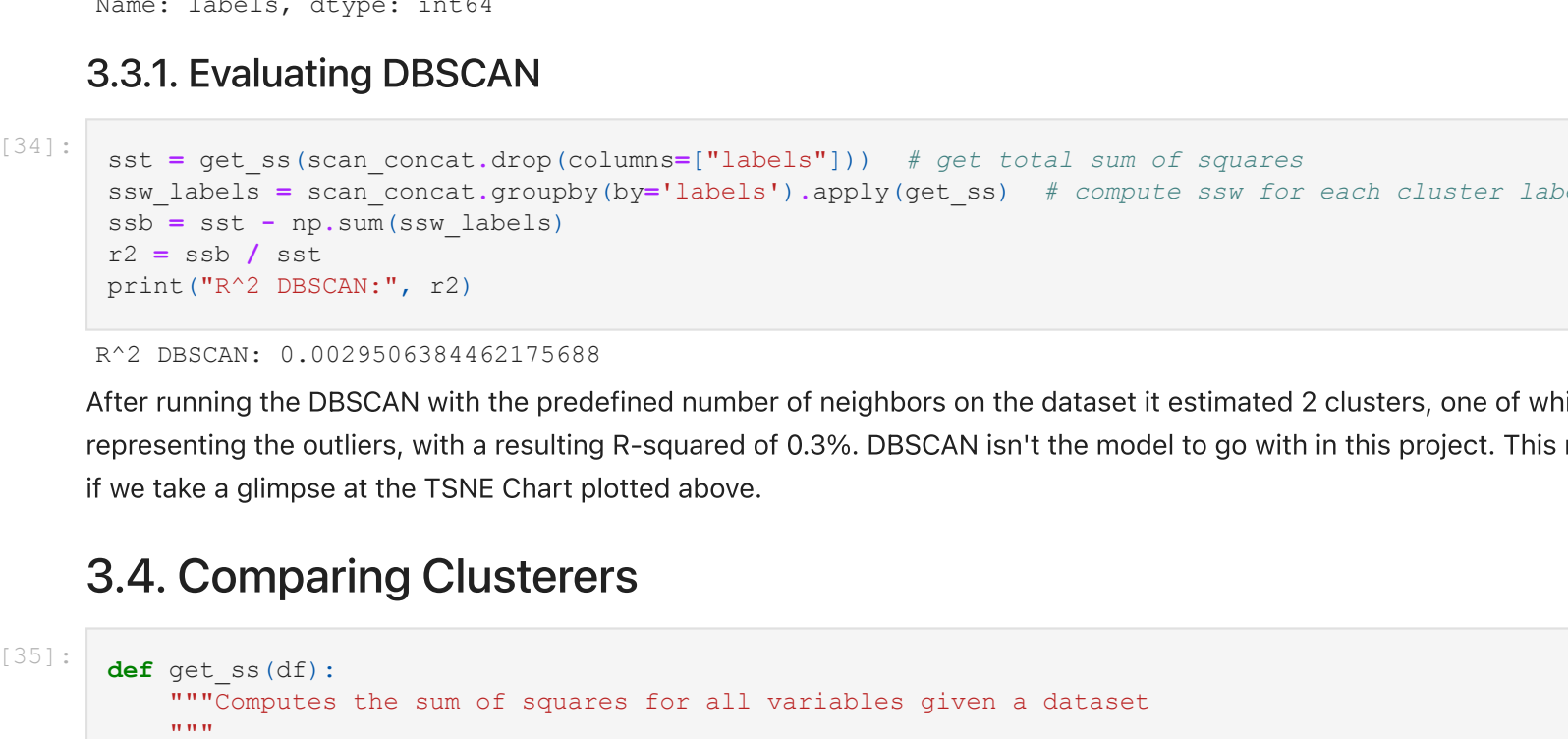
```
# create the counts of samples under each node (number of points being merged)
counts = np.zeros(hclust.children_.shape[0])
n_samples = len(hclust.labels_)

# hclust.children_ contains the observation ids that are being merged together
# At the i-th iteration, children[i][0] and children[i][1] are merged to form node n_samples + i
for i, merge in enumerate(hclust.children_):
    # track the number of observations in the current cluster being formed
    current_count = 0
    for child_idx in merge:
        if child_idx < n_samples:
            # If this is True, then we are merging an observation
            current_count += 1  # leaf node
        else:
            # Otherwise, we are merging a previously formed cluster
            current_count += counts[child_idx - n_samples]
    counts[i] = current_count

# the hclust.children_ is used to indicate the two points/clusters being merged (dendrogram's u-joins)
# the hclust.distances_ indicates the distance between the two points/clusters (height of the u-joins)
# the counts indicate the number of points being merged (dendrogram's x-axis)
linkage_matrix = np.column_stack(
    [hclust.children_, hclust.distances_, counts]
).astype(float)

# Plot the corresponding dendrogram
sns.set()
fig = plt.figure(figsize=(11,5))
# The Dendrogram parameters need to be tuned
y_threshold = 28
dendrogram(linkage_matrix, truncate_mode='level', p=5, color_threshold=y_threshold, above_threshold_color='k')
plt.hlines(y_threshold, 0, 1000, colors="r", linestyles="dashed")
plt.title(f'Hierarchical Clustering - {linkage.title()}\'s Dendrogram', fontsize=21)
plt.xlabel('Number of points in node (or index of point if no parenthesis)')
plt.ylabel(f'{distance.title()} Distance', fontsize=13)
plt.show()
```



3.3. DBSCAN

In [31]:

```
# K-distance graph to find out the right eps value
# neighbors 6 since we have 3 dimensions
neigh = NearestNeighbors(n_neighbors=6)
neigh.fit(pca_num)
distances, _ = neigh.kneighbors(pca_num)
distances = np.sort(distances[:, -1])

fig = plt.figure(figsize=(12,6))
plt.title("K-distance Graph", fontsize=21)
plt.plot(distances)
plt.show()
```



In [32]:

```
# Perform DBSCAN clustering
dbscan = DBSCAN(eps=0.08, min_samples=6, n_jobs=4)
dbscan_labels = dbscan.fit_predict(pca_num)

dbscan_n_clusters = len(np.unique(dbscan_labels))
print("Number of estimated clusters : %d" % dbscan_n_clusters)
```

```
Number of estimated clusters : 3
```

In [33]:

```
scan_concat = pd.concat([pca_num, pd.Series(dbscan_labels, index=df.index, name="labels")], axis=1)
scan_concat.labels.value_counts()
```

Out[33]:

```
 0    9645
-1     350
 1       5
Name: labels, dtype: int64
```

3.3.1. Evaluating DBSCAN

In [34]:

```
sst = get_ss(scan_concat.drop(columns=["labels"]))  # get total sum of squares
ssw_labels = scan_concat.groupby(by='labels').apply(get_ss)  # compute ssw for each cluster labels
ssb = sst - np.sum(ssw_labels)
r2 = ssb / sst
print("R^2 DBSCAN:", r2)
```

```
R^2 DBSCAN: 0.0029506384462175688
```

After running the DBSCAN with the predefined number of neighbors on the dataset it estimated 2 clusters, one of which only representing the outliers, with a resulting R-squared of 0.3%. DBSCAN isn't the model to go with in this project. This makes sense if we take a glimpse at the TSNE Chart plotted above.

3.4. Comparing Clusterers

In [35]:

```
def get_ss(df):
    """Computes the sum of squares for all variables given a dataset
    """
    ss = np.sum(df.var() * (df.count() - 1))
    return ss  # return sum of sum of squares of each df variable

def r2(df, labels):
    sst = get_ss(df)
    ssw = np.sum(df.groupby(labels).apply(get_ss))
    return 1 - ssw/sst

def get_r2_scores(df, clusterer, min_k=2, max_k=10):
    """
    Loop over different values of k. To be used with sklearn clusterers.
    """
    r2_clust = {}
    for n in range(min_k, max_k):
        clust = clone(clusterer).set_params(n_clusters=n)
        labels = clust.fit_predict(df)
        r2_clust[n] = r2(df, labels)
    return r2_clust
```

In [36]:

```
hierarchical = AgglomerativeClustering(
    affinity='euclidean')
```

In [37]:

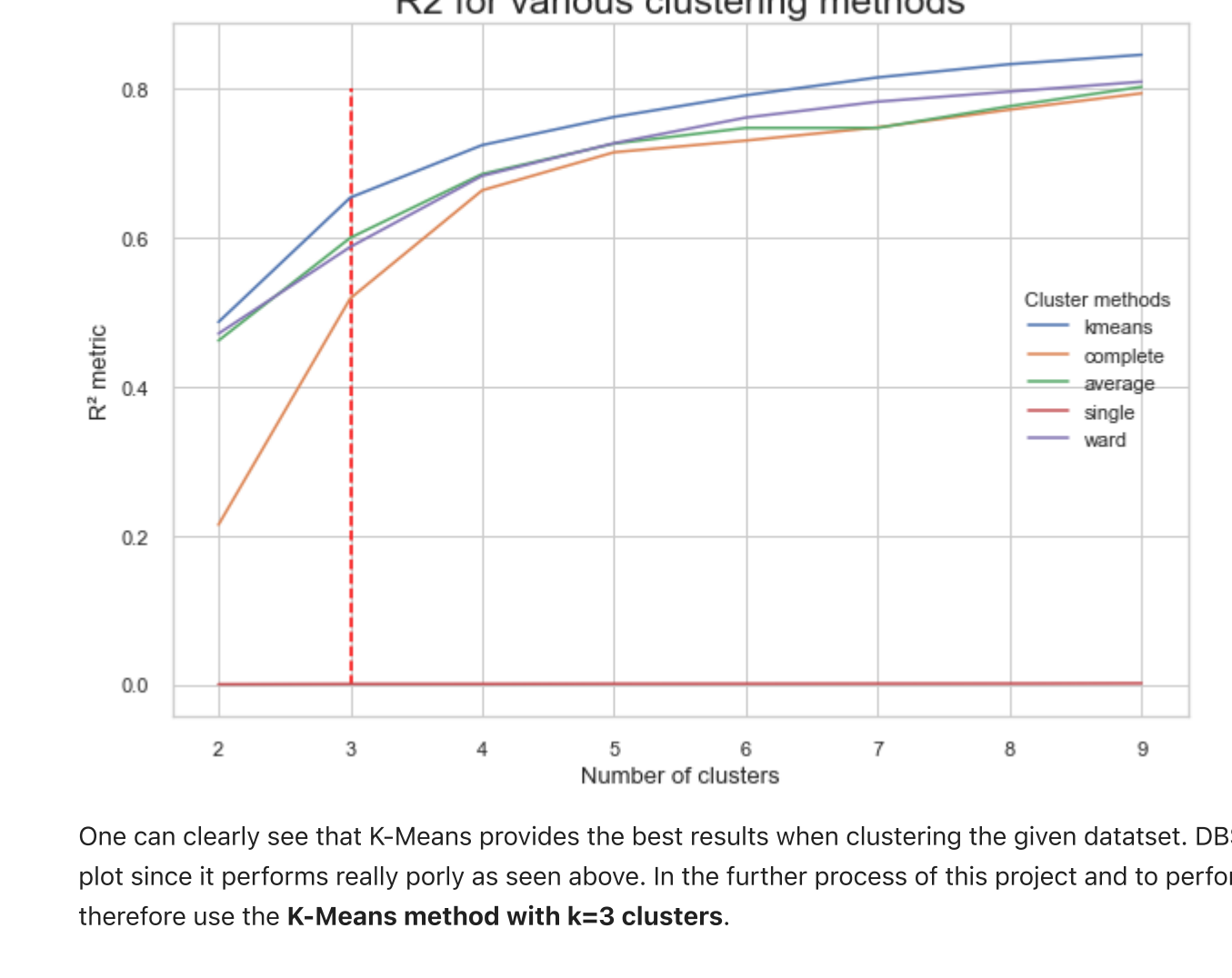
```
r2_scores = {}
r2_scores['kmeans'] = get_r2_scores(pca_num, kmclust)

for linkage in ['complete', 'average', 'single', 'ward']:
    r2_scores[linkage] = get_r2_scores(
        pca_num, hierarchical.set_params(linkage=linkage)
    )

pd.DataFrame(r2_scores)
```

Out[37]:

	kmeans	complete	average	single	ward
2	0.486901	0.214334	0.461985	0.000087	0.471378
3	0.654337	0.518873	0.600254	0.000483	0.588041
4	0.724879	0.664110	0.685985	0.000536	0.683515
5	0.762721	0.715235	0.726831	0.000778	0.727450
6	0.791865	0.730988	0.747939	0.000846	0.761872
7	0.815845	0.748666	0.748005	0.000977	0.783266
8	0.833632	0.772507	0.777162	0.001080	0.796798
9	0.846281	0.794466	0.803161	0.001377	0.810072

In [38]:

```
# Visualizing the R² scores for each cluster solution on demographic variables
sns.set_style("whitegrid")
pd.DataFrame(r2_scores).plot.line(figsize=(10,7))

plt.title("R2 for various clustering methods", fontsize=21)
plt.legend(title="Cluster methods", title_fontsize=11, loc=7)
plt.xlabel("Number of clusters", fontsize=13)
plt.ylabel("R² metric", fontsize=13)
plt.vlines(x=3, ymin=0, ymax=0.8, linestyles="dashed", colors="red")


plt.savefig("R2_clusterer.pdf")
plt.show()
```



One can clearly see that K-Means provides the best results when clustering the given datatset. DBSCAN isn't represented in this plot since it performs really porly as seen above. In the further process of this project and to perform the cluster analysis we will therefore use the **K-Means method with k=3 clusters**.

4. Cluster Analysis

4.1. Assess Feature Importance

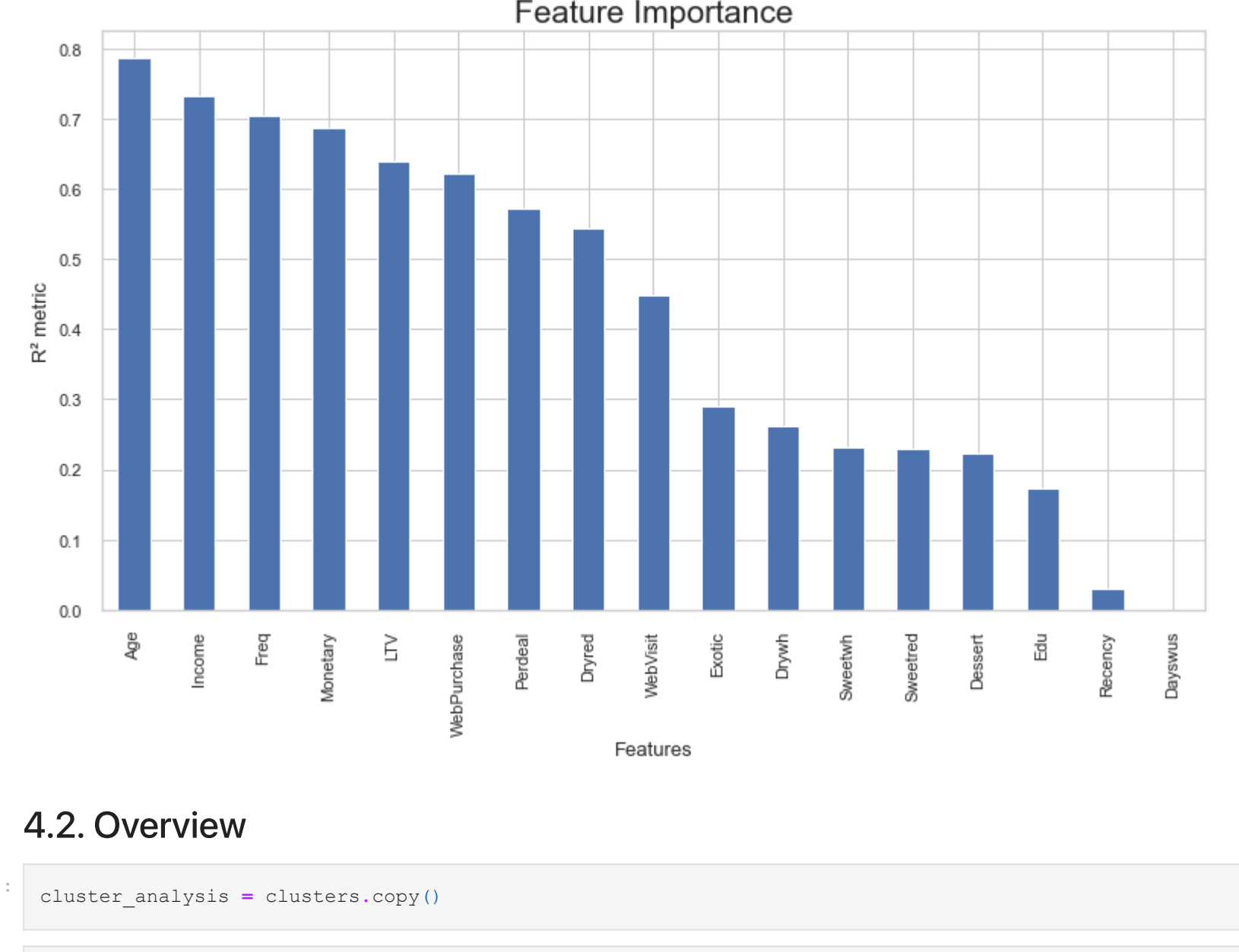
In [39]:

```
def get_ss_variables(df):
```

```
    """Get the SS for each variable
    """
    ss_vars = df.var() * (df.count() - 1)
    return ss_vars

def r2_variables(df, labels):
    """Get the R² for each variable
    """
    sst_vars = get_ss_variables(df)
    ssw_vars = np.sum(df.groupby(labels).apply(get_ss_variables))
    return 1 - ssw_vars/sst_vars
```

In [40]:

```
feature_importance = pd.concat((df_scaled, pd.Series(km_labels, name='labels')), axis=1)
feature_importance = r2_variables(feature_importance, "labels").sort_values(ascending=False).drop(["labels"])
feature_importance.to_frame().plot.bar(figsize=(13,7))
plt.title("Feature Importance", fontsize=21)
plt.legend().remove()
plt.xlabel("Features", fontsize=13)
plt.ylabel("R² metric", fontsize=13)
plt.show()
```



4.2. Overview

In [41]:

```
cluster_analysis = clusters.copy()
```

In [42]:

```
# replace cluster labels from 0 to 1, 1 to 2 and 2 to 3
cluster_analysis["labels"] = cluster_analysis.labels + 1
```

In [43]:

```
cluster_analysis.labels.value_counts()
```

Out[43]:

```
3    3536
2    3494
1    2970
Name: labels, dtype: int64
```

In [44]:

```
cluster_means = cluster_analysis.groupby("labels").mean()
cluster_means
```

Out[44]:

labels	Dayswus	Age	Edu	Income	Freq	Recency	Monetary	LTV	Perdeal	Dryred
1	896.751852	28.642761	15.635354	40350.769360	4.088215	80.229966	88.813468	1.044781	57.322559	29.408081
2	904.352604	66.675730	16.835146	98907.273612	27.896394	50.057813	1338.967945	525.390956	5.685461	46.499141
3	893.059672	45.599265	17.571267	66068.942590	10.370192	59.638857	362.958710	71.236708	37.856052	71.837387

In [45]:

```
cluster_means = cluster_means.append(df_before.mean(), ignore_index=True)
cluster_means["Cluster"] = ["Cluster 1", "Cluster 2", "Cluster 3", "Average"]
```

In [46]:

```
#ceil(len(features) / 3
fig, axes = plt.subplots(5, ceil(len(features) / 3), figsize=(21, 17))

metric_features = df_before.columns.to_list()
for ax, feat in zip(axes.flatten(), metric_features):
    sns.barplot(x="Cluster", y = feat, data=cluster_means.sort_values(feat, ascending=False),
                palette=["cornflowerblue" if x!='Average' else 'navy' for x in cluster_means.sort_values(
                feat, ascending=False).Cluster],
                ax=ax).set(xlabel='')
    sns.despine(right=True)

#title = "Cluster Comparison to Mean of Feature"
#plt.suptitle(title)

# Rotating X-axis labels
axes.flatten()[0].tick_params(axis='x', labelrotation = 90)
#axes.flatten()[1].tick_params(axis='x', labelrotation = 90)
axes.flatten()[2].tick_params(axis='x', labelrotation = 90)
plt.subplots_adjust(wspace=0.3, hspace=0.7)

plt.show()
```

4.3. Socio-Demographic Perspective

In [47]:

```
child = df['Child']
socio_demo = cluster_analysis.copy()
socio_demo = socio_demo.merge(child, how='outer', left_index=True, right_index=True)
socio_demo = socio_demo.groupby("labels").agg({"labels": "count",
                                 "Age": "mean",
                                 "Income": "mean",
                                 "Edu": "mean",
                                 "WebPurchase": "mean",
                                 "WebVisit": "mean",
                                 "Child": "mean" # non metric feature, but appended to table for comparison
                                 })

socio_demo
```

Out[47]:

labels	labels	Age	Income	Edu	WebPurchase	WebVisit	Child
1	2970	28.642761	40350.769360	15.635354	56.844444	6.687542	0.865993
2	3494	66.675730	98907.273612	16.835146	22.848598	3.117630	0.337722
3	3536	45.599265	66068.942590	17.571267	49.519514	6.055147	0.933824

In [48]:

```
# 1: young, lowest lifetime value, purchase web
# 2: really old, no webseacrh, almost no webpurchase, og, highest income, CASH COW (LTV)
# 3: 40-50, 2nd highest income - mittel zwischen den bei

# 1 und 3 have kids at home
```

In [49]:

```
# scaling data for visualization
scaled_w_clusters = pd.concat((df_scaled, pd.Series(km_labels, name='labels')), axis=1)
scaled_w_clusters["labels"] = scaled_w_clusters.labels + 1
```

In [50]:

```
# scaling data for visualization
socio_dem = scaled_w_clusters.groupby("labels").agg({
                                 "Age": "mean",
                                 "Income": "mean",
                                 "Edu": "mean"})
```

In [51]:

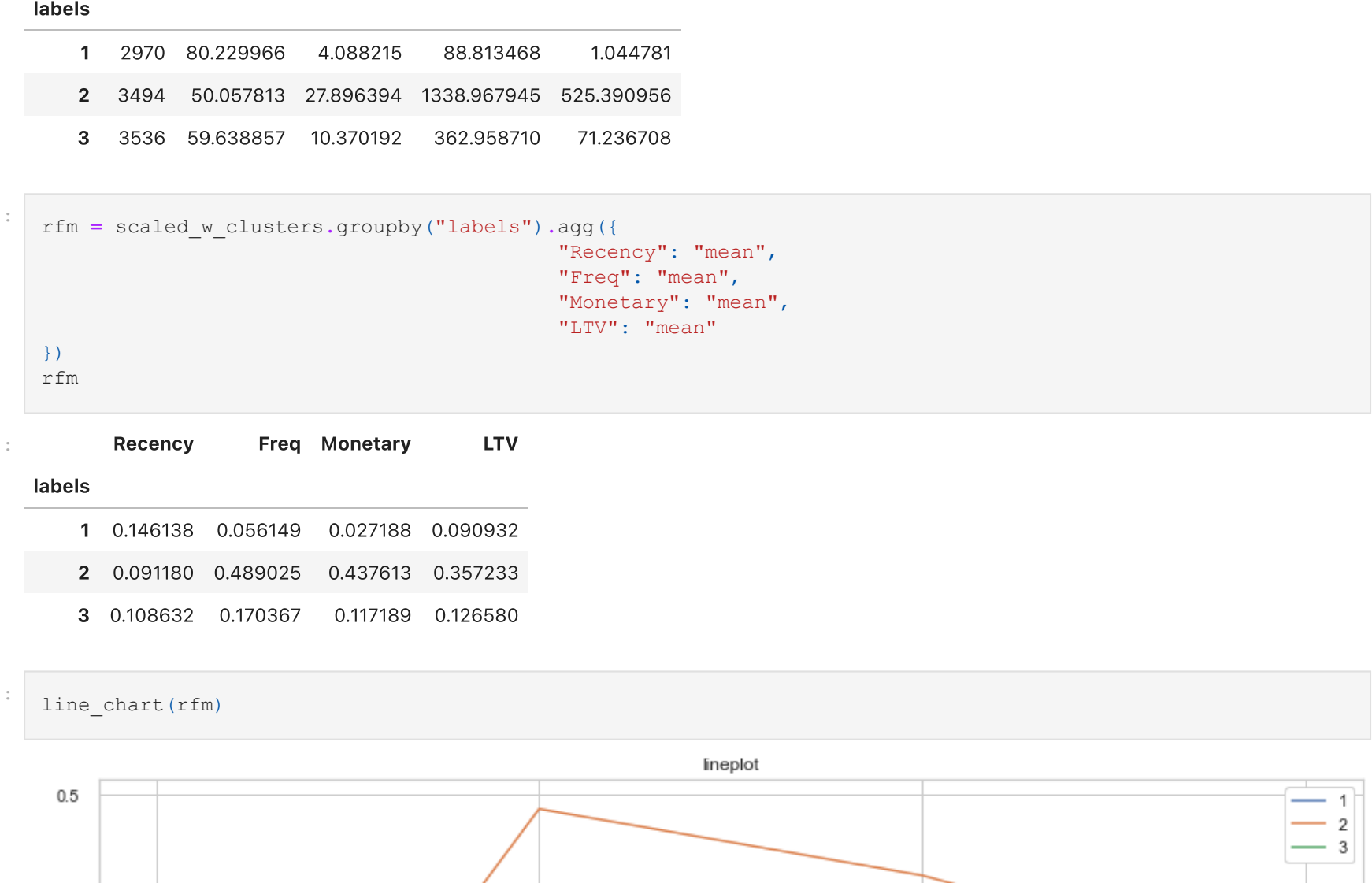
```
def line_chart(df):
    plt.subplots(figsize=(15,8))

    sns.color_palette("Paired")
    sns.lineplot(data=df.T, dashes=False)

    plt.xlabel('Features', fontweight ='bold')
    plt.ylabel('Value', fontweight ='bold')

    plt.title("lineplot")
    plt.legend(framealpha=1, frameon=True)
    plt.show()

def barplot(df):
    df.T.plot(kind="bar", figsize=(15,8))
    plt.show()
```

In [52]:

```
line_chart(socio_dem)
```

In [53]:

```
barplot(socio_dem)
```



4.4. Profitability RFM Perspective

In [54]:

```
rfm_ltv = cluster_analysis.groupby("labels").agg({"labels": "count",
                                 "Recency": "mean",
                                 "Freq": "mean",
                                 "Monetary": "mean",
                                 "LTV": "mean"})

rfm_ltv
```

Out[54]:

labels	labels	Recency	Freq	Monetary	LTV
1	2970	80.229966	4.088215	88.813468	1.044781
2	3494	50.057813	27.896394	1338.967945	525.390956
3	3536	59.638857	10.370192	362.958710	71.236708

In [55]:

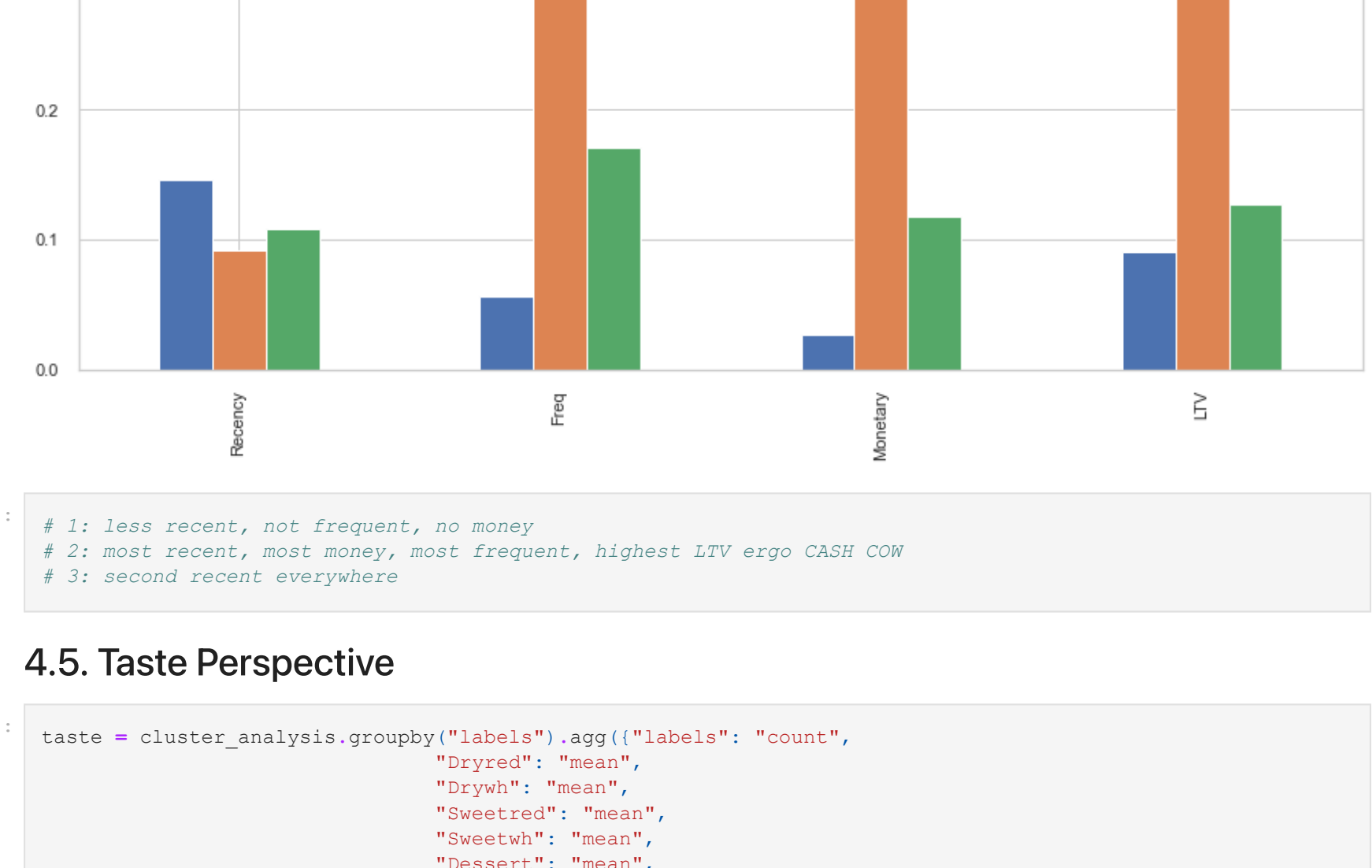
```
rfm = scaled_w_clusters.groupby("labels").agg({
                                 "Recency": "mean",
                                 "Freq": "mean",
                                 "Monetary": "mean",
                                 "LTV": "mean"
})
rfm
```

Out[55]:

labels	Recency	Freq	Monetary	LTV
1	0.146138	0.056149	0.027188	0.090932
2	0.091180	0.489025	0.437613	0.357233
3	0.108632	0.170367	0.117189	0.126580

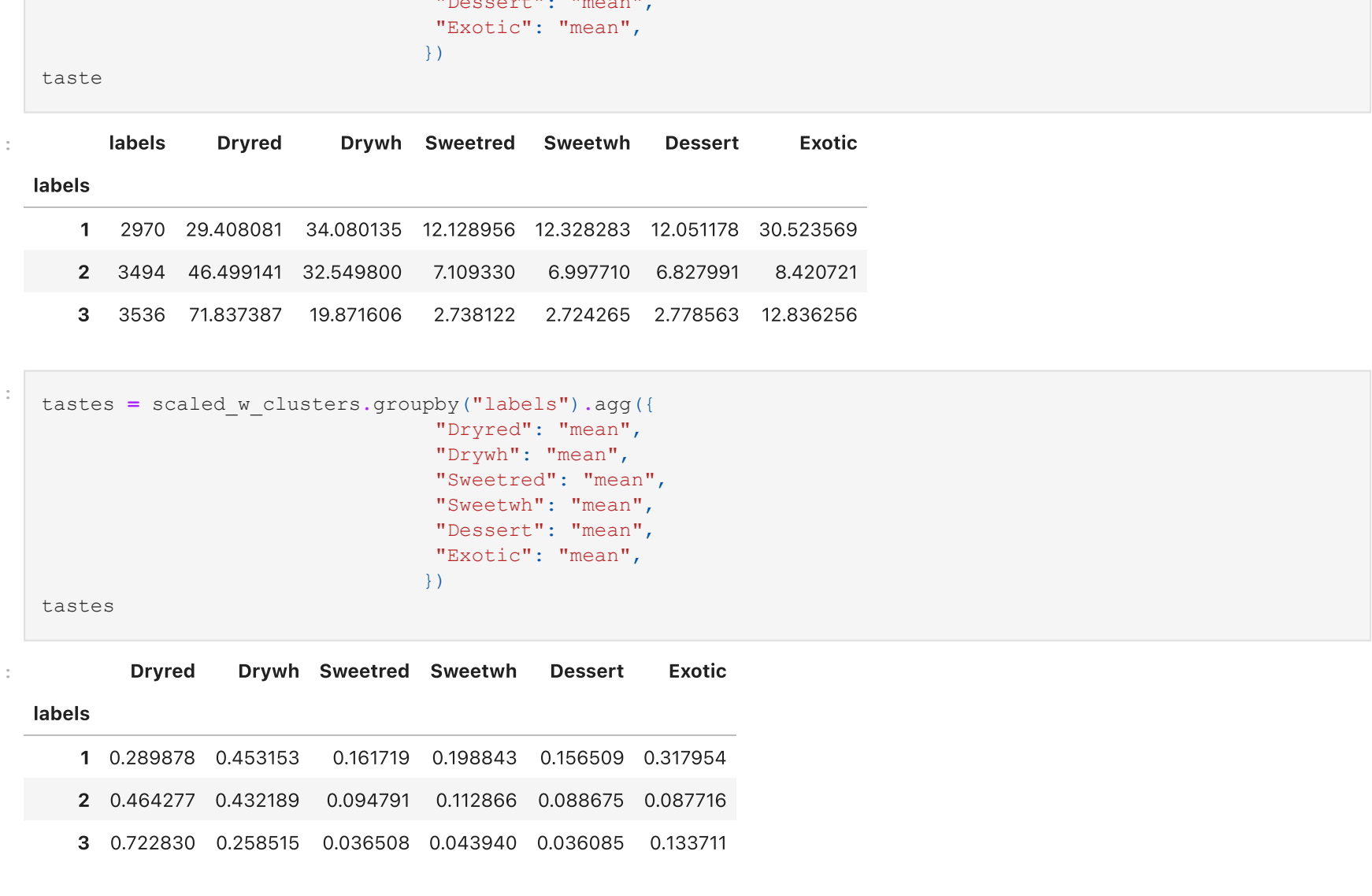
In [56]:

```
line_chart(rfm)
```



In [57]:

```
barplot(rfm)
```



In [58]:

```
# 1: less recent, not frequent, no money
# 2: most recent, most money, most frequent, highest LTV ergo CASH COW
# 3: second recent everywhere
```

4.5. Taste Perspective

In [59]:

```
taste = cluster_analysis.groupby("labels").agg({"labels": "count",
                                 "Dryred": "mean",
                                 "Drywh": "mean",
                                 "Sweetred": "mean",
                                 "Sweetwh": "mean",
                                 "Dessert": "mean",
                                 "Exotic": "mean",
                                 })
taste
```

Out[59]:

labels	labels	Dryred	Drywh	Sweetred	Sweetwh	Dessert	Exotic
1	2970	29.408081	34.080135	12.128956	12.328283	12.051178	30.523569
2	3494	46.499141	32.549800	7.109330	6.997710	6.827991	8.420721
3	3536	71.837387	19.871606	2.736263	2.724265	2.778563	12.636256

In [60]:

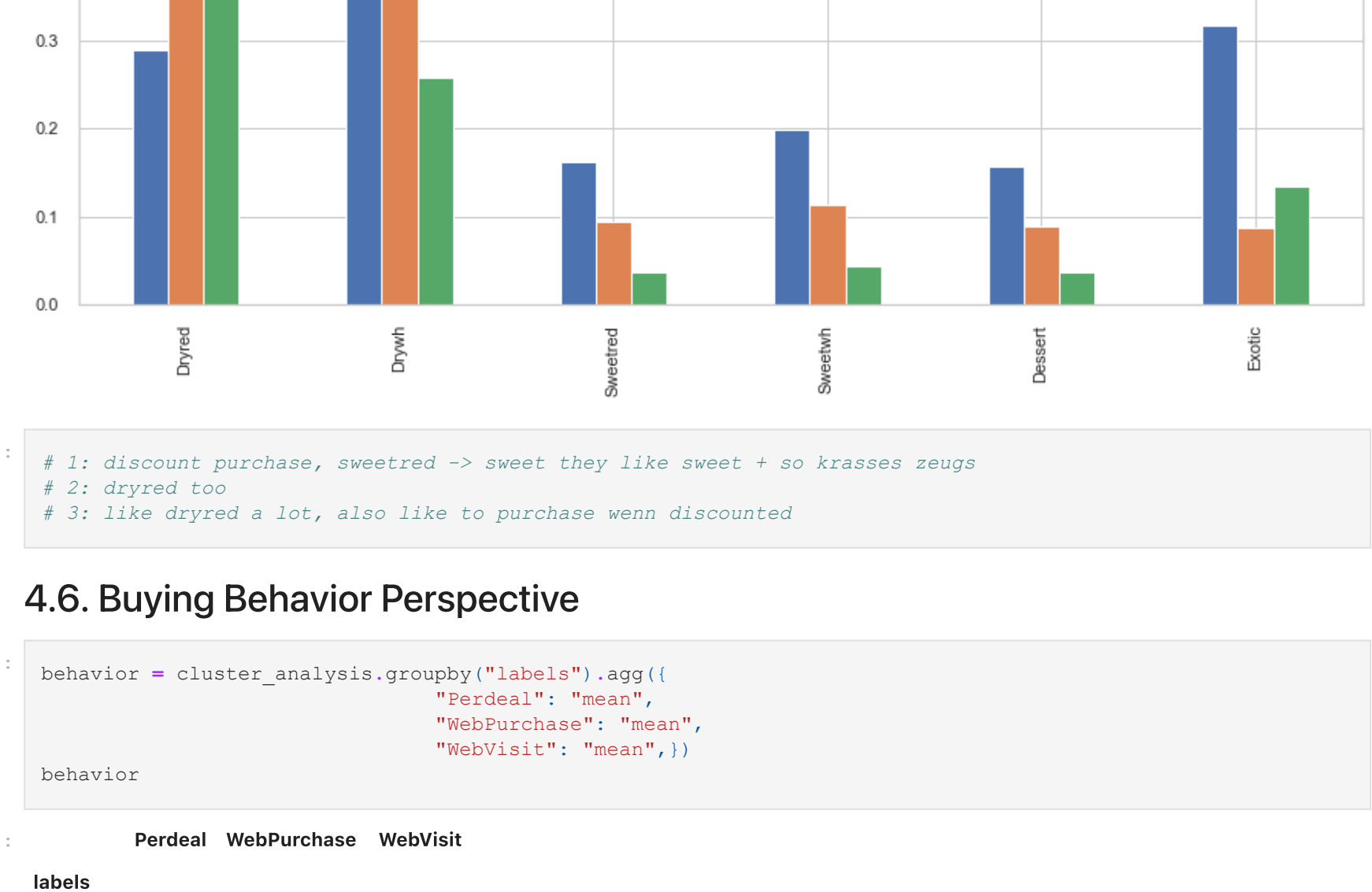
```
tastes = scaled_w_clusters.groupby("labels").agg({
                                 "Dryred": "mean",
                                 "Drywh": "mean",
                                 "Sweetred": "mean",
                                 "Sweetwh": "mean",
                                 "Dessert": "mean",
                                 "Exotic": "mean",
                                 })
tastes
```

Out[60]:

labels	Dryred	Drywh	Sweetred	Sweetwh	Dessert	Exotic
1	0.289878	0.453153	0.161719	0.168843	0.156509	0.317954
2	0.464277	0.432189	0.094791	0.112866	0.088675	0.087716
3	0.722630	0.258515	0.036508	0.043940	0.036085	0.133711

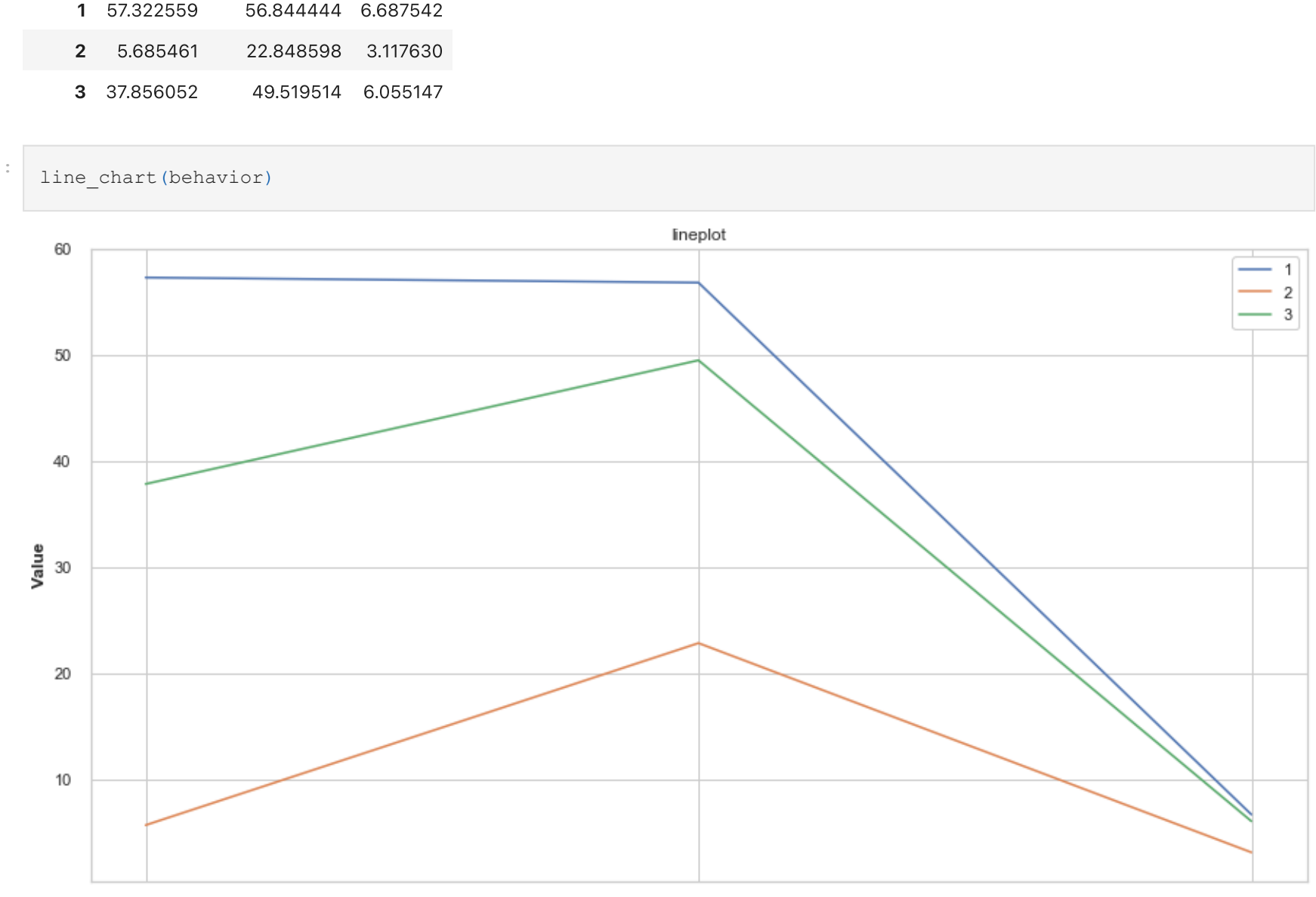
In [61]:

```
line_chart(tastes)
```



In [62]:

```
barplot(tastes)
```



In [63]:

```
# 1: discount purchase, sweetred -> sweet they like sweet + no krassen zeugs
# 2: dryred too
# 3: like dryred a lot, also like to purchase wenn discounted
```

4.6. Buying Behavior Perspective

In [64]:

```
behavior = cluster_analysis.groupby("labels").agg({
                                 "Perdeal": "mean",
                                 "WebPurchase": "mean",
                                 "WebVisit": "mean",})
behavior
```

Out[64]:

labels	Perdeal	WebPurchase	WebVisit
1	57.322559	56.844444	6.687542
2	5.685461	22.848598	3.117630
3	37.856052	49.519514	6.055147

In [65]:

```
line_chart(behavior)
```

In [66]:

```
barplot(behavior)
```


In [67]:

```
# 1: young buyers taht purchase online and like to shop on discount
# 2: dont shop online
# 3: same as cluster 1
```