Context

AllLife Bank wants to focus on its credit card customer base in the next financial year. They have been advised by their marketing research team, that the penetration in the market can be improved. Based on this input, the Marketing team proposes to run personalized campaigns to target new customers as well as upsell to existing customers. Another insight from the market research was that the customers perceive the support services of the back poorly. Based on this, the Operations team wants to upgrade the service delivery model, to ensure that customer queries are resolved faster. Head of Marketing and Head of Delivery both decide to reach out to the Data Science team for help

Objective

To identify different segments in the existing customer, based on their spending patterns as well as past interaction with the bank, using clustering algorithms, and provide recommendations to the bank on how to better market to and service these customers.

Data Description

The data provided is of various customers of a bank and their financial attributes like credit limit, the total number of credit cards the customer has, and different channels through which customers have contacted the bank for any queries (including visiting the bank, online and through a call center).

Data Dictionary

- Sl_No: Primary key of the records
- Customer Key: Customer identification number
- Average Credit Limit: Average credit limit of each customer for all credit cards
- Total credit cards: Total number of credit cards possessed by the customer
- Total visits bank: Total number of Visits that customer made (yearly) personally to the bank
- Total visits online: Total number of visits or online logins made by the customer (yearly)
- Total calls made: Total number of calls made by the customer to the bank or its customer service department (yearly)

Coding

Importing necessary libraries

In [1]:

```
# this will help in making the Python code more structured automatically (good coding practice)
%load_ext nb_black

# Libraries to help with reading and manipulating data
import pandas as pd
import numpy as np

# libaries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Removes the limit for the number of displayed columns
pd.set_option("display.max_columns", None)
# Sets the limit for the number of displayed rows
pd.set_option("display.max_rows", 200)

# to scale the data using z-score
from sklearn.preprocessing import StandardScaler

# to compute distances
from scipy.spatial.distance import cdist, pdist

# to perform k-means clustering and compute silhouette scores
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# to visualize the elbow curve and silhouette scores
from yellowbrick.cluster import KElbowVisualizer, SilhouetteVisualizer

# to perform hierarchical clustering, compute cophenetic correlation, and create dendrograms
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage, cophenet
```

In [2]:

```
# loading the dataset
data = pd.read_excel("Credit Card Customer Data.xlsx")
```

In [3]:
```python
data.shape
```

Out[3]:
```
(660, 7)
```

- The dataset has 660 rows and 7 columns

In [4]:
```python
# viewing the first 5 rows of the data
data.head()
```

Out[4]:

	Sl_No	Customer Key	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
0	1	87073	100000	2	1	1	0
1	2	38414	50000	3	0	10	9
2	3	17341	50000	7	1	3	4
3	4	40496	30000	5	1	1	4
4	5	47437	100000	6	0	12	3

In [5]:
```python
# copying the data to another variable to avoid any changes to original data
df = data.copy()
```

In [6]:
```python
# fixing column names
df.columns = [c.replace(" ", "_") for c in df.columns]
```

In [7]:
```python
# checking datatypes and number of non-null values for each column
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 660 entries, 0 to 659
Data columns (total 7 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Sl_No                660 non-null    int64
 1   Customer_Key         660 non-null    int64
 2   Avg_Credit_Limit     660 non-null    int64
 3   Total_Credit_Cards   660 non-null    int64
 4   Total_visits_bank    660 non-null    int64
 5   Total_visits_online  660 non-null    int64
 6   Total_calls_made     660 non-null    int64
dtypes: int64(7)
memory usage: 36.2 KB
```

- All the columns in the data are numeric.

In [8]:
```python
# checking for missing values
df.isnull().sum()
```

Out[8]:
```
Sl_No                  0
Customer_Key           0
Avg_Credit_Limit       0
Total_Credit_Cards     0
Total_visits_bank      0
Total_visits_online    0
Total_calls_made       0
dtype: int64
```

- There are no missing values in the data

- There are no missing values in the data.

In [9]:
```
# checking the number of unique values in each column
data.nunique()
```

Out[9]:
```
Sl_No                  660
Customer Key           655
Avg_Credit_Limit       110
Total_Credit_Cards      10
Total_visits_bank        6
Total_visits_online     16
Total_calls_made        11
dtype: int64
```

- There are less unique values in the *Customer_Key* column than the number of observations in the data. This means that there are duplicate values in the column.

Let's look at the duplicate values in the *Customer_Key* column closely.

In [10]:
```
# getting the count for each unique value in Customer_Key
data_grouped = df.groupby("Customer_Key").count()

for i in data_grouped.loc[data_grouped.Sl_No >= 2].index:
    display(data.loc[df.Customer_Key == i])
```

	Sl_No	Customer Key	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
48	49	37252	6000	4	0	2	8
432	433	37252	59000	6	2	1	2

	Sl_No	Customer Key	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
4	5	47437	100000	6	0	12	3
332	333	47437	17000	7	3	1	0

	Sl_No	Customer Key	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
411	412	50706	44000	4	5	0	2
541	542	50706	60000	7	5	2	2

	Sl_No	Customer Key	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
391	392	96929	13000	4	5	0	0
398	399	96929	67000	6	2	2	2

	Sl_No	Customer Key	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made
104	105	97935	17000	2	1	2	10
632	633	97935	187000	7	1	7	0

Observations

- There are 5 duplicate customer entries in the data.
- Most of these duplicates look like customer profile changes.
- There is no need to delete these records as these are actual occurrences at some point in the time.

We will drop the *Sl_No* and *Customer_Key* as they do not add any value to the analysis.

In [11]:
```
df.drop(columns=["Sl_No"], inplace=True)
df.drop(columns=["Customer_Key"], inplace=True)
```

In [12]:
```
# Let's look at the statistical summary of the data
df.describe().T
```

Out[12]:

	count	mean	std	min	25%	50%	75%	max
Avg_Credit_Limit	660.0	34574.242424	37625.487804	3000.0	10000.0	18000.0	48000.0	200000.0
Total_Credit_Cards	660.0	4.706061	2.167835	1.0	3.0	5.0	6.0	10.0
Total_visits_bank	660.0	2.403030	1.631813	0.0	1.0	2.0	4.0	5.0
Total_visits_online	660.0	2.606061	2.935724	0.0	1.0	2.0	4.0	15.0
Total_calls_made	660.0	3.583333	2.865317	0.0	1.0	3.0	5.0	10.0

Observations

- The average credit limit is heavily right-skewed with a median average credit limit of 18000 dollars.
- The total number of credit cards ranges from 1 to 10 and seems to be evenly distributed with a close values of mean and median.
- *Total_visits_bank* is evenly distributed, but there are some customers who have never visited the bank.
- *Total_Visits_online* seems to be right-skewed and there are some customers who never used the online banking services.
- *Total_calls_made* is right-skewed and there are some customers who never preferred to make any calls to the bank

EDA

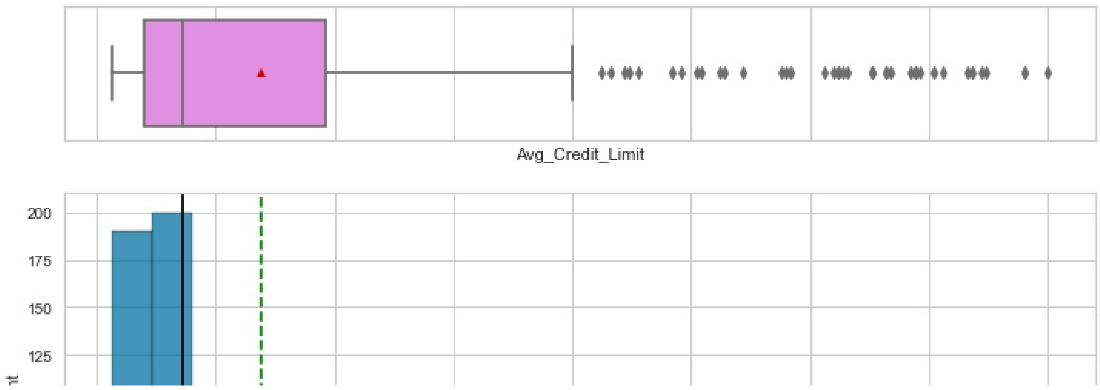
Univariate analysis

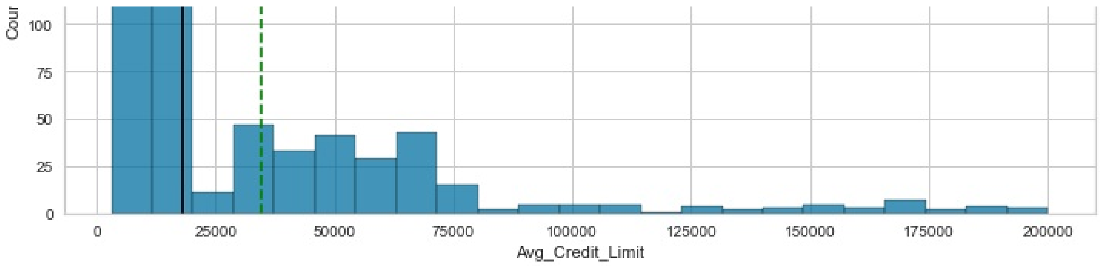
In [13]:

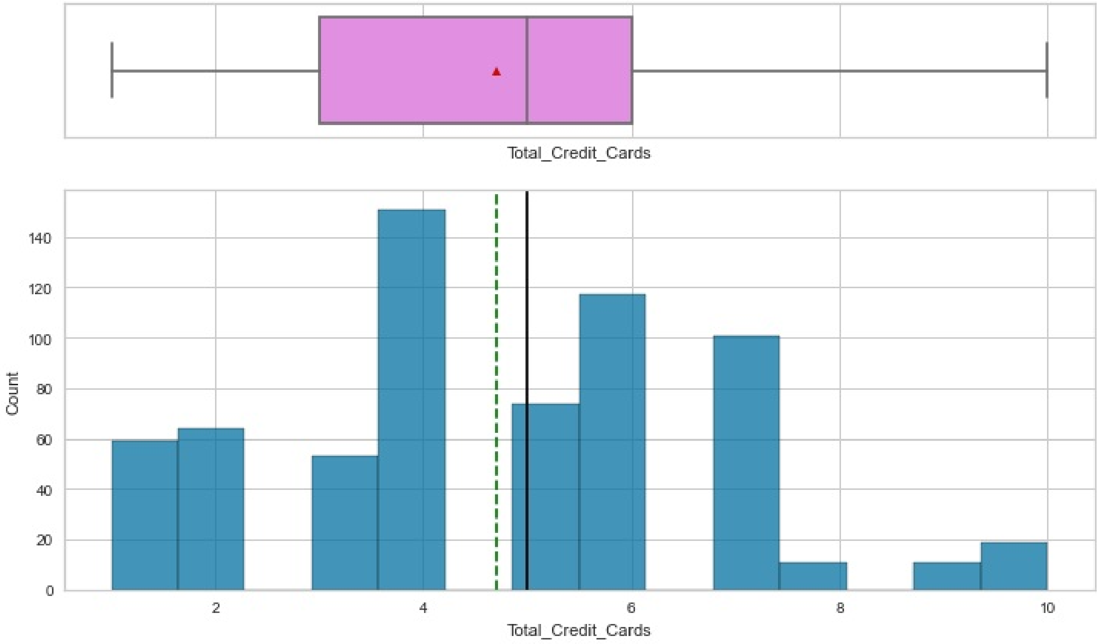
```
# function to plot a boxplot and a histogram along the same scale.


def histogram_boxplot(data, feature, figsize=(12, 7), kde=False, bins=None):
    """
    Boxplot and histogram combined

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (12,7))
    kde: whether to the show density curve (default False)
    bins: number of bins for histogram (default None)
    """
    f2, (ax_box2, ax_hist2) = plt.subplots(
        nrows=2,  # Number of rows of the subplot grid= 2
        sharex=True,  # x-axis will be shared among all subplots
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )  # creating the 2 subplots
    sns.boxplot(
        data=data, x=feature, ax=ax_box2, showmeans=True, color="violet"
    )  # boxplot will be created and a star will indicate the mean value of the column
    sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2, bins=bins, palette="winter"
    ) if bins else sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2
    )  # For histogram
    ax_hist2.axvline(
        data[feature].mean(), color="green", linestyle="--"
    )  # Add mean to the histogram
    ax_hist2.axvline(
        data[feature].median(), color="black", linestyle="-"
    )  # Add median to the histogram
```

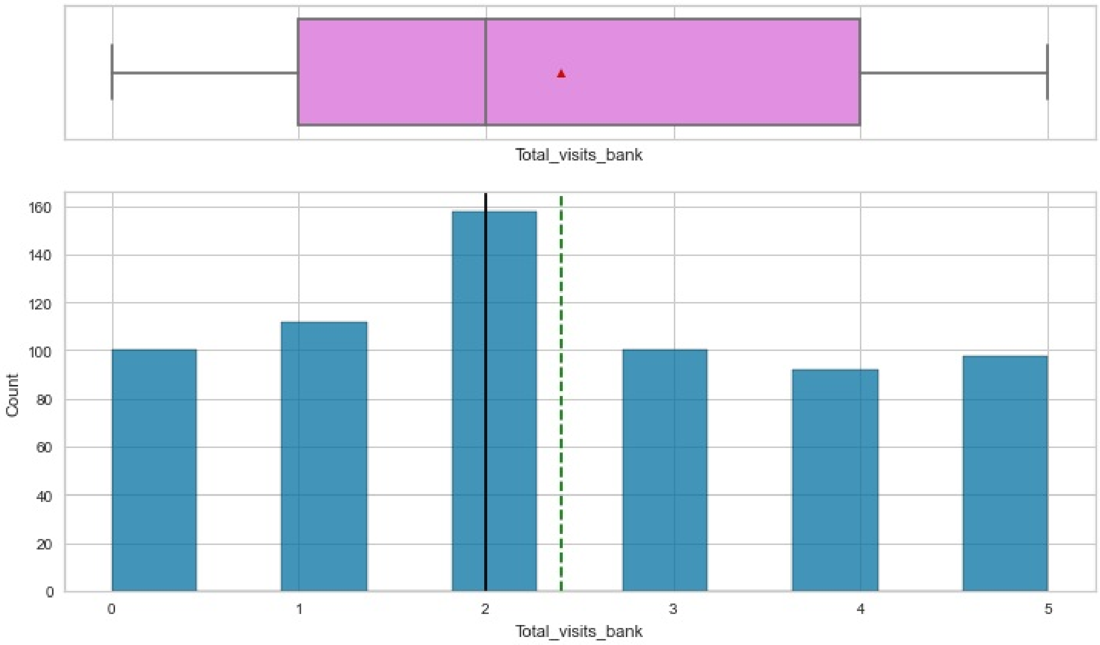
In [14]:

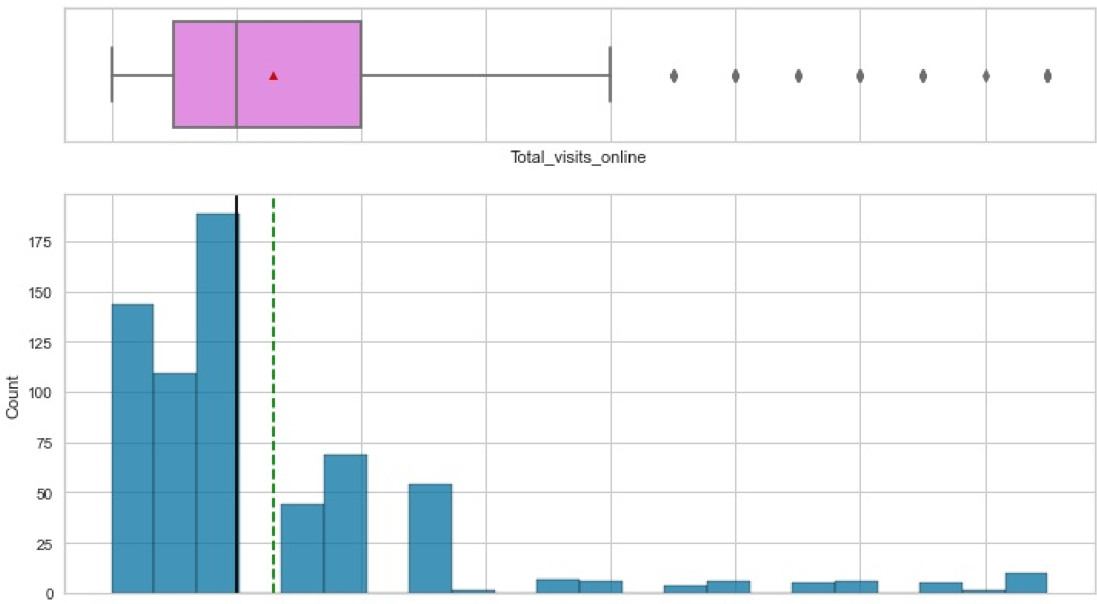
```
for col in df.columns:
    histogram_boxplot(data, col)
```

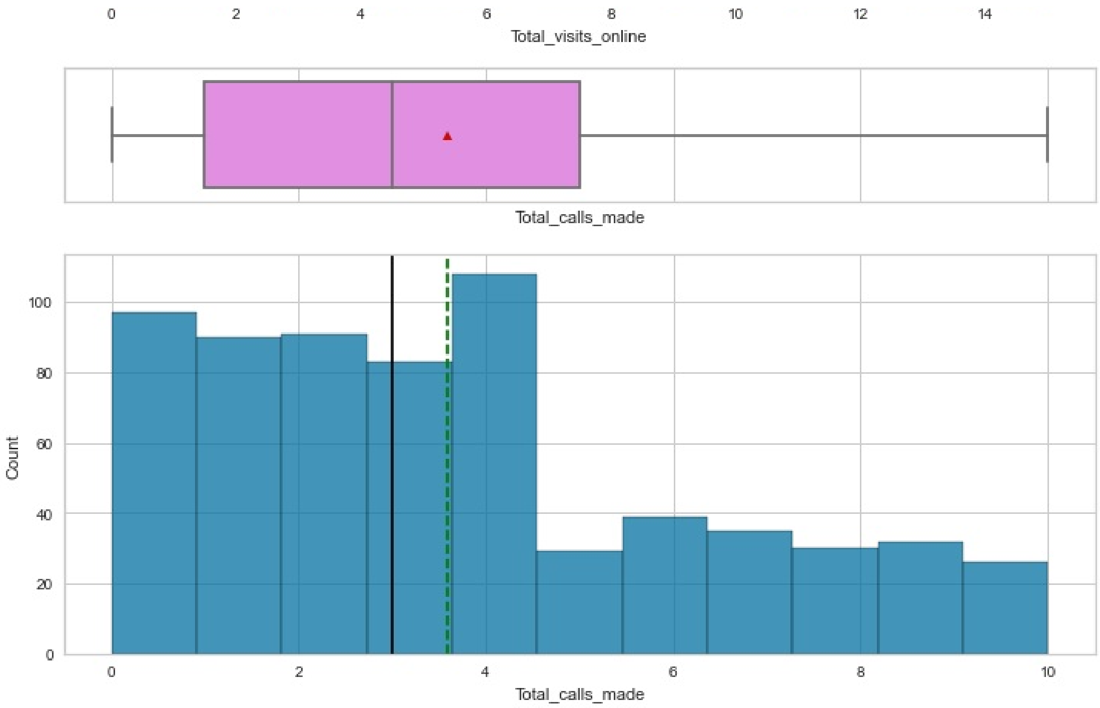



Count
0
25000
50000
75000
100000
125000
150000
175000
200000
Avg_Credit_Limit


Total_Credit_Cards
Count
2
4
6
8
10
Total_Credit_Cards


Total_visits_bank
Count
0
1
2
3
4
5
Total_visits_bank


Total_visits_online
Count



Observations

- There are outliers in the *Average_Credit_limit* column, but all the values are continuous, and the gap between the points is evenly distributed.
- In general, customers visit the bank twice a year, log in to the online portal twice a year, and make 3 calls to the customer service.
- We see some outliers in the Total_visits_online column, indicating that few customers log in to the online portal more frequently than the others.

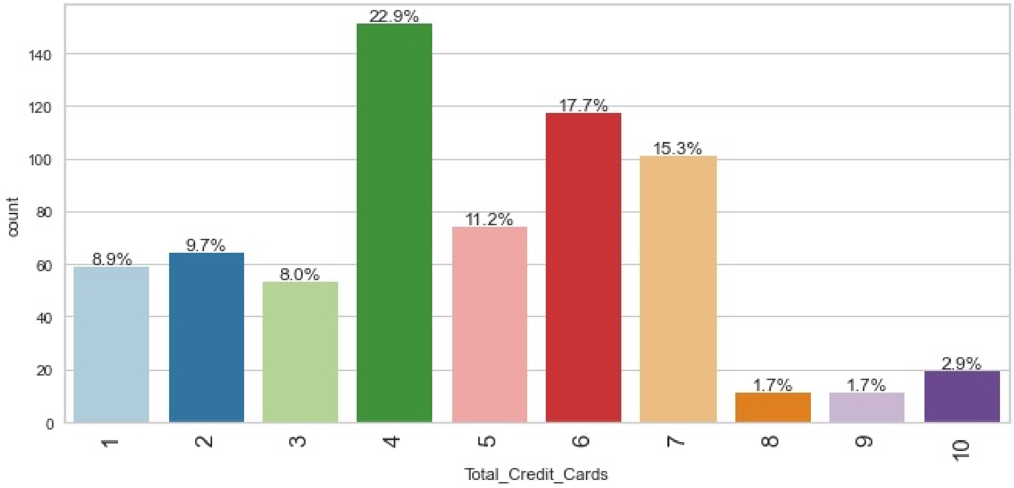
In [15]:

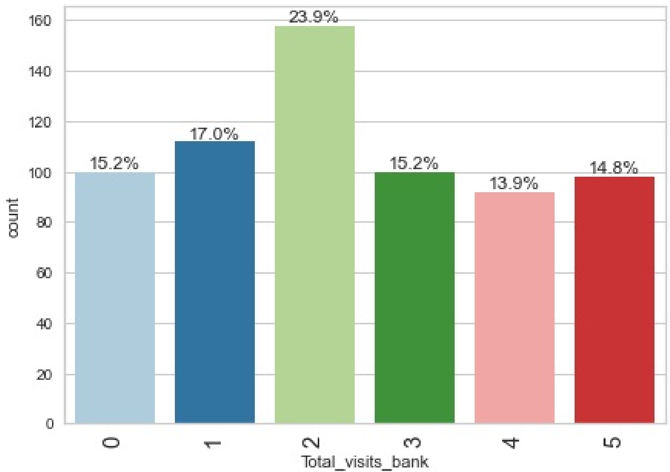
```
# function to create labeled barplots


def labeled_barplot(data, feature, perc=False, n=None):
    """
    Barplot with percentage at the top

    data: dataframe
    feature: dataframe column
    perc: whether to display percentages instead of count (default is False)
    n: displays the top n category levels (default is None, i.e., display all levels)
    """

    total = len(data[feature])  # length of the column
    count = data[feature].nunique()
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

    plt.xticks(rotation=90, fontsize=15)
    ax = sns.countplot(
        data=data,
        x=feature,
        palette="Paired",
        order=data[feature].value_counts().index[:n].sort_values(),
    )

    for p in ax.patches:
        if perc == True:
            label = "{:.1f}%".format(
                100 * p.get_height() / total
            )  # percentage of each class of the category
        else:
            label = p.get_height()  # count of each level of the category

        x = p.get_x() + p.get_width() / 2  # width of the plot
        y = p.get_height()  # height of the plot

        ax.annotate(
            label,
            (x, y),
```

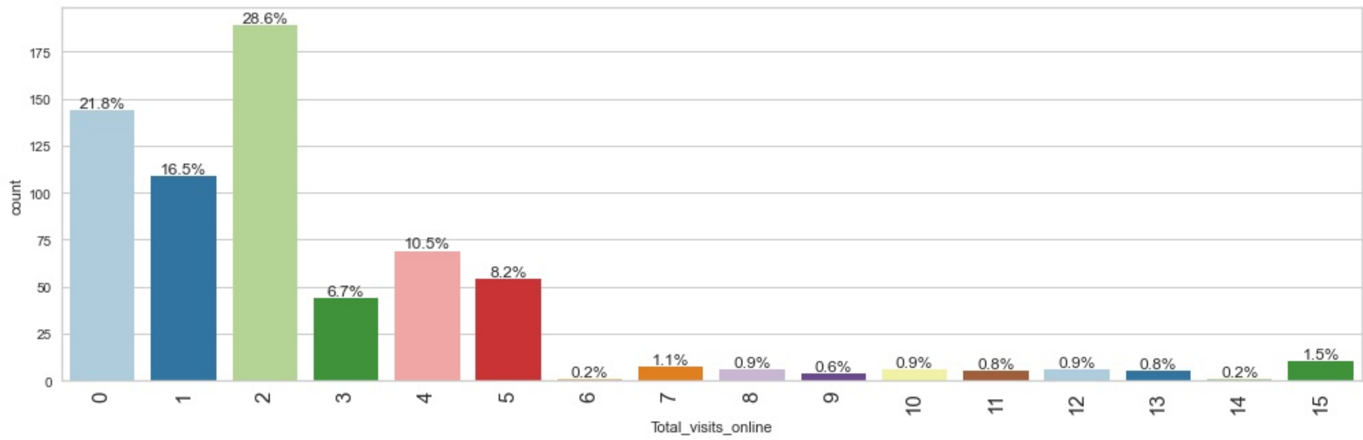
```
            ha="center",
            va="center",
            size=12,
            xytext=(0, 5),
            textcoords="offset points",
        )  # annotate the percentage

    plt.show()  # show the plot
```

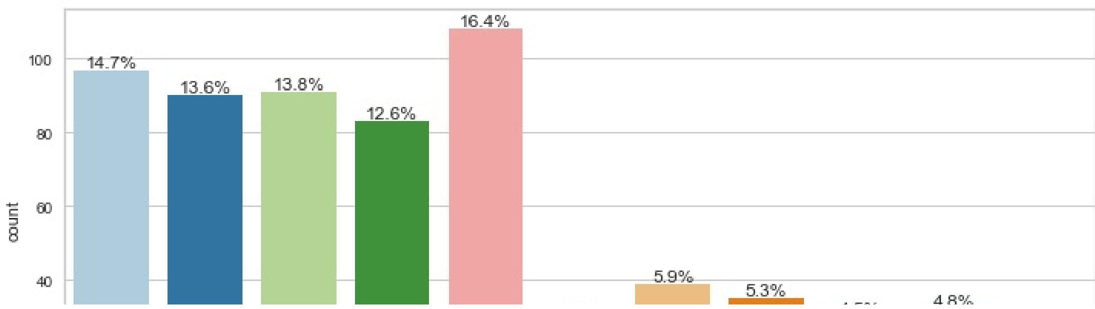
In [16]:

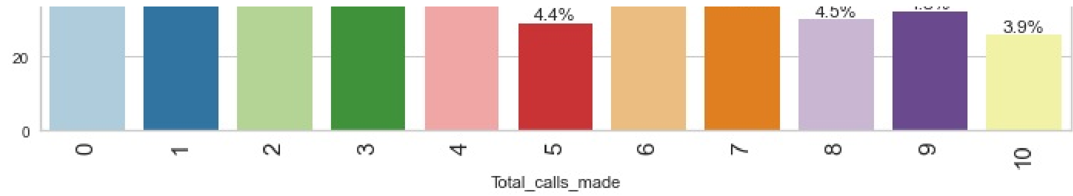
```
for col in df.columns.tolist()[1:]:
    labeled_barplot(df, col, perc=True)
```









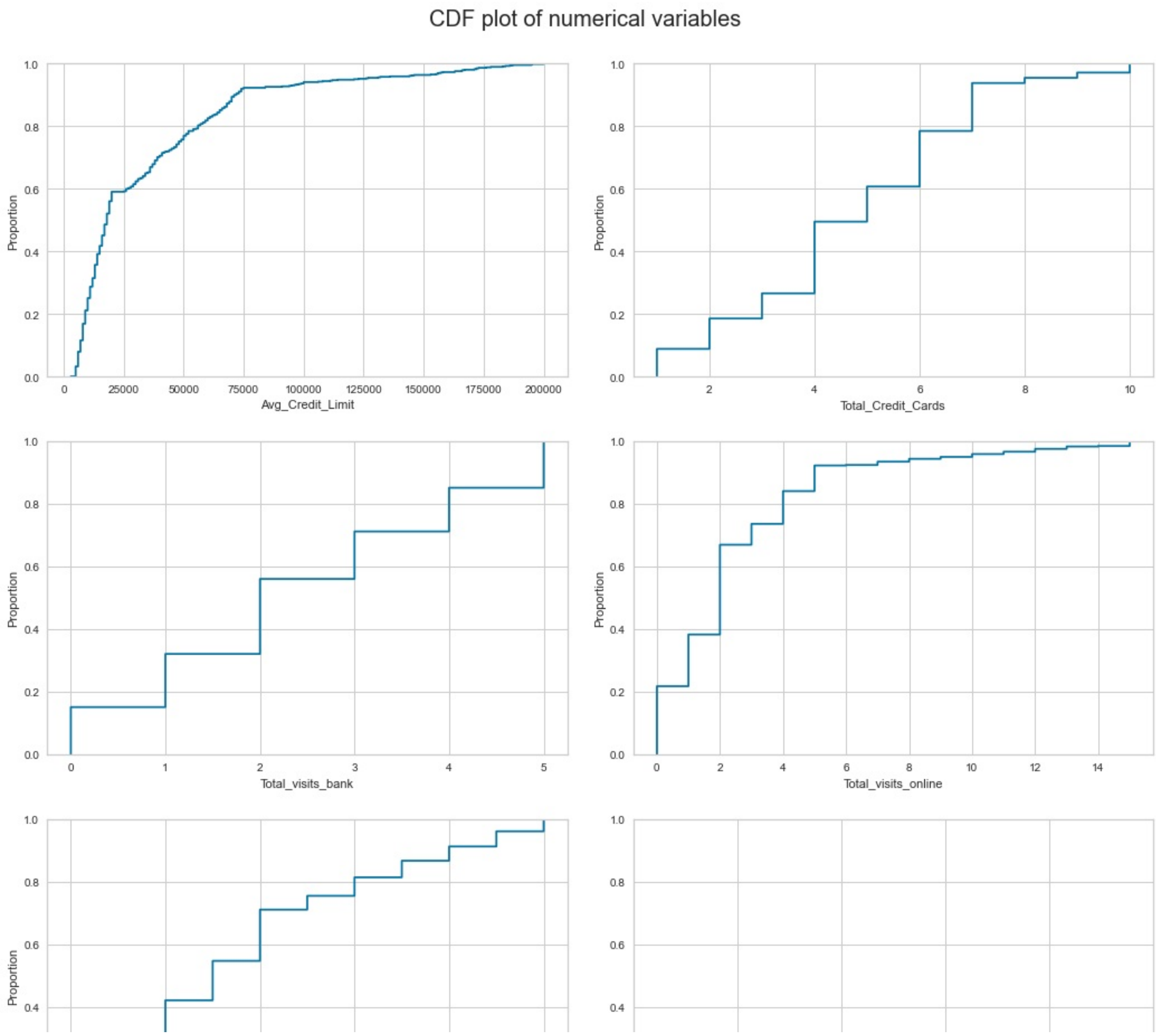


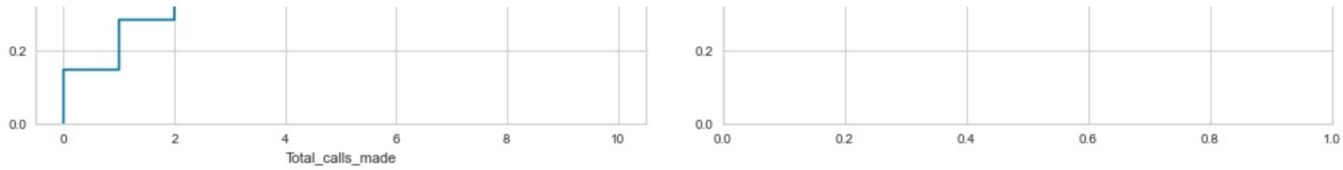
Observations

- Approximately half the customers in the data have 4 or fewer credit cards, and very few customers (approximately 6%) have more than 7 credit cards.
- Approximately 15% of the customers have never visited the bank.
- Approximately 22% of the customers have never logged in to the online portal, while ~7% of the customers used the online banking services more than 6 or more times yearly.
- Approximately 15% of the customers have never made a service-related call to the bank.

In [17]:

```
fig, axes = plt.subplots(3, 2, figsize=(15, 15))
fig.suptitle("CDF plot of numerical variables", fontsize=20)

counter = 0

for ii in range(3):
    sns.ecdfplot(data=df, ax=axes[ii][0], x=df.columns.tolist()[counter])
    counter = counter + 1
    if counter != 5:
        sns.ecdfplot(data=df, ax=axes[ii][1], x=df.columns.tolist()[counter])
        counter = counter + 1
    else:
        pass

fig.tight_layout(pad=2.0)
```





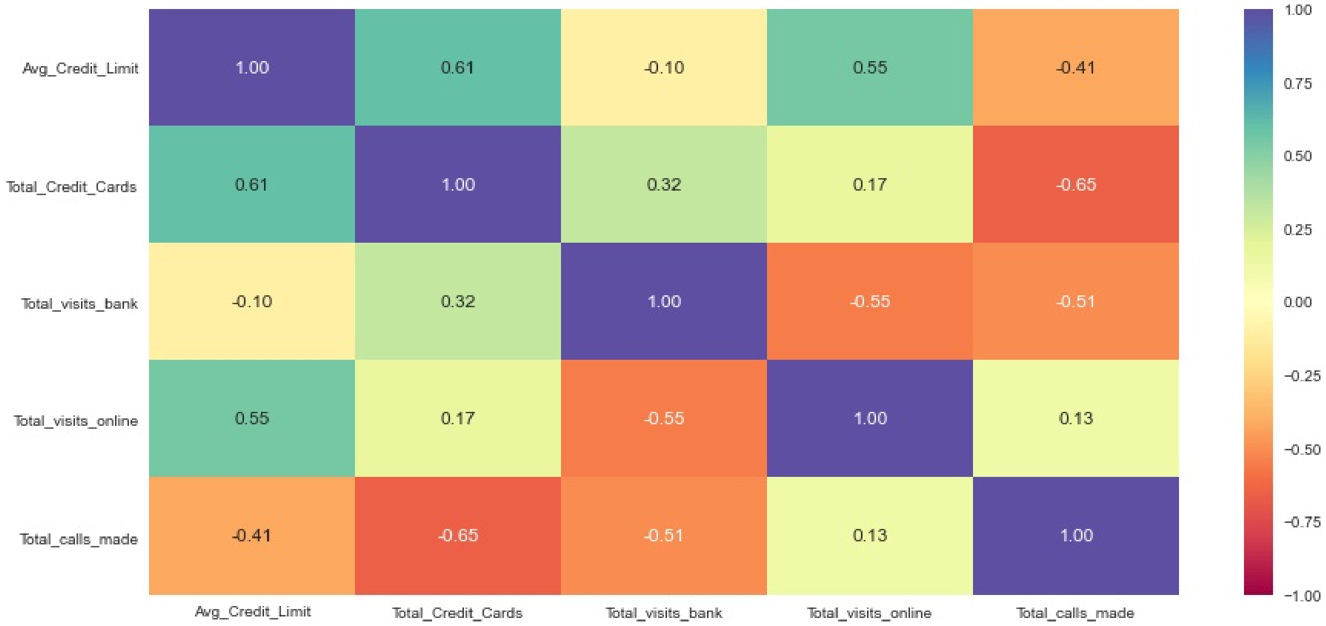
Observations

- ~90% of the customers have credit limits of less than 75,000.
- ~90% of the customers have less than 7 credit cards.
- ~85% of the customers visit the bank less than 4 times a year.
- ~90% of the customers visit the online platform 5 times or less a year.
- ~90% of the customers make 8 or fewer calls to the bank a year.

Bivariate Analysis

Let's check for correlations.

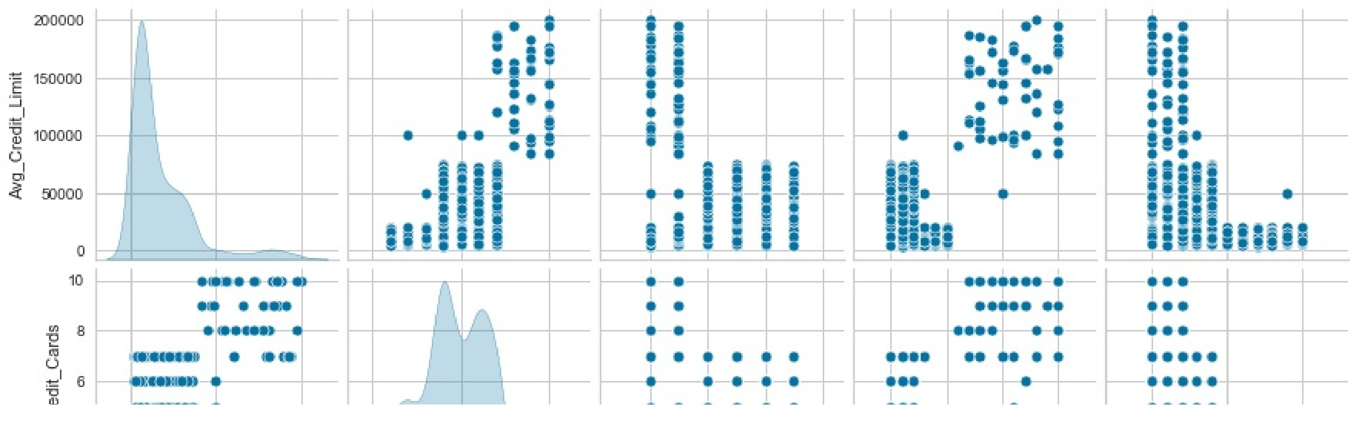
In [18]:
```
plt.figure(figsize=(15, 7))
sns.heatmap(df.corr(), annot=True, vmin=-1, vmax=1, fmt=".2f", cmap="Spectral")
plt.show()
```

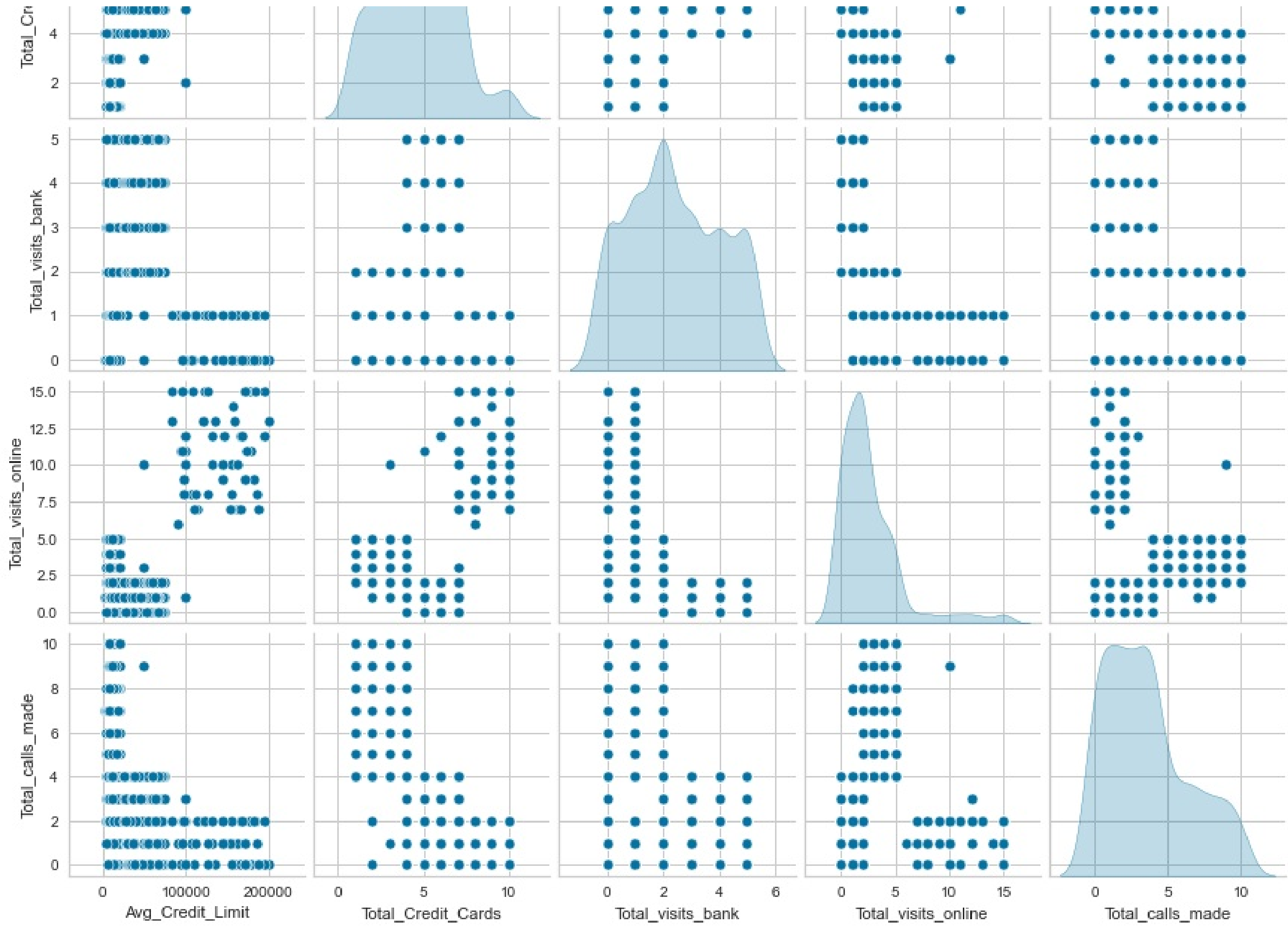


Observations

- There is a strong negative correlation between *Total_Calls_made* and *Total_credit_cards*.
- There is a strong positive correlation between *Total_credit_cards* and *Avg_credit_limit*, indicating customers with a high average credit limit tend to have more credit cards.

In [19]:
```
sns.pairplot(data=df, diag_kind="kde")
plt.show()
```



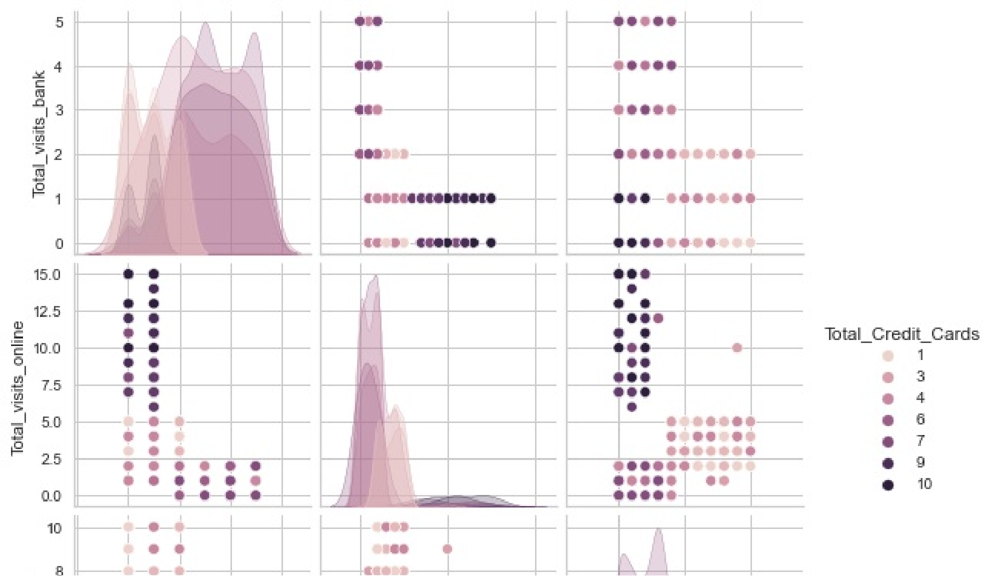


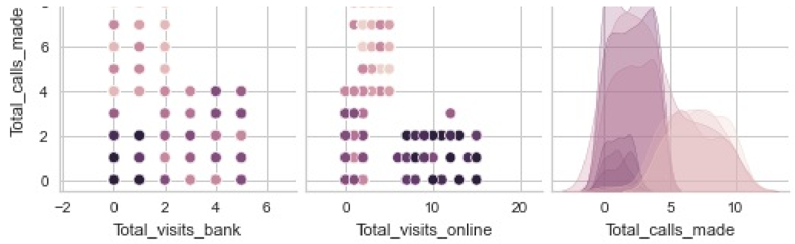
Observations

- There no clear linear correlation between the variables.
- *Total_credit_cards* may have some clusters formed w.r.t other variables.

We can add a hue and see if we can see some clustered distributions.

In [20]:
```
sns.pairplot(
    data=df[
        [
            "Total_visits_bank",
            "Total_visits_online",
            "Total_calls_made",
            "Total_Credit_Cards",
        ]
    ],
    hue="Total_Credit_Cards",
)

plt.show()
```



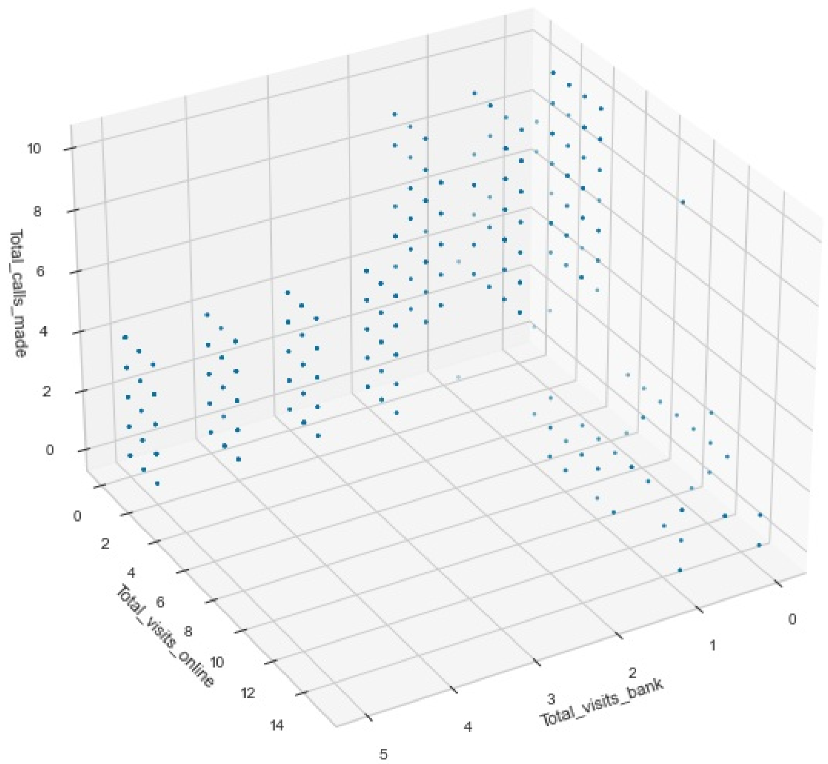


Observations

- *Total_Credit_Cards* seem to be higher for customers with higher visits online and lesser phone calls made.
- Customers who made more phone calls to the bank seem to have fewer credit cards.

Let's visualize the modes of contacting the bank in a 3D plot.

In [21]:
```
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(10, 10))
ax = plt.axes(projection="3d")

x = df["Total_visits_bank"]
y = df["Total_visits_online"]
z = df["Total_calls_made"]


ax.scatter(x, y, z, marker=".")
ax.set_xlabel("Total_visits_bank")
ax.set_ylabel("Total_visits_online")
ax.set_zlabel("Total_calls_made")
ax.view_init(azim=60)
plt.show()
```



- We can observe three segments of the customers by their preferred mode of contacting the bank.

Data Preprocessing

Outlier Detection

- Let's find outliers in the data using z-score with a threshold of 3.

In [22]:
```
threshold = 3
outlier = {}
for col in df.columns:
    i = df[col]
    mean = np.mean(df[col])
    std = np.std(df[col])
    list1 = []
    for v in i:
        z = (v - mean) / std
        if z > threshold:
            list1.append(v)
    list1.sort()
    outlier[i.name] = list1

print("The following are the outliers in the data:")
for key, value in outlier.items():
    print("\n", key, ":", value)
```

```
The following are the outliers in the data:

 Avg_Credit_Limit : [153000, 155000, 156000, 156000, 157000, 158000, 163000, 163000, 166000, 166000, 167000, 1710
00, 172000, 172000, 173000, 176000, 178000, 183000, 184000, 186000, 187000, 195000, 195000, 200000]

 Total_Credit_Cards : []

 Total_visits_bank : []

 Total_visits_online : [12, 12, 12, 12, 12, 12, 13, 13, 13, 13, 13, 14, 15, 15, 15, 15, 15, 15, 15, 15, 15, 15]

 Total_calls_made : []
```

Observations

- There are outliers in the columns *Avg_Credit_Limit* and *Total_Visits_online*.
- We will not treat the outliers as most of those outliers are not disjoint from the curve (continues curve).
- These outliers might also form their own cluster.

Scaling

- Let's scale the data before we proceed with clustering.

In [23]:
```
# scaling the data before clustering
scaler = StandardScaler()
subset = df.copy()
subset_scaled = scaler.fit_transform(subset)
```

In [24]:
```
# creating a dataframe of the scaled data
subset_scaled_df = pd.DataFrame(subset_scaled, columns=subset.columns)
```

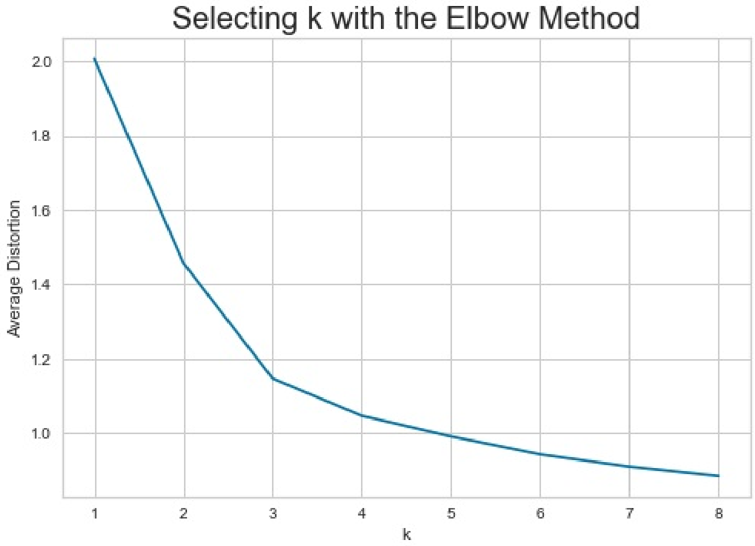
K-means Clustering

In [25]:
```
k_means_df = subset_scaled_df.copy()
```

In [26]:
```
clusters = range(1, 9)
meanDistortions = []

for k in clusters:
    model = KMeans(n_clusters=k, random_state=1)
    model.fit(subset_scaled_df)
    prediction = model.predict(k_means_df)
    distortion = (
        sum(np.min(cdist(k_means_df, model.cluster_centers_, "euclidean"), axis=1))
        / k_means_df.shape[0]
    )
```

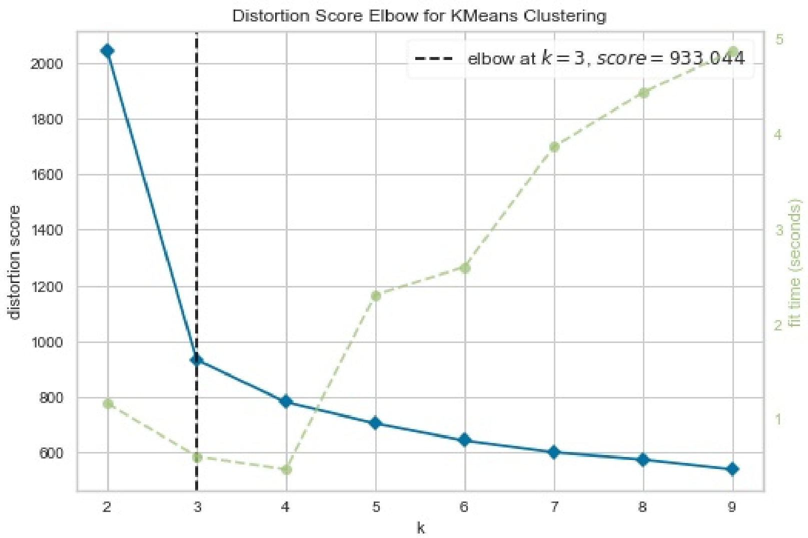
```
    meanDistortions.append(distortion)

    print("Number of Clusters:", k, "\tAverage Distortion:", distortion)

plt.plot(clusters, meanDistortions, "bx-")
plt.xlabel("k")
plt.ylabel("Average Distortion")
plt.title("Selecting k with the Elbow Method", fontsize=20)
plt.show()
```

```
Number of Clusters: 1   Average Distortion: 2.0069222262503614
Number of Clusters: 2   Average Distortion: 1.4571553548514269
Number of Clusters: 3   Average Distortion: 1.1466276549150365
Number of Clusters: 4   Average Distortion: 1.0463825294774465
Number of Clusters: 5   Average Distortion: 0.9908683849620168
Number of Clusters: 6   Average Distortion: 0.9426543606899347
Number of Clusters: 7   Average Distortion: 0.9093991915419353
Number of Clusters: 8   Average Distortion: 0.8843243844476886
```



The appropriate value of k from the Elbow curve seems to be 2 or 3.

In [27]:
```
model = KMeans(random_state=1)
visualizer = KElbowVisualizer(model, k=(2, 10), timings=True)
visualizer.fit(k_means_df)  # fit the data to the visualizer
visualizer.show()  # finalize and render figure
```



Out[27]: <AxesSubplot:title={'center':'Distortion Score Elbow for KMeans Clustering'}, xlabel='k', ylabel='distortion score'>

Let's check the silhouette scores.

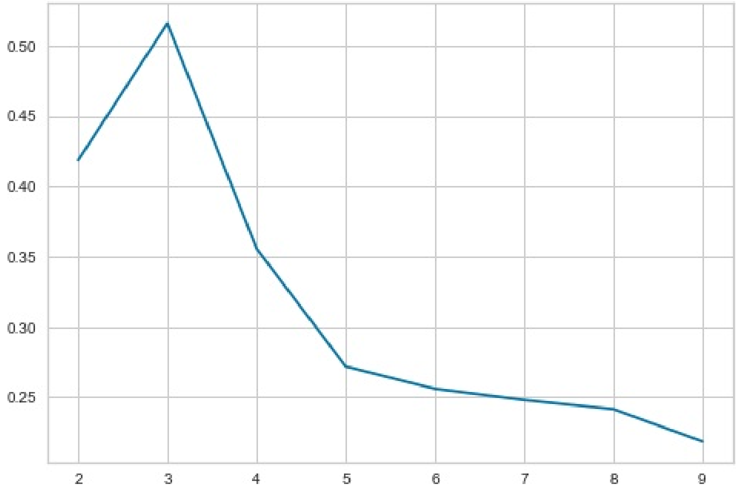
In [28]: sil_score = []

```
sil_score = []
cluster_list = range(2, 10)
for n_clusters in cluster_list:
    clusterer = KMeans(n_clusters=n_clusters, random_state=1)
    preds = clusterer.fit_predict((subset_scaled_df))
    score = silhouette_score(k_means_df, preds)
    sil_score.append(score)
    print("For n_clusters = {}, the silhouette score is {})".format(n_clusters, score))
```

```
For n_clusters = 2, the silhouette score is 0.41842496663230405)
For n_clusters = 3, the silhouette score is 0.5157182558882754)
For n_clusters = 4, the silhouette score is 0.355667061937737)
For n_clusters = 5, the silhouette score is 0.2717470361094591)
For n_clusters = 6, the silhouette score is 0.25590676529850875)
For n_clusters = 7, the silhouette score is 0.2479864465613871)
For n_clusters = 8, the silhouette score is 0.2414240144772954)
For n_clusters = 9, the silhouette score is 0.21846450507663684)
```

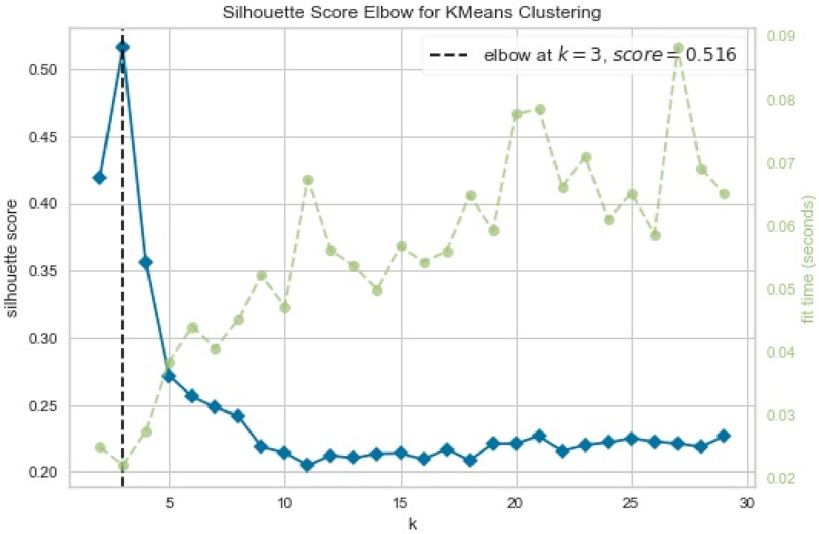
In [29]:

```
plt.plot(cluster_list, sil_score)
plt.show()
```



In [30]:

```
model = KMeans(random_state=1)
visualizer = KElbowVisualizer(model, k=(2, 30), metric="silhouette", timings=True)
visualizer.fit(k_means_df)  # fit the data to the visualizer
visualizer.show()  # finalize and render figure
```



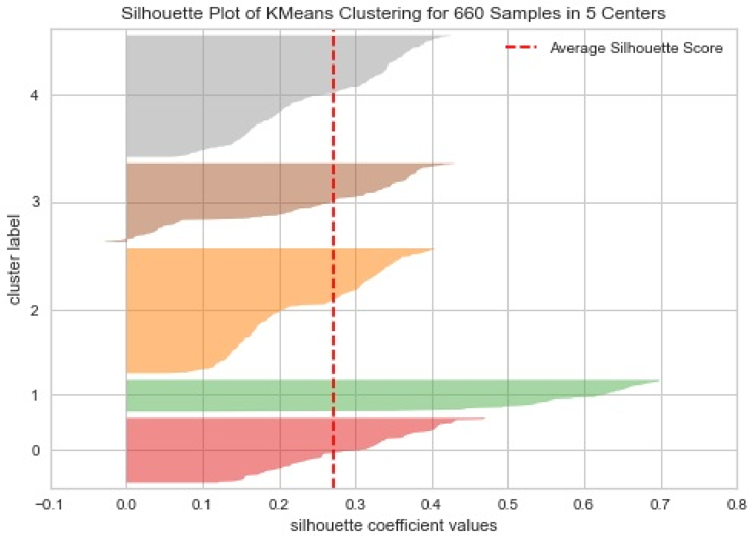
Out[30]:

```
<AxesSubplot:title={'center':'Silhouette Score Elbow for KMeans Clustering'}, xlabel='k', ylabel='silhouette scor
e'>
```

From the silhouette scores, it seems that 3 is a good value for k.

In [31]:

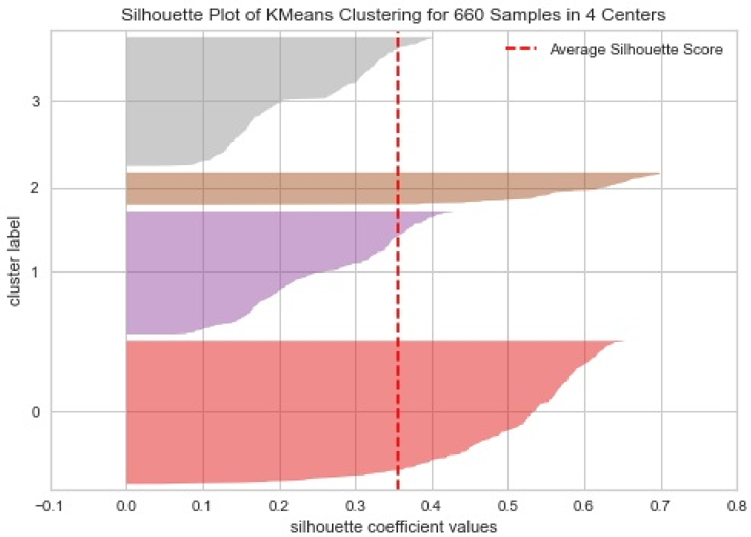
```python
# finding optimal no. of clusters with silhouette coefficients
visualizer = SilhouetteVisualizer(KMeans(5, random_state=1))
visualizer.fit(k_means_df)
visualizer.show()
```



Out[31]: <AxesSubplot:title={'center':'Silhouette Plot of KMeans Clustering for 660 Samples in 5 Centers'}, xlabel='silhouette coefficient values', ylabel='cluster label'>

In [32]:

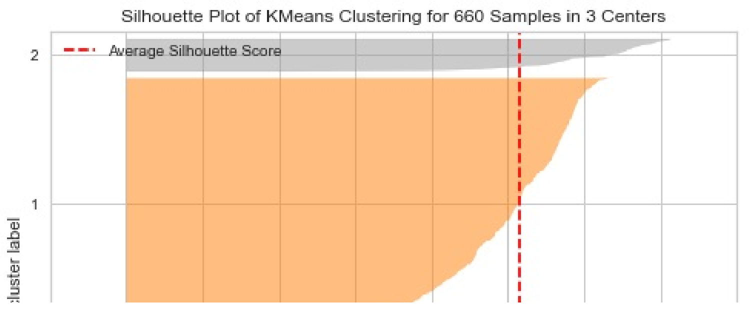
```python
# finding optimal no. of clusters with silhouette coefficients
visualizer = SilhouetteVisualizer(KMeans(4, random_state=1))
visualizer.fit(k_means_df)
visualizer.show()
```

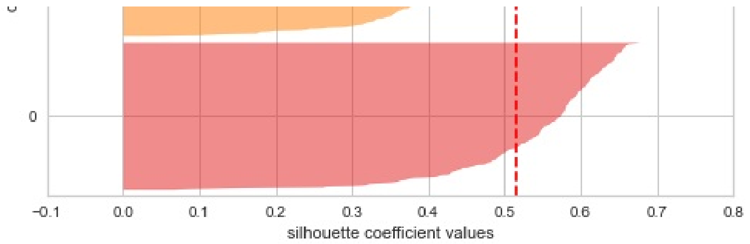


Out[32]: <AxesSubplot:title={'center':'Silhouette Plot of KMeans Clustering for 660 Samples in 4 Centers'}, xlabel='silhouette coefficient values', ylabel='cluster label'>

In [33]:

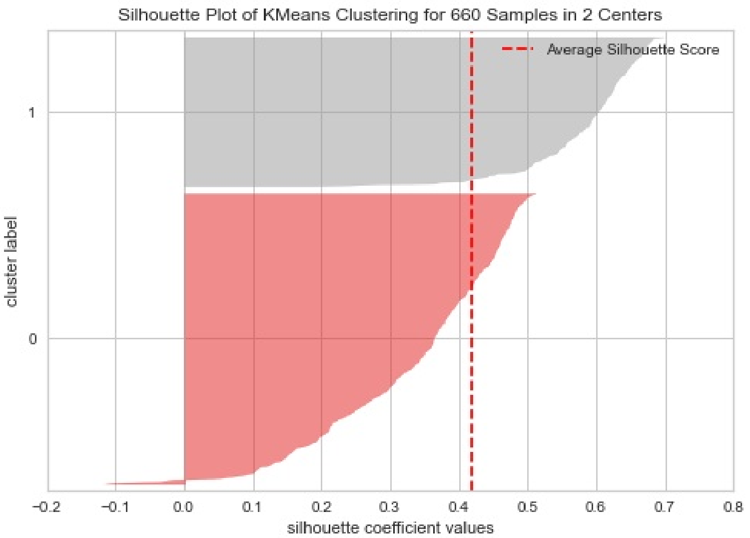
```python
# finding optimal no. of clusters with silhouette coefficients
visualizer = SilhouetteVisualizer(KMeans(3, random_state=1))
visualizer.fit(k_means_df)
visualizer.show()
```





Out[33]:
```
<AxesSubplot:title={'center':'Silhouette Plot of KMeans Clustering for 660 Samples in 3 Centers'}, xlabel='silhouette coefficient values', ylabel='cluster label'>
```

In [34]:
```python
# finding optimal no. of clusters with silhouette coefficients
visualizer = SilhouetteVisualizer(KMeans(2, random_state=1))
visualizer.fit(k_means_df)
visualizer.show()
```



Out[34]:
```
<AxesSubplot:title={'center':'Silhouette Plot of KMeans Clustering for 660 Samples in 2 Centers'}, xlabel='silhouette coefficient values', ylabel='cluster label'>
```

Observations

- The silhouette coefficient for 3 clusters is the highest.
- We can also see that the score for 3 clusters is close to the average score and the shape of the clusters is very uniform in SilhouetteVisualizer, even though the magnitude may be different.
- So, we will proceed with 3 clusters.

In [35]:
```python
kmeans = KMeans(n_clusters=3, random_state=0)
kmeans.fit(k_means_df)
```

Out[35]:
```
KMeans(n_clusters=3, random_state=0)
```

In [36]:
```python
# creating a copy of the original data
df1 = df.copy()

# adding kmeans cluster labels to the original and scaled dataframes
k_means_df["K_means_segments"] = kmeans.labels_
df1["K_means_segments"] = kmeans.labels_
```

Hierarchical Clustering

In [37]:
```python
hc_df = subset_scaled_df.copy()
```

In [38]:

```python
# list of distance metrics
distance_metrics = ["euclidean", "chebyshev", "mahalanobis", "cityblock"]

# list of linkage methods
linkage_methods = ["single", "complete", "average", "weighted"]

high_cophenet_corr = 0
high_dm_lm = [0, 0]

for dm in distance_metrics:
    for lm in linkage_methods:
        Z = linkage(hc_df, metric=dm, method=lm)
        c, coph_dists = cophenet(Z, pdist(hc_df))
        print(
            "Cophenetic correlation for {} distance and {} linkage is {}.".format(
                dm.capitalize(), lm, c
            )
        )
        if high_cophenet_corr < c:
            high_cophenet_corr = c
            high_dm_lm[0] = dm
            high_dm_lm[1] = lm
```

```
Cophenetic correlation for Euclidean distance and single linkage is 0.7391220243806552.
Cophenetic correlation for Euclidean distance and complete linkage is 0.8599730607972423.
Cophenetic correlation for Euclidean distance and average linkage is 0.8977080867389372.
Cophenetic correlation for Euclidean distance and weighted linkage is 0.8861746814895477.
Cophenetic correlation for Chebyshev distance and single linkage is 0.7382354769296767.
Cophenetic correlation for Chebyshev distance and complete linkage is 0.8533474836336782.
Cophenetic correlation for Chebyshev distance and average linkage is 0.8974159511838106.
Cophenetic correlation for Chebyshev distance and weighted linkage is 0.8913624010768603.
Cophenetic correlation for Mahalanobis distance and single linkage is 0.7058064784553605.
Cophenetic correlation for Mahalanobis distance and complete linkage is 0.6663534463875362.
Cophenetic correlation for Mahalanobis distance and average linkage is 0.8326994115042136.
Cophenetic correlation for Mahalanobis distance and weighted linkage is 0.780599061514252.
Cophenetic correlation for Cityblock distance and single linkage is 0.7252379350252723.
Cophenetic correlation for Cityblock distance and complete linkage is 0.8731477899179829.
Cophenetic correlation for Cityblock distance and average linkage is 0.896329431104133.
Cophenetic correlation for Cityblock distance and weighted linkage is 0.8825520731498188.
```

In [39]:

```python
# printing the combination of distance metric and linkage method with the highest cophenetic correlation
print(
    "Highest cophenetic correlation is {}, which is obtained with {} distance and {} linkage.".format(
        high_cophenet_corr, high_dm_lm[0].capitalize(), high_dm_lm[1]
    )
)
```

```
Highest cophenetic correlation is 0.8977080867389372, which is obtained with Euclidean distance and average linka
ge.
```

Let's explore different linkage methods with Euclidean distance only.

In [40]:

```python
# list of linkage methods
linkage_methods = ["single", "complete", "average", "centroid", "ward", "weighted"]

high_cophenet_corr = 0
high_dm_lm = [0, 0]

for lm in linkage_methods:
    Z = linkage(hc_df, metric="euclidean", method=lm)
    c, coph_dists = cophenet(Z, pdist(hc_df))
    print("Cophenetic correlation for {} linkage is {}.".format(lm, c))
    if high_cophenet_corr < c:
        high_cophenet_corr = c
        high_dm_lm[0] = "euclidean"
        high_dm_lm[1] = lm
```

```
Cophenetic correlation for single linkage is 0.7391220243806552.
Cophenetic correlation for complete linkage is 0.8599730607972423.
Cophenetic correlation for average linkage is 0.8977080867389372.
Cophenetic correlation for centroid linkage is 0.8939385846326323.
Cophenetic correlation for ward linkage is 0.7415156284827493.
Cophenetic correlation for weighted linkage is 0.8861746814895477.
```

In [41]:

```
# printing the combination of distance metric and linkage method with the highest cophenetic correlation
print()
print(
    "Highest cophenetic correlation is {}, which is obtained with {} linkage.".format(
        high_cophenet_corr, high_dm_lm[1]
    )
)
```

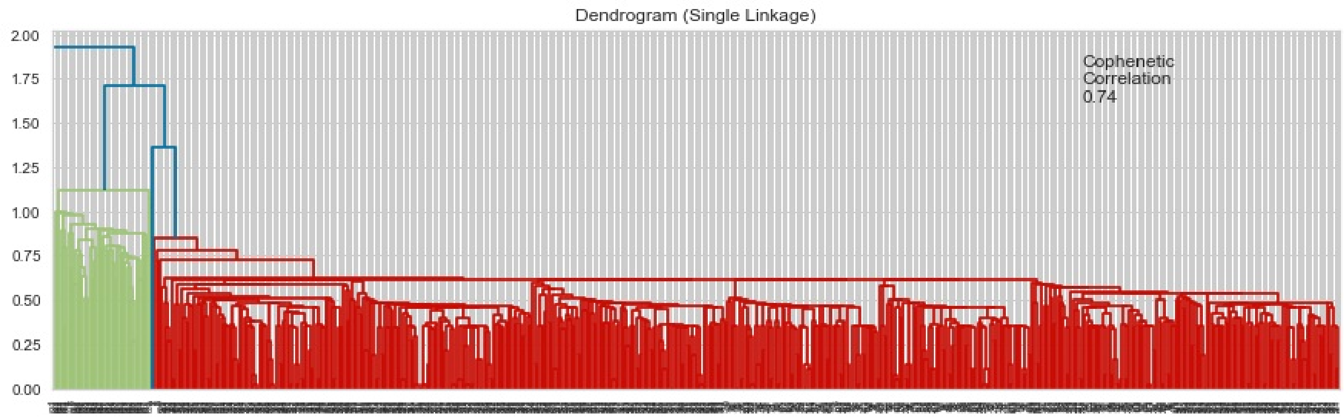
```
Highest cophenetic correlation is 0.8977080867389372, which is obtained with average linkage.
```

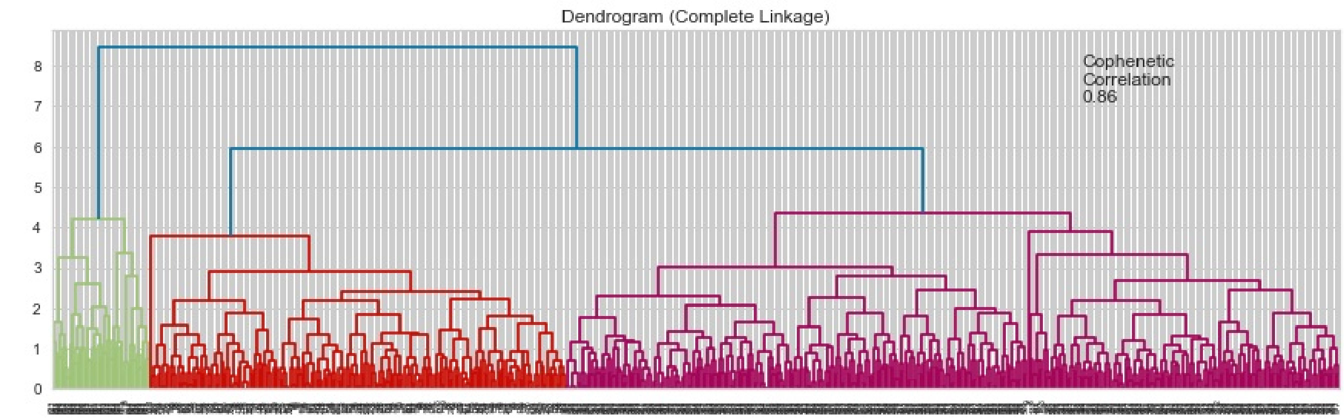
We see that the cophenetic correlation is maximum with Euclidean distance and average linkage.

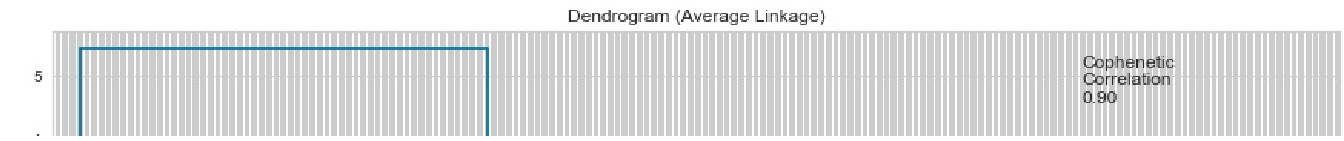
Let's view the dendrograms for the different linkage methods.

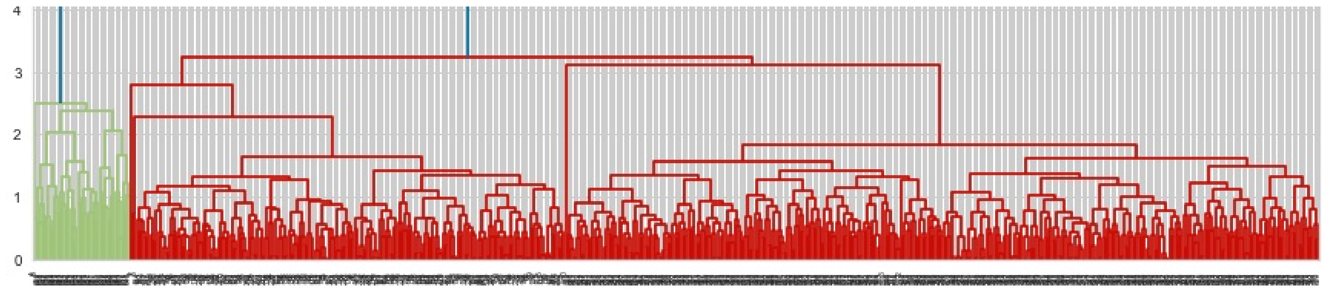
In [42]:

```
# list of linkage methods
linkage_methods = ["single", "complete", "average", "centroid", "ward", "weighted"]

# lists to save results of cophenetic correlation calculation
compare_cols = ["Linkage", "Cophenetic Coefficient"]
compare = []

# to create a subplot image
fig, axs = plt.subplots(len(linkage_methods), 1, figsize=(15, 30))

# We will enumerate through the list of linkage methods above
# For each linkage method, we will plot the dendrogram and calculate the cophenetic correlation
for i, method in enumerate(linkage_methods):
    Z = linkage(hc_df, metric="euclidean", method=method)

    dendrogram(Z, ax=axs[i])
    axs[i].set_title(f"Dendrogram ({method.capitalize()} Linkage)")

    coph_corr, coph_dist = cophenet(Z, pdist(hc_df))
    axs[i].annotate(
        f"Cophenetic\nCorrelation\n{coph_corr:0.2f}",
        (0.80, 0.80),
        xycoords="axes fraction",
    )

    compare.append([method, coph_corr])
```

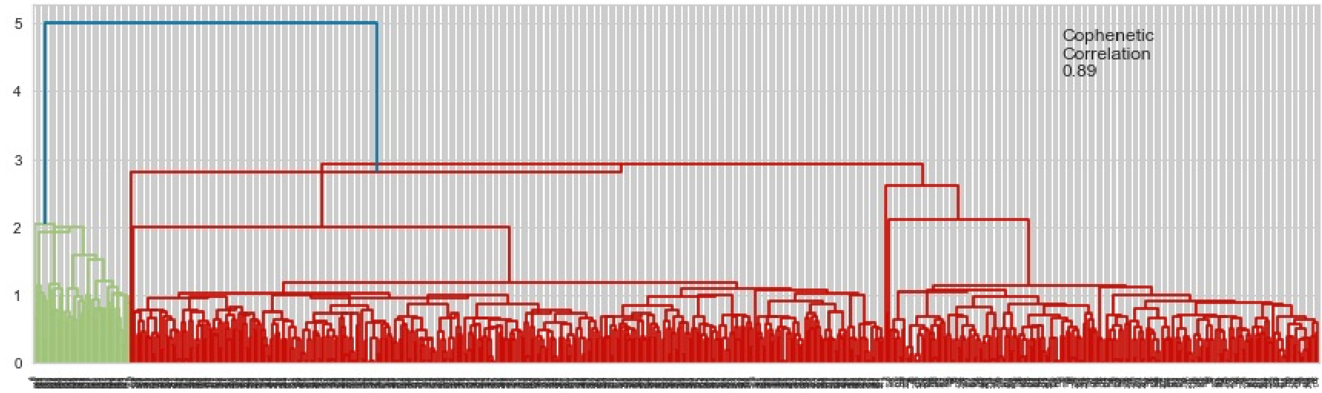




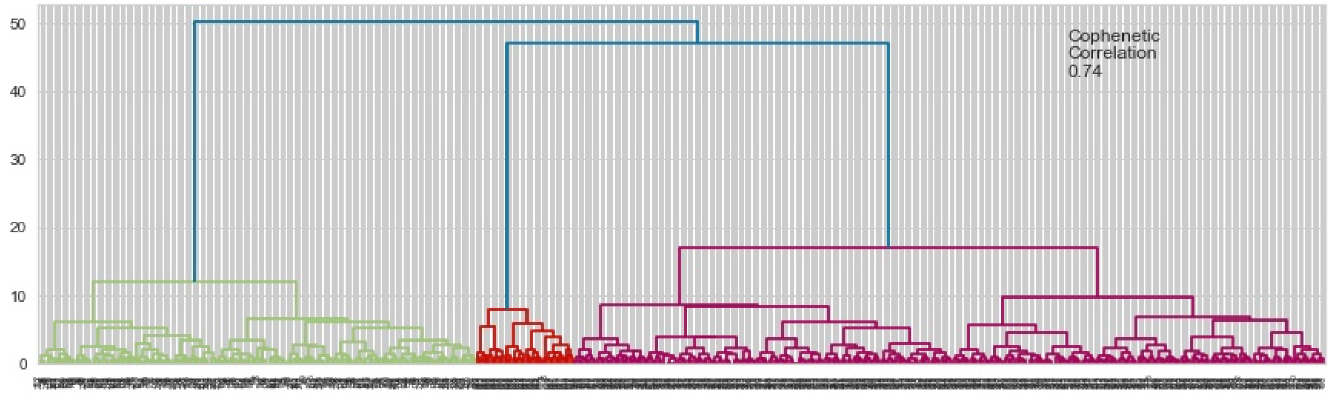




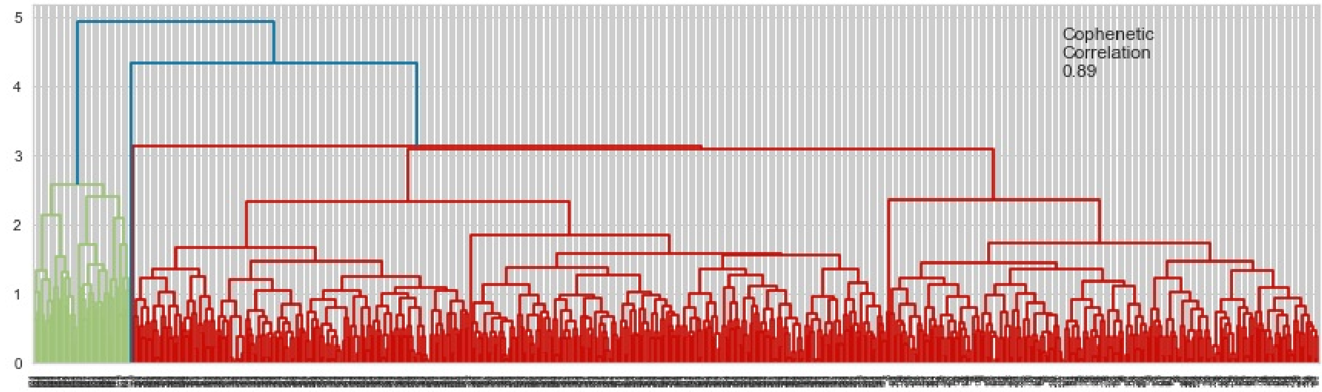
Dendrogram (Centroid Linkage)



Dendrogram (Ward Linkage)



Dendrogram (Weighted Linkage)



Dendrogram with average linkage shows distinct and separate cluster tree.

In [43]:

```
# create and print a dataframe to compare cophenetic correlations for different linkage methods
df_cc = pd.DataFrame(compare, columns=compare_cols)
df_cc = df_cc.sort_values(by="Cophenetic Coefficient")
df_cc
```

Out[43]:

	Linkage	Cophenetic Coefficient
0	single	0.739122
4	ward	0.741516
1	complete	0.859973
5	weighted	0.886175
3	centroid	0.893939
2	average	0.897708

Let's move ahead with 3 clusters, Euclidean distance, and average linkage.

In [44]:
```
HCmodel = AgglomerativeClustering(n_clusters=3, affinity="euclidean", linkage="average")
HCmodel.fit(hc_df)
```

Out[44]:
```
AgglomerativeClustering(linkage='average', n_clusters=3)
```

In [45]:
```
# creating a copy of the original data
df2 = df.copy()

# adding hierarchical cluster labels to the original and scaled dataframes
hc_df["HC_segments"] = HCmodel.labels_
df2["HC_segments"] = HCmodel.labels_
```

In [46]:
```
hc_df.head()
```

Out[46]:

	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	HC_segments
0	1.740187	-1.249225	-0.860451	-0.547490	-1.251537	0
1	0.410293	-0.787585	-1.473731	2.520519	1.891859	2
2	0.410293	1.058973	-0.860451	0.134290	0.145528	0
3	-0.121665	0.135694	-0.860451	-0.547490	0.145528	0
4	1.740187	0.597334	-1.473731	3.202298	-0.203739	1

In [47]:
```
df2.head()
```

Out[47]:

	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	HC_segments
0	100000	2	1	1	0	0
1	50000	3	0	10	9	2
2	50000	7	1	3	4	0
3	30000	5	1	1	4	0
4	100000	6	0	12	3	1

In [48]:
```
subset_scaled_df["HC_Clusters"] = HCmodel.labels_
df["HC_Clusters"] = HCmodel.labels_
```

Cluster Profiling and Comparison

Cluster Profiling: K-means Clustering

In [49]:
```
km_cluster_profile = df1.groupby("K_means_segments").mean()
```

In [50]:
```
km_cluster_profile["count_in_each_segment"] = (
    df1.groupby("K_means_segments")["Avg_Credit_Limit"].count().values
)
```

In [51]:
```
km_cluster_profile
```

Out[51]:

	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	count_in_each_segment

K_means_segments						
0	33782.383420	5.515544	3.489637	0.981865	2.000000	386
1	12174.107143	2.410714	0.933036	3.553571	6.870536	224
2	141040.000000	8.740000	0.600000	10.900000	1.080000	50

Cluster Profiling: Hierarchical Clustering

In [52]:

```
hc_cluster_profile = df2.groupby("HC_segments").mean()
```

In [53]:

```
hc_cluster_profile["count_in_each_segment"] = (
    df2.groupby("HC_segments")["Avg_Credit_Limit"].count().values
)
```

In [54]:

```
hc_cluster_profile
```

Out[54]:

HC_segments	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	count_in_each_segment
0	33713.178295	5.511628	3.485788	0.984496	2.005168	387
1	141040.000000	8.740000	0.600000	10.900000	1.080000	50
2	12197.309417	2.403587	0.928251	3.560538	6.883408	223

K-Means Clustering vs Hierarchical Clustering Comparison

In [55]:

```
km_cluster_profile.style.highlight_max(color="lightgreen", axis=0)
```

Out[55]:

K_means_segments	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	count_in_each_segment
0	33782.383420	5.515544	3.489637	0.981865	2.000000	386
1	12174.107143	2.410714	0.933036	3.553571	6.870536	224
2	141040.000000	8.740000	0.600000	10.900000	1.080000	50

In [56]:

```
hc_cluster_profile.style.highlight_max(color="lightgreen", axis=0)
```

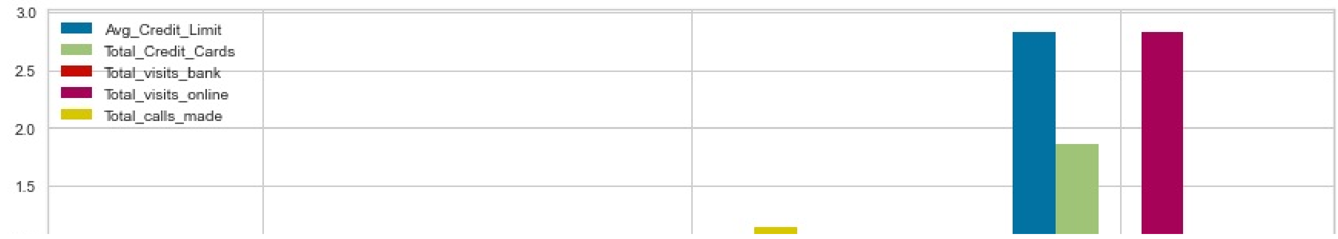
Out[56]:

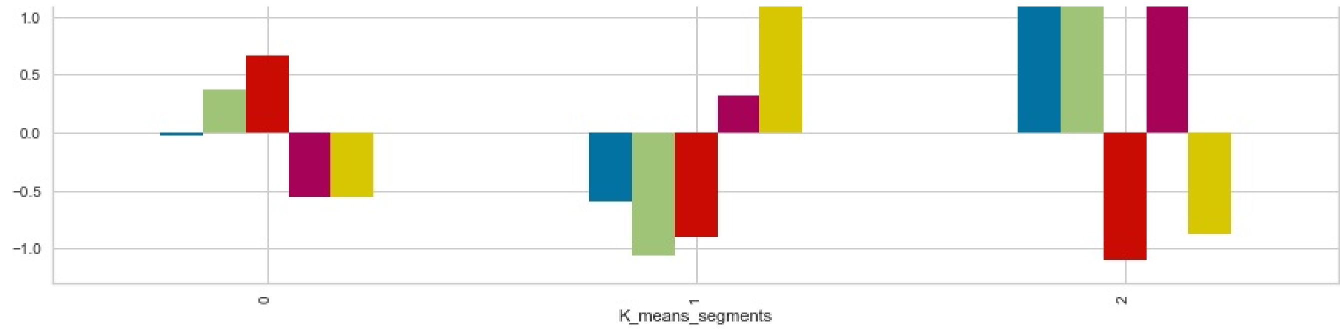
HC_segments	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	count_in_each_segment
0	33713.178295	5.511628	3.485788	0.984496	2.005168	387
1	141040.000000	8.740000	0.600000	10.900000	1.080000	50
2	12197.309417	2.403587	0.928251	3.560538	6.883408	223

In [57]:

```
k_means_df.groupby("K_means_segments").mean().plot.bar(figsize=(15, 6))
```

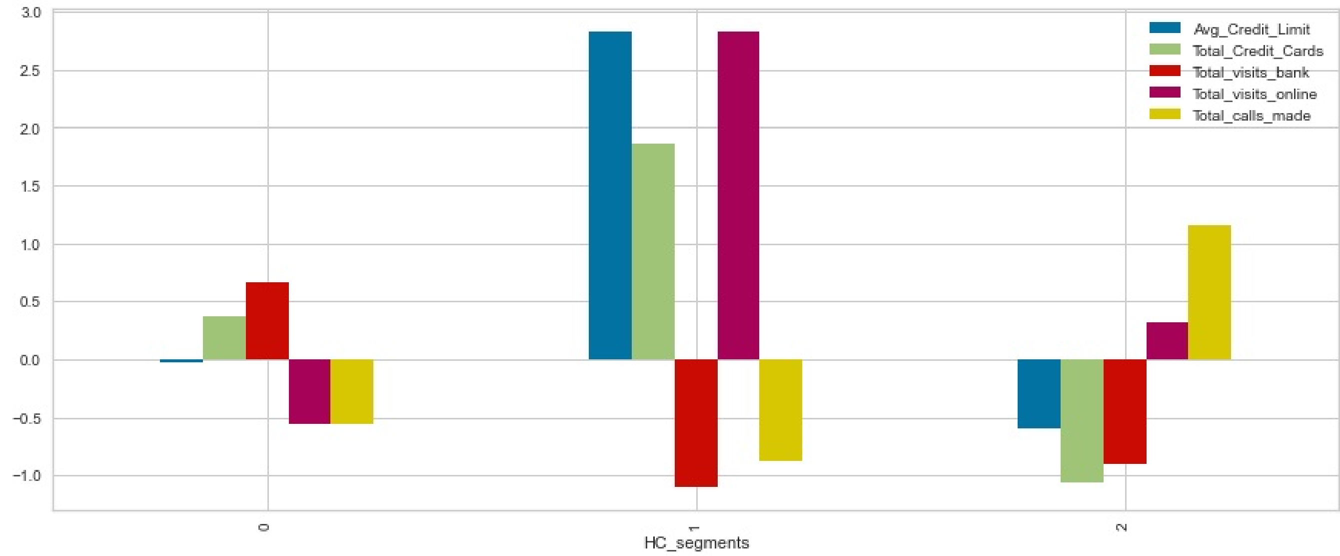
Out[57]: <AxesSubplot:xlabel='K_means_segments'>





In [58]:
```
hc_df.groupby("HC_segments").mean().plot.bar(figsize=(15, 6))
```

Out[58]: <AxesSubplot:xlabel='HC_segments'>



Looks like the K-Means and Hierarchical clusters are the same except that the labels are swapped between clusters 1 and 2.

Let's swap the labels for K-Means for better analysis and comparison.

In [59]:
```
k_means_df.loc[k_means_df["K_means_segments"] == 1, "K_means_segments"] = 3
k_means_df.loc[k_means_df["K_means_segments"] == 2, "K_means_segments"] = 1
k_means_df.loc[k_means_df["K_means_segments"] == 3, "K_means_segments"] = 2
df1["K_means_segments"] = k_means_df["K_means_segments"]

km_cluster_profile = df1.groupby("K_means_segments").mean()
km_cluster_profile["count_in_each_segment"] = (
    df1.groupby("K_means_segments")["Avg_Credit_Limit"].count().values
)
```

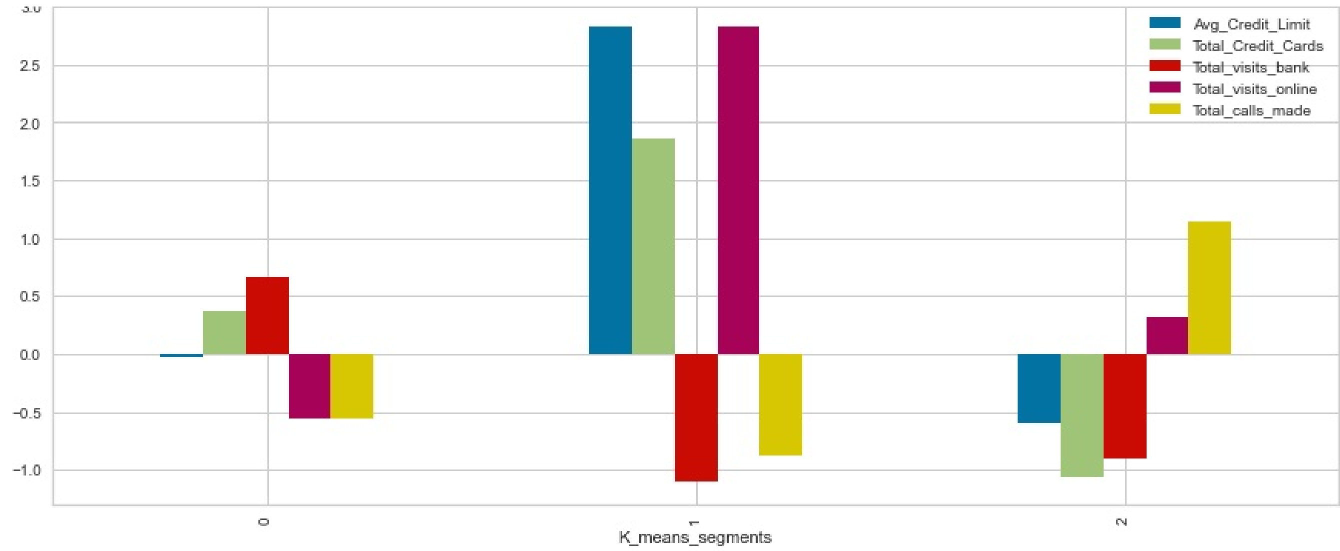
In [60]:
```
km_cluster_profile.style.highlight_max(color="lightgreen", axis=0)
```

Out[60]:

	Avg_Credit_Limit	Total_Credit_Cards	Total_visits_bank	Total_visits_online	Total_calls_made	count_in_each_segment
K_means_segments						
0	33782.383420	5.515544	3.489637	0.981865	2.000000	386
1	141040.000000	8.740000	0.600000	10.900000	1.080000	50
2	12174.107143	2.410714	0.933036	3.553571	6.870536	224

In [61]:
```
k_means_df.groupby("K_means_segments").mean().plot.bar(figsize=(15, 6))
```

Out[61]: <AxesSubplot:xlabel='K_means_segments'>

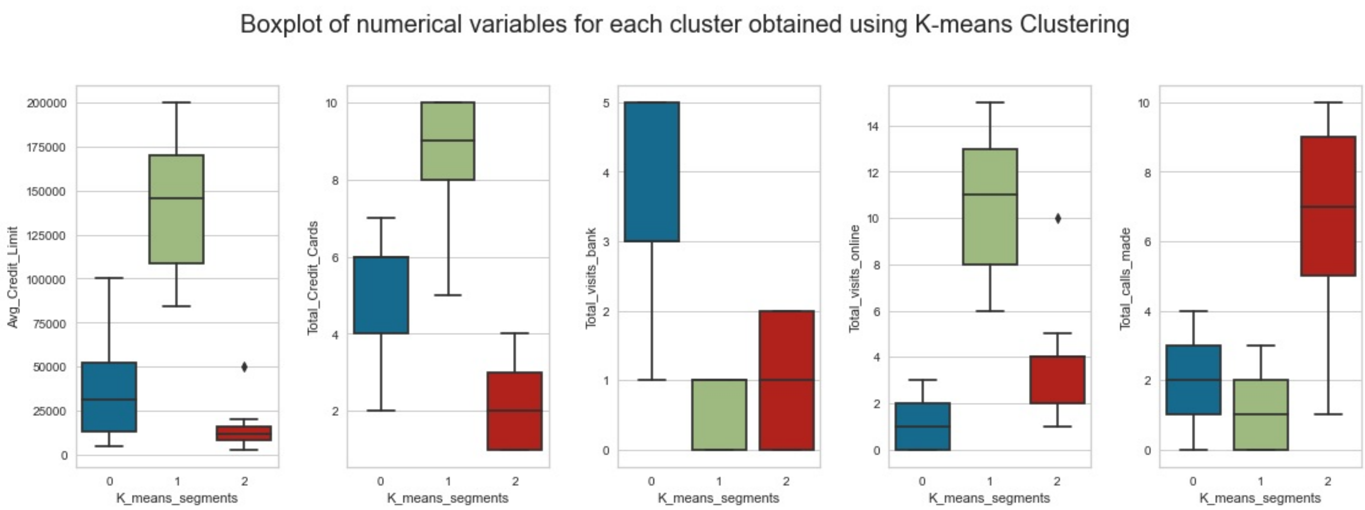


Observations

- The online user segment matches for both K-means and Hierarchical Clustering techniques.
- There is a clear distinction between customers who prefer online banking vs others.
- Online users have more credit cards and a larger credit limit, which is beneficial for the bank with respect to the revenue and cutting the costs of manual engagement with the customers.

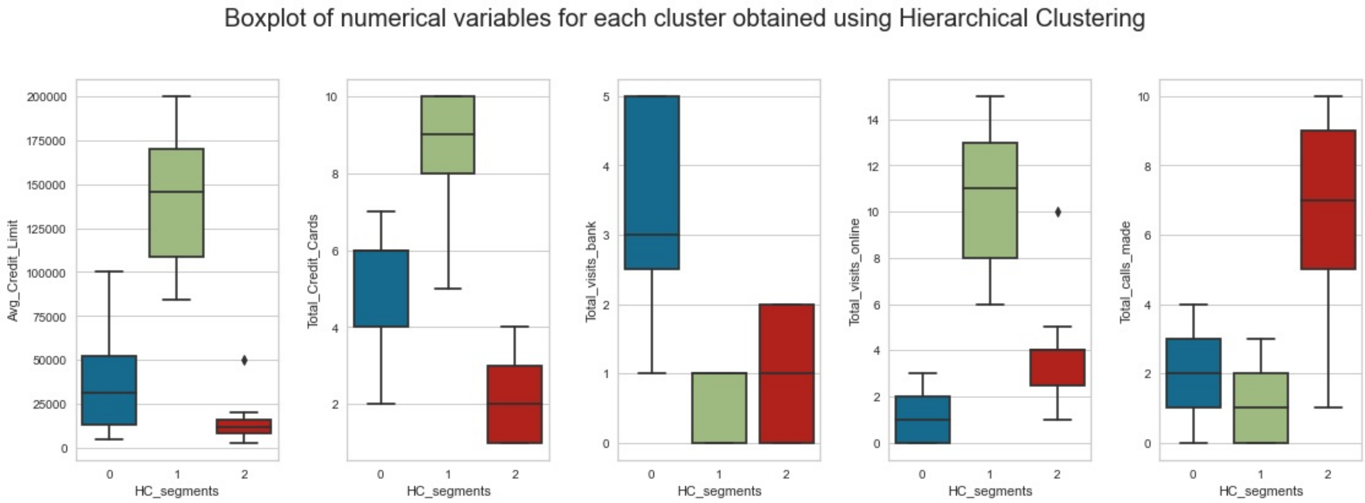
Let's create some plots on the original data to understand the customer distribution among the clusters.

In [62]:
```
fig, axes = plt.subplots(1, 5, figsize=(16, 6))
fig.suptitle(
    "Boxplot of numerical variables for each cluster obtained using K-means Clustering",
    fontsize=20,
)

counter = 0

for ii in range(5):
    sns.boxplot(
        ax=axes[ii], y=df1[df1.columns[counter]], x=k_means_df["K_means_segments"]
    )
    counter = counter + 1

fig.tight_layout(pad=2.0)
```



In [63]:
```
fig, axes = plt.subplots(1, 5, figsize=(16, 6))
fig.suptitle(
    "Boxplot of numerical variables for each cluster obtained using Hierarchical Clustering",
    fontsize=20,
)

counter = 0
```

```python
for ii in range(5):
    sns.boxplot(ax=axes[ii], y=df2[df2.columns[counter]], x=hc_df["HC_segments"])
    counter = counter + 1

fig.tight_layout(pad=2.0)
```



Cluster Comparison

Cluster 0:

- Close to 60% of the customers are in this group.
- This cluster has the second-highest credit limit and number of credit cards.
- Customers in this group prefer to visit the bank for their banking needs than doing business online or over the phone. Total visits to be bank are ranging between 1 and 5, but most of them are skewed to the left.
- There is almost equal distribution of phone bankers and online bankers in this cluster. Some of the customers have never visited online, while the highest number of online visits is 3. Some customers have never made any phone banking
- This may be the bank's second-best cluster as there are more cards and credit limits than cluster 1.

Cluster 1:

- There are very few customers in this segment (only around 7%).
- This cluster seems to be a premium cluster with the highest average credit limit and the highest number of credit cards.
- Average credit limit for this group is between 85000 and 200000 dollars, with an average of ~141000 dollars.
- Total credit cards are between 5 and 10 with a tail on the left, but most customers are within the 8 to 10 range.
- Customers in this group prefer online banking, with an even distribution of 6 to 15 visits.
- Customers in this group have the lowest phone calls made and visits to the bank, with some customers never making any phone calls and some never visiting the bank.

Cluster 2:

- Around 1/3rd of the customers are in this cluster.
- This cluster has the lowest number of credit cards, ranging from 1 to 4.
- This cluster has the lowest average credit limit and most of them are below 2500 dollars with an outlier of around 5000 dollars.
- The total number of calls made by this segment of customers is the highest among all the clusters and ranges between 1 and 10.
- Customers in this segment have the lowest online visits, ranging from 1 to 5 with an outlier of 10 visits.

Insights

- We have seen that 3 clusters are distinctly formed using both methodologies and the clusters are analogous to each other.
- Cluster 1 has premium customers with a high credit limit and more credit cards, indicating that they have more purchasing power. The customers in this group have a preference for online banking.
- Cluster 0 has customers who prefer to visit the bank for their banking needs than doing business online or over the phone. They have an average credit limit and a moderate number of credit cards.
- Cluster 2 has more overhead of customers calling in, and the bank may need to spend money on call centers.

Business Recommendations

- The premium customers of Cluster 1 have the potential to add more revenue to the bank, and the bank should run incentives to draw more customers of this kind. The bank can also run promotions and offer discounts for paperless billing and online banking to drive more customers into this group.

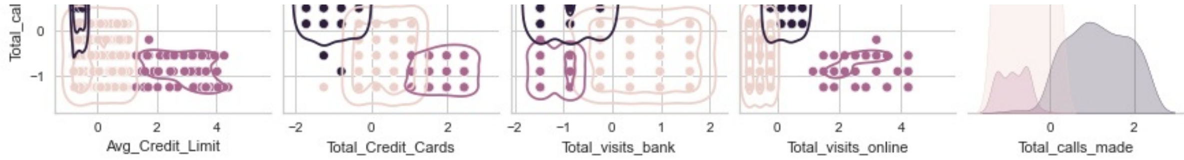
- Cluster 0 has customers who prefer to visit the bank for their banking needs than doing business online or over the phone. They have an average credit limit and number of credit cards. The bank can increase their revenue by focusing on the volume of customers in Cluster 0.
- Since the Cluster 2 customers prefer to use phone banking, the bank can invest in automating the phone banking so that the overhead can be reduced. Phone banking can also be expanded to chat applications like WhatsApp and Telegram.
- Bank should invest in making online banking more easier and secure. It should also run a campaign on the security and convenience feature of online banking.

Add-on: Cluster Overlapping

In [64]:

```
# let's see if there is any overlap in the clusters
g = sns.pairplot(
    k_means_df[
        [
            "Avg_Credit_Limit",
            "Total_Credit_Cards",
            "Total_visits_bank",
            "Total_visits_online",
            "Total_calls_made",
            "K_means_segments",
        ]
    ],
    diag_kind="kde",
    corner=True,
    hue="K_means_segments",
)
g.map_lower(sns.kdeplot, levels=3, color=".2")
plt.show()
```

```
/Users/arturocasasa/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:1182: UserWarning: No cont
our levels were found within the data range.
  cset = contour_func(
/Users/arturocasasa/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:1182: UserWarning: No cont
our levels were found within the data range.
  cset = contour_func(
/Users/arturocasasa/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:1182: UserWarning: No cont
our levels were found within the data range.
  cset = contour_func(
```



Here are refined insights and recommendations based on the clustering analysis of AllLife Bank's customer data:

Key Insights:

Customer Segmentation:

Cluster 0 (Moderate Users): Average Credit Limit: $33,782 Total Credit Cards: 5.5 Total Visits to Bank: 3.5 per year Total Visits Online: 1 per year Total Calls Made: 2 per year Proportion of Customers: ~59%

Cluster 1 (Premium Users): Average Credit Limit: $141,040 Total Credit Cards: 8.7 Total Visits to Bank: 0.6 per year Total Visits Online: 10.9 per year Total Calls Made: 1.1 per year Proportion of Customers: ~8%

Cluster 2 (Frequent Callers): Average Credit Limit: $12,174 Total Credit Cards: 2.4 Total Visits to Bank: 0.9 per year Total Visits Online: 3.6 per year Total Calls Made: 6.9 per year Proportion of Customers: ~34%

Behavioral Patterns:

Cluster 0: Customers prefer in-person visits to the bank and have moderate use of online banking and phone calls. Cluster 1: Premium customers with high online banking usage and minimal in-person visits and phone calls. Cluster 2: Customers who rely heavily on phone calls for their banking needs and have the lowest credit limits and number of credit cards. Correlation Insights:

Total Credit Cards and Average Credit Limit: Strong positive correlation. Higher credit limits tend to be associated with more credit cards. Total Calls Made and Total Credit Cards: Strong negative correlation. Customers who make more calls tend to have fewer credit cards. Recommendations: Marketing and Upselling Strategies:

Target Cluster 1 for Premium Services: Focus marketing efforts on upselling premium services and products to Cluster 1 customers. These customers have high credit limits and prefer online banking, making them ideal for digital-first products and services. Promote Online Banking to Cluster 0: Encourage Cluster 0 customers to use online banking more frequently. Offering incentives for online transactions could reduce the cost of in-person banking. Special Campaigns for Cluster 2: Implement targeted campaigns to convert Cluster 2 customers to more profitable segments. Highlight the benefits of online banking and offer support to reduce their reliance on phone calls. Service Delivery Improvements:

Enhance Online Banking Experience: Invest in making the online banking experience seamless and secure. Promote its convenience and security features to increase adoption among all customer segments. Automate Phone Banking for Cluster 2: Implement advanced IVR systems and chatbot solutions to handle frequent queries from Cluster 2 customers. This can reduce the load on call centers and improve service efficiency. Customer Retention and Satisfaction:

Personalized Customer Support for Cluster 1: Provide dedicated customer support for Cluster 1 to maintain their satisfaction and loyalty. Personalized communication and exclusive offers can enhance their experience. Improve In-Person and Phone Support: Ensure that the in-person and phone banking services are efficient and effective. Regular training for staff and investment in technology can improve query resolution times and overall customer satisfaction. Cross-Sell and Up-Sell Opportunities:

Cross-Sell to Cluster 0: Leverage the moderate engagement of Cluster 0 customers by cross-selling additional financial products such as insurance, loans, and investment services. Up-Sell Credit Cards to Cluster 2: Encourage Cluster 2 customers to upgrade their credit cards and increase their credit limits through tailored offers and promotions. Monitoring and Continuous Improvement:

Regularly Monitor Clusters: Continuously monitor the behavior of customers within each cluster to identify any shifts or emerging trends. Use this data to refine marketing and service strategies. Feedback Mechanisms: Implement feedback mechanisms to gather customer insights and improve services based on their preferences and needs.

In [ ]: