Project - Data Mining

Problem 1: Clustering

1.1 Read the data, do the necessary initial steps, and exploratory data analysis (Univariate, Bi-variate, and multivariate analysis).

In [7]:

```
df_1.head()
```

Out[7]:

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_sir
0	19.94	16.92	0.8752	6.675	3.763	3.252	
1	15.99	14.89	0.9064	5.363	3.582	3.336	
2	18.95	16.42	0.8829	6.248	3.755	3.368	
3	10.83	12.96	0.8099	5.278	2.641	5.182	
4	17.99	15.86	0.8992	5.890	3.694	2.068	

In [8]:

```
df_1.shape
```

Out[8]:

```
(210, 7)
```

In [9]:

```
df_1.isnull().sum()
```

Out[9]:

```
spending                        0
advance_payments                0
probability_of_full_payment     0
current_balance                 0
credit_limit                    0
min_payment_amt                 0
max_spent_in_single_shopping    0
dtype: int64
```

In [10]:

```
df_1.describe()
```

Out[10]:

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent
count	210.000000	210.000000	210.000000	210.000000	210.000000	210.000000	
mean	14.847524	14.559286	0.870999	5.628533	3.258605	3.700201	
std	2.909699	1.305959	0.023629	0.443063	0.377714	1.503557	
min	10.590000	12.410000	0.808100	4.899000	2.630000	0.765100	
25%	12.270000	13.450000	0.856900	5.262250	2.944000	2.561500	

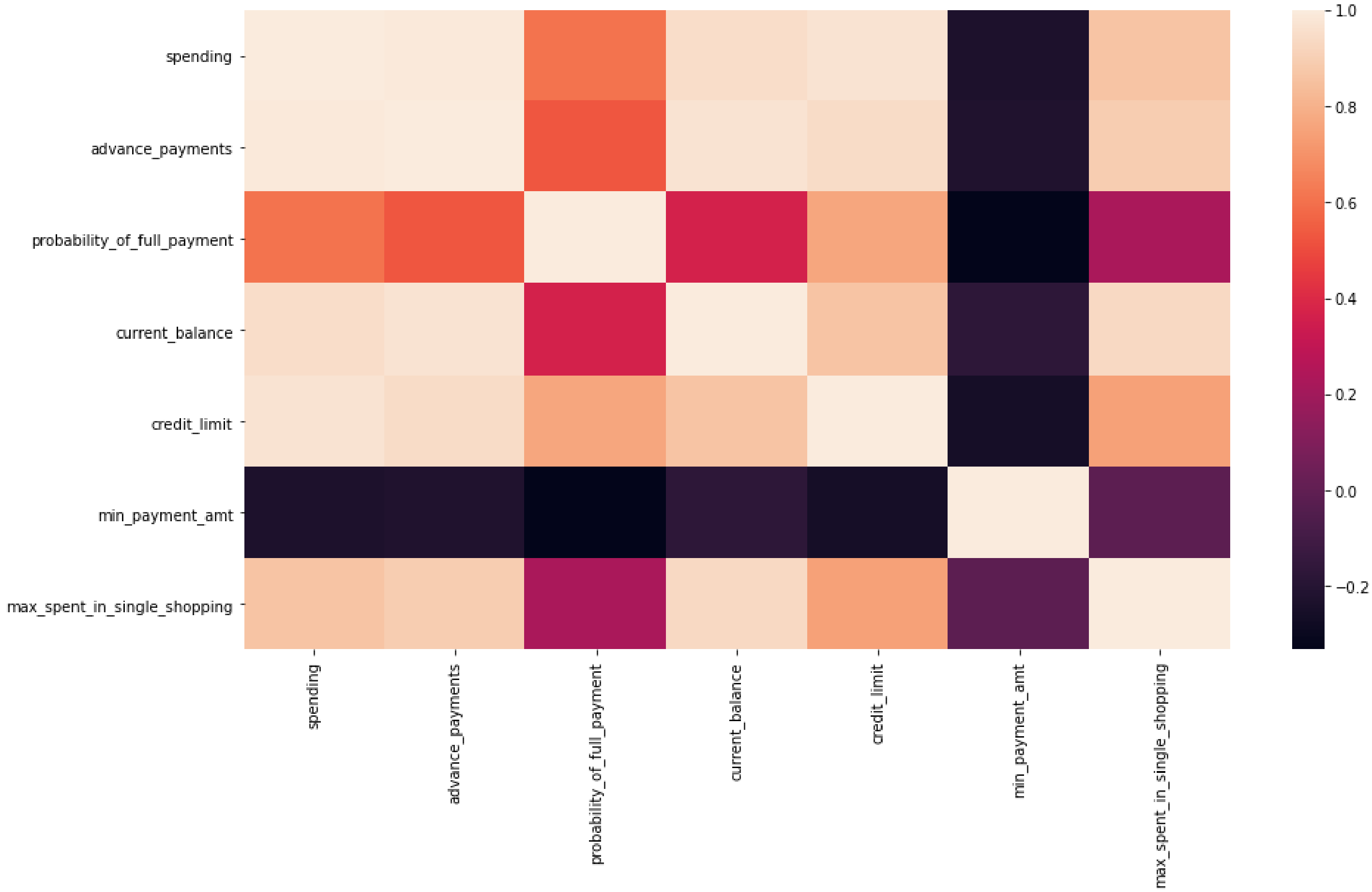
	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent
50%	14.355000	14.320000	0.873450	5.523500	3.237000	3.599000	
75%	17.305000	15.715000	0.887775	5.979750	3.561750	4.768750	
max	21.180000	17.250000	0.918300	6.675000	4.033000	8.456000	

In [25]:

```
plt.subplots(figsize= (15,8))
sns.heatmap(df_1.corr())
```

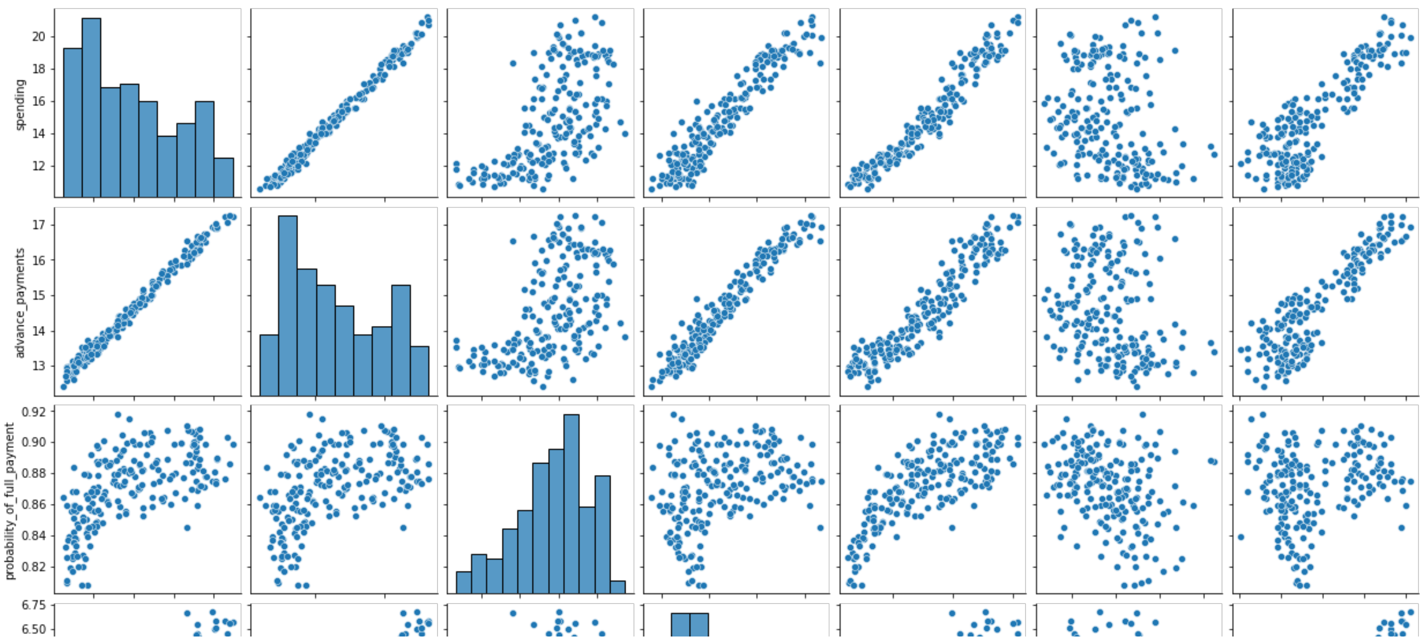
Out[25]:

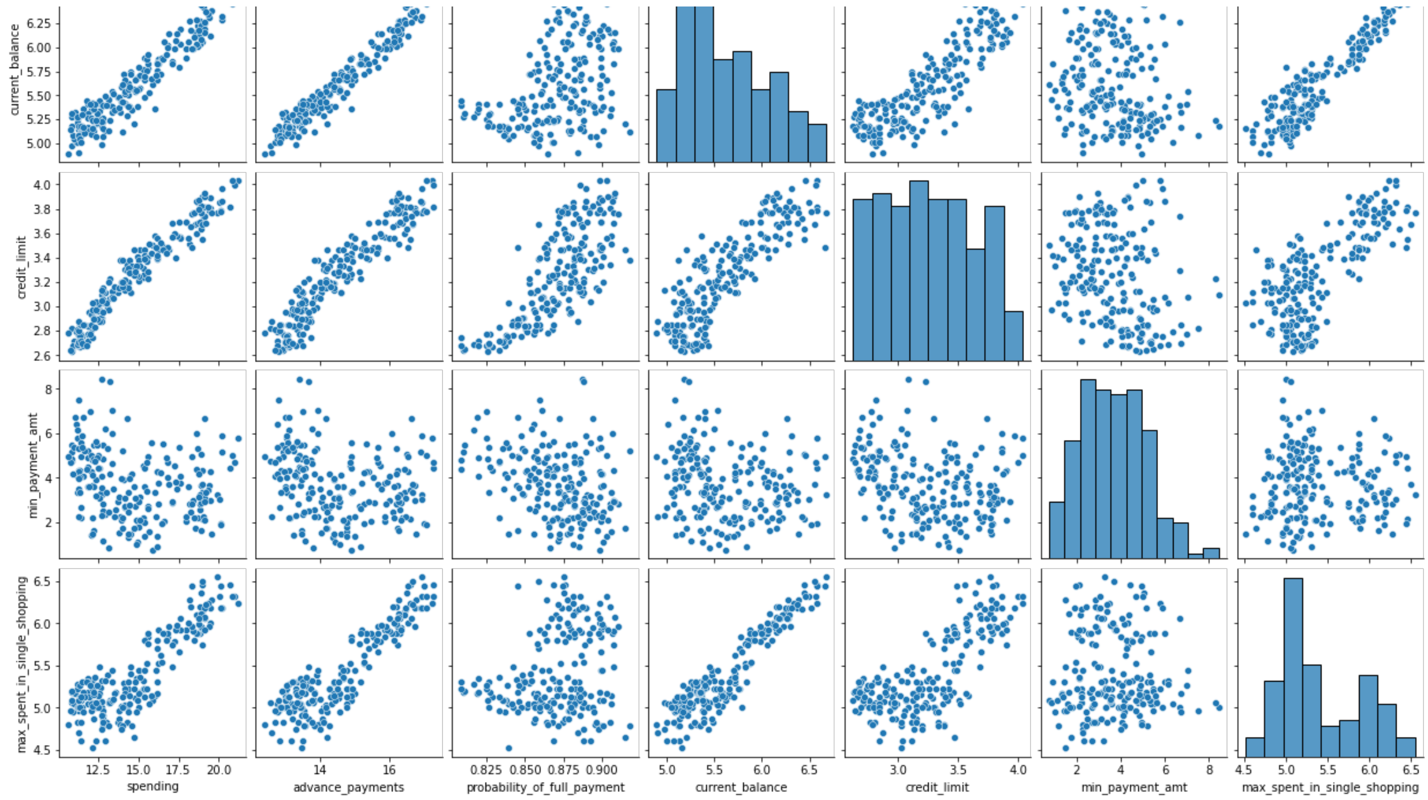
<AxesSubplot:>



In [26]:

```
sns.pairplot(data = df_1)
plt.show()
```



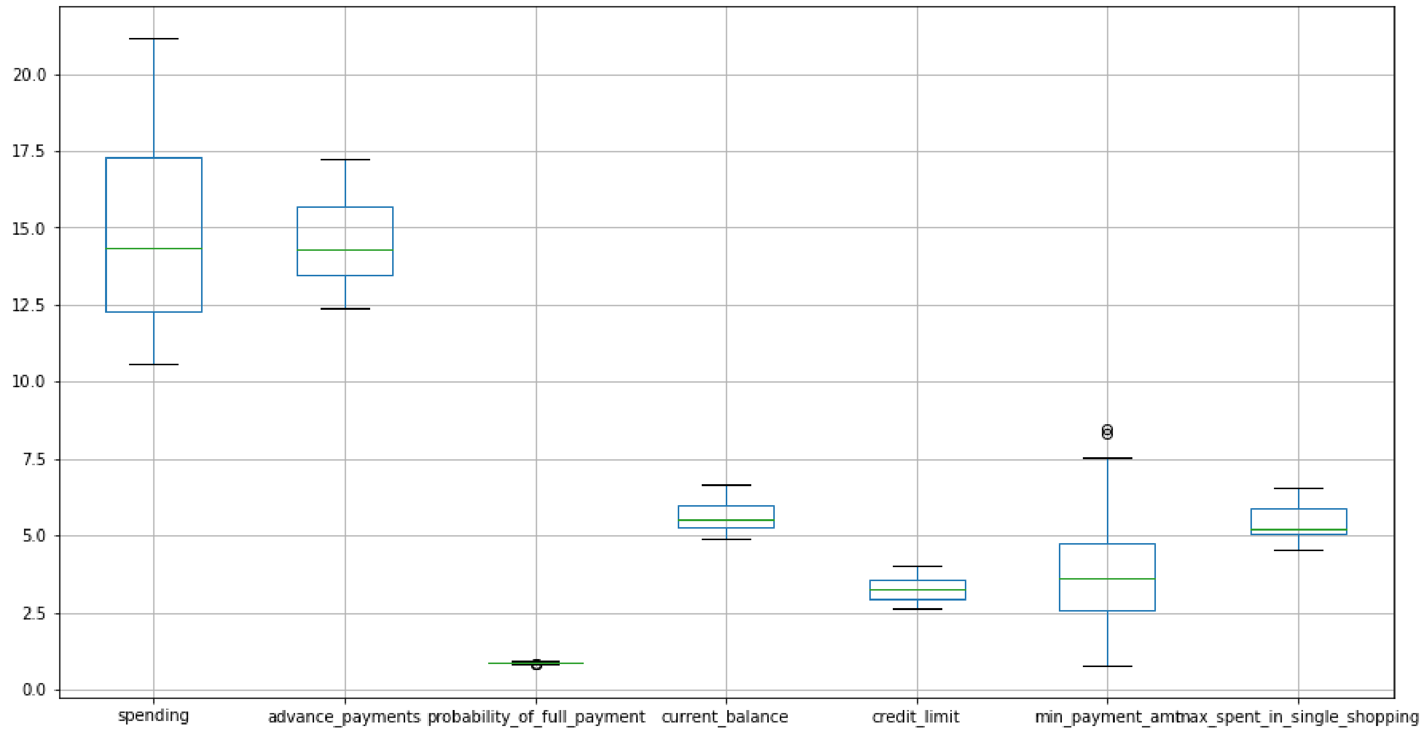


In [20]:

```
df_1.boxplot(figsize= (15,8))
```

Out[20]:

<AxesSubplot:>



1.2 Do you think scaling is necessary for clustering in this case? Justify

1.2 Inference: Yes I beleive that clustering is required in this case for the following reasons:

- **Scaling is necessary in this case as the values vary a lot by scale in different columns. Certain values are in decimals, whereas certain values are in double digits.**
- **Normalizing the data leads to better clustering.**

1.3 Apply hierarchical clustering to scaled data. Identify the number of optimum clusters using Dendrogram and briefly describe them

briefly describe them:

In [29]:

```
scaled_df_1 = pd.DataFrame(X.fit_transform(df_1), columns=df_1.columns)
```

In [30]:

```
scaled_df_1.head()
```

Out[30]:

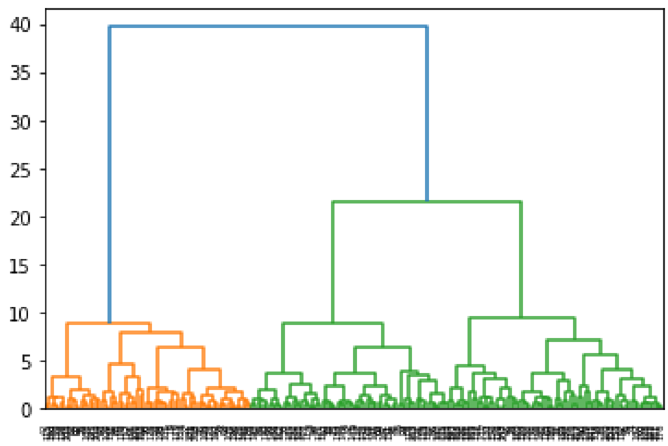
	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_sir
0	1.754355	1.811968	0.178230	2.367533	1.338579	-0.298806	
1	0.393582	0.253840	1.501773	-0.600744	0.858236	-0.242805	
2	1.413300	1.428192	0.504874	1.401485	1.317348	-0.221471	
3	-1.384034	-1.227533	-2.591878	-0.793049	-1.639017	0.987884	
4	1.082581	0.998364	1.196340	0.591544	1.155464	-1.088154	

In [32]:

```
wardlink = linkage(scaled_df_1, method = 'ward')
```

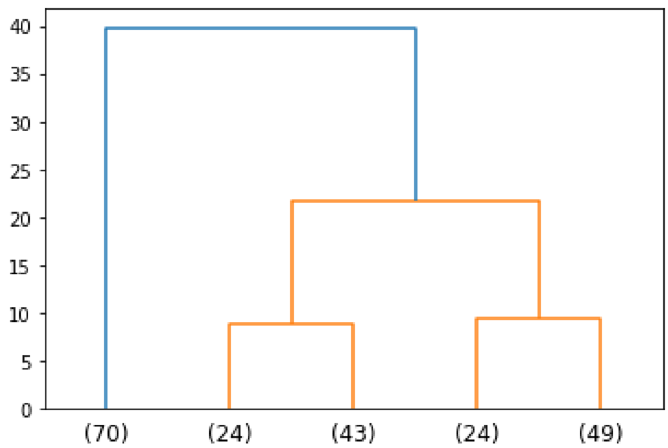
In [33]:

```
dend = dendrogram(wardlink)
```



In [34]:

```
dend = dendrogram(wardlink,
                  truncate_mode='lastp',
                  p = 5,
                  )
```



In [37]:

```
clusters = fcluster(wardlink, 2, criterion='maxclust')
clusters
```

Out[37]:

```
array([1, 2, 1, 2, 1, 2, 2, 2, 1, 2, 1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2,
       1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 2, 1, 1,
       2, 2, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 2, 2, 1, 2, 2, 2, 2, 2, 1,
       1, 2, 1, 2, 2, 2, 1, 1, 2, 1, 2, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 1,
       1, 2, 2, 1, 2, 2, 2, 1, 1, 1, 2, 1, 2, 1, 2, 1, 2, 1, 1, 2, 2, 1,
       2, 2, 1, 2, 2, 1, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2,
       2, 1, 2, 1, 1, 2, 1, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 1, 1, 2, 1, 1, 1, 2, 1, 2, 2, 2, 2, 2, 2, 1, 1, 1,
       2, 2, 1, 2, 2, 2, 2, 2, 1, 1, 2, 2, 2, 2, 2, 2, 2, 1, 2, 1, 1, 2,
       1, 2, 2, 1, 2, 2, 1, 2, 1, 2, 1, 2], dtype=int32)
```

1.3 Inference: The optimal number of clusters is 2

1.4 Apply K-Means clustering on scaled data and determine optimum clusters. Apply elbow curve and silhouette score. Explain the results properly. Interpret and write inferences on the finalized clusters.

In [42]:

```
k_means = KMeans(n_clusters = 2,random_state=1)
```

In [44]:

```
k_means.fit(scaled_df_1)
```

Out[44]:

```
KMeans(n_clusters=2, random_state=1)
```

In [45]:

```
k_means.labels_
```

Out[45]:

```
array([1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1,
       0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1,
       1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1,
       1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1,
       1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1,
       0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0,
       1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1])
```

In [46]:

```
wss =[]
```

In [48]:

```
for i in range(1,11):
    KM = KMeans(n_clusters=i)
    KM.fit(scaled_df_1)
    wss.append(KM.inertia_)
```

In [49]:

```
wss
```

Out[49]:

```
[1469.9999999999998,
 659.171754487041,
 430.6589731513006,
```

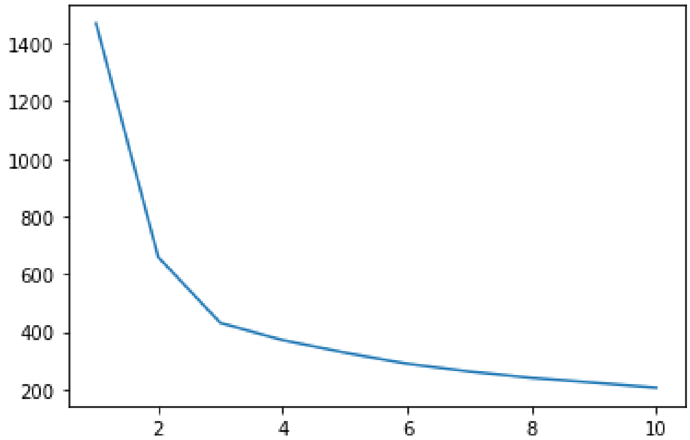
```
 371.29354819439664,
 327.55521940626613,
 289.42530694598116,
 262.25851135061475,
 240.01730394201434,
 223.6400463892972,
 206.22762187342786]
```

In [50]:

```
plt.plot(range(1,11), wss)
```

Out[50]:

```
[<matplotlib.lines.Line2D at 0x204f9b9da60>]
```



In [53]:

```
silhouette_score(scaled_df_1,labels,random_state=1)
```

Out[53]:

```
0.4007270552751299
```

1.4 Inference: The optimal number of clusters is 3.

1.5 Describe cluster profiles for the clusters defined. Recommend different promotional strategies for different clusters.

1.5 Inference:

Cluster Profile 0: Has medium spending, hence campaigns should be made in a way accounting for the same. Cluster Profile 1: Has low spending, hence campaigns should be made in a way accounting for the same. Lower end products can be targeted for Cluster 1. Cluster Profile 2: Has high spending, high probability of full payment hence campaigns should be made in a way accounting for the same. Higher end products can be targeted for Cluster 2.

Problem 2: CART-RF-ANN

2.1 Read the data, do the necessary initial steps, and exploratory data analysis (Univariate, Bi-variate, and multivariate analysis).

In [6]:

```
df.head()
```

Out[6]:

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destination
0	48	C2B	Airlines	No	0.70	Online	7	2.51	Customised Plan	ASIA

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destination
1	36	EPX	Travel Agency	No	0.00	Online	34	20.00	Customised Plan	ASIA
2	39	CWT	Travel Agency	No	5.94	Online	3	9.90	Customised Plan	Americas
3	36	EPX	Travel Agency	No	0.00	Online	4	26.00	Cancellation Plan	ASIA
4	33	JZI	Airlines	No	6.30	Online	53	18.00	Bronze Plan	ASIA

In [7]:

```
df.shape
```

Out[7]:

```
(3000, 10)
```

In [8]:

```
df.isnull().sum()
```

Out[8]:

```
Age             0
Agency_Code     0
Type            0
Claimed         0
Commision       0
Channel         0
Duration        0
Sales           0
Product Name    0
Destination     0
dtype: int64
```

In [9]:

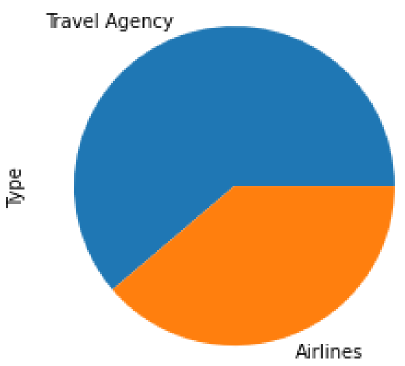
```
df.describe()
```

Out[9]:

	Age	Commision	Duration	Sales
count	3000.000000	3000.000000	3000.000000	3000.000000
mean	38.091000	14.529203	70.001333	60.249913
std	10.463518	25.481455	134.053313	70.733954
min	8.000000	0.000000	-1.000000	0.000000
25%	32.000000	0.000000	11.000000	20.000000
50%	36.000000	4.630000	26.500000	33.000000
75%	42.000000	17.235000	63.000000	69.000000
max	84.000000	210.210000	4580.000000	539.000000

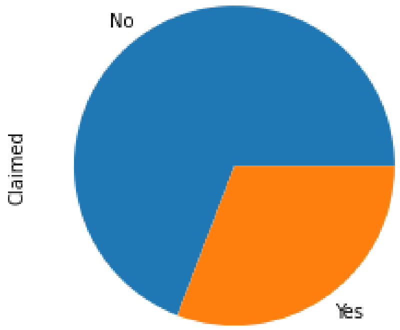
In [10]:

```
df.Type.value_counts(normalize=True).plot.pie()
plt.show()
```



In [11]:

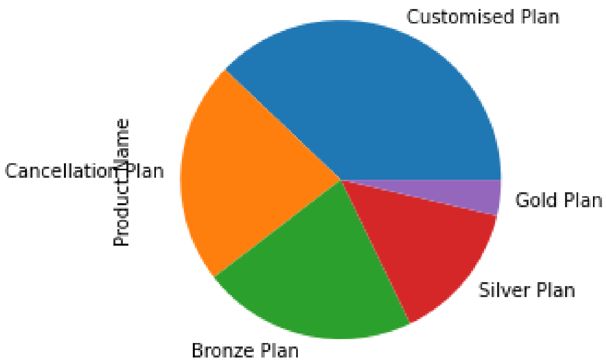
```
df.Claimed.value_counts(normalize=True).plot.pie()
plt.show()
```



In [12]:

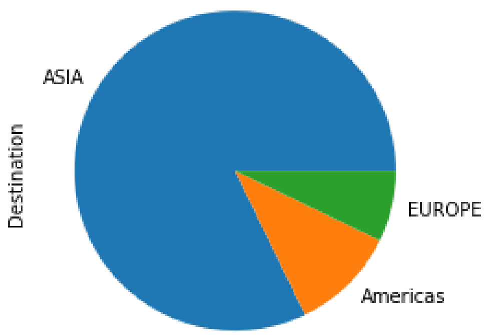
```
df['Product Name'].value_counts(normalize=True).plot.pie()
plt.show()
```

```
C:\Users\Yash Joshi\anaconda3\lib\site-packages\pandas\plotting\_matplotlib\core.py:1547:
MatplotlibDeprecationWarning: normalize=None does not normalize if the sum is less than 1
but this behavior is deprecated since 3.3 until two minor releases later. After the depre
cation period the default value will be normalize=True. To prevent normalization pass nor
malize=False
  results = ax.pie(y, labels=blabels, **kwds)
```



In [13]:

```
df.Destination.value_counts(normalize=True).plot.pie()
plt.show()
```

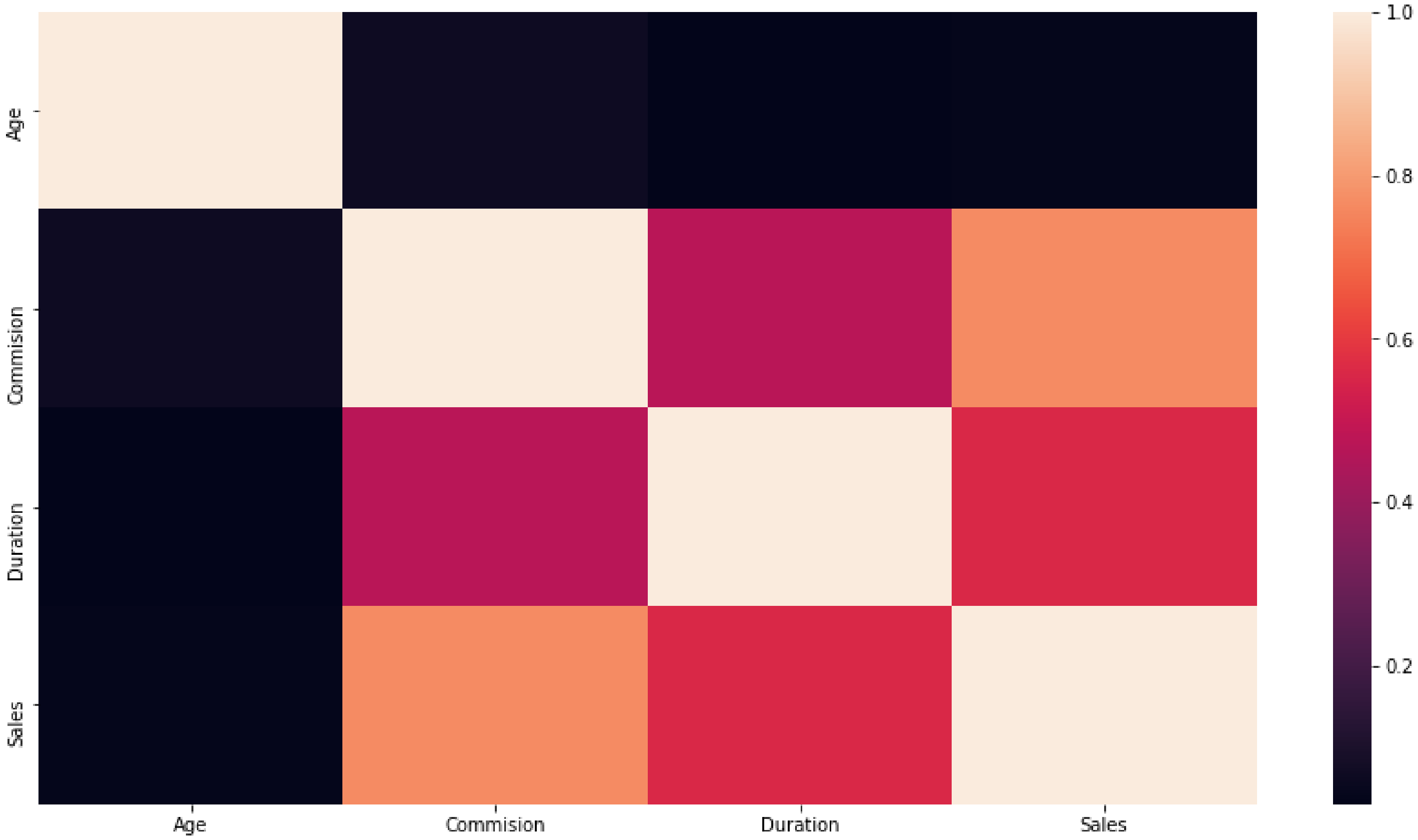


In [14]:

```
plt.subplots(figsize= (15,8))
sns.heatmap(df.corr())
```

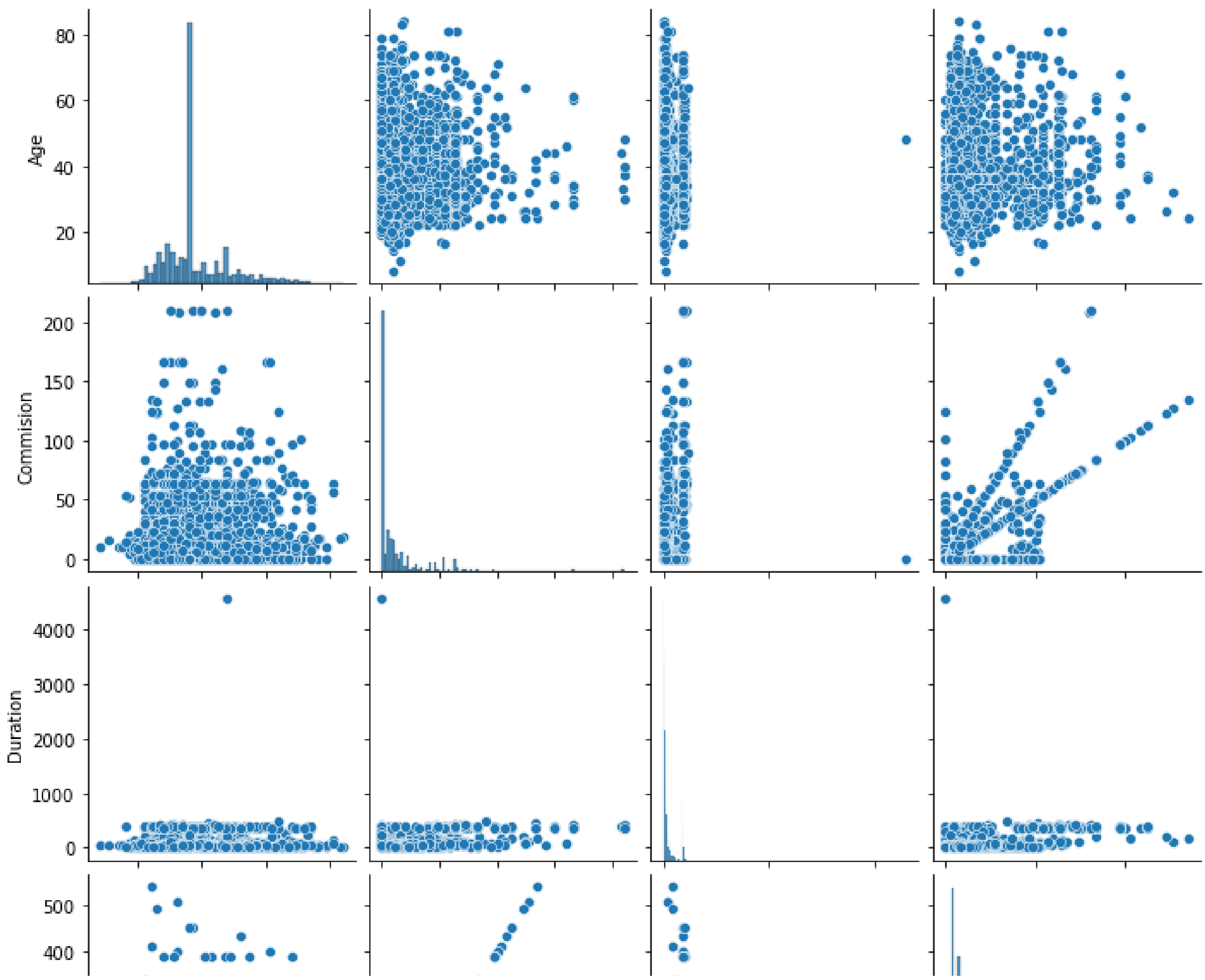
Out[14]:

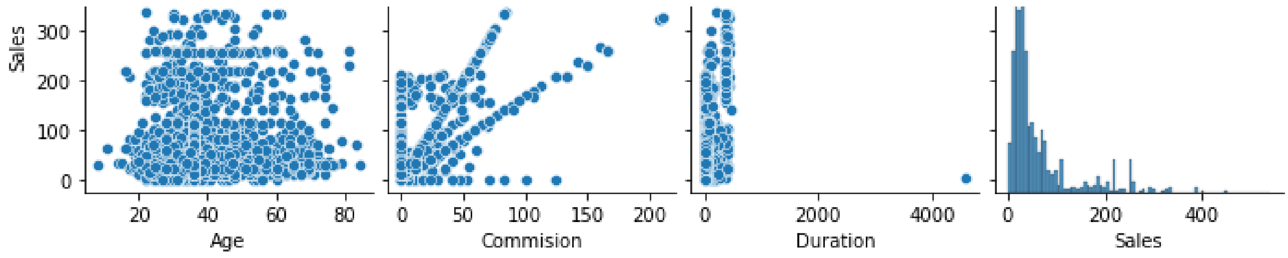
<AxesSubplot:>



In [15]:

```
sns.pairplot(data = df)
plt.show()
```



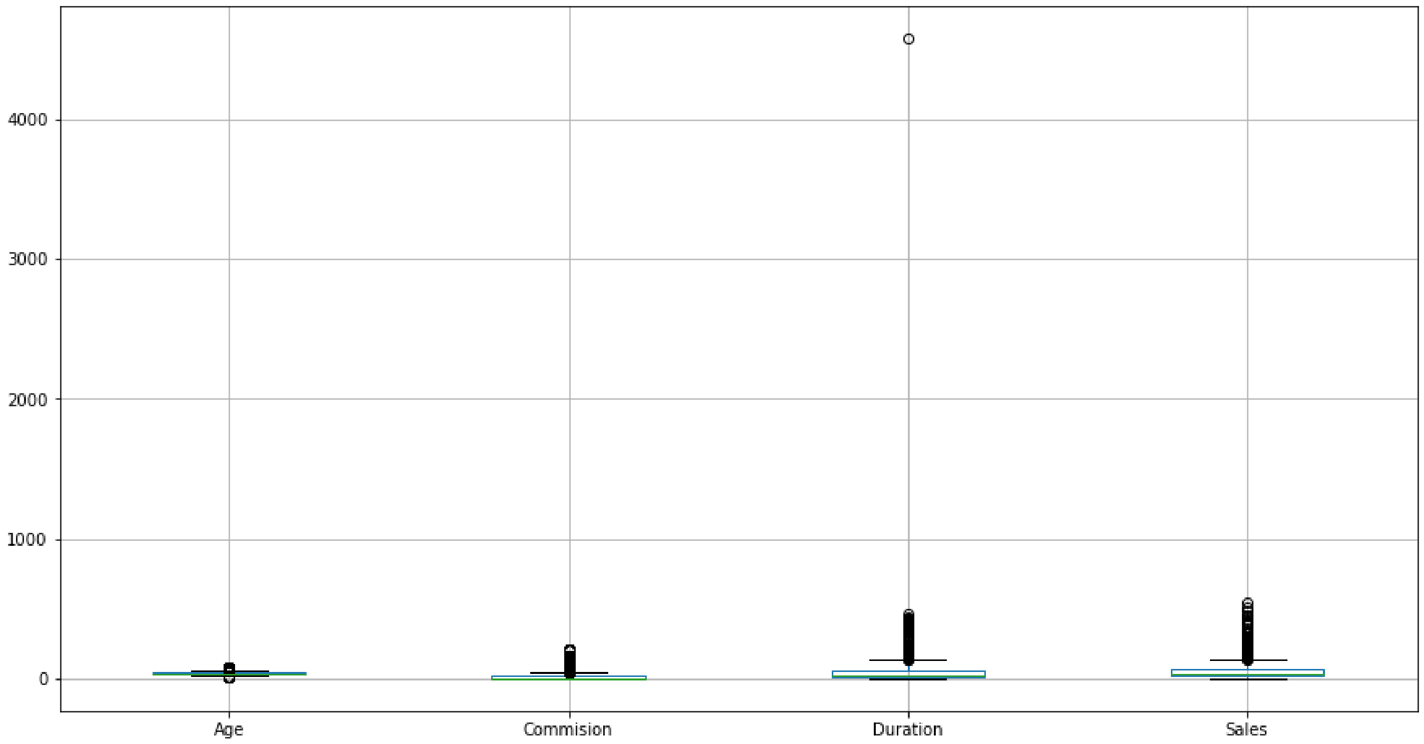


In [16]:

```
df.boxplot(figsize= (15,8))
```

Out[16]:

```
&lt;AxesSubplot:&gt;
```



2.2 Data Split: Split the data into test and train, build classification model CART, Random Forest, Artificial Neural Network

2.3 Performance Metrics: Comment and Check the performance of Predictions on Train and Test sets using Accuracy, Confusion Matrix, Plot ROC curve and get ROC_AUC score, classification reports for each model.

Building a Decision Tree Classifier

In [119]:

```
print(pd.DataFrame(dt_model.feature_importances_, columns=["Imp"], index=X_train.columns
).sort_values('Imp',ascending=False))
```

```
                   Imp
Duration      0.255256
Sales         0.224921
Age           0.199497
Agency_Code   0.166962
Commision     0.087446
Product Name  0.033870
Destination   0.028140
Channel       0.003908
Type          0.000000
```

In [134]:

```
cart_metrics=classification_report(train_labels, ytrain_predict,output_dict=True)
```

```
df=pd.DataFrame(cart_metrics).transpose()
cart_train_f1=round(df.loc["1"][2],2)
cart_train_recall=round(df.loc["1"][1],2)
cart_train_precision=round(df.loc["1"][0],2)
print ('cart_train_precision ',cart_train_precision)
print ('cart_train_recall ',cart_train_recall)
print ('cart_train_f1 ',cart_train_f1)
```

```
cart_train_precision  0.69
cart_train_recall  0.58
cart_train_f1  0.63
```

In [131]:

```
cart_metrics=classification_report(test_labels, ytest_predict,output_dict=True)
df=pd.DataFrame(cart_metrics).transpose()
cart_test_precision=round(df.loc["1"][0],2)
cart_test_recall=round(df.loc["1"][1],2)
cart_test_f1=round(df.loc["1"][2],2)
print ('cart_test_precision',cart_test_precision)
print ('cart_test_recall ',cart_test_recall)
print ('cart_test_f1 ',cart_test_f1)
```

```
cart_test_precision 0.68
cart_test_recall  0.57
cart_test_f1  0.62
```

Building a Random Forest Classifier

In [157]:

```
best_grid = RandomForestClassifier(max_depth=10, max_features=6, min_samples_leaf=5,
min_samples_split=50, n_estimators=300, random_state=1)

best_grid.fit(X_train, train_labels)
```

Out[157]:

```
RandomForestClassifier(max_depth=10, max_features=6, min_samples_leaf=5,
                       min_samples_split=50, n_estimators=300, random_state=1)
```

In [161]:

```
rf_metrics=classification_report(train_labels, ytrain_predict,output_dict=True)
df=pd.DataFrame(rf_metrics).transpose()
rf_train_f1=round(df.loc["1"][2],2)
rf_train_recall=round(df.loc["1"][1],2)
rf_train_precision=round(df.loc["1"][0],2)
print ('rf_train_precision ',rf_train_precision)
print ('rf_train_recall ',rf_train_recall)
print ('rf_train_f1 ',rf_train_f1)
```

```
rf_train_precision  0.75
rf_train_recall  0.61
rf_train_f1  0.67
```

In [163]:

```
rf=classification_report(test_labels, ytest_predict,output_dict=True)
df=pd.DataFrame(rf).transpose()
rf_test_precision=round(df.loc["1"][0],2)
rf_test_recall=round(df.loc["1"][1],2)
rf_test_f1=round(df.loc["1"][2],2)
print ('rf_test_precision',rf_test_precision)
print ('rf_test_recall ',rf_test_recall)
print ('rf_test_f1 ',rf_test_f1)
```

```
rf_test_precision 0.69
rf_test_recall  0.57
rf_test_f1  0.62
```

Building a Neural Network Classifier

In [31]:

```
nn_metrics=classification_report(train_labels, ytrain_predict,output_dict=True)
df=pd.DataFrame(nn_metrics).transpose()
nn_train_precision=round(df.loc["1"][0],2)
nn_train_recall=round(df.loc["1"][1],2)
nn_train_f1=round(df.loc["1"][2],2)
print ('nn train precision ',nn_train_precision)
print ('nn train recall ',nn_train_recall)
print ('nn train f1 ',nn_train_f1)
```

```
nn train precision  0.66
nn train recall  0.55
nn train f1  0.6
```

In [32]:

```
nn_metrics=classification_report(test_labels, ytest_predict,output_dict=True)
df=pd.DataFrame(nn_metrics).transpose()
nn_test_precision=round(df.loc["1"][0],2)
nn_test_recall=round(df.loc["1"][1],2)
nn_test_f1=round(df.loc["1"][2],2)
print ('nn test precision ',nn_test_precision)
print ('nn test recall ',nn_test_recall)
print ('nn test f1 ',nn_test_f1)
```

```
nn test precision  0.67
nn test recall  0.52
nn test f1  0.59
```

2.4 Final Model: Compare all the models and write an inference which model is best/optimized.

Comparing the precision, recall and F1 scores: Out of all of the model Random Forest Classifier is the best suited for this dataset.

2.5 Inference: Based on the whole Analysis, what are the business insights and recommendations

The company should implement Random Forest Classifier method.