E-tivity 3: Clustering and Manifold Learning

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Use this notebook to complete Tasks 1 and 2 in E-tivity3.

Import Python Modules

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn import manifold
from sklearn import cluster
from sklearn import preprocessing
from sklearn.preprocessing import power_transform
from sklearn.metrics import silhouette_samples
from sklearn.metrics import silhouette_score
from matplotlib.ticker import FixedLocator
from matplotlib.ticker import FixedFormatter
```

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Task 1

Task 2

Task 1 (CS5062)

Inspect and Analyse Dataset to begin with

In [2]:

```
df = pd.read_csv("./loans_dataset_et3.csv")

print("Number of Samples  in Dataset:\t",df.shape[0])
print("Number of Features in Dataset:\t",df.shape[1])
```

```
Number of Samples  in Dataset:	 332
Number of Features in Dataset:	 5
```

In [3]:

```
df.head()
```

Out[3]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	2483	2466.0	90	180	0
1	4917	0.0	130	360	0
2	4106	0.0	40	180	1
3	3859	3300.0	142	180	1
4	6417	0.0	157	180	1

In [4]:

```
df.tail()
```

Out[4]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
327	5417	4196.0	267	360	1
328	16666	0.0	275	360	1
329	10750	0.0	312	360	1
330	5955	5625.0	315	360	1
331	6133	3906.0	324	360	1

In [5]:

```
# Print statistical summary for all attributes
df.describe(include='all')
```

Out[5]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	332.000000	332.000000	332.000000	332.000000	332.000000
mean	5201.093373	1495.508795	140.882530	341.710843	0.978916
std	4584.815491	1982.742932	75.544237	61.651497	0.143882
min	645.000000	0.000000	17.000000	60.000000	0.000000
25%	2912.750000	0.000000	100.000000	360.000000	1.000000
50%	3858.500000	1211.500000	128.000000	360.000000	1.000000
75%	5818.250000	2250.000000	162.000000	360.000000	1.000000
max	39999.000000	20000.000000	600.000000	480.000000	1.000000

In [6]:

```
# Quick Check to Ensure no missing data
print(df.isnull().any())
```

```
ApplicantIncome      False
CoapplicantIncome    False
LoanAmount           False
Loan_Amount_Term     False
Credit_History       False
dtype: bool
```

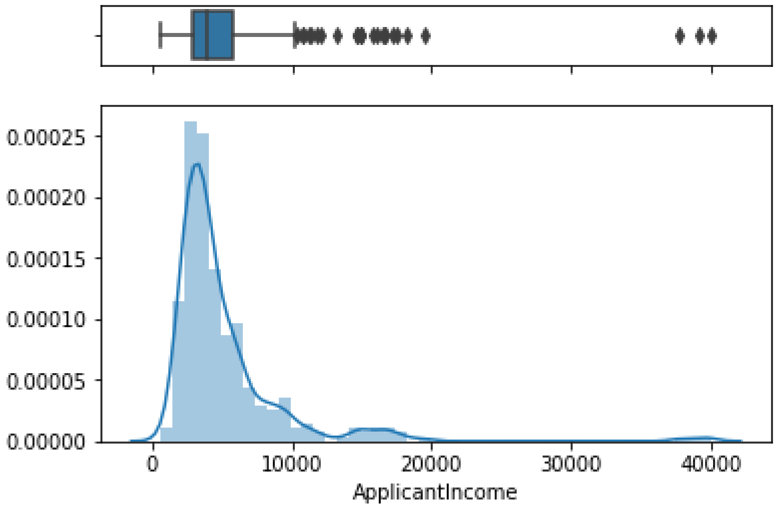
In [7]:

```
def plot_hist_with_box(feature):
    # From https://python-graph-gallery.com/24-histogram-with-a-boxplot-on-top-seaborn/
    # Cut the window in 2 parts
    f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw={"height_ratios": (
.15, .85)})

    # Add a graph in each part
    sns.boxplot(feature, ax=ax_box)
    sns.distplot(feature, ax=ax_hist)

    # Remove x axis name for the boxplot
    ax_box.set(xlabel='')
    plt.show()
    return
```

In [8]:

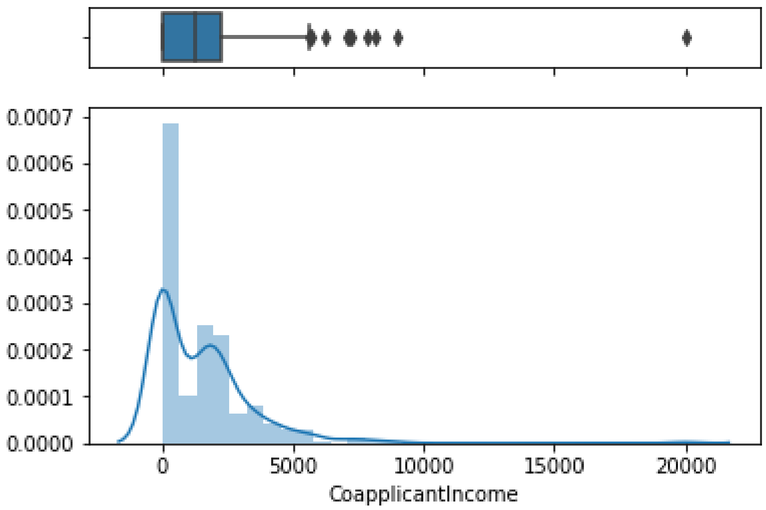
```
plot_hist_with_box(df['ApplicantIncome'])

#plot_hist_with_box(power_transform(np.expand_dims(df['ApplicantIncome'], axis=1), meth
od='box-cox'))
#df['bc_age'] = power_transform(np.expand_dims(df['age'], axis=1), method='box-cox')
```

```
C:\Users\mpower1\AppData\Local\Continuum\anaconda3\lib\site-packages\scipy
\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence for multid
imensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[s
eq]`. In the future this will be interpreted as an array index, `arr[np.ar
ray(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



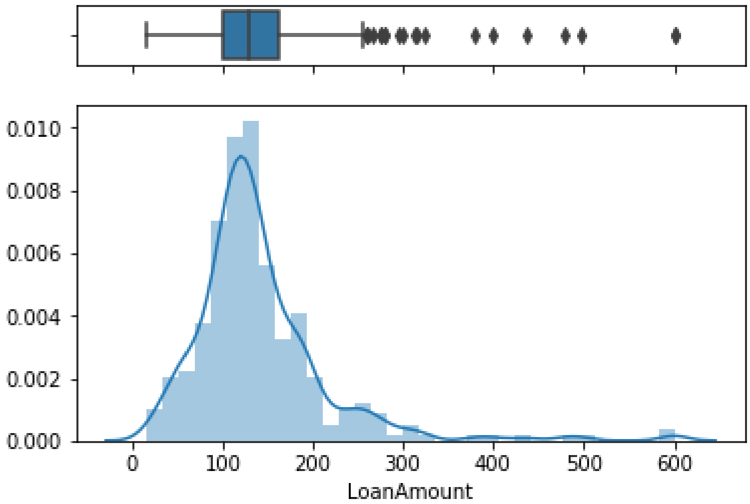
In [9]:

```
plot_hist_with_box(df['CoapplicantIncome'])
#plot_hist_with_box(power_transform(np.expand_dims(df['CoapplicantIncome'], axis=1), me
thod='yeo-johnson'))
#plot_hist_with_box(power_transform(np.expand_dims(df['CoapplicantIncome']+1, axis=1),
 method='box-cox'))
```



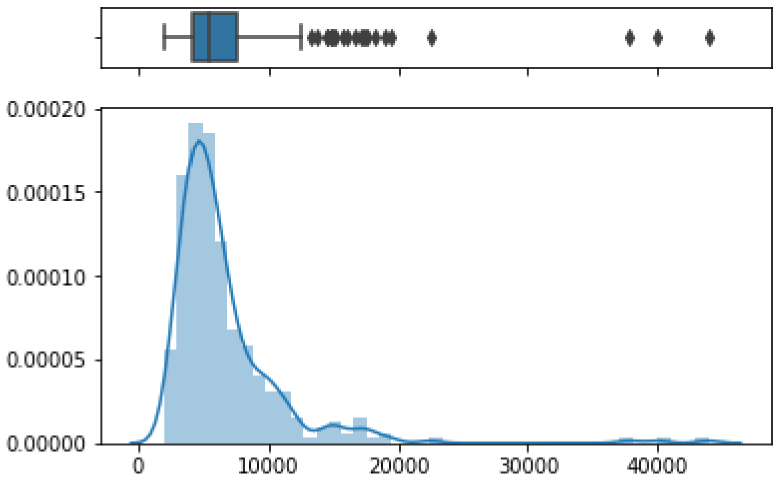
In [10]:

```
plot_hist_with_box(df['LoanAmount'])
#plot_hist_with_box(power_transform(np.expand_dims(df['LoanAmount'], axis=1), method='y
eo-johnson'))
#plot_hist_with_box(power_transform(np.expand_dims(df['LoanAmount']+1, axis=1), method
='box-cox'))
```



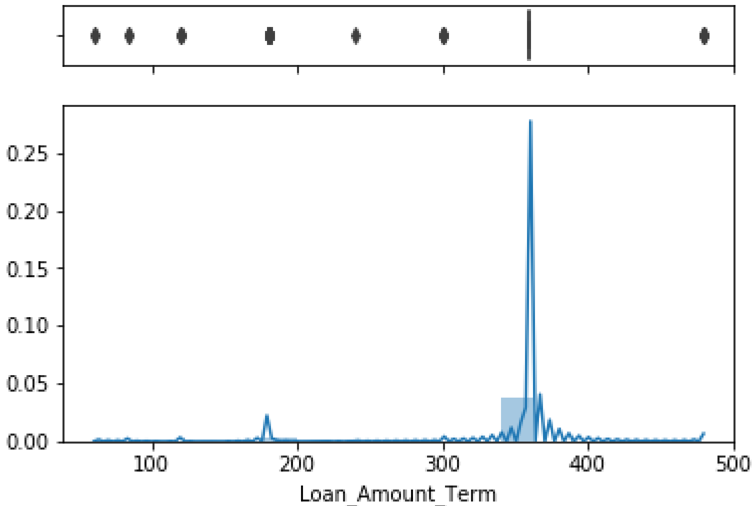
In [11]:

```
plot_hist_with_box(df['ApplicantIncome']+df['CoapplicantIncome'])
#plot_hist_with_box(power_transform(np.expand_dims(df['ApplicantIncome']+df['Coapplican
tIncome'], axis=1), method='box-cox'))
```



In [12]:

```
plot_hist_with_box(df['Loan_Amount_Term'])

#plot_hist_with_box(power_transform(np.expand_dims(df['Loan_Amount_Term'], axis=1), met
hod='box-cox'))

#min_max_scaler = preprocessing.MinMaxScaler()
#lab3_data = min_max_scaler.fit_transform(lab3_data)
#plot_hist_with_box(min_max_scaler.fit_transform(np.expand_dims(df['Loan_Amount_Term'],
axis=1)))

#min_max_scaler = preprocessing.MinMaxScaler()
#lab3_data = min_max_scaler.fit_transform(lab3_data)
#plot_hist_with_box(min_max_scaler.fit_transform(np.expand_dims(df['Loan_Amount_Term']/
12, axis=1)))

#robust_scaler = preprocessing.RobustScaler()
#lab3_data = min_max_scaler.fit_transform(lab3_data)
#plot_hist_with_box(robust_scaler.fit_transform(np.expand_dims(df['Loan_Amount_Term']/1
2, axis=1)))
```



In [13]:

```
print(df['Loan_Amount_Term'].nunique())
df['Loan_Amount_Term'].value_counts()
```

```
8
```

Out[13]:

```
360    292
180     24
480      4
300      4
120      3
84       2
60       2
240      1
Name: Loan_Amount_Term, dtype: int64
```

In [14]:

```
print(df['Credit_History'].nunique())
df['Credit_History'].value_counts()
```

```
2
```

Out[14]:

```
1    325
0      7
Name: Credit_History, dtype: int64
```

In [15]:

```
print(df['LoanAmount'].nunique())
#df['LoanAmount'].value_counts() # Too many to print without cluttering notebook
```

```
148
```

Task 1 - Feature Scaling

In [16]:

```
# Reusing code from Lab3

# Fixed typo in code where 'blue' appeared twice. Replaced with 'yellow'
colors = np.array(['orange', 'blue', 'lime', 'yellow', 'khaki', 'pink', 'green', 'purpl
e'])

bookcolors_key = np.array(['crimson', 'red', 'redorange', 'orange', 'yellow', 'sky', 'b
abyblue', 'lightblue', 'blue', 'purple'])

bookcolors = {
         'crimson': '#a50026', 'red': '#d73027',
         'redorange': '#f46d43', 'orange': '#fdae61',
         'yellow': '#fee090', 'sky': '#e0f3f8',
         'babyblue': '#abd9e9', 'lightblue': '#74add1',
         'blue': '#4575b4', 'purple': '#313695'
     }

# points - a 2D array of (x,y) coordinates of data points
# labels - an array of numeric labels in the interval [0..k-1], one for each point
# centers - a 2D array of (x, y) coordinates of cluster centers
# title - title of the plot

def clustering_scatterplot(points, labels, centers, title):
    # plot the examples, i.e. the data points

    n_clusters = np.unique(labels).size
    for i in range(n_clusters):
        h = plt.scatter(points[labels==i,0],
                        points[labels==i,1],
                        c=colors[i%colors.size],
                        #c=bookcolors[bookcolors_key[i%bookcolors_key.size]],
                        label = 'cluster '+str(i))

    # plot the centers of the clusters
    if centers is not None:
        plt.scatter(centers[:,0], centers[:,1], c='r', marker='*', s=500)

    _ = plt.title(title)
    _ = plt.legend()
    _ = plt.xlabel('x')
    _ = plt.ylabel('y')
```

In [17]:

```
scale_data = np.array(df.values, dtype=float)
print('(number of examples, number of attributes): ', scale_data.shape)
```

```
(number of examples, number of attributes):  (332, 5)
```

Apply Min-Max Scaling

In [18]:

```
min_max_scaler = preprocessing.MinMaxScaler()
scale_data = min_max_scaler.fit_transform(scale_data)
```

Run K-Means on Scaled Data

In [19]:

```
# K-Means Parameters
k = 4

# Number of time the k-means algorithm will be run with different centroid seeds.
# The final results will be the best output of n_init consecutive runs in terms of iner
tia.
n_init = 20

# Maximum number of iterations of the k-means algorithm for a single run.
max_iter = 500
random_state = 0 # Use this to make results repeable for analysis in Markdown cells
```

In [20]:

```
clustered_data_sklearn = cluster.KMeans(n_clusters=k, n_init=n_init, max_iter=max_iter,
random_state=random_state).fit(scale_data)
```

In [21]:

```
# append the cluster centers to the dataset
scale_data_and_centers = np.r_[scale_data,clustered_data_sklearn.cluster_centers_]
```

Task 1 - MDS Visualisation

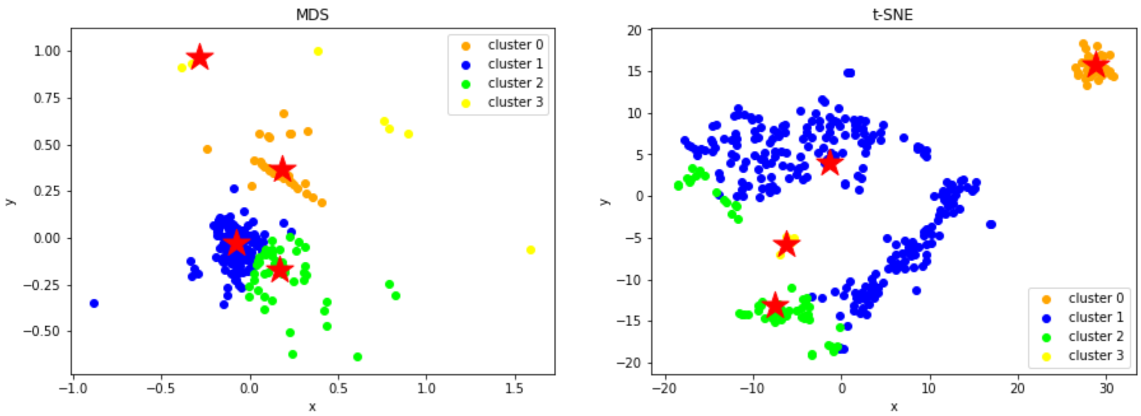
Task 1 - t-SNE Visualisation

In [22]:

```
def plot_mds_tsne(n_clusters, plot_data, plot_labels, n_components=2, random_state=0):
    # Plot MDS and t-SNE visualisations for data

    plt.subplots(1, 2, figsize=(15, 5))

    # MDS Plot
    plt.subplot(1,2,1)
    # project both th data and the k-Means cluster centers to a 2D space
    XYcoordinates = manifold.MDS(n_components=n_components, random_state=random_state).
fit_transform(plot_data)
    clustering_scatterplot(points=XYcoordinates[:-n_clusters,:],
                           labels=plot_labels,
                           centers=XYcoordinates[-n_clusters:,:],
                           title='MDS')

    # t-SNE Plot
    plt.subplot(1,2,2)
    XYcoordinates = manifold.TSNE(n_components=n_components, random_state=random_state)
.fit_transform(plot_data)
    clustering_scatterplot(points=XYcoordinates[:-n_clusters,:],
                           labels=plot_labels,
                           centers=XYcoordinates[-n_clusters:,:],
                           title='t-SNE')
    # Plot graphs
    plt.show()
```

In [23]:

```
plot_mds_tsne(k, scale_data_and_centers, clustered_data_sklearn.labels_, n_components=2
)
```

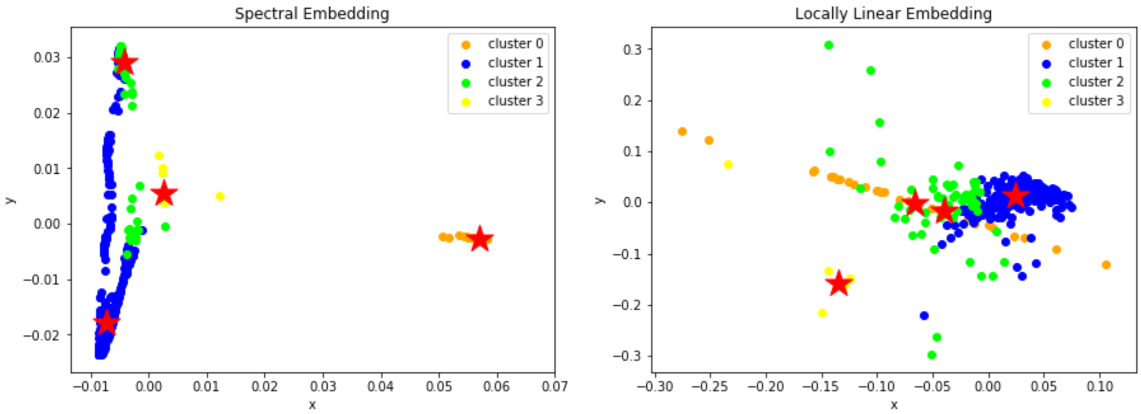


In [24]:

```
def plot_se_lle(n_clusters, n_neighbors,plot_data, plot_labels, n_components=2, random_
state=0):
    # Plot Spectral Embedding and  Locally Linear Embedding visualisations for data

    plt.subplots(1, 2, figsize=(15, 5))

    # SE Plot
    plt.subplot(1,2,1)
    XYcoordinates = manifold.SpectralEmbedding(n_components=n_components,n_neighbors=n_
neighbors,random_state=random_state).fit_transform(plot_data)
    clustering_scatterplot(points=XYcoordinates[:-n_clusters,:],
                           labels=plot_labels,
                           centers=XYcoordinates[-n_clusters:,:],
                           title='Spectral Embedding')

    # LLE Plot
    plt.subplot(1,2,2)
    XYcoordinates = manifold.LocallyLinearEmbedding(n_components=n_components,n_neighbo
rs=n_neighbors,random_state=random_state).fit_transform(plot_data)
    clustering_scatterplot(points=XYcoordinates[:-n_clusters,:],
                           labels=plot_labels,
                           centers=XYcoordinates[-n_clusters:,:],
                           title='Locally Linear Embedding')
    # Plot graphs
    plt.show()
```

In [25]:

```
plot_se_lle(k, 10, scale_data_and_centers, clustered_data_sklearn.labels_, n_components
=2)
```



Task 1 - Cluster Description

In [26]:

```
# Append the cluster labels to the original data
df['cluster_k4'] = pd.Series(clustered_data_sklearn.labels_, index=df.index)
```

In [27]:

```
print(df['cluster_k4'].nunique())
df['cluster_k4'].value_counts()
```

```
4
```

Out[27]:

```
1    241
2     54
0     30
3      7
Name: cluster_k4, dtype: int64
```

In [28]:

```
df.groupby('cluster_k4').mean()
```

Out[28]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_
cluster_k4					
0	5146.966667	1297.126666	116.333333	161.600000	
1	3829.493776	1541.436183	118.419087	361.493776	
2	10840.166667	1322.629630	246.296296	357.777778	
3	9153.857143	2098.142857	206.285714	308.571429	

Task 1 - Cluster Characteristics

Task 2 (CS5062)

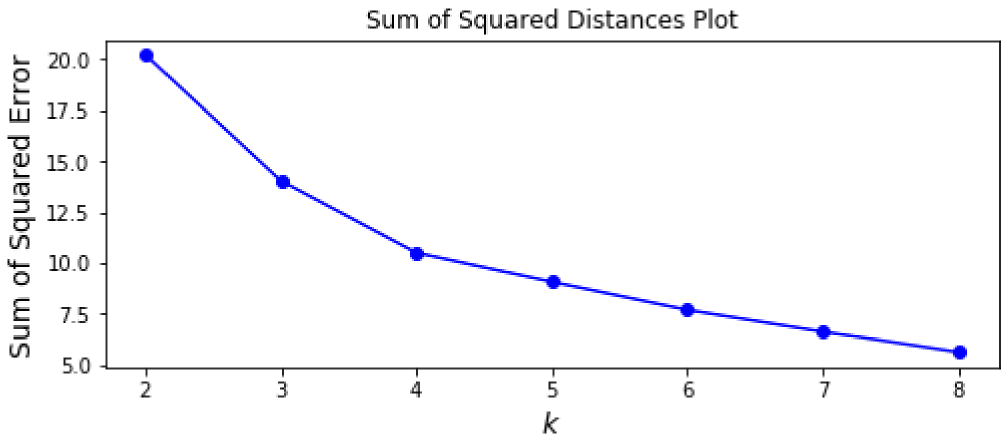
Task 2 - Sum of Squared Distances Plot

In [29]:

```
min_k = 2
max_k = 8

kvals = np.array(range(min_k,max_k+1))
```

In [30]:

```
sse = np.empty(len(kvals))

for i in range(len(kvals)):
    clustered_data_sklearn = cluster.KMeans(n_clusters=kvals[i],  n_init=n_init, max_it
er=max_iter, random_state=random_state).fit(scale_data)

    # Store Sum of Squared Error Value
    sse[i] = clustered_data_sklearn.inertia_


plt.figure(figsize=(8, 3))
plt.title("Sum of Squared Distances Plot")
plt.plot(kvals,  sse, "bo-")
plt.xlabel("$k$", fontsize=14)
plt.ylabel("Sum of Squared Error", fontsize=14)
plt.show()
```



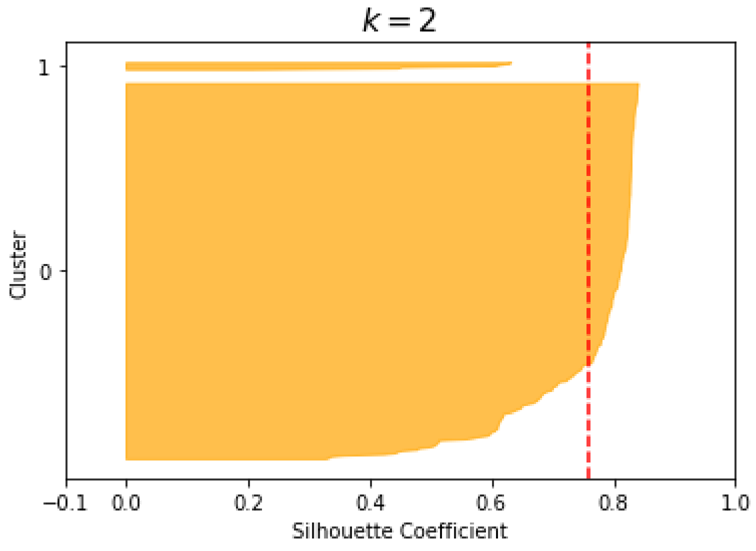
Task 2 - Elbow Method to Find Best k

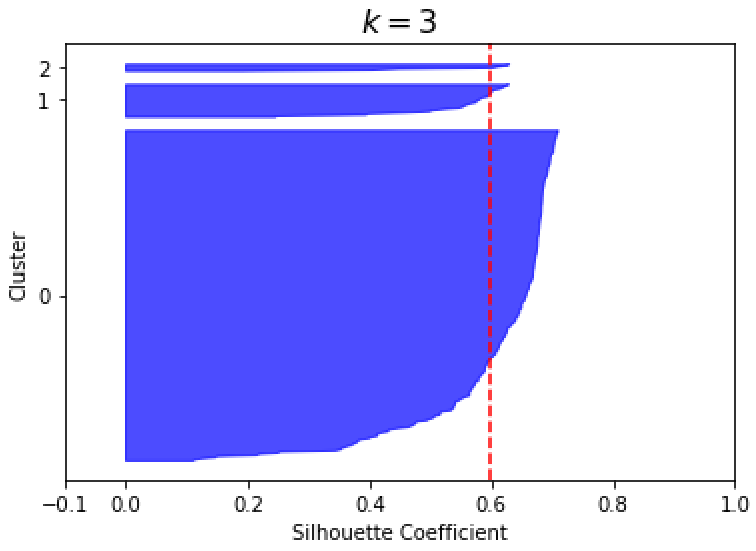
Task 2 - Silhouette Coefficient Method to Find Best k

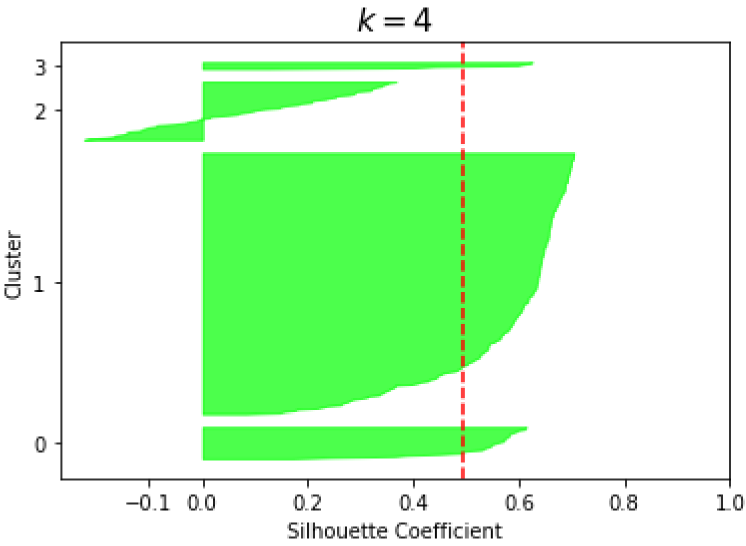
In [31]:

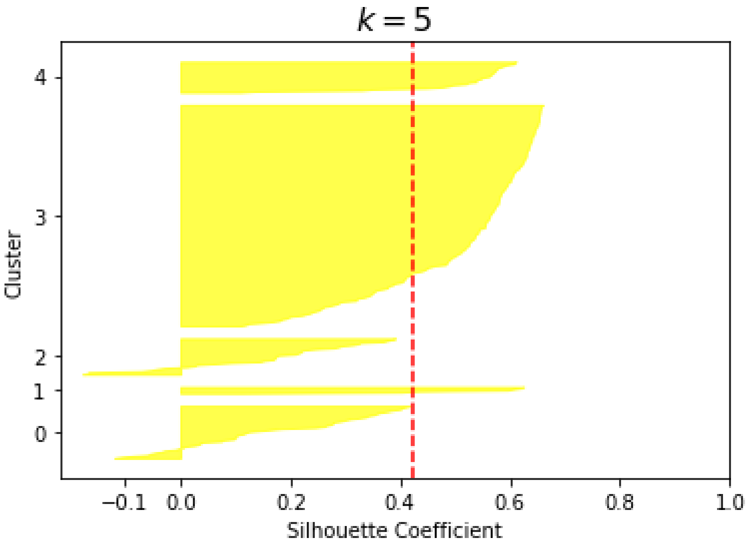
```
# From https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_silhouette_ana
lysis.html
# From https://github.com/ageron/handson-ml2/blob/master/09_unsupervised_learning.ipynb

# Empty Array to Store Silhouette values
silhouette_avg = np.empty(len(kvals))


for i in range(len(kvals)):

    clustered_data_sklearn = cluster.KMeans(n_clusters=kvals[i],  n_init=n_init, max_it
er=max_iter, random_state=random_state).fit(scale_data)


    cluster_labels = clustered_data_sklearn.labels_

    # The silhouette_score gives the average value for all the samples.
    # This gives a perspective into the density and separation of the formed
    # clusters
    silhouette_avg[i] = silhouette_score(scale_data, cluster_labels)


    # Compute the silhouette scores for each sample
    sample_silhouette_values = silhouette_samples(scale_data, cluster_labels)

    padding = len(scale_data) // 30
    pos = padding
    ticks = []


    for j in range(kvals[i]):
        coeffs = sample_silhouette_values[cluster_labels==j]
        coeffs.sort()

        plt.fill_betweenx(np.arange(pos, pos + len(coeffs)), 0, coeffs,
                          facecolor=colors[i%colors.size], edgecolor=colors[i%colors.si
ze], alpha=0.7)

        ticks.append(pos + len(coeffs) // 2)
        pos += len(coeffs) + padding

    plt.gca().yaxis.set_major_locator(FixedLocator(ticks))
    plt.gca().yaxis.set_major_formatter(FixedFormatter(range(kvals[i])))
    plt.gca().set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])
    plt.xlabel("Silhouette Coefficient")
    plt.ylabel("Cluster")
    plt.axvline(x=silhouette_avg[i], color="red", linestyle="--")
    plt.title("$k={}$".format(kvals[i]), fontsize=16)
    plt.show()


# Plot Silhoette Scores

plt.figure(figsize=(8, 3))
plt.plot(kvals,  silhouette_avg, "bo-")
plt.xlabel("$k$", fontsize=14)
plt.ylabel("Silhouette score", fontsize=14)
plt.show()
```

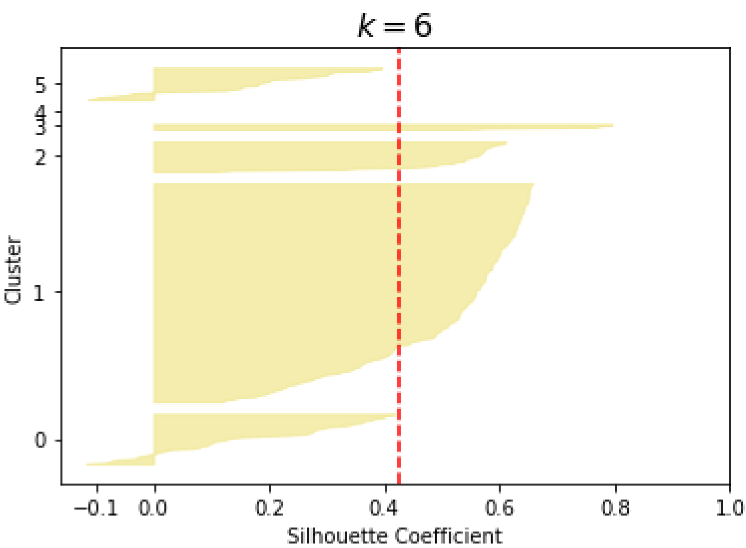
```
for i in range(len(kvals)):
    print("For k =", kvals[i], "The average silhouette_score is :", silhouette_avg[i])
```

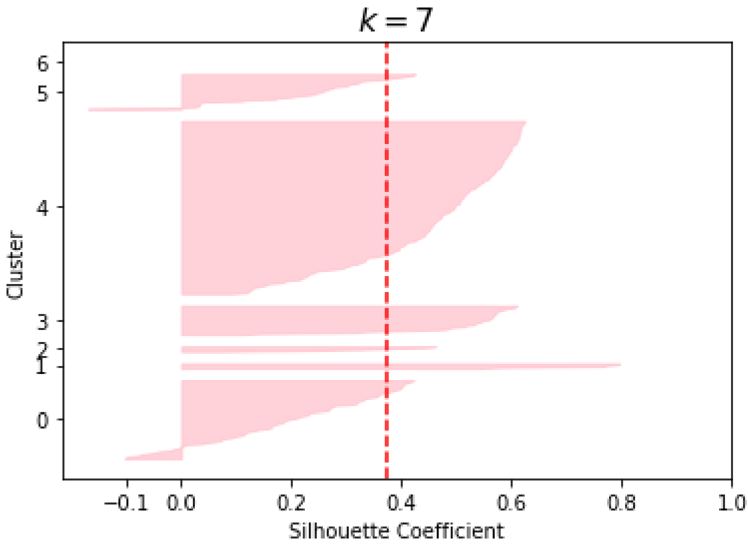

$k = 2$
1
0
Cluster
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
Silhouette Coefficient

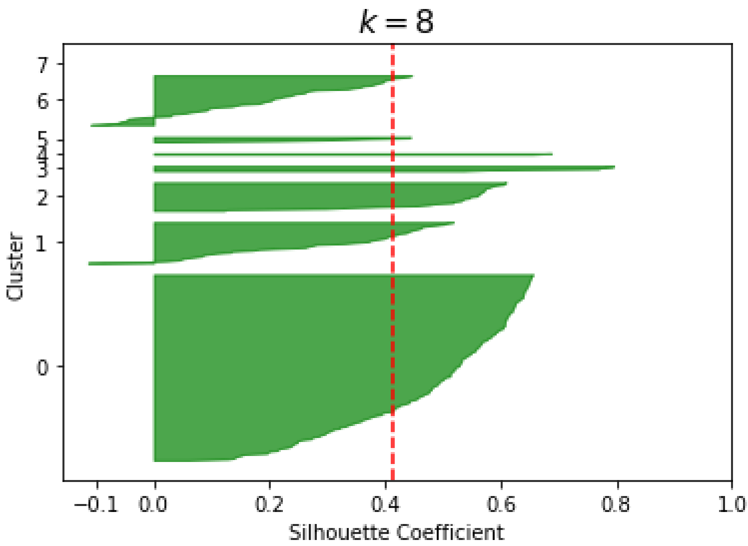

$k = 3$
2
1
0
Cluster
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
Silhouette Coefficient

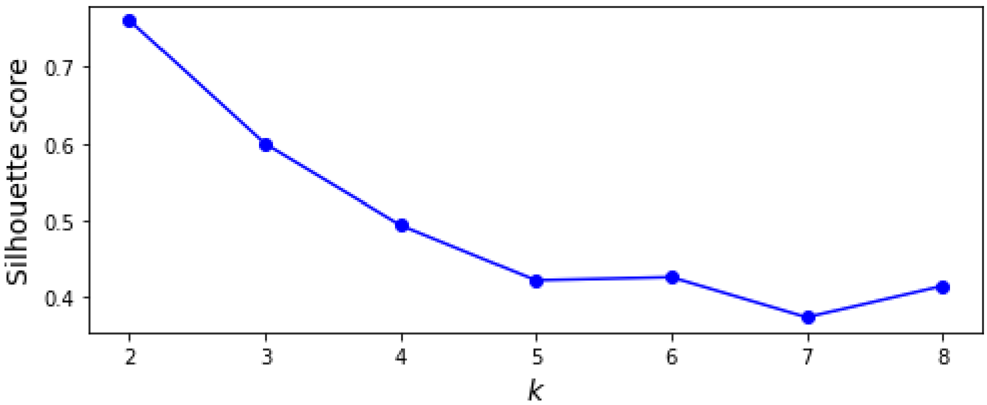

$k = 4$
Cluster
Silhouette Coefficient
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0


$k = 5$
Cluster
Silhouette Coefficient
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0


$k = 6$
Cluster
Silhouette Coefficient
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0








```
For k = 2 The average silhouette_score is : 0.7596807546208396
For k = 3 The average silhouette_score is : 0.5993683877939564
For k = 4 The average silhouette_score is : 0.49382717460168524
For k = 5 The average silhouette_score is : 0.4222843719671475
For k = 6 The average silhouette_score is : 0.42634925012082986
For k = 7 The average silhouette_score is : 0.3741853059971289
For k = 8 The average silhouette_score is : 0.41493989203937404
```

Re-Run with K = 3

In [32]:

```
# K-Means Parameters
k = 3
```

In [33]:

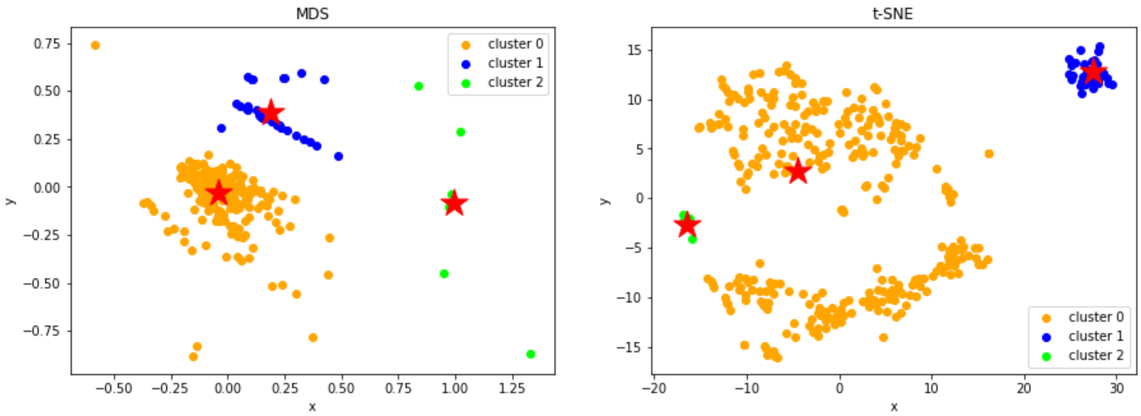
```
km_k_3 = cluster.KMeans(n_clusters=k, n_init=n_init, max_iter=max_iter, random_state=random_state).fit(scale_data)
```

In [34]:

```
# append the cluster centers to the dataset
km_k_3_data_and_centers = np.r_[scale_data,km_k_3.cluster_centers_]
```

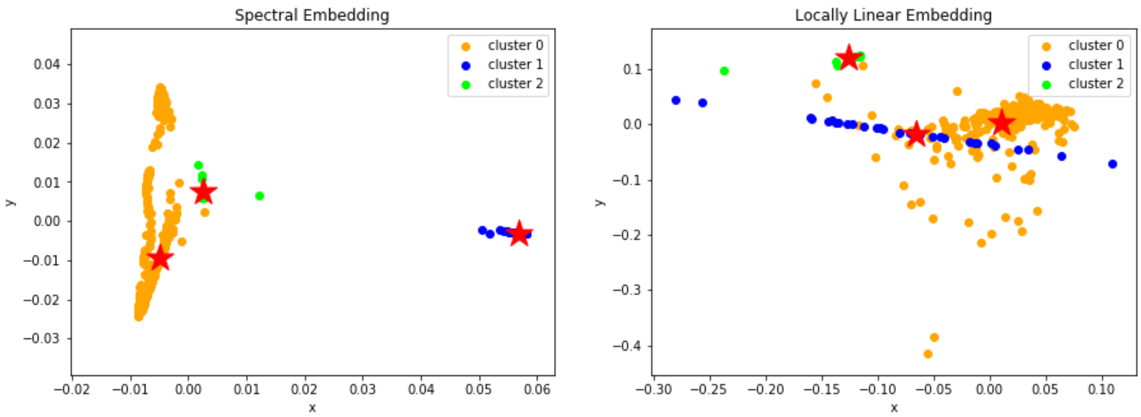
In [35]:

```
plot_mds_tsne(k, km_k_3_data_and_centers,km_k_3.labels_, n_components=2)
```



In [36]:

```
plot_se_lle(k, 10, km_k_3_data_and_centers,km_k_3.labels_, n_components=2)
```



In [37]:

```
# Append the cluster labels to the original data
df['cluster_k3'] = pd.Series(km_k_3.labels_, index=df.index)
```

In [38]:

```
print(df['cluster_k3'].nunique())
df['cluster_k3'].value_counts()
```

```
3
```

Out[38]:

```
0    295
1     30
2      7
Name: cluster_k3, dtype: int64
```

In [39]:

```
df.groupby('cluster_k3').mean()
```

Out[39]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_
cluster_k3					
0	5112.803390	1501.383458	141.827119	360.813559	
1	5146.966667	1297.126666	116.333333	161.600000	
2	9153.857143	2098.142857	206.285714	308.571429	

Task 2 - Additional Clustering Algorithm

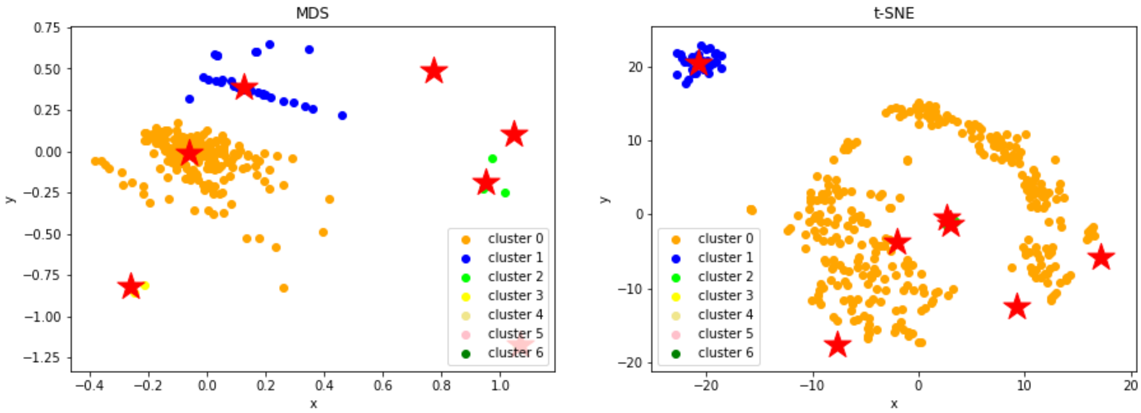
In [86]:

```
# https://learning.oreilly.com/library/view/machine-learning-with/9781491989371/ch19.html#clustering
# https://scikit-learn.org/stable/auto_examples/cluster/plot_mean_shift.html#sphx-glr-auto-examples-cluster-plot-mean-shift-py
from sklearn.cluster import MeanShift

bandwidth = cluster.estimate_bandwidth(scale_data, quantile=0.8)

# Create meanshift object
#ms = MeanShift(bandwidth=bandwidth, bin_seeding=True, cluster_all=False)
ms = MeanShift(bandwidth=bandwidth, bin_seeding=True, cluster_all=True) # MPP -> Set to true until visualisations debugged

# Train model
model = ms.fit(scale_data)

ms_labels = ms.labels_
ms_cluster_centers = ms.cluster_centers_

ms_labels_unique = np.unique(ms_labels)
ms_n_clusters_ = len(ms_labels_unique)

# append the cluster centers to the dataset
ms_scale_data_and_centers = np.r_[scale_data, ms.cluster_centers_]

print("number of estimated clusters : %d" % ms_n_clusters_)
```

```
number of estimated clusters : 7
```

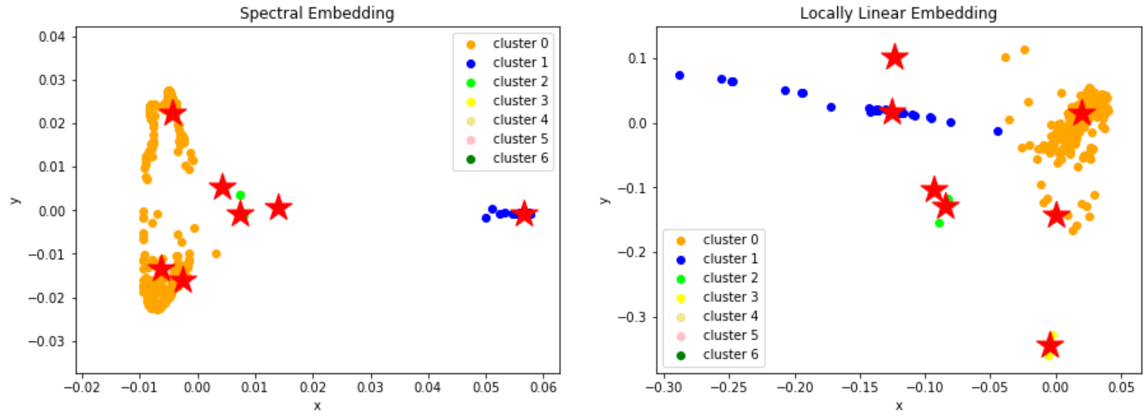
In [87]:

```
plot_mds_tsne(ms_n_clusters_,ms_scale_data_and_centers, ms.labels_, n_components=2)
```



In [88]:

```
plot_se_lle(ms_n_clusters_, 10, ms_scale_data_and_centers, ms.labels_, n_components=2)
```



In [89]:

```
# Append the cluster labels to the original data
df['cluster_ms'] = pd.Series(ms.labels_, index=df.index)
```

In [90]:

```
print(df['cluster_ms'].nunique())
df['cluster_ms'].value_counts()
```

```
7
```

Out[90]:

```
0    292
1     30
2      5
3      2
6      1
5      1
4      1
Name: cluster_ms, dtype: int64
```

In [91]:

```
df.groupby('cluster_ms').mean()
```

Out[91]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_Hi
cluster_ms					
0	4893.530822	1432.048356	142.000000	360.821918	
1	5146.966667	1297.126666	116.333333	161.600000	
2	4319.000000	2444.200000	150.800000	360.000000	
3	38433.000000	2375.000000	136.000000	360.000000	
4	39999.000000	0.000000	600.000000	180.000000	
5	2500.000000	20000.000000	103.000000	360.000000	
6	2483.000000	2466.000000	90.000000	180.000000	

Task 2 - Additional Manifold Learning Technique

Task 2 - Visual Comparison of Clusterings

Task 2 - Difference Between K-Means And Second Algorithm Discussion

Cell Graveyard

In [ ]:

```
def zero_encode(x):
    if(x>0):
        return 1
    else:
        return 0

my_df = pd.DataFrame()
my_df = my_df.append(df, ignore_index = True)

my_df['JointIncome'] = my_df['ApplicantIncome'] + my_df['CoapplicantIncome']


my_df['JointApplicantion'] = my_df['CoapplicantIncome'].apply(zero_encode)
```

In [ ]:

```
my_df.head()
```

In [ ]:

```
plot_hist_with_box(my_df['JointIncome'])
```

In [ ]:

```
my_df = my_df.drop(['ApplicantIncome'], axis=1)
```

In [ ]:

```
my_df = my_df.drop(['CoapplicantIncome'], axis=1)
```

In [ ]:

```
my_df = my_df.drop(['cluster'], axis=1)
```

In [ ]:

```
my_df.head()
```

In [ ]:

```
my_data = np.array(my_df.values, dtype=float)
print('(number of examples, number of attributes): ', my_data.shape)
```

In [ ]:

```
my_min_max_scaler = preprocessing.MinMaxScaler()
my_data = my_min_max_scaler.fit_transform(my_data)
```

In [ ]:

```
k = 4

clustered_data_sklearn = cluster.KMeans(n_clusters=k, n_init=10, max_iter=300).fit(my_d
ata)

# append the cluster centers to the dataset
my_data_and_centers = np.r_[my_data,clustered_data_sklearn.cluster_centers_]
```

In [ ]:

```
# project both th data and the k-Means cluster centers to a 2D space
XYcoordinates = manifold.MDS(n_components=2).fit_transform(my_data_and_centers)
print("transformation complete")
```

In [ ]:

```
# plot the transformed examples and the centers
# use the cluster assignment to colour the examples
clustering_scatterplot(points=XYcoordinates[:-k,:],
                       labels=clustered_data_sklearn.labels_,
                       centers=XYcoordinates[-k:,:],
                       title='MDS')
```

In [ ]:

```
# project both th data and the k-Means cluster centers to a 2D space
XYcoordinates = manifold.TSNE(n_components=2).fit_transform(my_data_and_centers)
print("transformation complete")
```

In [ ]:

```
# plot the transformed examples and the centers
# use the cluster assignment to colour the examples
# plot the transformed examples and the centers
# use the cluster assignment to colour the examples
clustering_scatterplot(points=XYcoordinates[:-k,:],
                       labels=clustered_data_sklearn.labels_,
                       centers=XYcoordinates[-k:,:],
                       title='TSNE')
```

In [ ]:

```
# Append the cluster labels to the original data
df['cluster'] = pd.Series(clustered_data_sklearn.labels_, index=df.index)
```

In [ ]:

```
df.groupby('cluster').mean()
```

In [ ]:

```
scale_df = pd.DataFrame()
```

In [ ]:

```
scale_df = scale_df.append(df, ignore_index = True)
```

In [ ]:

```
scale_df.head()
```

In [ ]:

```
scale_df['ApplicantIncome'] = power_transform(np.expand_dims(scale_df['ApplicantIncome'
], axis=1), method='box-cox')
```

In [ ]:

```
scale_df['CoapplicantIncome'] = power_transform(np.expand_dims(df['CoapplicantIncome'],
axis=1), method='yeo-johnson')
```

In [ ]:

```
scale_df['LoanAmount'] = power_transform(np.expand_dims(df['LoanAmount'], axis=1), meth
od='box-cox')
```

In [ ]:

```
min_max_scaler2 = preprocessing.MinMaxScaler()
#lab3_data = min_max_scaler.fit_transform(lab3_data)
scale_df['Loan_Amount_Term'] = min_max_scaler2.fit_transform(np.expand_dims(df['Loan_Amount_Term'], axis=1))
#scale_df['ApplicantIncome'] = min_max_scaler2.fit_transform(np.expand_dims(df['ApplicantIncome'], axis=1))
#scale_df['CoapplicantIncome'] = min_max_scaler2.fit_transform(np.expand_dims(df['CoapplicantIncome'], axis=1))
#scale_df['LoanAmount'] = min_max_scaler2.fit_transform(np.expand_dims(df['LoanAmount'], axis=1))
```

In [ ]:

```
scale_df.head()
```

In [ ]:

```
scale_df.describe(include='all')
```

In [ ]:

```
### DEBUG CODE
#scale_df['ApplicantIncome'] = scale_df['ApplicantIncome'] + abs(scale_df['ApplicantIncome'].min())
```

In [ ]:

```
#scale_df['CoapplicantIncome'] = scale_df['CoapplicantIncome'] + abs(scale_df['CoapplicantIncome'].min())
#scale_df['LoanAmount'] = scale_df['LoanAmount'] + abs(scale_df['LoanAmount'].min())
```

In [ ]:

```
scale_df.describe(include='all')
```

In [ ]:

```
# scale_df['ApplicantIncome'] = df['ApplicantIncome']
# plot_hist_with_box(scale_df['ApplicantIncome'])
# scale_df['ApplicantIncome'] = power_transform(np.expand_dims(scale_df['ApplicantIncome'], axis=1), method='box-cox')
# plot_hist_with_box(scale_df['ApplicantIncome'])
# scale_df['ApplicantIncome'] = min_max_scaler2.fit_transform(np.expand_dims(df['ApplicantIncome'], axis=1))
# plot_hist_with_box(scale_df['ApplicantIncome'])
```