BDA- Experiment 5

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Dataset used: Loan Prediction / Clustering.csv

Import the necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from IPython.display import display
import warnings
warnings.filterwarnings('ignore')
```

Load the dataset

In [2]:
```
df = pd.read_csv(r"C:\sia\clustering.csv")
```

Explore the dataset

In [3]:
```
display(df.head())
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
1	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
2	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
3	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y
4	LP001013	Male	Yes	0	Not Graduate	No	2333	1516.0	95.0	360.0	1.0	Urban	Y

In [4]:
```
display("Statistics of the dataset: ",df.describe())
```

'Statistics of the dataset: '

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	381.000000	381.000000	381.000000	370.000000	351.000000
mean	3579.845144	1277.275381	104.986877	340.864865	0.837607
std	1419.813818	2340.818114	28.358464	68.549257	0.369338
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2600.000000	0.000000	90.000000	360.000000	1.000000
50%	3333.000000	983.000000	110.000000	360.000000	1.000000
75%	4288.000000	2016.000000	127.000000	360.000000	1.000000
max	9703.000000	33837.000000	150.000000	480.000000	1.000000

In [5]:
```
#Check for missing values:
print(df.isnull().sum())
```

```
Loan_ID              0
Gender               5
Married              0
Dependents           8
Education            0
Self_Employed       21
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term    11
Credit_History      30
Property_Area        0
Loan_Status          0
dtype: int64
```

In [6]:
```
#drop rows with missing values
df.dropna(inplace=True)
```

In [7]:
```
print("Shape of the dataset",df.shape)
```

```
Shape of the dataset (308, 13)
```

Preprocess the data

In [8]:
```
df.drop(['Loan_ID', 'Loan_Status'], axis=1, inplace=True)
df['Gender'].fillna(df['Gender'].mode()[0], inplace=True)
df['Married'].fillna(df['Married'].mode()[0], inplace=True)
df['Dependents'].fillna(df['Dependents'].mode()[0], inplace=True)
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0], inplace=True)
df['LoanAmount'].fillna(df['LoanAmount'].mean(), inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0], inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0], inplace=True)
df['Property_Area'].fillna(df['Property_Area'].mode()[0], inplace=True)

# Encoding categorical variables
df = pd.get_dummies(df, columns=['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed', 'Property_Area'])
```

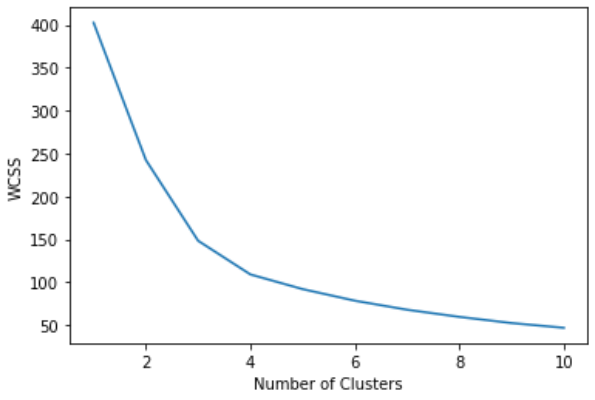
Scaling the data:

In [9]:
```
# Select the features to use for clustering
X = df[['ApplicantIncome', 'LoanAmount']]

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [10]:
```
from sklearn.preprocessing import MinMaxScaler, RobustScaler

# MinMaxScaler
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# RobustScaler
scaler = RobustScaler()
X_scaled = scaler.fit_transform(X)
```

Find the optimal number of clusters using the elbow method

In [11]:
```
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



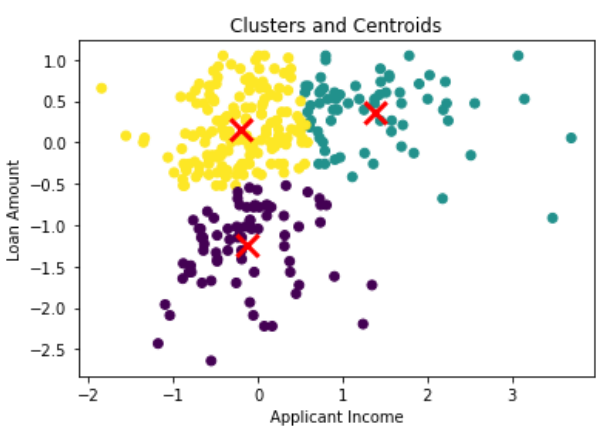
Fit K-Means to the dataset

In [12]:
```
# Set the number of clusters
k = 3

# Initialize the KMeans object
kmeans = KMeans(n_clusters=k, random_state=42)

# Fit the KMeans model
kmeans.fit(X_scaled)
```

Out[12]:
```
KMeans(n_clusters=3, random_state=42)
```

Visualize the clusters and centroids

In [13]:
```
# Get the labels and centroids
labels = kmeans.labels_
centroids = kmeans.cluster_centers_

# Plot the clusters
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=labels, cmap='viridis')
plt.scatter(centroids[:, 0], centroids[:, 1], marker='x', s=200, linewidths=3, color='r')
plt.title('Clusters and Centroids')
plt.xlabel('Applicant Income')
plt.ylabel('Loan Amount')
plt.show()
```



> ## Observations:
>
> The scatter plot also shows that there is a positive correlation between 'ApplicantIncome' and 'LoanAmount'. As ApplicantIncome increases, so does the LoanAmount. This relationship is consistent across all three clusters.
>
> Based on the scatter plot, we can also see that there are a few outliers in the dataset. These are data points that fall far away from the centroids and do not belong to any of the three clusters. These outliers may be worth further investigation to determine why they are different from the rest of the dataset.

Conclusion:

Finally, we can conclude that K-Means clustering can be a useful tool for identifying patterns and structure within the loan prediction dataset. It can help us group similar loan applicants together, which can be useful for tasks such as credit risk assessment and loan approval.