# Kmeans_PCA

March 10, 2024

# 1 "Clustering Universities: Analyzing Patterns and Insights Using Unsupervised KMeans and PCA"

## 1.1 Problem Statement:

### 1.1.1 Project Overview:

The project aims to explore patterns and gain insights from a dataset containing information about various universities. The primary objectives include:

### 1.1.2 1. Cluster Analysis:

Apply the KMeans clustering algorithm to group universities based on selected features. Identify the optimal number of clusters using the Elbow Method.

### 1.1.3 2. Dimensionality Reduction:

Utilize Principal Component Analysis (PCA) to reduce the dimensionality of the data and visualize university clusters in a lower-dimensional space.

### 1.1.4 3. Insights Discovery:

Explore and interpret the clusters to uncover potential relationships and characteristics among universities. Understand the distribution of universities based on the chosen features.

## 1.2 Project Components:

### 1.2.1 1. Cluster Analysis:

- **Algorithm:** KMeans Clustering
- **Methodology:** Utilize the Elbow Method to determine the optimal number of clusters.
- **Implementation:** Apply KMeans to group universities based on selected features.

### 1.2.2 2. Dimensionality Reduction:

- **Technique:** Principal Component Analysis (PCA)
- **Implementation:** Use PCA to reduce the dimensionality of the data, enabling insightful visualizations.

### 1.2.3 3. Insights Discovery:

- **Exploration:** Investigate the identified clusters to understand patterns and potential relationships.
- **Interpretation:** Analyze the distribution of universities within each cluster baof higher education or related fields. atures.

[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 sklearn.decomposition import PCA

# Suppress warnings for cleaner output
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
# Load the dataset
df = pd.read_excel("University_clustering.xlsx")
df.head()
```

[2]:

| | Univ | State | SAT | Top10 | Accept | SFRatio | Expenses | GradeRate |
|---|---|---|---|---|---|---|---|---|
| 0 | Brown | RI | 1310 | 89 | 22 | 13 | 22704 | 94 |
| 1 | CalTech | CA | 1415 | 100 | 25 | 6 | 63575 | 81 |
| 2 | CMU | PA | 1260 | 62 | 59 | 9 | 25026 | 72 |
| 3 | Columbia | NY | 1310 | 76 | 24 | 12 | 31510 | 88 |
| 4 | Cornell | NY | 1280 | 83 | 33 | 13 | 21864 | 90 |

[3]:
```
# Display the shape of the dataset
df_shape = df.shape
print(f"Dataset Shape: {df_shape}")
```

```
Dataset Shape: (25, 8)
```

[4]:
```
# Display information about the dataset
df_info = df.info()
print(df_info)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25 entries, 0 to 24
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Univ      25 non-null     object
 1   State     25 non-null     object
 2   SAT       25 non-null     int64
 3   Top10     25 non-null     int64
 4   Accept    25 non-null     int64
```

```
 5   SFRatio    25 non-null     int64
 6   Expenses   25 non-null     int64
 7   GradeRate  25 non-null     int64
dtypes: int64(6), object(2)
memory usage: 1.7+ KB
None
```

[5]:
```python
# Selecting Features
# Drop non-numeric columns ("Univ" and "State") for clustering
X = df.drop(["Univ", "State"], axis=1)
```

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### Scaling Data

[6]:
```python
# Scaling the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)  # Standardize features
X_scaled_df = pd.DataFrame(X_scaled,columns=X.columns)  # Convert 2D numpy␣
 ↪array to a DataFrame
X_scaled_df.head()
```

[6]:

| | SAT | Top10 | Accept | SFRatio | Expenses | GradeRate |
|---|---|---|---|---|---|---|
| 0 | 0.410284 | 0.657519 | -0.889867 | 0.070260 | -0.331413 | 0.820303 |
| 1 | 1.399259 | 1.235212 | -0.734657 | -1.686251 | 2.560381 | -0.644524 |
| 2 | -0.060657 | -0.760454 | 1.024382 | -0.933460 | -0.167121 | -1.658634 |
| 3 | 0.410284 | -0.025208 | -0.786394 | -0.180670 | 0.291649 | 0.144229 |
| 4 | 0.127719 | 0.342414 | -0.320766 | 0.070260 | -0.390846 | 0.369587 |

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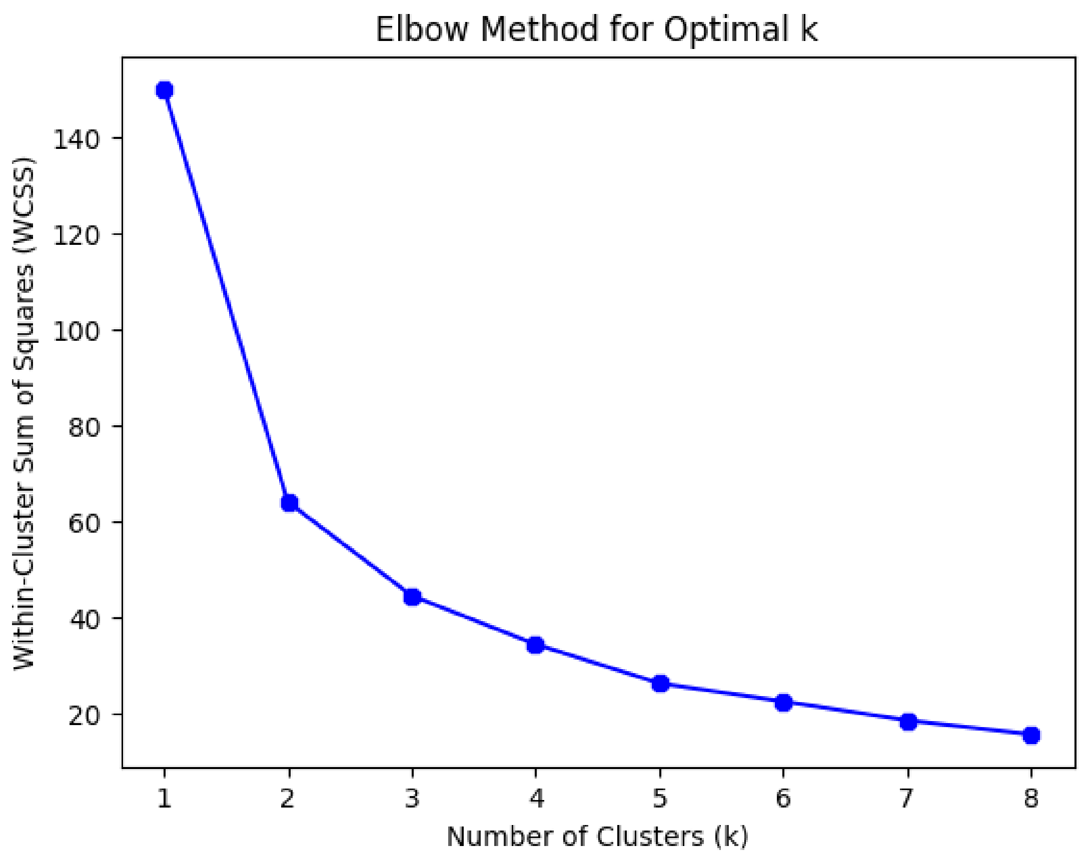
### Elbow Method

[7]:
```python
# Selecting the best number of clusters using the elbow method
wcss = []
clusters = list(range(1, 9))
for i in clusters:
    kmeans = KMeans(n_clusters=i)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)
```

[8]:
```python
# Plotting the Elbow Method
plt.plot(clusters, wcss, color='b', marker="8")
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
plt.show()
```

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**K-Means**

[9]:
```
# Applying KMeans clustering with the optimal number of clusters
kmeans = KMeans(n_clusters=3)
df["Cluster"] = kmeans.fit_predict(X_scaled)
```

[10]:
```
# displaying clustered data
print(df[["Univ","Cluster"]])
```

```
         Univ  Cluster
0       Brown        1
1     CalTech        2
2         CMU        1
3    Columbia        1
4     Cornell        1
5   Dartmouth        2
6        Duke        2
7   GeorgeTown        1
8     Harvard        2
9  JhonsHopkins        2
```

```
10           MIT        2
11   Northwestern        1
12      NotreDame        1
13      PennState        0
14       Priceton        2
15         Purdue        0
16       Stanford        2
17       TexasA&M        0
18     UCBerkeley        1
19       UChicago        1
20      UMichigan        1
21          UPenn        1
22            UVA        1
23     UWisconsin        0
24           Yale        2
```

[11]:
```
# Getting cluster labels
labels = kmeans.labels_
labels
```

[11]:
```
array([1, 2, 1, 1, 1, 2, 2, 1, 2, 2, 2, 1, 1, 0, 2, 0, 2, 0, 1, 1, 1, 1,
       1, 0, 2])
```

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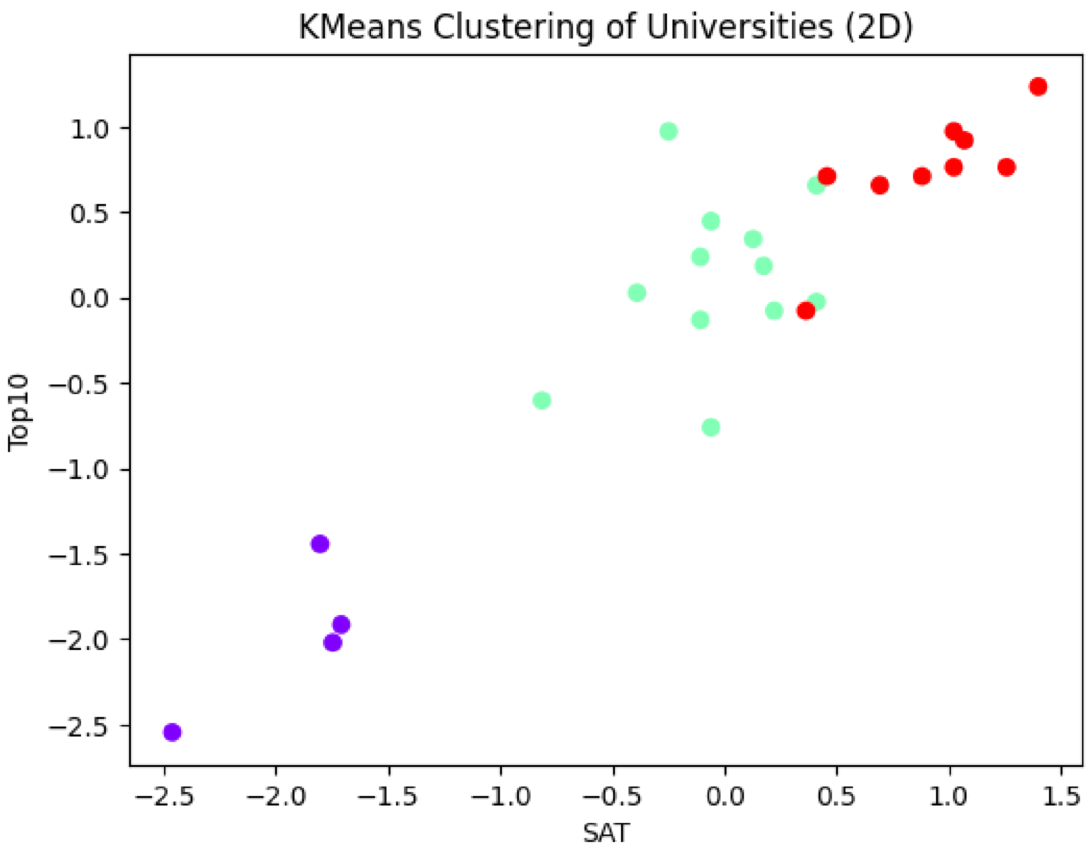
**Visualizing Clusters in 2D**

[12]:
```
# 2D plot of the clusters
plt.scatter(X_scaled_df.iloc[:, 0], X_scaled_df.iloc[:, 1], c=df['Cluster'],␣
 ↪cmap='rainbow')
plt.xlabel('SAT')
plt.ylabel('Top10')
plt.title('KMeans Clustering of Universities (2D)')
plt.show()
```

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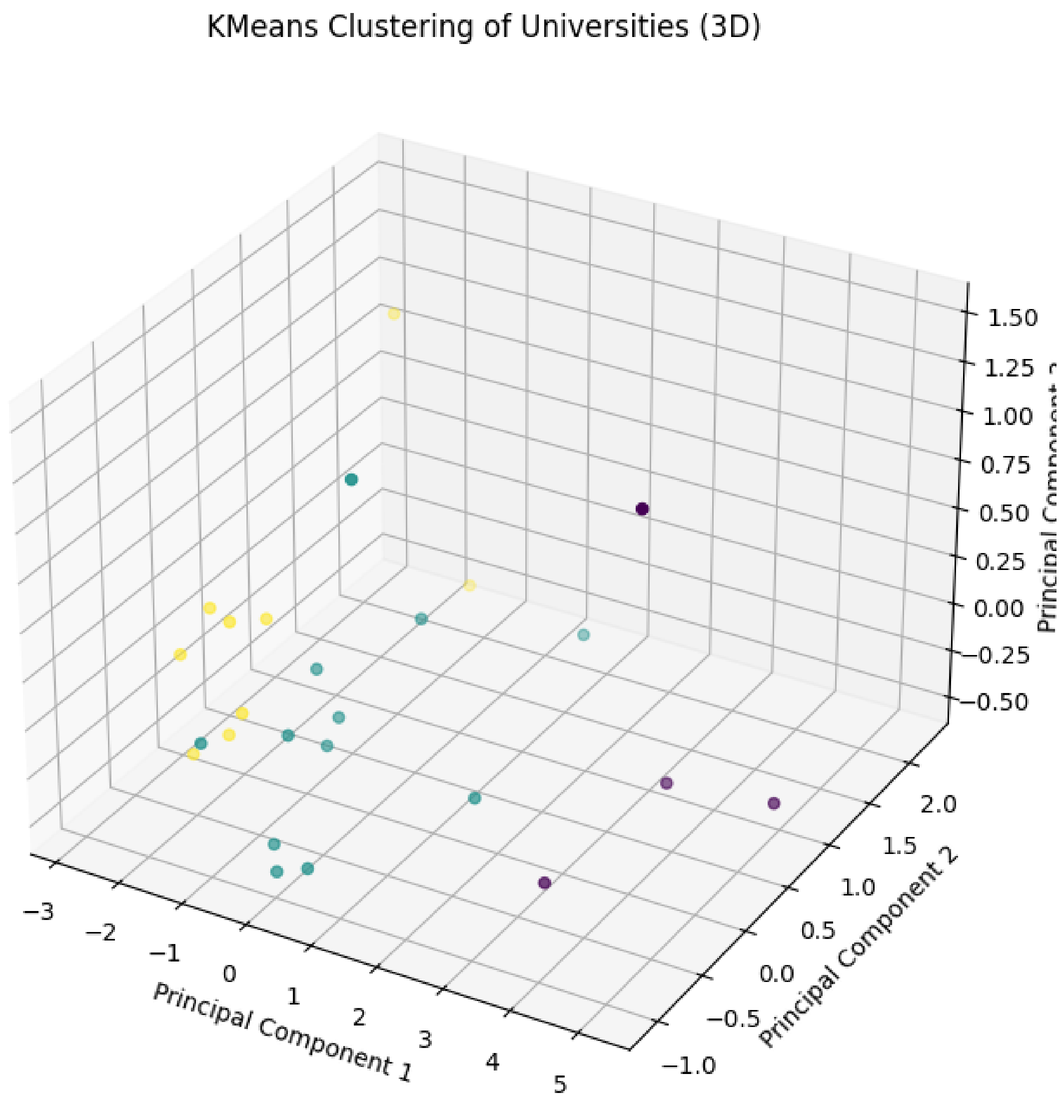
**PCA (Principle Component Analysis)**

[13]:
```
# Applying PCA for dimensionality reduction
pca = PCA(n_components=3, random_state=1)
components = pca.fit_transform(X_scaled)
```

[14]:
```
# 3D plot of the clusters
fig = plt.figure(figsize=(8, 8))
ax=plt.axes(projection='3d')
ax.scatter(components[:, 0], components[:, 1], components[:, 2],␣
 ↪c=df['Cluster'])
ax.set_xlabel('Principal Component 1')
ax.set_ylabel('Principal Component 2')
ax.set_zlabel('Principal Component 3')
ax.set_title('KMeans Clustering of Universities (3D)')
plt.show()
```


KMeans Clustering of Universities (3D)
Principal Component 1
Principal Component 2
Principal Component
−3
−2
−1
0
1
2
3
4
5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50