# Machine Learning Model Prediction

## Data Preparation

### Required Specific Libraries

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as matplt
from matplotlib import rcParams
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import StandardScaler, LabelEncoder, OrdinalEncoder, OneHotEncoder
from sklearn.compose import make_column_transformer
from imblearn.over_sampling import SMOTE

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,ConfusionMatrixDisplay, accuracy_score, confusion_matrix, precision_score, recall_score
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

## Import dataset

```
dataframe = pd.read_csv('/content/drive/My Drive/Colab Notebooks/Exam/LA4PSchools.csv')
```

```
dataframe['Year3_Writing_At_Risk'] = dataframe['Year3_Writing_At_Risk'].map({False: 0, True: 1})
```

## Preprocess the data

```
dataframe.drop(["StudentID"],axis=1,inplace=True)
```

## For Encoding Categorical data

```
change_values = {
  'Gender': {
    'Male': 0,
    'Female': 1
  }
}

dataframe.replace(change_values, inplace=True)
```

```
dataframe.head()
```

| | Gender | Year_02 | Kinder_Age | Disability | NCCD-Funded | 01.SES | 02.SES | NumSibling | SiblingOrder | NumAbvYear9 | ... | HRSIW-01-SOY | Counting-01 | Coun |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 2020 | 5.5 | Disability_Non-disable | 0 | 104 | 104 | 3 | 3 | 2 | ... | 49 | 4 | |
| **1** | 1 | 2018 | 5.8 | Disability_Non-disable | 0 | 112 | 112 | 2 | 2 | 2 | ... | 37 | 2 | |
| **2** | 0 | 2021 | 5.9 | Disability_Non-disable | 0 | 120 | 109 | 2 | 2 | 2 | ... | 30 | 2 | |
| **3** | 0 | 2021 | 5.7 | Disability_Non-disable | 0 | 95 | 93 | 2 | 1 | 0 | ... | 30 | 2 | |
| **4** | 0 | 2021 | 5.8 | Disability_Non-disable | 0 | 98 | 98 | 1 | 1 | 2 | ... | 32 | 2 | |

5 rows × 33 columns

```
dataframe_copy = dataframe
```

```
disability_transformer = make_column_transformer(
  (OneHotEncoder(), ['Disability']),
  remainder='passthrough',
  verbose_feature_names_out=False
)

dataframe = dataframe_copy

work_type_transformed = disability_transformer.fit_transform(dataframe)
dataframe = pd.DataFrame(work_type_transformed, columns=disability_transformer.get_feature_names_out())
dataframe.head(5)
```

| | Disability_Disability_Cognitive | Disability_Disability_Non-disable | Disability_Disability_Physical | Disability_Disability_Sensory | Disabilit |
|---|---|---|---|---|---|
| **0** | 0.0 | 1.0 | 0.0 | 0.0 | |
| **1** | 0.0 | 1.0 | 0.0 | 0.0 | |
| **2** | 0.0 | 1.0 | 0.0 | 0.0 | |
| **3** | 0.0 | 1.0 | 0.0 | 0.0 | |
| **4** | 0.0 | 1.0 | 0.0 | 0.0 | |

5 rows × 37 columns

## Model Training

```
depent_axis = dataframe["Year3_Writing_At_Risk"]
independent_axis = dataframe.drop(["Year3_Writing_At_Risk"],axis=1)
```

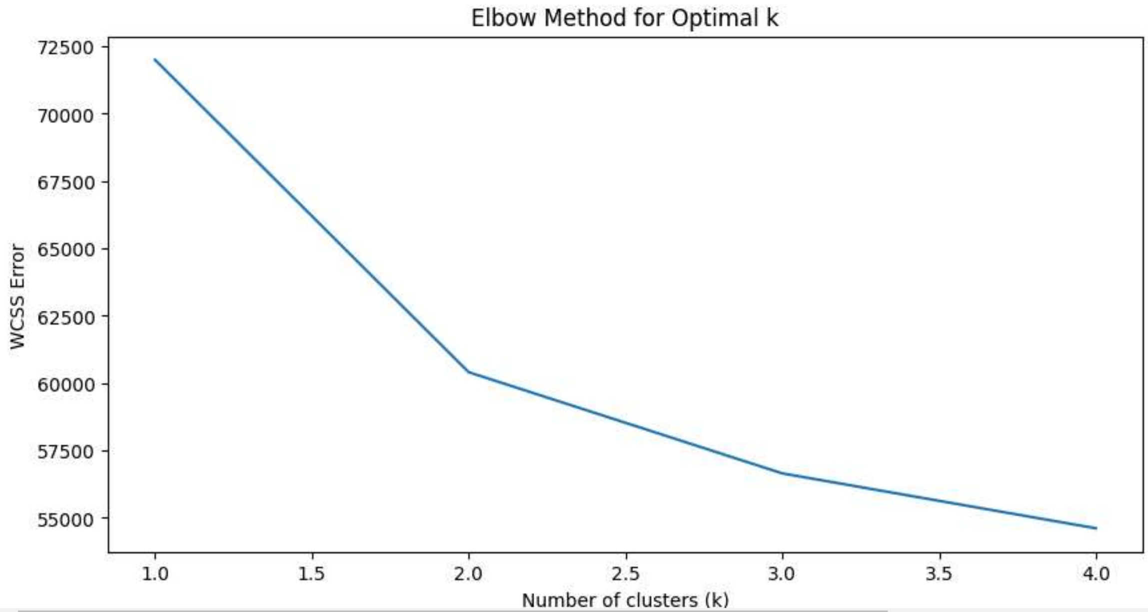
## Scaling Dataset from Standardize

```
scaler = StandardScaler()
independent_axis = scaler.fit_transform(independent_axis)
independent_axis
```

```
array([[-0.55347604,  0.66949677, -0.18617505, ...,  1.50799757,
         1.10357108,  0.26241365],
       [-0.55347604,  0.66949677, -0.18617505, ...,  0.64257572,
        -1.28381903,  0.26241365],
       [-0.55347604,  0.66949677, -0.18617505, ..., -1.08826797,
         1.10357108, -1.03345623],
       ...,
       [-0.55347604,  0.66949677, -0.18617505, ..., -0.22284613,
        -1.28381903,  0.26241365],
       [-0.55347604,  0.66949677, -0.18617505, ...,  1.50799757,
```

```
        -0.09012398,  0.26241365],
       [ 1.80676294, -1.49365919, -0.18617505, ..., -0.22284613,
         1.10357108,  2.85415341]])
```

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt


# Determine the number of clusters (k) using the Elbow Method
wcss = []  # Within-cluster sum of squares
for i in range(1, 5):
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(independent_axis)  # Using the features
    wcss.append(kmeans.inertia_)

# Plotting the elbow curve
plt.figure(figsize=(10, 5))
plt.plot(range(1, 5), wcss)
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('WCSS Error')
plt.show()
```

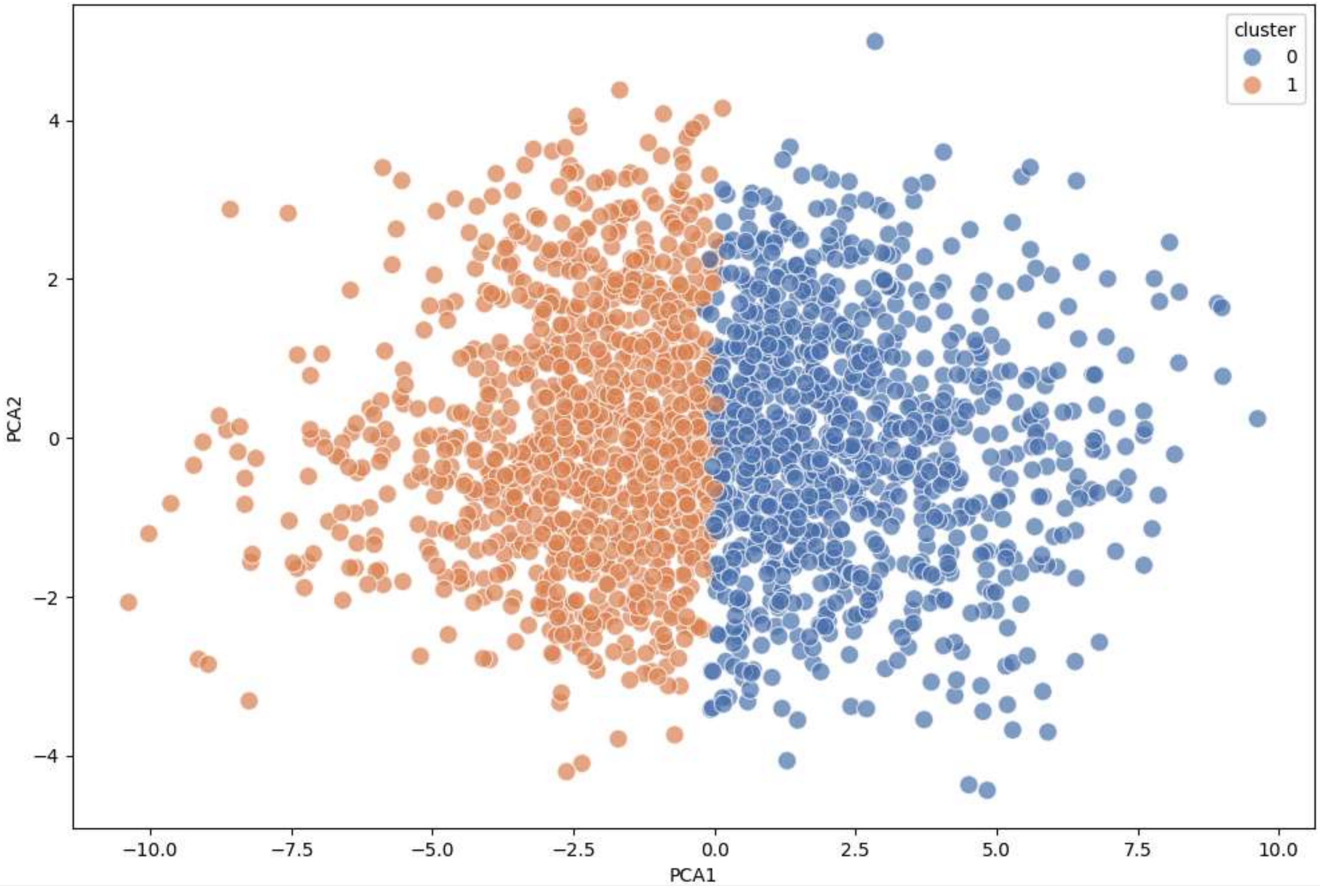



```
wcss
```

```
[71999.99999999997, 60408.88619173092, 56653.825553083385, 54615.53781676896]
```

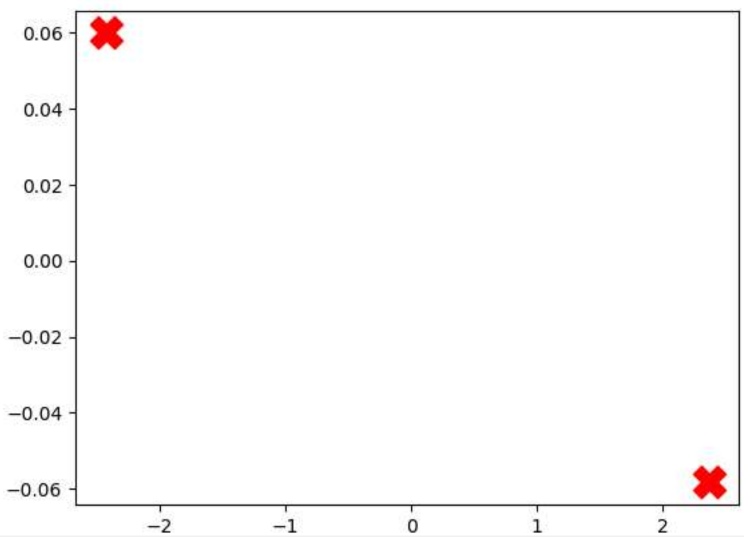
```
# Assuming optimal k is chosen, say k=2
optimal_k = 2
kmeans = KMeans(n_clusters=optimal_k, random_state=42)


# Fit and predict clusters
clusters = kmeans.fit_predict(independent_axis)
dataframe['cluster'] = clusters


# Optional: Use PCA to reduce dimensions to 2 for visualization
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
reduced_data = pca.fit_transform(independent_axis)


visualization_df = pd.DataFrame(reduced_data, columns=['PCA1', 'PCA2'])
visualization_df['cluster'] = clusters


# Plotting clusters
plt.figure(figsize=(12, 8))
sns.scatterplot(data=visualization_df, x='PCA1', y='PCA2', hue='cluster', palette='deep', s=100, alpha=0.7)
```

```
<Axes: xlabel='PCA1', ylabel='PCA2'>
```




```
# Plotting centroids
centroids = pca.transform(kmeans.cluster_centers_)  # Transform centroids to PCA space
plt.scatter(centroids[:, 0], centroids[:, 1], s=300, c='red', marker='X', label='Centroids')
```

```
<matplotlib.collections.PathCollection at 0x7a0d0c99ab30>
```




```
labels = kmeans.labels_
```

```
correct_labels = sum(depent_axis == labels)
```

```
print("Result: %d out of %d samples were correctly labeled." % (correct_labels, depent_axis.size))
```

```
Result: 1373 out of 2000 samples were correctly labeled.
```

```
print('Accuracy score: {0:0.2f}'. format(correct_labels/float(depent_axis.size)))
```

```
Accuracy score: 0.69
```