HW5_Part2_Henry_Romero

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[18]: import pandas as pd
      import numpy as np
      from sklearn.impute import SimpleImputer
      from sklearn.preprocessing import StandardScaler, LabelEncoder
      from sklearn.decomposition import PCA
      from sklearn.cluster import KMeans
      from sklearn.model_selection import train_test_split
      from sklearn.metrics import accuracy score, confusion matrix
      import matplotlib.pyplot as plt
      import seaborn as sns
      from scipy.stats import mode
      # I continued the Titanic dataset route and selected the data from the cluster
       ⇔dataset folder
      # This accuracy will be dependent on PSA transformed data on an unsupervised
       \hookrightarrow algorithm
      # Load the dataset
      df = pd.read_csv('Titanic-Dataset.csv')
      # View column names and basic info
      print("Columns:\n", df.columns)
      print("\nMissing Values:\n", df.isnull().sum())
      print("Rows",len(df))
      print(df.describe())
      # Feature selection
      features = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked']
      target = 'Survived' if 'Survived' in df.columns else 'survived' # Just in case_
       ⇔casing differs in data
      # preprocessing
      # missing values
      df['Age'] = SimpleImputer(strategy='mean').fit_transform(df[['Age']])
      df['Embarked'] = SimpleImputer(strategy='most_frequent').

→fit_transform(df[['Embarked']]).ravel()
      # Encode categoricals
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df['Sex'] = LabelEncoder().fit_transform(df['Sex'])
df['Embarked'] = LabelEncoder().fit_transform(df['Embarked'])
# Prepare features and labels
X = df[features]
y = df[target]
# Train/Test split with 30% on state 42
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,_
→random_state=42)
# PCA on Training
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Initialize PCA
pca = PCA(n_components=2) #Used 2 components for PCA
X_train_pca = pca.fit_transform(X_train_scaled)
X_test_pca = pca.transform(X_test_scaled)
# KMeans clustering
kmeans = KMeans(n_clusters=2, random_state=42) # 2 clusters on state 42
kmeans.fit(X_train_pca)
y_train_pred = kmeans.predict(X_train_pca)
y_test_pred = kmeans.predict(X_test_pca)
# Flip cluster labels
# Align KMeans output with survived labels
def align_clusters(y_true, y_pred):
   labels = np.zeros like(y pred)
   for cluster in np.unique(y_pred):
        mask = (y_pred == cluster)
        labels[mask] = mode(y_true[mask])[0]
   return labels
y_test_aligned = align_clusters(y_test.values, y_test_pred)
# Evaluation and confusion matrix added with a plot
# High accuracy score of 69% for the PCA transformed data
accuracy = accuracy_score(y_test, y_test_aligned)
print("\nKMeans Accuracy after alignment:", accuracy)
cm = confusion_matrix(y_test, y_test_aligned)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
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xticklabels=['Predicted 0', 'Predicted 1'],
             yticklabels=['Actual 0', 'Actual 1'])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix (Aligned KMeans Output)")
plt.show()
# Plotting Clusters with scatterplot
# Plotted graph has 2 distinct clusters near component 1 and component 2
plt.figure(figsize=(8, 6))
sns.scatterplot(x=X_test_pca[:, 0], y=X_test_pca[:, 1], hue=y_test_aligned,_u
  →palette='coolwarm')
plt.title('KMeans Clustering Results on PCA Titanic Data')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend(title='Predicted Cluster')
plt.grid(True)
plt.tight_layout()
plt.show()
print("The kmeans clustering on PCA data gives an accuracy of 69% with proper__
 ⇔class distribution as shown in the scatt")
# KMeans clusters to actual survival on the data, a comparison of the accuracy
 ⇔shown before.
kmeans_vs_true = pd.DataFrame({
     'KMeans_Cluster': kmeans.labels_,
     'Actual_Survived': y_train.values
})
print("\nKMeans Cluster vs. Actual Survival:\n")
print(kmeans_vs_true.head(5))
print(pd.crosstab(kmeans_vs_true['KMeans_Cluster'],__
  ⇔kmeans_vs_true['Actual_Survived']))
Columns:
 Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
Missing Values:
PassengerId
                  0
Survived
                 0
Pclass
                 0
Name
                 0
Sex
                 0
               177
Age
SibSp
                 0
```

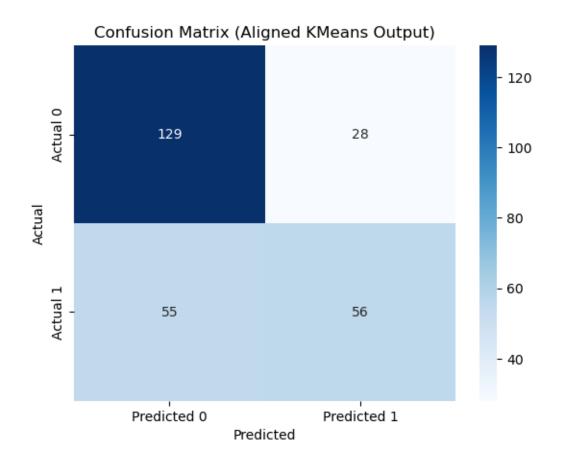
Parch 0 Ticket 0 Fare 0 Cabin 687 Embarked 2 dtype: int64 Rows 891 PassengerId Survived **Pclass** Age SibSp \ count 891.000000 891.000000 891.000000 714.000000 891.000000 446.000000 0.383838 2.308642 29.699118 mean 0.523008 257.353842 14.526497 1.102743 std 0.486592 0.836071 1.000000 0.000000 1.000000 0.420000 0.000000 min 25% 0.000000 2.000000 20.125000 0.00000 223.500000 50% 446.000000 0.000000 3.000000 28.000000 0.000000 75% 668.500000 38.000000 1.000000 1.000000 3.000000 891.000000 1.000000 3.000000 80.000000 8.000000 maxParch Fare 891.000000 891.000000 countmean 0.381594 32.204208 0.806057 std 49.693429 min 0.000000 0.000000 25% 0.000000 7.910400 50% 0.000000 14.454200 31.000000 75% 0.000000

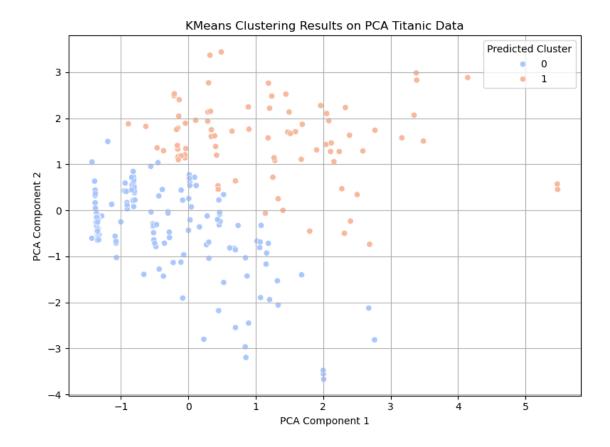
KMeans Accuracy after alignment: 0.6902985074626866

512.329200

6.000000

max





The kmeans clustering on PCA data gives an accuracy of 69% with proper class distribution as shown in the scatt

KMeans Cluster vs. Actual Survival:

| KMeans_Cluste | er | Actu | al_Survive | d |
|-----------------|----|------|------------|---|
| 0 | 1 | | | 1 |
| 1 | 0 | | | 0 |
| 2 | 0 | | | 1 |
| 3 | 0 | | | 0 |
| 4 | 0 | | | 0 |
| Actual_Survived | | 0 | 1 | |
| KMeans_Cluster | | | | |
| 0 | 33 | 0 1 | 34 | |
| 1 | 6 | 2 | 97 | |
| | | | | |