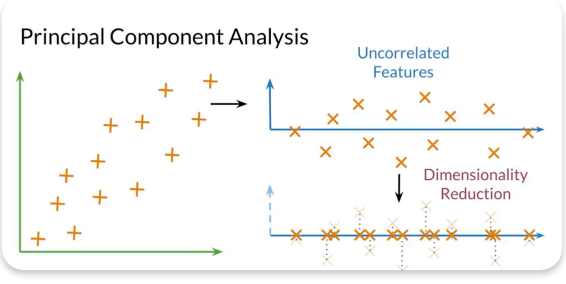
Definition: rincipal Component Analysis (PCA) is a dimensionality reduction method that reduces large data sets into fewer variables while preserving key data trends. It simplifies data by identifying uncorrelated components that capture the most variance, making analysis faster and more efficient.



Code :

Importing required libraries

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

Creating Sample Dataset

```
data = {
    'Height': [170, 165, 180, 175, 160, 172, 168, 177, 162, 158],
    'Weight': [65, 59, 75, 68, 55, 70, 62, 74, 58, 54],
    'Age': [30, 25, 35, 28, 22, 32, 27, 33, 24, 21],
    'Gender': [1, 0, 1, 1, 0, 1, 0, 1, 0, 0]  # 1 = Male, 0 = Female
}
df = pd.DataFrame(data)
print(df)
```

Standardizing the Data

This makes all features have mean = 0 and standard deviation = 1

```
X = df.drop('Gender', axis=1)
y = df['Gender']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(df)
```

Apply PCA

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- We split the data into 70% training and 30% testing sets.

```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

X_train, X_test, y_train, y_test = train_test_split(X_pca, y,
test_size=0.3, random_state=42)

model = LogisticRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
```

Evaluate with Confusion Matix

```
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=['Female', 'Male'], yticklabels=['Female', 'Male'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

Visualizing PCA Result

```
y_numeric = pd.factorize(y)[0]

plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=y_numeric,
cmap='coolwarm', edgecolor='k', s=80)
plt.xlabel('Original Feature 1')
plt.ylabel('Original Feature 2')
plt.title('Before PCA: Using First 2 Standardized Features')
plt.colorbar(label='Target classes')

plt.subplot(1, 2, 2)
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y_numeric,
cmap='coolwarm', edgecolor='k', s=80)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('After PCA: Projected onto 2 Principal Components')
plt.colorbar(label='Target classes')

plt.tight_layout()
plt.show()
```