



Laxmi Charitable Trust's
Sheth L.U.J College of Arts & Sir
M.V. College
Of Science & Commerce

RAM KUMAR SINGH

PRACTICAL NO.9

AIM:Principal Component Analysis (PCA)

Perform PCA on a dataset to reduce dimensionality.

Evaluate the explained variance and select the appropriate number of principal components.

Visualize the data in the reduced-dimensional space.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.impute import SimpleImputer
```

```
df = pd.read_csv("/content/energy_dataset.csv")
```

```
print("\nFirst 5 Rows of Dataset:")
print(df.head())
print("Shape:", df.shape)
```

```
      time  generation biomass \
0  2015-01-01 00:00:00+01:00      447.0
1  2015-01-01 01:00:00+01:00      449.0
2  2015-01-01 02:00:00+01:00      448.0
3  2015-01-01 03:00:00+01:00      438.0
4  2015-01-01 04:00:00+01:00      428.0
```

```
           generation fossil brown coal/lignite  generation fossil coal-derived gas \
0                      329.0                         0.0
1                      328.0                         0.0
2                      323.0                         0.0
3                      254.0                         0.0
4                      187.0                         0.0
```

```
           generation fossil gas  generation fossil hard coal  generation fossil oil \
0                      4844.0                         4821.0                  162.0
1                      5196.0                         4755.0                  158.0
```

```

generation fossil oil shale generation fossil peat generation geothermal \
0 0.0 0.0 0.0
1 0.0 0.0 0.0
2 0.0 0.0 0.0
3 0.0 0.0 0.0
4 0.0 0.0 0.0

... generation waste generation wind offshore generation wind onshore \
0 ... 196.0 0.0 6378.0
1 ... 195.0 0.0 5890.0
2 ... 196.0 0.0 5461.0
3 ... 191.0 0.0 5238.0
4 ... 189.0 0.0 4935.0

forecast solar day ahead forecast wind offshore eday ahead \
0 17.0 NaN
1 16.0 NaN
2 8.0 NaN
3 2.0 NaN
4 9.0 NaN

forecast wind onshore day ahead total load forecast total load actual \
0 6436.0 26118.0 25385.0
1 5856.0 24934.0 24382.0
2 5454.0 23515.0 22734.0
3 5151.0 22642.0 21286.0
4 4861.0 21785.0 20264.0

price day ahead price actual
0 50.10 65.41
1 48.10 64.92
2 47.33 64.48
3 42.27 59.32
4 38.41 56.04

[5 rows x 29 columns]
Shape: (35064, 29)

```

```

numeric_cols = df.select_dtypes(include=[np.number]).columns.tolist()
print("\nNumeric Columns:", numeric_cols)

X = df[numeric_cols].copy()

```

Numeric Columns: ['generation biomass', 'generation fossil brown coal/lignite', 'genera

```

if "price actual" in X.columns:
    y = X["price actual"].copy()
    X = X.drop(columns=["price actual"])
    target_name = "price actual"
    print("Using 'price actual' as pseudo-target.")
else:
    y = pd.Series(np.zeros(len(X)), name="target")
    target_name = "target"
    print("Using dummy target.")

```

Using 'price actual' as pseudo-target.

```
cols_all_nan = X.columns[X.isna().all()]
print("\nColumns completely NaN (removed):", list(cols_all_nan))

X = X.drop(columns=cols_all_nan)
print("Shape after removing NaN-only columns:", X.shape)
```

Columns completely NaN (removed): ['generation hydro pumped storage aggregated', 'forec
Shape after removing NaN-only columns: (35064, 25)

```
imputer = SimpleImputer(strategy="mean")
X_imputed = pd.DataFrame(imputer.fit_transform(X), columns=X.columns)

# Also handle NaNs in target, if any
if y.isna().any():
    y = y.fillna(y.mean())

print("Remaining NaNs:", X_imputed.isna().sum().sum())
print("First 5 rows after imputation:")
print(X_imputed.head())
```

```
generation fossil coal-derived gas  generation fossil gas \
0                  0.0              4844.0
1                  0.0              5196.0
2                  0.0              4857.0
3                  0.0              4314.0
4                  0.0              4130.0

generation fossil hard coal  generation fossil oil \
0                4821.0            162.0
1                4755.0            158.0
2                4581.0            157.0
3                4131.0            160.0
4                3840.0            156.0

generation fossil oil shale  generation fossil peat  generation geothermal \
0                  0.0              0.0              0.0
1                  0.0              0.0              0.0
2                  0.0              0.0              0.0
3                  0.0              0.0              0.0
4                  0.0              0.0              0.0

generation hydro pumped storage consumption ... \
0                  863.0      ...
1                  920.0      ...
```

```
5          75.0          50.0          191.0
4          74.0          42.0          189.0
```

```
generation wind offshore  generation wind onshore \
0                  0.0          6378.0
1                  0.0          5890.0
2                  0.0          5461.0
3                  0.0          5238.0
4                  0.0          4935.0

forecast solar day ahead  forecast wind onshore day ahead \
0                  17.0         6436.0
1                  16.0         5856.0
2                  8.0          5454.0
3                  2.0          5151.0
4                  9.0          4861.0

total load forecast  total load actual  price day ahead
0          26118.0        25385.0      50.10
1          24934.0        24382.0      48.10
2          23515.0        22734.0      47.33
3          22642.0        21286.0      42.27
4          21785.0        20264.0      38.41
```

[5 rows x 25 columns]

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

print("\nStandardScaler Parameters:")
print(scaler.get_params())
```

StandardScaler Parameters:
{'copy': True, 'with_mean': True, 'with_std': True}

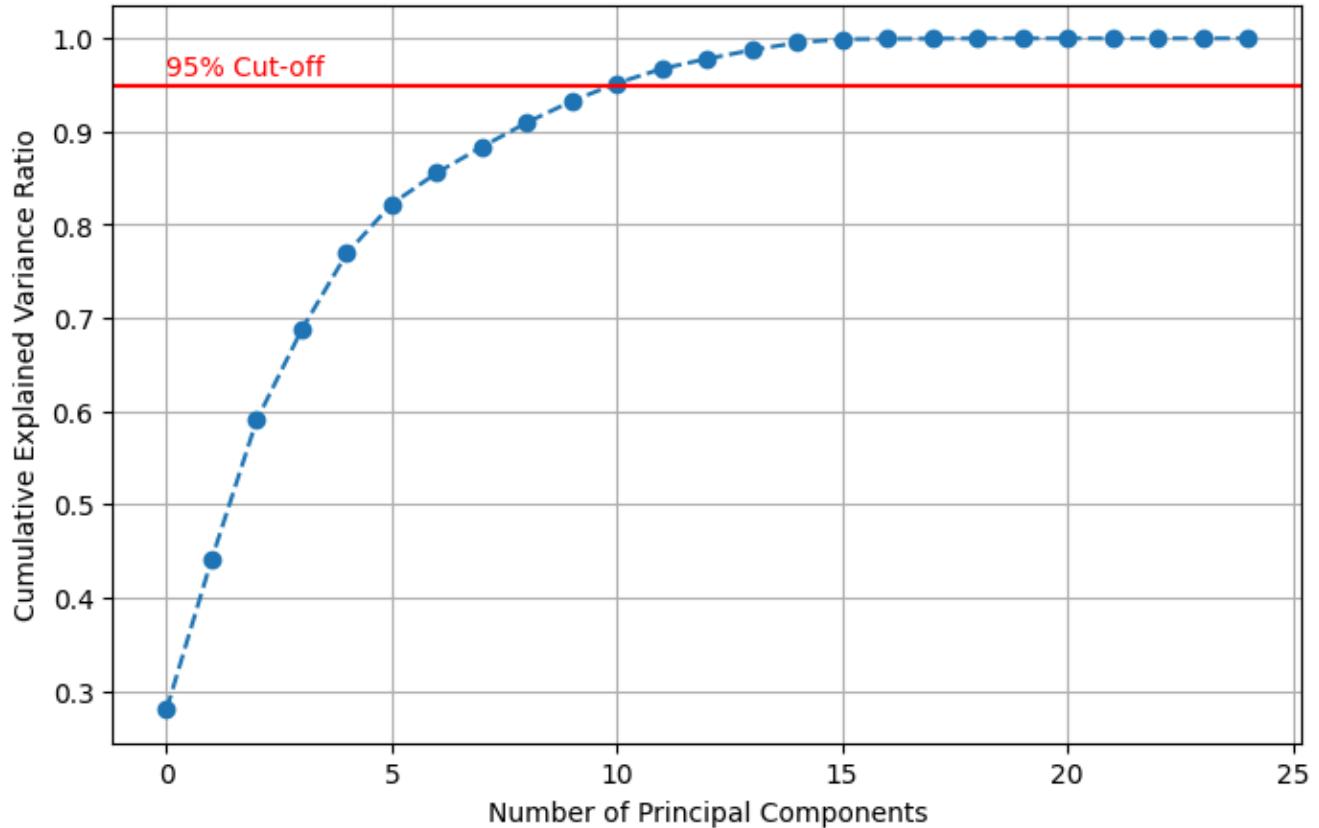
```
pca_full = PCA()
pca_full.fit(X_scaled)

explained_variance_ratio = pca_full.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance_ratio)

plt.figure(figsize=(8, 5))
plt.plot(cumulative_variance, marker='o', linestyle='--')
plt.axhline(y=0.95, linestyle='-', color='r')
plt.text(0, 0.96, '95% Cut-off', color='red')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance Ratio')
plt.title('PCA - Cumulative Explained Variance (Energy Dataset)')
plt.grid(True)
plt.show()

n_components = np.argmax(cumulative_variance >= 0.95) + 1
print(f"\nNumber of components for 95% variance: {n_components}")
```

PCA - Cumulative Explained Variance (Energy Dataset)



Number of components for 95% variance: 11

```
pca = PCA(n_components=n_components)
X_reduced = pca.fit_transform(X_scaled)

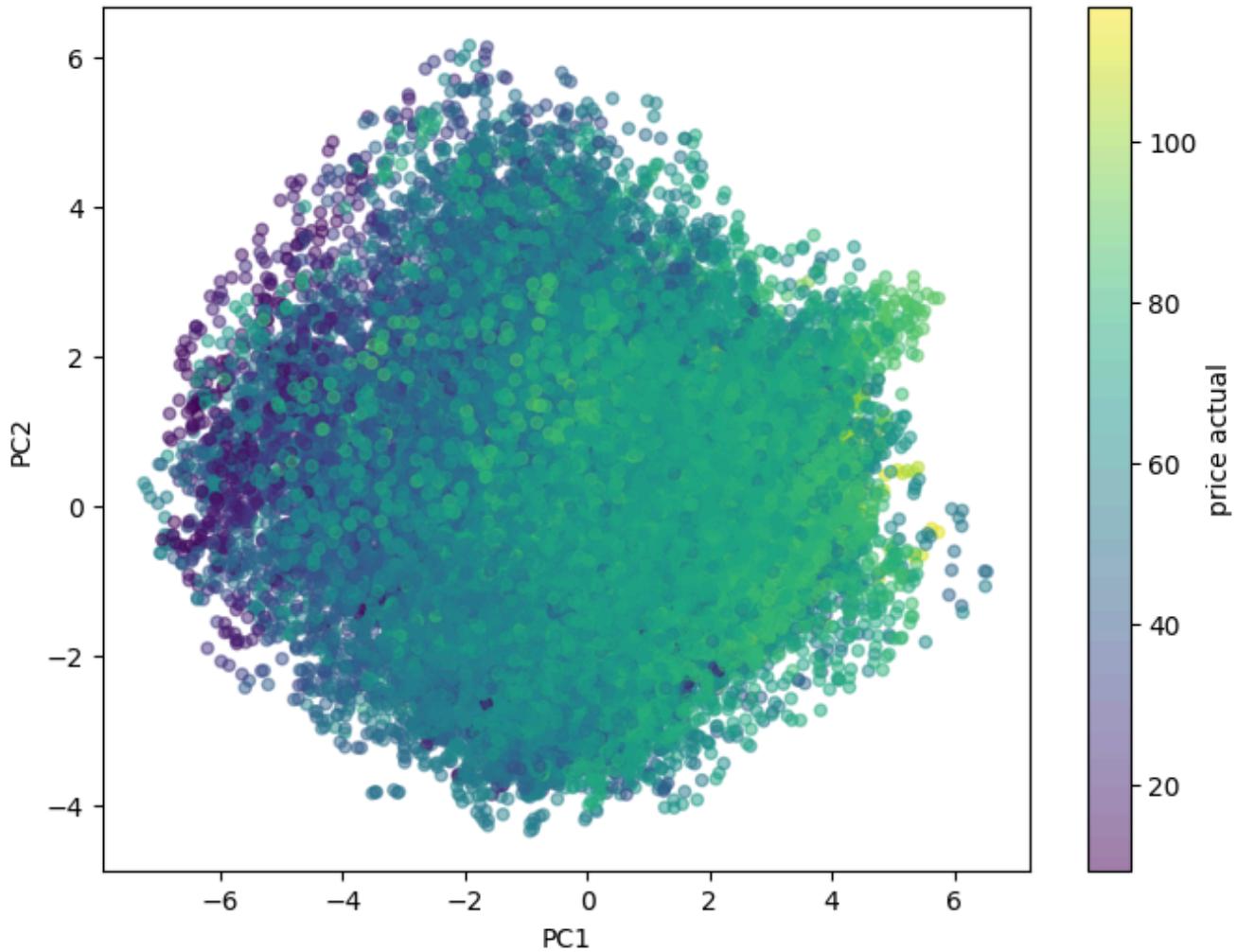
print("\nFinal PCA Parameters:")
print(pca.get_params())
```

Final PCA Parameters:

```
{'copy': True, 'iterated_power': 'auto', 'n_components': np.int64(11), 'n_oversamples':
```

```
plt.figure(figsize=(8, 6))
plt.scatter(X_reduced[:, 0], X_reduced[:, 1], c=y, cmap='viridis', s=20, alpha=0.5)
plt.colorbar(label=target_name)
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('Energy Data PCA Projection')
plt.show()
```

Energy Data PCA Projection



```
pca_cols = [f"PC{i+1}" for i in range(n_components)]
pca_df = pd.DataFrame(X_reduced, columns=pca_cols)
pca_df[target_name] = y.values

output_file = "/content/energy_pca_reduced.csv"
pca_df.to_csv(output_file, index=False)

print("\nFirst 5 rows of PCA reduced data:")
print(pca_df.head())
print("\nSaved to:", output_file)
```

First 5 rows of PCA reduced data:

| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | \ |
|---|-----------|-----------|----------|-----------|----------|----------|-----------|---|
| 0 | -1.939891 | -0.803230 | 0.699363 | -0.021090 | 0.369430 | 0.884504 | -1.011903 | |
| 1 | -2.057097 | -1.116139 | 0.845545 | 0.238332 | 0.443172 | 0.891167 | -1.141480 | |
| 2 | -2.373668 | -1.533295 | 0.908606 | 0.482030 | 0.434244 | 0.877217 | -1.069578 | |
| 3 | -2.960248 | -1.804342 | 0.940045 | 0.750306 | 0.321394 | 0.845386 | -1.062811 | |
| 4 | -3.439316 | -1.948464 | 0.951263 | 1.003525 | 0.372551 | 0.862805 | -1.207829 | |

| | PC8 | PC9 | PC10 | PC11 | price actual |
|---|-----------|-----------|-----------|-----------|--------------|
| 0 | -0.882678 | -1.921679 | -0.832382 | -0.884281 | 65.41 |
| 1 | -0.863688 | -1.850541 | -0.963886 | -0.791646 | 64.92 |
| 2 | -0.859786 | -1.585825 | -0.897589 | -0.875170 | 64.48 |
| 3 | -0.716736 | -1.185771 | -0.887189 | -0.939449 | 59.32 |
| 4 | -0.789941 | -0.925156 | -0.895755 | -0.876701 | 56.04 |

Saved to: /content/energy_pca_reduced.csv