Iris 데이터셋 PCA 이용하여 차원 축소

라이브러리 및 패키지 불러오기

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix
import re
```

데이터셋 불러오기

```
In [2]: # 데이터 로드
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target)
target_names = iris.target_names

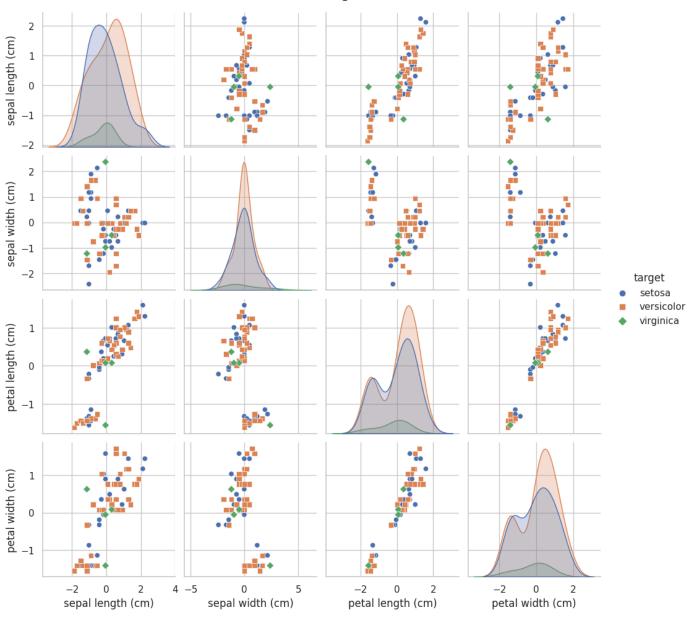
# 데이터 분할 (훈련 데이터와 테스트 데이터)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42

# 데이터 스케일링
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

PCA 적용 전 데이터 차원 시각화

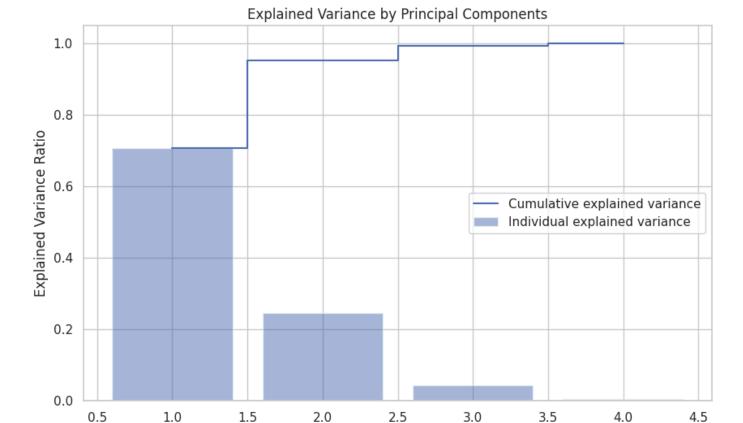
```
In [3]: # 각 특성 간의 산점도 시각화
sns.set(style='whitegrid', context='notebook')
df_train = pd.DataFrame(X_train, columns=iris.feature_names)
df_train['target'] = y_train.map(lambda i: target_names[i])
sns.pairplot(df_train, hue='target', markers=["o", "s", "D"])
plt.suptitle('Scatter Plots of Original Data Features', y=1.02)
plt.show()
```

Scatter Plots of Original Data Features



PCA 차원 축소 적용

```
# PCA 변환 (모든 주성분)
In [4]:
        pca_full = PCA()
        pca_full.fit(X_train)
        # 주성분의 설명력
        explained_variance = pca_full.explained_variance_ratio_
        cumulative_variance = np.cumsum(explained_variance)
        print(explained_variance)
        # 설명력 시각화
        plt.figure(figsize=(10, 6))
        plt.bar(range(1, len(explained_variance) + 1), explained_variance, alpha=0.5, align='cen
        plt.step(range(1, len(cumulative_variance) + 1), cumulative_variance, where='mid', label
        plt.xlabel('Principal Component Index')
        plt.ylabel('Explained Variance Ratio')
        plt.title('Explained Variance by Principal Components')
        plt.legend(loc='best')
        plt.show()
```

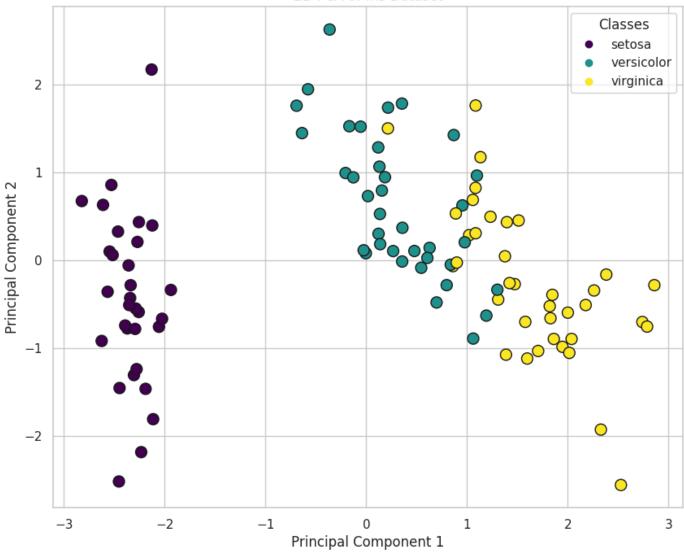


Principal Component Index

```
In [5]: # PCA 변환 (2개 주성분)
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)

# 2차원 산점도 시각화
plt.figure(figsize=(10, 8))
scatter = plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1], c=y_train, cmap='viridis', e handles, labels = scatter.legend_elements(prop="colors")
labels = [target_names[int(re.sub(r'[^0-9]', '', label))] for label in labels]
plt.legend(handles, labels, title="Classes")
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('2D PCA of Iris Dataset')
plt.show()
```

2D PCA of Iris Dataset



SVM 모델 학습(PCA 없이)

```
In [6]: # SVM 모델 학습 (PCA 없이)
svm = SVC(kernel='linear')
svm.fit(X_train, y_train)

# 모델 예측 (PCA 없이)
y_pred = svm.predict(X_test)

# 평가 (PCA 없이)
print("Evaluation without PCA")
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[ 0 0 13]]
                      precision
                                   recall f1-score
                                                       support
                   0
                           1.00
                                      1.00
                                                1.00
                                                            19
                   1
                           1.00
                                     0.92
                                                0.96
                                                            13
                   2
                           0.93
                                      1.00
                                                0.96
                                                            13
                                                0.98
                                                            45
            accuracy
                           0.98
                                                0.97
                                                            45
           macro avg
                                      0.97
        weighted avg
                           0.98
                                      0.98
                                                0.98
                                                            45
        SVM 모델 학습(PCA 적용)
In [7]: # 2개의 주성분을 사용하여 PCA 변환
        pca_2d = PCA(n_components=2)
        X_{train_pca_2d} = pca_2d.fit_transform(X_train)
        X_{test_pca_2d} = pca_2d.transform(X_{test_pca_2d})
        # SVM 모델 학습 (2개의 주성분)
        svm_pca_2d = SVC(kernel='linear')
        svm_pca_2d.fit(X_train_pca_2d, y_train)
        # 모델 예측 (PCA 적용)
        y_pred_pca = svm_pca_2d.predict(X_test_pca_2d)
        # 평가 (PCA 적용)
        print("Evaluation with PCA")
        print(confusion_matrix(y_test, y_pred_pca))
        print(classification_report(y_test, y_pred_pca))
        Evaluation with PCA
        [[19 0 0]
         [ 0 11 2]
         [ 0 1 12]]
                      precision
                                   recall f1-score
                                                       support
                   0
                           1.00
                                     1.00
                                                1.00
                                                            19
                   1
                           0.92
                                      0.85
                                                0.88
                                                            13
                   2
                           0.86
                                      0.92
                                                0.89
                                                            13
                                                0.93
                                                            45
            accuracy
           macro avg
                           0.92
                                      0.92
                                                0.92
                                                            45
        weighted avg
                           0.93
                                      0.93
                                                0.93
                                                            45
In [8]: # 결정 경계 시각화 함수
        def plot_decision_boundaries(X, y, model, target_names, title='Decision Boundaries'):
            # Create a mesh to plot in
            h = .02 # step size in the mesh
            x_{min}, x_{max} = X[:, 0].min() - 1, <math>X[:, 0].max() + 1
            y_{min}, y_{max} = X[:, 1].min() - 1, X[:, 1].max() + 1
            xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                                  np.arange(y_min, y_max, h))
            # Plot the decision boundary by assigning a color to each point in the mesh
            Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
            Z = Z.reshape(xx.shape)
            plt.contourf(xx, yy, Z, alpha=0.8, cmap=ListedColormap(('lightblue', 'lightyellow',
```

so the training points

Loading [MathJax]/extensions/Safe.js

Evaluation without PCA

[[19 0 0] [0 12 1]

```
scatter = plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', cmap=ListedColormap(('b handles, labels = scatter.legend_elements(prop="colors")
labels = [target_names[int(re.sub(r'[^0-9]', '',label))] for label in labels]
plt.legend(handles, labels, title="Classes")
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title(title)
plt.show()

# 결정 경계 시각화
plot_decision_boundaries(X_train_pca, y_train, svm_pca_2d, target_names, title='Decision')
```

Decision Boundaries with PCA

