## ml-lab-4

## April 17, 2024

```
[51]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     from sklearn import datasets
     from sklearn.model_selection import cross_val_score, GridSearchCV
     from sklearn.preprocessing import StandardScaler
     from sklearn.svm import SVC
     from sklearn.metrics import accuracy_score
     from sklearn.decomposition import PCA
     from mlxtend.plotting import plot_decision_regions
     from sklearn.model_selection import train_test_split
     cancer = datasets.load_breast_cancer()
     X = cancer.data
     y = cancer.target
     target_names = cancer.target_names
     df = pd.DataFrame(data=cancer.data)
     print(df.head())
                          2
                                                           6
           0
                  1
                                  3
                                           4
                                                   5
                                                                    7
                                                                            8
                                                                                \
       17.99
               10.38
                     122.80
                              1001.0
                                     0.11840 0.27760
                                                      0.3001
                                                               0.14710
                                                                       0.2419
     1 20.57
               17.77
                    132.90
                              1326.0
                                     0.08474
                                              0.07864
                                                       0.0869
                                                               0.07017
                                                                        0.1812
     2 19.69
               21.25
                     130.00
                              1203.0
                                     0.10960
                                              0.15990
                                                       0.1974
                                                               0.12790
                                                                        0.2069
     3 11.42
               20.38
                      77.58
                               386.1
                                     0.14250
                                              0.28390
                                                       0.2414
                                                               0.10520
     4 20.29
               14.34
                     135.10 1297.0
                                     0.10030 0.13280 0.1980 0.10430
             9
                       20
                              21
                                      22
                                              23
                                                      24
                                                             25
                                                                     26
                                                                             27
     0 0.07871
                    25.38
                          17.33 184.60 2019.0 0.1622
                                                         0.6656
                                                                0.7119 0.2654
     1 0.05667
                ... 24.99
                           23.41
                                 158.80
                                         1956.0 0.1238
                                                         0.1866
                                                                0.2416 0.1860
     2 0.05999
                    23.57
                           25.53 152.50
                                         1709.0 0.1444
                                                         0.4245
                                                                 0.4504 0.2430
     3 0.09744 ... 14.91
                           26.50
                                                                 0.6869 0.2575
                                   98.87
                                          567.7
                                                 0.2098
                                                         0.8663
     4 0.05883
                    22.54
                          16.67 152.20 1575.0 0.1374 0.2050 0.4000 0.1625
            28
                     29
     0 0.4601 0.11890
     1 0.2750 0.08902
     2 0.3613 0.08758
```

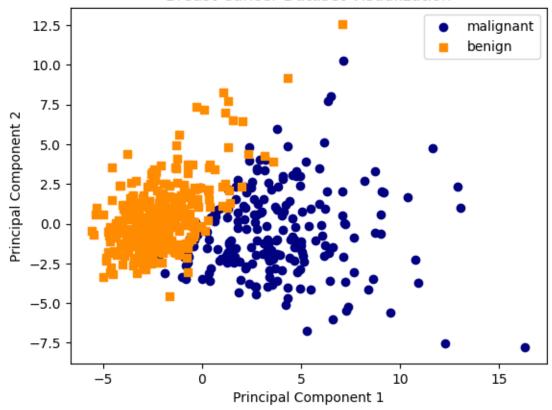
```
3 0.6638 0.17300
    4 0.2364 0.07678
     [5 rows x 30 columns]
[52]: scaler = StandardScaler()
     scaler.fit(X)
[52]: StandardScaler()
[53]: X_scaled = scaler.fit_transform(X)
     print(X_scaled)
     [[ 1.09706398 -2.07333501 1.26993369 ... 2.29607613 2.75062224
       1.93701461]
     0.281189997
     [ 1.57988811  0.45618695  1.56650313 ... 1.95500035  1.152255
       0.201391217
     [ 0.70228425  2.0455738
                            0.67267578 ... 0.41406869 -1.10454895
      -0.31840916]
     2.219635287
     -0.75120669]]
[54]: # Print the mean and standard deviation of each feature
     print("Mean of each feature:")
     print(scaler.mean_)
     print("\nStandard Deviation of each feature:")
     print(scaler.scale )
    Mean of each feature:
     [1.41272917e+01 1.92896485e+01 9.19690334e+01 6.54889104e+02
     9.63602812e-02 1.04340984e-01 8.87993158e-02 4.89191459e-02
     1.81161863e-01 6.27976098e-02 4.05172056e-01 1.21685343e+00
     2.86605923e+00 4.03370791e+01 7.04097891e-03 2.54781388e-02
     3.18937163e-02 1.17961371e-02 2.05422988e-02 3.79490387e-03
     1.62691898e+01 2.56772232e+01 1.07261213e+02 8.80583128e+02
     1.32368594e-01 2.54265044e-01 2.72188483e-01 1.14606223e-01
     2.90075571e-01 8.39458172e-02]
    Standard Deviation of each feature:
     [3.52095076e+00 4.29725464e+00 2.42776193e+01 3.51604754e+02
     1.40517641e-02 5.27663291e-02 7.96497253e-02 3.87687325e-02
     2.73901809e-02 7.05415588e-03 2.77068942e-01 5.51163427e-01
     2.02007710e+00 4.54510134e+01 2.99987837e-03 1.78924359e-02
```

```
3.01595231e-02 6.16486075e-03 8.25910439e-03 2.64374475e-03
      4.82899258e+00 6.14085432e+00 3.35730016e+01 5.68856459e+02
      2.28123569e-02 1.57198171e-01 2.08440875e-01 6.56745545e-02
      6.18130785e-02 1.80453893e-02]
[55]: param_grid = {'C': [0.01, 0.1, 1, 10, 100], 'kernel': ['linear', 'rbf', 'poly']}
[56]: from sklearn.model_selection import KFold
      kfold = KFold(n_splits=10, shuffle=True, random_state=42)
[57]: pca = PCA(n_components=2)
      grid_search = GridSearchCV(estimator=SVC(), param_grid=param_grid,__
      ⇔scoring='accuracy', cv=kfold)
      grid_search.fit(pca.fit_transform(X_scaled), y)
[57]: GridSearchCV(cv=KFold(n_splits=10, random_state=42, shuffle=True),
                   estimator=SVC(),
                   param_grid={'C': [0.01, 0.1, 1, 10, 100],
                               'kernel': ['linear', 'rbf', 'poly']},
                   scoring='accuracy')
[58]: best_model = grid_search.best_estimator_
      best_params = grid_search.best_params_
[59]: print("Best Params: ", best_params)
     Best Params: {'C': 1, 'kernel': 'linear'}
[60]: | y_pred = best_model.predict(pca.transform(X_scaled))
[61]: accuracy = accuracy_score(y, y_pred)
      print(f"Accuracy with best model: {accuracy:.4f}")
     Accuracy with best model: 0.9543
[62]: colors = ['red' if label == 0 else 'blue' for label in y]
      markers = ['o' if kernel == 'linear' else '^' if kernel == 'rbf' else 'x' for
       →kernel in best_params['kernel']]
[63]: # Apply PCA
      pca = PCA(n_components=2)
      X_pca = pca.fit_transform(X_scaled)
[64]: # Plot the transformed data
      colors = ['navy', 'darkorange']
      markers = ['o', 's']
      for target, color, marker in zip(np.unique(y), colors, markers):
```

```
plt.scatter(X_pca[y == target, 0], X_pca[y == target, 1], color=color, use marker=marker, label=target_names[target])

plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('Breast Cancer Dataset Visualization')
plt.legend(loc='upper right')
plt.show()
```

## **Breast Cancer Dataset Visualization**



```
NameError Traceback (most recent call last)

Cell In[65], line 3

1 # Split the dataset into training and testing sets

2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2

Grandom_state=42)
```

```
----> 3 y_pred = best_svm_classifier.predict(X_test_scaled)
     NameError: name 'best_svm_classifier' is not defined
[]: print("\nClassification Report:")
     print(classification_report(y_test, y_pred))
    Classification Report:
                  precision
                               recall f1-score
                                                   support
               0
                        1.00
                                  0.95
                                            0.98
                                                        43
               1
                       0.97
                                  1.00
                                            0.99
                                                        71
                                            0.98
                                                       114
        accuracy
                                            0.98
                                                       114
                       0.99
                                  0.98
       macro avg
    weighted avg
                       0.98
                                  0.98
                                            0.98
                                                       114
[]: confusion_matrix(best_svm_classifier, X_test_scaled, y_test, cmap=plt.cm.Blues,_
      ⇒display_labels=data.target_names)
     plt.title('Confusion Matrix')
     plt.show()
     TypeError
                                                Traceback (most recent call last)
     Cell In[35], line 1
      ----> 1<sub>11</sub>
       confusion_matrix(best_svm_classifier, X_test_scaled, y_test, cmap=plt.cm_Blue;, display_la
            2 plt.title('Confusion Matrix')
            3 plt.show()
      File ~/.pyenv/versions/3.11.7/lib/python3.11/site-packages/sklearn/utils/
       → param_validation.py:191, in validate_params.<locals>.decorator.<locals>.
       ⇔wrapper(*args, **kwargs)
          188 func_sig = signature(func)
          190 # Map *args/**kwargs to the function signature
      --> 191 params = func_sig.bind(*args, **kwargs)
          192 params.apply_defaults()
          194 # ignore self/cls and positional/keyword markers
     File ~/.pyenv/versions/3.11.7/lib/python3.11/inspect.py:3212, in Signature.
       ⇒bind(self, *args, **kwargs)
        3207 def bind(self, /, *args, **kwargs):
                  """Get a BoundArguments object, that maps the passed `args`
         3208
         3209
                  and `kwargs` to the function's signature. Raises `TypeError`
         3210
                  if the passed arguments can not be bound.
```

```
0.00
   3211
-> 3212
            return self._bind(args, kwargs)
File ~/.pyenv/versions/3.11.7/lib/python3.11/inspect.py:3138, in Signature.
 →_bind(self, args, kwargs, partial)
   3134 else:
            if param.kind in (_VAR_KEYWORD, _KEYWORD_ONLY):
   3135
                # Looks like we have no parameter for this positional
   3136
   3137
                # argument
-> 3138
                raise TypeError(
   3139
                    'too many positional arguments') from None
   3141
            if param.kind == _VAR_POSITIONAL:
                # We have an '*args'-like argument, let's fill it with
   3142
                # all positional arguments we have left and move on to
   3143
   3144
                # the next phase
                values = [arg_val]
   3145
TypeError: too many positional arguments
```