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	Panel C, Batch CI
	ML Lab Assignment 4
	Enol-
	FAQ'S
ı'	What is a classifier?
0 -	A classifier is a type of algorithm used in machine
	learning to categorize input data into predefined
	learning to categorize input data into predefined classes or categories based on this their features or
	attributes. Essentially a function that maps input data to
	a category or class label.
2	Compare SUM with decision tree classifiers.
	Support vector machines (SUM'S) aim to find the optimal
	hyperplane that separates different classes in the data.
	maximizing the margin beth classes. Decision trees split the data into subsets based on features, aiming to
	create simple decision rules for classification.
	Touch Tourism
3)	How would you tune SVM parameters?
<u> </u>	To tune sum parameters, focus on adjusting the regulariz- -ation parameter ((tradeoff bet missclassification
	-ation parameter ((tradeoff beth missclassification
	and margin) and the choice of Kernel (eg. linear, polynomial radial basis function). Use techniques like grid search or
	radial basis tunction). Use techniques like grid search or
	random search with cross validation to find the optimal values.
	Opinion variable
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4)	Describe unclose types of kernel functions.
<u> </u>	Describe various types of kernel functions. 1] Linear Kernel: Computes the dot product of input
	features.
	2] Polynomial Kernel: Computes the dot product roised
	to a specific power
	3] Radial Basis Function (RBF) Kernel: Uses a Gaussian like function to map data into high dimensional
	function to map data into high dimensional
	space.
1 - y	4] Sigmoid Kernel: Applies a hyperbolic tangent function
	to input features
5)	Give the applications of SVM clossifier.
-	Image Recognition: Identifying object/pattern in images. Text classification: Categorizing documents into different topics
	Text classification: Categorizing documents into different topics
	or sentiments.
	Bioinformatics: Predicting protein function or classifying
	gene expression
6)	State the significance of kernel function.
-	The kind of the alless SUNI I am a least of the late
	high - dimensional space renabling the separation of complex patterns that may not be linearly separable in original feature space.
	complex patterns that may not be linearly separable
	in original feature space.
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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())
                                                                     7
                                  3
                                                            6
                                                                             8
       17.99
               10.38
                      122.80
                              1001.0
                                      0.11840
                                               0.27760
                                                        0.3001
                                                                0.14710
                                                                         0.2419
     1 20.57
                              1326.0
                                      0.08474
               17.77
                      132.90
                                              0.07864
                                                        0.0869
                                                                0.07017
       19.69
               21.25
                      130.00
                              1203.0 0.10960
                                               0.15990
                                                        0.1974
                                                                0.12790
                                                                         0.2069
       11.42
               20.38
                       77.58
                               386.1
                                      0.14250
                                               0.28390
                                                        0.2414
                                                                0.10520
        20.29
               14.34
                      135.10
                              1297.0 0.10030 0.13280
                                                       0.1980 0.10430
                       20
                              21
                                      22
                                              23
                                                      24
                                                              25
                                                                      26
                                                                              27
       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
     2 0.05999
                    23.57
                           25.53
                                  152.50
                                          1709.0 0.1444
                                                          0.4245
                                                                  0.4504
     3 0.09744
                 ... 14.91
                           26.50
                                   98.87
                                           567.7 0.2098 0.8663
                                                                  0.6869
        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
```

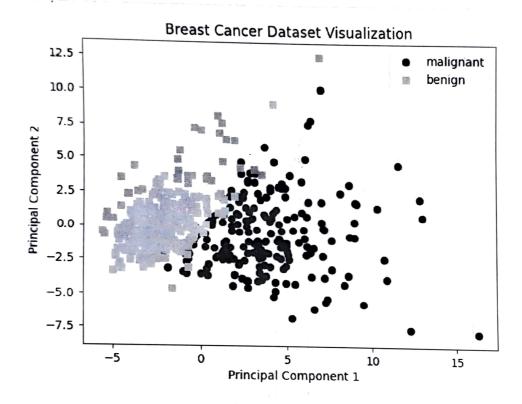
```
3 0.6638 0.17300
     4 0.2364 0.07678
     [5 rows x 30 columns]
[52]: scaler = StandardScaler()
     scaler.fit(X)
[52]: StandardScaler()
[53]: X_scaled = scaler.fit_transform(X)
      print(X_scaled)
     [[ 1.09706398 -2.07333501 1.26993369 ... 2.29607613 2.75062224
        1.93701461]
      [ 1.82982061 -0.35363241 1.68595471 ... 1.0870843 -0.24388967
      [ 1.57988811  0.45618695  1.56650313 ... 1.95500035  1.152255
        0.20139121]
      [ 1.83834103 2.33645719 1.98252415 ... 2.28998549 1.91908301
      [-1.80840125 1.22179204 -1.81438851 ... -1.74506282 -0.04813821
[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
```

```
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):
```

3.01595231e-02 6.16486075e-03 8.25910439e-03 2.64374475e-03

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



```
----> 3 y_pred = best_svm_classifier.predict(X_test_scaled)
     MameError: name 'best_svm_classifier' is not defined
[]: print("\nClassification Report:")
    print(classification_report(y_test, y_pred))
    Classification Report:
                              recall f1-score
                                                support
                 precision
                                                     43
                                          0.98
                                0.95
               0
                      1.00
                                                     71
                                          0.99
                                1.00
                      0.97
                                                    114
                                          0.98
        accuracy
                                                    114
                                          0.98
                                0.98
                       0.99
       macro avg
                                                    114
                                          0.98
                                0.98
                       0.98
    weighted avg
[]: 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()
                                              Traceback (most recent call last)
       TypeError
      Cell In[35], line 1.
         confusion_matrix(best_svm_classifier, X_test_scaled, y_test, cmap=plt.cm.Blue:, display_lal
       ---> 1
            2 plt.title('Confusion Matrix')
            3 plt.show()
      File -/.pyenv/versions/3.11.7/lib/python3.11/site-packages/sklearn/utils/
          * per (*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 Signatur4
          orna(self, *args, **kwargs)
          3207 def bind(self, /, *args, **kwargs):
                  """Get a BoundArguments object, that maps the passed `args`
          3208
                 and `kwargs` to the function's signature. Raises `TypeError`
          3209
                  if the passed arguments can not be bound.
```

```
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:
   3135
            if param.kind in (_VAR_KEYWORD, _KEYWORD_ONLY):
   3136
                # Looks like we have no parameter for this positional
   3137
                # argument
-> 3138
                raise TypeError(
   3139
                    'too many positional arguments') from None
            if param.kind == _VAR_POSITIONAL:
   3141
                # We have an '*args'-like argument, let's fill it with
   3142
   3143
                # all positional arguments we have left and move on to
   3144
                # the next phase
   3145
                values = [arg_val]
TypeError: too many positional arguments
```

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