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In [ ]: #Question 1
 In [1]: from __future__ import division
          import time
          import numpy as np
          from sklearn.svm import SVR
          from sklearn.model_selection import GridSearchCV
          from sklearn.model selection import learning curve
          import matplotlib.pyplot as plt
In [2]: #load dataset
          from sklearn.datasets import load boston
          boston = load boston()
         print(boston.data.shape)
         X=boston.data
          y=boston.target
         print (X.shape)
         print (y.shape)
          (506, 13)
          (506, 13)
          (506,)
In [3]: train size = 100
          # Parameters are already given in the question, no grid search required.
 In [4]: #Implementing RBF kernel
          svr rbf = SVR(kernel='rbf', C=100, degree=2, gamma=0.1)
          train sizes, train scores svr, test scores svr = \
              learning curve(svr rbf, X[:100], y[:100], train sizes=np.linspace(0.1, 1, 10),
                             scoring="neg_mean_squared_error", cv=10)
          print (test scores svr.shape)
         plt.plot(train_sizes, -test_scores_svr.mean(1), 'o-', color="r",
                   label="SVR")
         plt.xlabel("Train size")
          plt.ylabel("Mean Squared Error")
          plt.title('Learning curves')
         plt.legend(loc="best")
          #Plotting learning curves
         plt.show()
          (10, 10)
                             Learning curves
                                                 SVR
            60
          Mean Squared Error
            55
            50
            45
            40
                     20
                                   50
                                Train size
 In [5]: #Implementing Poly Kernel
          svr_poly = SVR(kernel='poly', C=100, degree=2, gamma=0.1)
          train_sizes, train_scores_svr, test_scores_svr = \
              learning\_curve (svr\_poly, X[:100], y[:100], train\_sizes=np.linspace (0.1, 1, 10),\\
                             scoring="neg_mean_squared_error", cv=10)
          print (test_scores_svr.shape)
          plt.plot(train_sizes, -test_scores_svr.mean(1), 'o-', color="r",
                   label="SVR1")
          plt.xlabel("Train size")
         plt.ylabel("Mean Squared Error")
         plt.title('Learning curves')
         plt.legend(loc="best")
          #Plotting learning curves
         plt.show()
          (10, 10)
                             Learning curves
              le10
                                                ─ SVR1
          Mean Squared Error
            0 -
               10
                                       60
                    20
                         30
                             40
                                Train size
 In [6]: #Implementing Linear kernel
          svr_linear = SVR(kernel='linear', C=100, degree=2, gamma=0.1)
          train_sizes, train_scores_svr, test_scores_svr = \
              learning_curve(svr_linear, X[:100], y[:100], train_sizes=np.linspace(0.1, 1, 10),
                             scoring="neg_mean_squared_error", cv=10)
          print (test_scores_svr.shape)
          plt.plot(train_sizes, -test_scores_svr.mean(1), 'o-', color="r",
                   label="SVR1")
          plt.xlabel("Train size")
         plt.ylabel("Mean Squared Error")
         plt.title('Learning curves')
         plt.legend(loc="best")
          #Plotting learning curves
         plt.show()
          (10, 10)
                               Learning curves
            1600
                                                  ─ SVR1
            1400
            1200
          Mean Squared Error
            1000
             800
             600
             400
             200
                                         60
                                                  80
                 10
                      20
                           30
                                40
                                    50
                                              70
 In [7]: #Fitting the model
          svr_rbf.fit(X[:train_size], y[:train_size])
          svr_poly.fit(X[:train_size], y[:train_size])
          svr_linear.fit(X[:train_size], y[:train_size])
 Out[7]: SVR(C=100, cache_size=200, coef0=0.0, degree=2, epsilon=0.1, gamma=0.1,
           kernel='linear', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
 In [8]: #Accuracy for SVR
          from sklearn.metrics import mean_squared_error
         prediction = svr_linear.predict(X[train_size:])
         mean_squared_error(y[train_size:], prediction)
Out[8]: 6646.9704301698221
 In [9]: #Accuracy for Poly
          prediction = svr_poly.predict(X[train_size:])
         mean_squared_error(y[train_size:], prediction)
Out[9]: 93652818478.405212
In [10]: #Accuracy for RBF
         prediction = svr_rbf.predict(X[train_size:])
         mean_squared_error(y[train_size:], prediction)
Out[10]: 96.691254372778118
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In [11]: # Lowest error obtained for rbf model

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In [ ]: #Question 2
In [1]: from sklearn import tree
        from sklearn import datasets
        from sklearn import model selection
        from sklearn.model_selection import train test split
        from sklearn.utils import shuffle
        from sklearn.metrics import classification report
        from sklearn.grid search import GridSearchCV
        from sklearn.ensemble import GradientBoostingClassifier
        C:\Users\Renuka\Anaconda3\lib\site-packages\sklearn\cross validation.py:41: DeprecationWarni
        ng: This module was deprecated in version 0.18 in favor of the model selection module into w
        hich all the refactored classes and functions are moved. Also note that the interface of the
        new CV iterators are different from that of this module. This module will be removed in 0.2
         "This module will be removed in 0.20.", DeprecationWarning)
        C:\Users\Renuka\Anaconda3\lib\site-packages\sklearn\grid search.py:42: DeprecationWarning: T
        his module was deprecated in version 0.18 in favor of the model selection module into which
        all the refactored classes and functions are moved. This module will be removed in 0.20.
          DeprecationWarning)
In [2]: #Load breast cancer dataset
        from sklearn.datasets import load breast cancer
        bc = load breast cancer()
        X = bc.data
        y = bc.target
        print (X.max())
        print (y.shape)
        #Classification using train-test split
        X, y = \text{shuffle}(X, y, random state=0)
        4254.0
        (569,)
In [3]: #Optimizing for different values of n estimators and max depth for Gradient Boost implementatio
        cv params = {'n estimators':[10,100,200,500],'max depth': [2,3,5,7]}
        optimized GBM = GridSearchCV(estimator=GradientBoostingClassifier(n estimators=100, learning ra
        te=1.0, random state=0), param grid=cv params, scoring = 'accuracy', cv = 5)
In [4]: optimized_GBM.fit(X, y)
Out[4]: GridSearchCV(cv=5, error score='raise',
               estimator=GradientBoostingClassifier(criterion='friedman mse', init=None,
                      learning rate=1.0, loss='deviance', max depth=3,
                      max features=None, max leaf nodes=None,
                      min impurity decrease=0.0, min impurity split=None,
                      min samples leaf=1, min samples split=2,
                      min weight fraction leaf=0.0, n estimators=100,
                      presort='auto', random state=0, subsample=1.0, verbose=0,
                      warm start=False),
               fit params={}, iid=True, n jobs=1,
               param_grid={'n_estimators': [10, 100, 200, 500], 'max_depth': [2, 3, 5, 7]},
               pre dispatch='2*n jobs', refit=True, scoring='accuracy', verbose=0)
In [5]: optimized_GBM.grid_scores_
Out[5]: [mean: 0.95431, std: 0.02197, params: {'max_depth': 2, 'n_estimators': 10},
         mean: 0.96309, std: 0.02041, params: {'max_depth': 2, 'n_estimators': 100},
         mean: 0.96309, std: 0.02041, params: {'max_depth': 2, 'n_estimators': 200},
         mean: 0.96309, std: 0.02041, params: {'max_depth': 2, 'n_estimators': 500},
         mean: 0.93673, std: 0.02208, params: {'max_depth': 3, 'n_estimators': 10},
         mean: 0.95255, std: 0.01752, params: {'max_depth': 3, 'n_estimators': 100},
         mean: 0.95255, std: 0.01752, params: {'max depth': 3, 'n estimators': 200},
         mean: 0.95255, std: 0.01752, params: {'max depth': 3, 'n estimators': 500},
         mean: 0.95255, std: 0.02370, params: {'max_depth': 5, 'n_estimators': 10},
         mean: 0.95606, std: 0.01830, params: {'max_depth': 5, 'n_estimators': 100},
         mean: 0.95606, std: 0.01830, params: {'max depth': 5, 'n estimators': 200},
         mean: 0.95606, std: 0.01830, params: {'max_depth': 5, 'n_estimators': 500},
         mean: 0.92794, std: 0.02627, params: {'max_depth': 7, 'n_estimators': 10},
         mean: 0.92794, std: 0.02627, params: {'max_depth': 7, 'n_estimators': 100},
         mean: 0.92794, std: 0.02627, params: {'max_depth': 7, 'n_estimators': 200},
         mean: 0.92794, std: 0.02627, params: {'max_depth': 7, 'n_estimators': 500}]
In [6]: #Best parameters obtained
        optimized_GBM.best_params_
Out[6]: {'max_depth': 2, 'n_estimators': 100}
In [7]: optimized_GBM.best_score_
Out[7]: 0.9630931458699473
In [9]: #Splitting dataset into equal parts
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
        gbc=GradientBoostingClassifier(n_estimators=100, max_depth =2, learning_rate=1.0,random_state=0
        ).fit(X_train,y_train)
        Results=gbc.predict(X test)
        #Classification accuracy report
        print(classification_report(Results, y_test))
                     precision
                                  recall f1-score
                                                     support
                  0
                          0.94
                                    0.98
                                               0.96
                                                           46
```

1

0.99

0.97

0.98

97

```
In [ ]: #Question 3
 In [1]: from sklearn.ensemble import BaggingClassifier
         from sklearn import tree
         from sklearn import datasets
         from sklearn import model selection
         from sklearn.model_selection import train test split
         from sklearn.utils import shuffle
         from sklearn.metrics import classification report
 In [2]: #Load breast cancer dataset
         from sklearn.datasets import load breast cancer
         bc2 = load breast cancer()
         X = bc2.data
         y = bc2.target
         print (X.max())
         print (y.shape)
         #Classification using train-test split
         X, y = \text{shuffle}(X, y, random state=0)
         4254.0
         (569,)
 In [7]: | #Optimizing for different values of n estimators for Bagging Implementation
         from sklearn.grid_search import GridSearchCV
         cv params = {'n estimators':[10,100,200,500]}
         optimized bag = GridSearchCV(BaggingClassifier(tree.DecisionTreeClassifier(), n estimators=100,
          random state=0),param grid=cv params,scoring = 'accuracy', cv = 5)
 In [8]: optimized bag.fit(X, y)
Out[8]: GridSearchCV(cv=5, error_score='raise',
                estimator=BaggingClassifier(base estimator=DecisionTreeClassifier(class weight=None,
         criterion='gini', max depth=None,
                     max features=None, max leaf nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     ..., n estimators=100, n jobs=1, oob score=False,
                  random state=0, verbose=0, warm start=False),
                fit_params={}, iid=True, n_jobs=1,
                param grid={'n estimators': [10, 100, 200, 500]},
                pre dispatch='2*n jobs', refit=True, scoring='accuracy', verbose=0)
 In [9]: optimized bag.grid scores
Out[9]: [mean: 0.94200, std: 0.02219, params: {'n_estimators': 10},
          mean: 0.95782, std: 0.01799, params: {'n estimators': 100},
          mean: 0.95782, std: 0.01799, params: {'n estimators': 200},
          mean: 0.95958, std: 0.01533, params: {'n estimators': 500}]
In [10]: #Best parameters
         optimized_bag.best_params_
Out[10]: {'n estimators': 500}
In [11]: optimized_bag.best_score_
Out[11]: 0.9595782073813708
In [13]: #Splitting dataset into equal parts
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
         bagging = BaggingClassifier(tree.DecisionTreeClassifier(),n_estimators=200,oob_score=True,max_s
         amples=0.5, max_features=0.5).fit(X_train,y_train)
         Results=bagging.predict(X test)
         #Classification accuracy report
         print (classification_report(Results,y_test))
                                   recall f1-score support
                      precision
                           0.90
                                     0.96
                                               0.93
                                                            49
                   1
                           0.98
                                     0.95
                                               0.96
                                                            94
         avg / total
                           0.95
                                     0.95
                                               0.95
                                                          143
In [14]: #Classification using Cross-validation
         X, y = shuffle(X, y, random state=0)
         bg = BaggingClassifier(tree.DecisionTreeClassifier(),n_estimators=500,oob_score=True,max_sample
         s=0.5, max_features=0.5).fit(X_train,y_train)
         results = model_selection.cross_val_score(bg, X, y, cv=5)
         #Average score
         print (results.mean())
         0.957799153521
```

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In [ ]: #Question 4
 In [1]: from sklearn import tree
         from sklearn import datasets
         from sklearn import model selection
         from sklearn.model_selection import train test split
         from sklearn.utils import shuffle
         from sklearn.metrics import classification report
         from sklearn.ensemble import RandomForestClassifier
In [3]: #Load Breast Cancer dataset
         from sklearn.datasets import load breast cancer
         bc3 = load breast cancer()
         X = bc3.data
         y = bc3.target
         print (X.max())
         print (y.shape)
         ####perform classification with train-test split###
         X, y = shuffle(X, y, random_state=0)
         4254.0
         (569,)
In [6]: #Optimizing for different values of n_estimators and max_depth for Random Forest Implementation
         from sklearn.grid_search import GridSearchCV
         cv params = {'n estimators':[10,100,200,500],'max depth': [2,3,5,7]}
         optimized rf = GridSearchCV(estimator=RandomForestClassifier(n estimators=100, random state=0),p
         aram grid=cv params, scoring = 'accuracy', cv = 5)
 In [8]: optimized rf.fit(X, y)
Out[8]: GridSearchCV(cv=5, error score='raise',
                 estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                      max depth=None, max features='auto', max leaf nodes=None,
                      min impurity decrease=0.0, min impurity split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      \label{lem:min_weight_fraction_leaf} \\ \text{min\_weight\_fraction\_leaf=0.0, n\_estimators=100, n\_jobs=1,} \\
                      oob score=False, random state=0, verbose=0, warm start=False),
                 fit_params={}, iid=True, n_jobs=1,
                 param_grid={'n_estimators': [10, 100, 200, 500], 'max_depth': [2, 3, 5, 7]},
                pre_dispatch='2*n_jobs', refit=True, scoring='accuracy', verbose=0)
 In [9]: #Best parameters
         optimized_rf.best_params_
Out[9]: {'max_depth': 7, 'n_estimators': 100}
In [10]: optimized_rf.best_score_
Out[10]: 0.9595782073813708
In [11]: #Splitting dataset into equal parts
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
         clf = RandomForestClassifier(n_estimators=100, max_depth=7,min_samples_split=2, random_state=0)
         .fit(X_train,y_train)
         Results=clf.predict(X_test)
         #Classification accuracy report
         print (classification report(Results, y test))
                      precision recall f1-score support
                                      0.96
                                                0.92
                            0.90
                                                             45
                   1
                            0.98
                                      0.95
                                               0.96
                                                             98
                            0.95
                                      0.95
                                             0.95
                                                           143
         avg / total
In [12]: #Classification using Cross-validation
         clf = RandomForestClassifier(n estimators=10, max depth=None, min samples split=2, random state=
         0).fit(X train, y train)
         results = model_selection.cross_val_score(clf, X, y, cv=5)
```

#Average score

print (results.mean())