Report

Task 3 & Task 4

Task 3

Parameter analysis (only for digits dataset):

1. Perceptron

max_iter	eta0	Accuracy for training	Accuracy for testing
		data	data
50	0.1	0.979	0.933
50	0.001	0.967	0.926
50	0.00001	0.967	0.926
10	0.1	0.975	0.931
50	0.1	0.979	0.933
100	0.1	0.979	0.933

Based on the different set of max_iter and eta0, the accuracy doesn't vary too much. Therefore, max_iter and eta0 are set as 50 and 0.1.

2. svm_linear

C1	Accuracy for training data	Accuracy for testing data
1	1	0.978
5	1	0.978
10	1	0.978

Three different C1 values lead to the same accuracy and thus C1 is set as 1.

3. svm nonlinear

C2	gamma	Accuracy for training	Accuracy for testing
		data	data
1	0.1	1	0.948
10	0.1	1	0.948
20	0.1	1	0.948
10	0.1	1	0.948
10	0.2	1	0.813
10	0.5	1	0.369

The magnitude of C2 doesn't influence the accuracy too much. However, the accuracy of testing decreases as the increase of gamma. Therefore, C2 and gamma are set as 1 and 0.1.

4. tree_model

max_depth	Accuracy for training data	Accuracy for testing data
10	0.982	0.841
50	1	0.857
100	1	0.857

Three values of max_depth are selected and the highest accuracy is achieved with the max_dpeth of 50.

5. knn

n_neighbor	Accuracy for training data	Accuracy for testing data
2	0.983	0.985
5	0.983	0.985
10	0.983	0.985

Three numbers of n_neighbor are selected and the same accuracy can be obtained. Thus 2 is set in the classifier.

Run result of data2:

Training data:

Misclassified samples: 196

Accuracy for training data: 0.945

Testing data:

Misclassified samples: 3589

Accuracy for testing data: 0.568

Training data:

Misclassified samples: 2

Accuracy for training data: 0.999

Testing data:

Misclassified samples: 3613

Accuracy for testing data: 0.565

Training data:

Misclassified samples: 0

Accuracy for training data: 1.000

Testing data:

Misclassified samples: 2508

Accuracy for testing data: 0.698

Training data:

Misclassified samples: 152

Accuracy for training data: 0.958

Testing data:

Misclassified samples: 5440

Accuracy for testing data: 0.345

Training data:

Misclassified samples: 150

Accuracy for training data: 0.958

Testing data:

Misclassified samples: 2050

Accuracy for testing data: 0.753

Task 4

Strategies:

1. Pre-prune:

Provide parameters such as min-samples_leaf, min_impurity_split, max_leaf_nodes, max_depth, etc. to prevent a tree from overfitting.

2. Post-prune:

Compute the pruning path during Minimal Cost-Complexity Pruning. Complexity parameter (ccp_alpha) is used for Minimal Cost-Complexity Pruning.

3. The lines of code for **pre-prune**: lines: [205-319]

The code of min-sample leaf and min sample split are attached below.

```
205
               if isinstance(self.min_samples_leaf, numbers.Integral):
206
                   if not 1 <= self.min_samples_leaf:</pre>
                       raise ValueError("min samples leaf must be at least 1 "
207
                                         "or in (0, 0.5], got %s"
208
                                         % self.min_samples_leaf)
209
210
                   min_samples_leaf = self.min_samples_leaf
211
              else: # float
                   if not 0. < self.min_samples_leaf <= 0.5:</pre>
212
213
                       raise ValueError("min_samples_leaf must be at least 1 "
                                         "or in (0, 0.5], got %s"
214
                                         % self.min_samples_leaf)
215
                   min_samples_leaf = int(ceil(self.min_samples_leaf * n_samples))
216
              if isinstance(self.min_samples_split, numbers.Integral):
218
219
                  if not 2 <= self.min_samples_split:</pre>
                      raise ValueError("min samples split must be an integer "
220
221
                                       "greater than 1 or a float in (0.0, 1.0]; "
                                       "got the integer %s"
222
                                       % self.min_samples_split)
223
224
                  min_samples_split = self.min_samples_split
225
              else: # float
                  if not 0. < self.min_samples_split <= 1.:</pre>
226
                      raise ValueError("min_samples_split must be an integer "
227
                                       "greater than 1 or a float in (0.0, 1.0]; "
228
                                       "got the float %s"
229
230
                                       % self.min samples split)
231
                  min_samples_split = int(ceil(self.min_samples_split * n_samples))
232
                  min_samples_split = max(2, min_samples_split)
              min_samples_split = max(min_samples_split, 2 * min_samples_leaf)
234
```

4. The lines of code for **post-prune**: lines [523-560]

```
523
         def cost_complexity_pruning_path(self, X, y, sample_weight=None):
              """Compute the pruning path during Minimal Cost-Complexity Pruning.
524
526
              See :ref:`minimal_cost_complexity_pruning` for details on the pruning
527
              process.
528
529
              Parameters
530
              X : {array-like, sparse matrix} of shape (n_samples, n_features)
531
                  The training input samples. Internally, it will be converted to
532
                  ``dtype=np.float32`` and if a sparse matrix is provided
533
                  to a sparse ``csc_matrix``.
534
535
              y : array-like of shape (n_samples,) or (n_samples, n_outputs)
536
537
                  The target values (class labels) as integers or strings.
538
              sample weight: array-like of shape (n samples,), default=None
539
                  Sample weights. If None, then samples are equally weighted. Splits
540
541
                  that would create child nodes with net zero or negative weight are
                  ignored while searching for a split in each node. Splits are also
                  ignored if they would result in any single class carrying a
543
544
                  negative weight in either child node.
546
             Returns
547
548
              ccp_path : Bunch
                  Dictionary-like object, with attributes:
549
550
551
                  ccp_alphas : ndarray
552
                      Effective alphas of subtree during pruning.
553
554
                  impurities : ndarray
555
                      Sum of the impurities of the subtree leaves for the
556
                      corresponding alpha value in ``ccp_alphas``.
557
558
             est = clone(self).set_params(ccp_alpha=0.0)
559
              est.fit(X, y, sample_weight=sample_weight)
              return Bunch(**ccp_pruning_path(est.tree_))
560
```