0ras3csxj

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CS589 ASSIGNMENT 6

Name: Dorian Benhamou Goldfajn Email: dbenhamougol@umass.edu Discussed With: Aryan Nair

```
[2]: import numpy as np

stuff=np.load("data.npz")
X_trn = stuff["X_trn"]
y_trn = stuff["y_trn"]
X_tst = stuff["X_tst"]
# no Y_tst !
```

```
[100]: X = [1.0, 2.0, 3.0, 4.0, 5.0]
       Y = [1, 1, 0, 0, 1]
       splits = [0.5, 1.5, 2.5, 3.5, 4.5, 5.5]
       # calculate parent entropy
       parent_p1 = sum(Y) / len(Y)
       parent_p0 = 1 - parent_p1
       parent_entropy = (-parent_p1*np.log2(parent_p1)) + (- parent_p0*np.
        →log2(parent_p0))
       # calculate child entropy for each split
       child_entropy = \{.5: -1, 1.5: -1, 2.5: -1, 3.5: -1, 4.5: -1, 5.5: -1\}
       for split in splits:
           # split data
           left = []
           right = []
           for i in range(len(X)):
               if X[i] < split:</pre>
                   left.append(Y[i])
               else:
```

```
right.append(Y[i])
    # calculate I(p1) and I(p2) for both left and right sides (if empty, set to
 ⇔0)
    left_p1 = 0
    if len(left) != 0:
        left_p1 = sum(left) / len(left)
    left_p0 = 1 - left_p1
    right_p1 = 0
    if len(right) != 0:
        right_p1 = sum(right) / len(right)
    right_p0 = 1 - right_p1
    if left_p1 == 0:
        left_entropy = -left_p0*np.log2(left_p0)
    elif left p0 == 0:
        left_entropy = -left_p1*np.log2(left_p1)
    else:
        left_entropy = (-left_p1*np.log2(left_p1)) + (- left_p0*np.
  ⇒log2(left p0))
    if right_p1 == 0:
        right_entropy = -right_p0*np.log2(right_p0)
    elif right_p0 == 0:
        right_entropy = -right_p1*np.log2(right_p1)
    else:
        right_entropy = (-right_p1*np.log2(right_p1)) + (- right_p0*np.
 →log2(right_p0))
    # calculate child entropy and store
    child_entropy[split] = ((len(left))*left_entropy +
 ⇔(len(right))*right_entropy) / len(Y)
# calculate information gain and print
information_gain = {split: parent_entropy - child_entropy[split] for split in_
 ⇔splits}
print("Split | Information Gain")
for split in splits:
    print(f" {split} | {information_gain[split]}")
Split | Information Gain
```

```
0.5 | 0.0

1.5 | 0.17095059445466854

2.5 | 0.4199730940219748

3.5 | 0.01997309402197489
```

```
4.5 | 0.17095059445466854
5.5 | 0.0
```

```
[101]: class ClassificationStump():
           def __init__(self):
               return
           def fit(self, X_trn, y_trn):
               # do stuff here
               D = len(X_trn[0])
               N = len(X trn)
               dim = -1
               thresh = -1
               min_error = np.inf
               c_left = 0
               c_right = 0
               for i in range(D):
                    sorted_indices = np.argsort(X_trn[:, i])
                    Z = X_trn[sorted_indices]
                   y_sorted = y_trn[sorted_indices]
                   for n in range(N-1):
                       t = (Z[n][i] + Z[n+1][i])/2
                        R1 = y_sorted[:n+1] # x <= t
                       R2 = y_sorted[n+1:] # x > t
                        R1_count = np.bincount(R1, minlength=np.max(y_sorted) + 1)
                        R2_count = np.bincount(R2, minlength=np.max(y_sorted) + 1)
                        c1 = np.argmax(R1_count)
                        c2 = np.argmax(R2_count)
                        p1 = R1_count / len(R1) # probability of each class in R1
                        p2 = R2_count / len(R2) # probability of each class in R2
                        gini_left = np.sum(p1 * (1-p1)) # sum pi(1-pi) for each class_{\square}
        \hookrightarrow in R1
                        gini_right = np.sum(p2 * (1-p2))
                        gini\_total = (len(R1) / N) * gini\_left + (len(R2) / N) *_{\sqcup}
        →gini_right # weighted average of gini impurity
```

```
error = gini_total
               if error < min_error:</pre>
                   min_error = error
                   dim = i
                   c_left = c1
                   c_right = c2
                   thresh = t
      self.model = (dim, thresh, c_left, c_right)
       self.model = {'dim': dim, 'thresh': thresh, 'c_left': c_left, 'c_right':
→ c_right}
      return
  def predict(self, X_val, y_val=None):
      assert hasattr(self, "model"), "No fitted model!"
       # do stuff here (use self.model for prediction)
      y_pred = []
      for x_val in X_val:
           y_pred.append(self.model['c_left'] if x_val[self.model['dim']] <=__</pre>
self.model['thresh'] else self.model['c_right'])
      return y_pred
```

```
[102]: data = np.load('data.npz')
    X_trn = data['X_trn']
    y_trn = data['Y_trn']
    X_tst = data['X_tst']

clf = ClassificationStump()

X_trn = X_trn.reshape((6000, 3 * 29 * 29))

clf.fit(X_trn, y_trn)
    y_pred = clf.predict(X_trn)
    correct_pred = sum(y_pred == y_trn)
    e = 1 - correct_pred / len(y_pred)
    print("Training classification error: ", e)
```

Training classification error: 0.6421666666666667

```
[103]: # train classification trees
from sklearn.tree import DecisionTreeClassifier
```

```
data = np.load('data.npz')
X_trn = data['X_trn']
y_trn = data['y_trn']

X_trn = X_trn.reshape((len(X_trn), 3 * 29 * 29))

max_depths = [1,3,6,9,12,14]
# return a 6x1 table of classification errors
print(" DEPTH | TRAINING ERROR")
for max_depth in max_depths:
    clf = DecisionTreeClassifier(max_depth=max_depth)
    clf.fit(X_trn, y_trn)
    y_pred = clf.predict(X_trn)
    correct_pred = sum(y_pred == y_trn)
    acc = correct_pred / len(y_trn)
    e = 1 - acc
    print(f" {max_depth} | {e}")
```

Order of O(M). For each depth in the tree, we check a single threshold value (O(1)) until we get to the end of the tree where we make final classication, giving rise O(M * 1) = O(M).

Question 5

O(D*Nlogn). We must iterate through each D, and for each D we sort N items and iterate through N items. This is equivalent to O(D*(NlogN+N)) = O(D*NlogN), although I think it slightly depends on implementation.

```
lambda_vals = [0.1, 1, 10, 100, 1000]
      # report training classification error and logistic loss for each lambda value
      print(" LAMBDA | TRAINING ERROR | LOGISTIC LOSS")
      for lambda_val in lambda_vals:
          clf = LogisticRegression(penalty='12', C=1/lambda_val, max_iter=10000, tol=.
        →001)
          clf.fit(X_trn, y_trn)
          confidence scores = clf.decision function(X_trn) # qet confidence score per_
        ⇔class per sample
          exp_scores = np.exp(confidence_scores) # prepare for softmax
          sum_exp_scores_per_sample = [sum(scores) for scores in exp_scores]
          probs = [exp_scores[i] / sum_exp_scores_per_sample[i] for i in_
        →range(len(exp_scores))] # softmax to get probs
          y_pred = [np.argmax(prob) for prob in probs] # qet prediction from highest⊔
        \hookrightarrow prob
          logistic_loss = log_loss(y_trn, probs) # calculate logistic loss
          correct_preds = np.sum(y_pred == y_trn)
          e = 1 - (correct_preds / len(y_trn)) # calculate classification error
          print(f" {lambda_val} | {e} | {logistic_loss}")
       LAMBDA | TRAINING ERROR | LOGISTIC LOSS
        0.1 | 0.1700000000000004 | 0.4771340095214954
        1 | 0.2138333333333333 | 0.582162089440951
        10 | 0.264499999999999 | 0.6939481457195188
        100 | 0.3031666666666667 | 0.7863802988369172
        Question 7
[105]: # K nearest neighbors classifier
      from sklearn.neighbors import KNeighborsClassifier
      data = np.load('data.npz')
      X_trn = data['X_trn']
      y_trn = data['y_trn']
      X_tst = data['X_tst']
      X_{trn} = X_{trn.reshape}((len(X_{trn}), 3 * 29 * 29))
```

 $X_{trn} = X_{trn.reshape}((6000, 3*29*29))$

```
k_neighbors = [1, 3, 5, 7, 9, 11]

print(" K | TRAINING ERROR")

for k in k_neighbors:
    clf = KNeighborsClassifier(n_neighbors=k)
    clf.fit(X_trn, y_trn)
    y_pred = clf.predict(X_trn)
    correct_pred = sum(y_pred == y_trn)
    acc = correct_pred / len(y_trn)
    e = 1 - acc
    print(f" {k} | {e}")
```

```
K | TRAINING ERROR
```

- 1 | 0.0
- 3 | 0.29200000000000004
- 5 | 0.3163333333333333
- 7 | 0.3478333333333333
- 9 | 0.362666666666667
- 11 | 0.3663333333333333

Order of O(N * (N * D + NlogN)). For each of x1,..., xN values in X_tst, we get the distance for each D for each x in X_trn (N * (N * D)). Per x in X_tst, we must also sort the distances to get K nearest neighbor and select majority class, giving rise to (N * ((N * D) + NlogN + K + K)), but since K is usally much smaller than N, we can abstract it to the order mentioned above.

PART 2 - Cross Validation

```
[4]: from sklearn.model_selection import KFold

class Classifier():
    def __init__(self, model):
        self.model = model
        return

def fit(self, X_trn, y_trn):
        self.model.fit(X_trn, y_trn)
        # self.model is stored
        return

def predict(self, X_val, y_val=None):
        # self.model is used
        y_pred = self.model.predict(X_val)
        return y_pred
```

```
def cross_validation(classifier, X_trn, y_trn, n_folds=5):
    # do stuff here

kf = KFold(n_splits=n_folds)
    outputs = []

for train_index, test_index in kf.split(X_trn):

    x_train, x_test = X_trn[train_index], X_trn[test_index]
    y_train, y_test = y_trn[train_index], y_trn[test_index]

    classifier.fit(x_train, y_train)
    y_pred = classifier.predict(x_test)
    correct_preds = np.sum(y_pred == y_test)
    e = 1 - (correct_preds / len(y_test))

    outputs.append((classifier, e))

# Return the paired (model and error) for all folds
    return outputs # [(model1, error1), (model2, error2), ..., (modelK, errorK)]
```

```
[5]: # Usage for the cross_validation function:
     from sklearn.tree import DecisionTreeClassifier
     import pandas as pd
     data = np.load('data.npz')
     X_trn = data['X_trn']
     y_trn = data['y_trn']
     X_{trn} = X_{trn.reshape}((6000, 3 * 29 * 29))
     results = []
     # Perform cross-validation for different max_depth values
     for max_depth in [1, 3, 6, 9, 12, 14]:
         classifier = Classifier(DecisionTreeClassifier(max_depth=max_depth))
         outputs = cross_validation(classifier, X_trn, y_trn, n_folds=N)
         # Collect the errors for each fold
         fold_errors = [out_[1] for out_ in outputs]
         avg_error = np.mean(fold_errors)
         # Append the results to the list
```

```
MAX_DEPTH FOLD_1_ERROR FOLD_2_ERROR FOLD_3_ERROR FOLD_4_ERROR FOLD_5_ERROR
AVG ERROR
                0.654167
                              0.661667
                                            0.635833
                                                          0.637500
                                                                        0.630000
0.643833
                0.527500
                              0.569167
                                            0.565000
                                                          0.547500
                                                                        0.540000
0.549833
                0.486667
                              0.493333
                                            0.497500
                                                          0.482500
                                                                        0.480833
0.488167
                0.460000
                              0.499167
                                            0.470833
                                                          0.464167
                                                                        0.463333
0.471500
                0.480833
                              0.489167
                                            0.464167
                                                          0.463333
        12
                                                                        0.479167
0.475333
                0.470000
                              0.510000
                                            0.478333
                                                          0.457500
                                                                        0.472500
        14
0.477667
```

```
fold_errors = [out_[1] for out_ in outputs]
    avg_error = np.mean(fold_errors)

# Append the results to the list
    results.append([lambda_val] + fold_errors + [avg_error])

# Create a DataFrame from the results
columns = ["LAMBDA", "FOLD_1_ERROR", "FOLD_2_ERROR", "FOLD_3_ERROR",
    "FOLD_4_ERROR", "FOLD_5_ERROR", "AVG_ERROR"]

df = pd.DataFrame(results, columns=columns)

# Display the DataFrame as a table
print(df.to_string(index=False))
```

```
LAMBDA FOLD_1_ERROR FOLD_2_ERROR FOLD_3_ERROR FOLD_4_ERROR FOLD_5_ERROR
AVG_ERROR
   0.1
            0.458333
                          0.484167
                                       0.482500
                                                     0.472500
                                                                   0.480833
0.475667
   1.0
            0.422500
                          0.427500
                                       0.435000
                                                     0.428333
                                                                   0.412500
0.425167
            0.377500
                          0.407500
                                       0.392500
                                                     0.397500
                                                                   0.353333
   10.0
0.385667
  100.0
            0.342500
                          0.379167
                                       0.348333
                                                     0.361667
                                                                   0.327500
0.351833
 1000.0
            0.350833
                          0.374167
                                       0.352500
                                                     0.357500
                                                                   0.340000
0.355000
```

```
[8]: class KNNClassifier():
         def __init__(self, n_neighbors):
             self.n_neighbors = n_neighbors
             return
         def fit(self, X_trn, y_trn):
             # Just store X_trn, y_trn
             self.model = (X_trn, y_trn)
         def predict(self, X_val, y_val=None):
             assert hasattr(self, "model"), "No fitted model!"
             # do stuff here (use self.model for prediction)
             def KNN_predict_(X_trn, y_trn, x, K):
                 # Dictionary to store n: distance pairs
                 distances = {}
                 for n in range(len(X_trn)):
                     # Calculate distance between x and x[n]
                     distance = np.sqrt(np.sum((x - X_trn[n])**2))
```

```
distances[n] = distance
    # Sort distances in ascending order
    sorted_distances = sorted(distances.items(), key=lambda x: x[1])
    # Get the K nearest neighbors
    y_neighbor = []
    for n in range(K):
        n_nearest = sorted_distances[n][0]
        y_neighbor.append(y_trn[n_nearest])
    # get majority class
    c_pred = np.argmax(np.bincount(y_neighbor))
    return c_pred
X_trn, y_trn = self.model
y_pred = []
for x in X_val:
    y_pred.append(KNN_predict_(X_trn, y_trn, x, self.n_neighbors))
return y_pred
```

```
[9]: k_neighbors = [1, 3, 5, 7, 9, 11]
     # Initialize a list to store the results
     results = []
     # Perform cross-validation for different k values
     for k in k_neighbors:
         knn = KNNClassifier(k)
         knn.fit(X_trn, y_trn)
         models = cross_validation(knn, X_trn, y_trn, n_folds=5)
         # Collect the errors for each fold
         fold_errors = [model[1] for model in models]
         avg_error = np.mean(fold_errors)
         # Append the results to the list
         results.append([k] + fold_errors + [avg_error])
     # Create a DataFrame from the results
     columns = ["K", "FOLD_1_ERROR", "FOLD_2_ERROR", "FOLD_3_ERROR", "FOLD_4_ERROR", "

¬"FOLD_5_ERROR", "AVG_ERROR"]
     df = pd.DataFrame(results, columns=columns)
     # Display the DataFrame as a table
     print(df.to_string(index=False))
```

```
K FOLD_1_ERROR FOLD_2_ERROR FOLD_3_ERROR FOLD_4_ERROR FOLD_5_ERROR
AVG_ERROR
         0.470000
                                            0.457500
                                                             0.440833
 1
                          0.458333
                                                                              0.457500
0.456833
 3
         0.482500
                          0.458333
                                            0.465833
                                                             0.454167
                                                                              0.486667
0.469500
 5
         0.455000
                          0.441667
                                           0.451667
                                                             0.432500
                                                                              0.465000
0.449167
                          0.429167
                                            0.446667
                                                             0.426667
                                                                              0.448333
 7
         0.438333
0.437833
                          0.425833
                                            0.433333
                                                                              0.445000
 9
         0.433333
                                                             0.433333
0.434167
                          0.435000
                                                             0.427500
         0.430833
                                           0.440833
                                                                              0.430833
0.433000
Question 13
Model | hyper-parameters | cross-validation avg. error | public leaderboard accuracy \
Classification Tree | max depth = 9 \mid .474 \mid .57866 \setminus
Classification Tree | \max_{depth} = 7 \mid .4743 \mid x \setminus depth
Logistic Regression | lambda = 10 \mid .388 \mid .62133 \setminus
Logistic Regression | lambda = 100 \mid .352 \mid x \setminus
KNN Classification | K = 7 | 0.438 | .55733 \rangle
KNN Classification | K = 9 | 0.434 | x |
KNN Classification | K = 11 | 0.434 | x \rangle
```

THE FIRST MODEL WAS USED FOR INITIAL SUBMISSION, EXPERIMENTING WITH THE REST AS WELL AS I ACTUALLY THINK BEST PERFORMANCES WOULD BE: Tree with max depth of 9, logistic regression with lambda = 100, KNN with K = 9 or 11.

```
[117]: # Train best tree model on test data and save predictions

data = np.load('data.npz')
X_trn = data['X_trn']
y_trn = data['y_trn']
```

```
X_tst = data['X_tst']

X_trn = X_trn.reshape((len(X_trn), 3 * 29 * 29))

X_tst = X_tst.reshape((len(X_tst), 3 * 29 * 29))

clf = DecisionTreeClassifier(max_depth = 9)

clf.fit(X_trn, y_trn)

y_pred = clf.predict(X_tst)

write_csv(y_pred, 'tree_predictions_9.csv')
```

```
[118]: # Train best logistic regression model on test data and save predictions

data = np.load('data.npz')
X_trn = data['X_trn']
y_trn = data['Y_trn']
X_tst = data['X_tst']

X_trn = X_trn.reshape((len(X_trn), 3 * 29 * 29))
X_tst = X_tst.reshape((len(X_tst), 3 * 29 * 29))

lambda_val = 100
clf = LogisticRegression(penalty='12', C=1/lambda_val, max_iter=10000, tol=.001)
clf.fit(X_trn, y_trn)
y_pred = clf.predict(X_tst)
write_csv(y_pred, 'logistic_predictions_100.csv')
```

```
[121]: # Train best k nearest neighbor on test data and save predictions

data = np.load('data.npz')
X_trn = data['X_trn']
y_trn = data['y_trn']
X_tst = data['X_tst']

X_trn = X_trn.reshape((len(X_trn), 3 * 29 * 29))
X_tst = X_tst.reshape((len(X_tst), 3 * 29 * 29))

k = 9
clf = KNNClassifier(k)
clf.fit(X_trn, y_trn)
y_pred = clf.predict(X_tst)
write_csv(y_pred, 'knn_predictions_9.csv')
```

Private Scoring Predictions:

1) Tree Classification model: I believe the error range would be similar to the error present in the public set and slightly lower than cross validations errors, as depth of 9 should be balanced

- to avoid overfitting while trying to minimize error on unseen data. The public set seems to be performing better than cross validation predicted, indicating slightly better performance overall which I'd expect to continue in private set.
- 2) Logistic Regression model: The cross validation classification error is very similar to that of public test set, indicating a decent prediction job by cross validation. I'd expect a similar error range in the private test set, with room for slight variations.
- 3) KNN Classification model: I believe the error would slightly increase on the private set as the performance in public set seems to perform worse than cross validation predicted, indicating that the model seems to struggle more than expected and I would expect the trend to continue in private set.