```
1 # -*- coding: utf-8 -*-
 2 """Hyperparameter_Testing
 4 Automatically generated by Colaboratory.
 6 Original file is located at
       https://colab.research.google.com/drive/1Tkjs6AN6HaRH09FqtLdYzPa6BQHDaYwC
 9 <center><h1>Mini Project 1 - Logistic Regression</h1>
10 <h4>This is a testing file aiming to find the best hyperparameters for the
  model.</h4></center>
11
12 <h3>Team Members:</h3>
13 <center>
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15 Fei Peng, 260712440<br>
16 Yukai Zhang, 260710915
17 </center>
18 """
19
20 from google.colab import drive
21 drive.mount('/content/drive')
22
23 import numpy as np
24 import pandas as pd
25 import matplotlib.pyplot as plt
26 import seaborn as sns
27 import time
28
29 class LogisticRegression:
30
           This is the logistic regression class, containing fit, perdict and
31
  accu_eval functions,
32
           as well as many other useful functions.
33
34
35
       def __init__(self, data, folds, lr=0.01, max_iter=10000, beta=0.99, epsilon
  =5e-3):
36
           self.data = data
37
           self.folds = folds
38
           self.lr = lr
39
           self.max_iter = max_iter
40
           self.beta = beta
41
           self.epsilon = epsilon
42
43
       def shuffle_data(self):
44
45
               This function randomly shuffles the input dataset.
46
47
           # Load data from data file.
48
           self.data.insert(0, column='Bias', value=1)
49
50
           self.data = self.data.sample(frac=1)
51
52
       def set_learning_rate(self, lr):
53
           self.lr = lr
54
55
       def set_max_iter(self, max_iter):
56
           self.max_iter = max_iter
57
58
       def set_epsilon(self, epsilon):
59
           self.epsilon = epsilon
60
```

```
61
        def set beta(self, beta):
 62
            self.beta = beta
 63
 64
        def partition(self, fold):
 65
                This function divides the dataset into training and validation set
 66
 67
                fold - the current fold
 68
 69
 70
            data = self.data
 71
            # to exclude last term in previous partition for training data
 72
            train_add = 1 if fold < self.folds else 0
 73
            # to exclude last term in previous partition for testing data
 74
            test_add = 1 if fold > 0 else 0
 75
 76
            # number of data sets
 77
            n = len(self.data)
 78
            train_set_1 = data.iloc[0:int((fold)/self.folds*n), :]
 79
 80
            train_set_2 = data.iloc[int((fold+1)/self.folds*n)+train_add:n, :]
 81
            train_set = pd.concat([train_set_1, train_set_2])
 82
 83
            test_set = data.iloc[int((fold)/self.folds*n+test_add):int((fold+1)/
    self.folds*n), :]
 84
 85
            train_X = train_set.iloc[:, :-1].values
 86
            train_y = train_set.iloc[:, -1].values
 87
            train_y = np.reshape(train_y, (-1,1))
 88
 89
            test_X = test_set.iloc[:, :-1].values
 90
            test_y = test_set.iloc[:, -1].values
 91
            test_y = np.reshape(test_y, (-1,1))
 92
 93
            return train_X, train_y, test_X, test_y
 94
 95
        def normalization(self, X, v_X):
 96
 97
                This function performs the z-score normalization
 98
 99
                X - training data
                v_X - validation data
100
101
102
            mean = np.mean(X[:,1:], axis = 0)
103
            sigma = np.std(X[:,1:], axis = 0)
104
            mean = np.reshape(mean, (1,-1))
105
            sigma = np.reshape(sigma, (1,-1))
            X[:,1:] = (X[:,1:] - mean) / sigma
106
107
            v_X[:,1:] = (v_X[:,1:] - mean) / sigma
108
            return X, v_X
109
110
        def fit(self, X, y, v_X, v_y, normalize=False):
111
                This function takes the training data X and its corresponding
112
    labels vector y
113
                as well as other hyperparameters (such as learning rate) as input,
                and execute the model training through modifying the model
114
    parameters (i.e. W).
115
116
                X – training data
117
                y – class of training data
118
                v_X - validation data
119
                v_y - class of validation data
```

```
120
                epsilon - the threshold value for gradient descent
121
                normalize - whether to perform normalization
122
123
            gradient_values, t_acc_val, v_acc_val = [], [], []
124
125
            if normalize:
126
                X, v_X = self.normalization(X, <math>v_X)
127
128
            # Retrive the learning rate, maximum iteration, momentum (beta)
129
            lr, max_iter, beta, epsilon = self.lr, self.max_iter, self.beta, self.
    epsilon
130
131
            # initial weight vector
132
            w = np.zeros((len(X[0]), 1))
133
            # record the best weight vector
134
            best_w = w
135
            # iteration number, validation accuracy, last validation accuracy
136
            # the step to take in gradient descent, maximum validation accuracy
137
            iteration, v_acc, step, v_acc_max = 0, 0, 0, 0
138
139
            dw = np.inf
140
            # if the gradient delta w is smaller than threshold or achieved
    maximum iteration, stop
141
            while (np.linalg.norm(dw) > epsilon and iteration <= max_iter):</pre>
142
                dw = self.gradient(X, y, w)
143
                gradient_values.append(np.linalg.norm(dw))
144
                # if beta = 0, it will be the same as general gradient descent
                step = beta * step + (1 - beta) * dw # gradient descent with
145
    momentum
146
                w = w - lr * step
147
148
                # predict once every 10 interations
149
                if iteration % 10 == 0:
150
                     t_y_pred = self.predict(X, w)
151
                     t_acc = self.accu_eval(t_y_pred, y)
152
                     v_y_pred = self.predict(v_X, w)
153
                     v_acc = self.accu_eval(v_y_pred, v_y)
154
155
                # record the next best value
156
                if v_acc >= v_acc_max:
157
                     v_{acc_max} = v_{acc}
158
                     best_w = w
159
                     self.marker = iteration # move the iteration marker
160
161
                t_acc_val.append(t_acc)
162
                v_acc_val.append(v_acc)
163
164
                iteration = iteration + 1
165
            return gradient_values, t_acc_val, v_acc_val, best_w
166
167
        def predict(self, X, w):
168
                 This function takes a set of data as input and outputs predicted
169
    labels for the input points.
            1.1.1
170
171
            result = self.log_func(np.dot(X, w))
172
            # the prediction result converted to binary
173
            predict_bin = []
174
            for i in result:
175
                if i>=0.5:
176
                     predict_bin.append(1)
177
                else:
178
                     predict_bin.append(0)
```

```
179
            return predict bin
180
181
        def accu_eval(self, y_pred, y):
182
183
                This function evaluates the models' accuracy.
184
185
            count = 0
186
            for i in range(len(y_pred)):
                if y_pred[i] == y[i]:
187
188
                    count = count + 1
189
            # return the accuracy ratio: #corret prediction / #data points
190
            return count / len(y)
191
192
        def log_func(self, alpha):
193
            return 1 / (1 + np.exp(-alpha))
194
195
        def gradient(self, X, y, w):
196
            N = len(X[0])
197
            y_hat = self.log_func(np.dot(X, w))
198
            delta = np.dot(X.T, y_hat - y) / N
199
            return delta
200
201 class KFoldValidation:
202
        def __init__(self, folds, path, lr, max_iter, epsilon, beta):
203
            self.folds = folds
204
            self.data = pd.read_csv(path)
            self.lr = lr
205
            self.max_iter = max_iter
206
            self.epsilon = epsilon
207
208
            self.beta = beta
209
            self.log_reg = LogisticRegression(data=self.data, folds=folds, lr=lr,
    max_iter=max_iter, beta=beta, epsilon=epsilon)
210
            self.log_reg.shuffle_data()
211
212
        def set_learning_rate(self, lr):
213
            self.log_reg.set_learning_rate(lr)
214
215
        def set_max_iter(self, max_iter):
216
            self.log_reg.set_max_iter(max_iter)
217
218
        def set_epsilon(self, epsilon):
219
            self.log_reg.set_epsilon(epsilon)
220
221
        def set_beta(self, beta):
222
            self.log_reg.set_beta(beta)
223
224
        def k_fold_validation(self):
225
226
                This function performs the k-fold validation
227
228
                normalize - whether to perform normalization
229
                inc_od - whether to increase the feature order
230
                order - the order of the added feature
            111
231
232
            folds = self.folds
233
            data = self.data
234
            log_reg = self.log_reg
235
            accuracies = []
236
            tic = time.time()
237
238
            for fold in range(folds):
239
                t_X, t_y, v_X, v_y = log_reg.partition(fold)
240
                # t_X --> test value X, v_X --> validation value X
```

```
241
                gradient_val, t_acc_val, v_acc_val, best_w = log_reg.fit(t_X, t_y
    , v_X, v_y)
242
                accuracies.append(np.mean(v_acc_val))
243
244
245
               # # Uncommant this block to display the accuracy diagram
246
                # plt.figure()
247
                # plt.plot(t_acc_val, label = 'Training accuracy')
248
                # plt.plot(v_acc_val, label='Validation accuracy')
249
                # plt.axvline(log_reg.marker, color='r', label='Best Weights')
250
                # plt.xlabel('Iteration Number')
                # plt.ylabel('Accuracy')
251
252
                # plt.legend()
253
                # plt.show()
                # print("Learning Rate: " + str(log_reg.lr))
254
255
                # print("Average Accuracy: "+str(np.mean(accuracies)))
256
257
               # # Uncommant this block to display the gradiant diagram
258
               # plt.figure()
259
               # plt.plot(gradient_val)
260
               # plt.xlabel('Iteration Number')
261
               # plt.ylabel('Gradiant')
262
                # plt.show()
                # print("----")
263
264
265
           mean_acc = np.max(accuracies)
            toc = time.time()
266
267
            return mean_acc, toc-tic
268
        def rise_order(self, data, order=3):
269
270
           ret_val = data
271
            for i in range(2, order + 1):
                data_powered = data.pow(i)
272
                ret_val = ret_val.iloc[:, :-1]
273
274
                ret_val = pd.concat([ret_val, data_powered],axis=1)
275
            return ret_val
276
277 def plot_fig(x, y, xlabel, ylabel, log_x=False, plt_name="Untitled_Figure.png"
    , download=False):
278
        plt.plot(x, y)
279
        if log_x:
280
            plt.xscale("log")
281
        plt.xlabel(xlabel)
282
        plt.ylabel(ylabel)
283
        if download:
284
            plt.savefig(plt_name, dpi = 1200)
285
            files.download(plt_name)
286
        plt.show()
287
288 """### Default Values for Hepatitis Analysis"""
289
290 path = "/content/drive/My Drive/ECSE_551_F_2020/Mini_Project_01/hepatitis.csv"
291 dataset_name = "Hepatitis"
292 defult_lr = 0.01
293 default_max_iter = 10000
294 default_epsilon = 5e-3
295 defulat_beta = 0.99
296
297 """### Learning rate testing"""
298
299 lr_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter=
    default_max_iter, epsilon=default_epsilon, beta=defulat_beta)
300
```

```
301 Learning rates = [0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1]
303 \text{ mean\_acc} = []
304 proc_time = []
306 for lr in Learning_rates:
        lr_testing.set_learning_rate(lr)
308
        mean_acc_temp, time_temp = lr_testing.k_fold_validation()
309
        mean_acc.append(mean_acc_temp)
310
        proc_time.append(time_temp)
311
312 plot_fig(Learning_rates, mean_acc, "log(Learning Rate)", "Mean Accuracy",
    log_x=True, plt_name="Validation_Accuracy_vs_Learning_Rate_for_{{}}.png".format(
    dataset_name))
313 plot_fig(Learning_rates, proc_time, "log(Learning Rate)", "Processing Time",
    log_x=True, plt_name="Validation_Accuracy_vs_Learning_Rate_for_{{}.png".format(
    dataset_name))
314
315 """### Maximum Iteration Test"""
316
317 max_iter_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter
    =default_max_iter, epsilon=1e-3, beta=defulat_beta)
318
319 max_iters = [500, 1000, 5000, 10000, 25000]
320
321 \text{ mean\_acc} = []
322 proc_time = []
323
324 for max_iter in max_iters:
325
        max_iter_testing.set_max_iter(max_iter)
326
        mean_acc_temp, time_temp = max_iter_testing.k_fold_validation()
327
        mean_acc.append(mean_acc_temp)
328
        proc_time.append(time_temp)
329
330 plot_fig(max_iters, mean_acc, "log(Maximum Iterations)", "Mean Accuracy",
    log_x=True, plt_name="Validation_Accuracy_vs_Maximum_Iterations_for_{{}}.png".
    format(dataset_name))
331 plot_fig(max_iters, proc_time, "log(Maximum Iterations)", "Processing Time",
    log_x=True, plt_name="Processing_Time_vs_Maximum_Iterations_for_{}.png".format
    (dataset_name))
332
333 """### Epsilon Test"""
334
335 epsilon_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter=
    default_max_iter, epsilon=default_epsilon, beta=defulat_beta)
336
337 epsilons = [1e-3, 5e-3, 1e-2, 5e-2, 1e-1, 0.5]
338
339 \text{ mean\_acc} = []
340 proc_time = []
341
342 for epsilon in epsilons:
343
        epsilon_testing.set_epsilon(epsilon)
344
        mean_acc_temp, time_temp = epsilon_testing.k_fold_validation()
345
        mean_acc.append(mean_acc_temp)
346
        proc_time.append(time_temp)
347
348 plot_fig(epsilons, mean_acc, "log(Epsilons)", "Mean Accuracy", log_x=True,
    plt_name="Validation_Accuracy_vs_Epsilons_for_{{}}.png".format(dataset_name))
349 plot_fig(epsilons, proc_time, "log(Epsilons)", "Processing Time", log_x=True,
    plt_name="Processing_Time_vs_Epsilons_for_{}.png".format(dataset_name))
351 """### Momentum Gradient Descent Constant - Beta Testing"""
```

```
352
353 beta_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter=
    default_max_iter, epsilon=default_epsilon, beta=defulat_beta)
354
355 \text{ betas} = [0, 0.5, 0.9, 0.99, 0.999]
356
357 \text{ mean\_acc} = []
358 proc_time = []
359
360 for beta in betas:
        beta_testing.set_beta(beta)
361
362
        mean_acc_temp, time_temp = beta_testing.k_fold_validation()
363
        mean_acc.append(mean_acc_temp)
364
        proc_time.append(time_temp)
365
366 plot_fig(betas, mean_acc, "betas", "Mean Accuracy", log_x=False, plt_name="
    Validation_Accuracy_vs_betas_for_{}.png".format(dataset_name))
367 plot_fig(betas, proc_time, "betas", "Processing Time", log_x=False, plt_name="
    Processing_Time_vs_betas_for_{}.png".format(dataset_name))
368
369 """<hr>
370
371 ### Default Values for Bankruptcy Analysis
372 """
373
374 path = "/content/drive/My Drive/ECSE_551_F_2020/Mini_Project_01/bankrupcy.csv"
375 dataset_name = "Bankruptcy"
376 defult_lr = 0.1
377 default_max_iter = 25000
378 default_epsilon = 1e-3
379 defulat_beta = 0.99
380
381 """### Learning rate testing"""
382
383 lr_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter=
    default_max_iter, epsilon=default_epsilon, beta=defulat_beta)
384
385 Learning_rates = [0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1]
386
387 \text{ mean\_acc} = []
388 proc_time = []
389
390 for lr in Learning_rates:
        lr_testing.set_learning_rate(lr)
391
392
        mean_acc_temp, time_temp = lr_testing.k_fold_validation()
393
        mean_acc.append(mean_acc_temp)
394
        proc_time.append(time_temp)
395
396 plot_fig(Learning_rates, mean_acc, "log(Learning Rate)", "Mean Accuracy",
    log_x=True, plt_name="Validation_Accuracy_vs_Learning_Rate_for_{{}}.png".format(
    dataset_name))
397 plot_fig(Learning_rates, proc_time, "log(Learning Rate)", "Processing Time",
    log_x=True, plt_name="Validation_Accuracy_vs_Learning_Rate_for_{{}}.png".format(
    dataset_name))
398
399 """### Maximum Iteration Test"""
400
401 max_iter_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter
    =default_max_iter, epsilon=1e-3, beta=defulat_beta)
402
403 max_iters = [500, 1000, 5000, 10000, 25000]
404
405 \text{ mean\_acc} = []
```

```
406 proc time = []
407
408 for max_iter in max_iters:
        max_iter_testing.set_max_iter(max_iter)
409
410
        mean_acc_temp, time_temp = max_iter_testing.k_fold_validation()
411
        mean_acc.append(mean_acc_temp)
412
        proc_time.append(time_temp)
413
414 plot_fig(max_iters, mean_acc, "log(Maximum Iterations)", "Mean Accuracy",
    log_x=True, plt_name="Validation_Accuracy_vs_Maximum_Iterations_for_{{}}.png".
    format(dataset_name))
415 plot_fig(max_iters, proc_time, "log(Maximum Iterations)", "Processing Time",
    log_x=True, plt_name="Processing_Time_vs_Maximum_Iterations_for_{}.png".format
    (dataset_name))
416
417 """### Epsilon Test"""
418
419 epsilon_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter=
    default_max_iter, epsilon=default_epsilon, beta=defulat_beta)
420
421 epsilons = [1e-3, 5e-3, 1e-2, 5e-2, 1e-1, 0.5]
422
423 \text{ mean\_acc} = []
424 proc_time = []
425
426 for epsilon in epsilons:
427
        epsilon_testing.set_epsilon(epsilon)
428
        mean_acc_temp, time_temp = epsilon_testing.k_fold_validation()
429
        mean_acc.append(mean_acc_temp)
430
        proc_time.append(time_temp)
431
432 plot_fig(epsilons, mean_acc, "log(Epsilons)", "Mean Accuracy", log_x=True,
    plt_name="Validation_Accuracy_vs_Epsilons_for_{{}}.png".format(dataset_name))
433 plot_fig(epsilons, proc_time, "log(Epsilons)", "Processing Time", log_x=True,
    plt_name="Processing_Time_vs_Epsilons_for_{{}}.png".format(dataset_name))
434
435 """### Momentum Gradient Descent Constant - Beta Testing"""
436
437 beta_testing = KFoldValidation(folds=10, path=path, lr=defult_lr, max_iter=
    default_max_iter, epsilon=default_epsilon, beta=defulat_beta)
438
439 betas = [0, 0.5, 0.9, 0.99, 0.999]
440
441 \text{ mean\_acc} = []
442 proc_time = []
443
444 for beta in betas:
445
        beta_testing.set_beta(beta)
446
        mean_acc_temp, time_temp = beta_testing.k_fold_validation()
447
        mean_acc.append(mean_acc_temp)
448
        proc_time.append(time_temp)
449
450 plot_fig(betas, mean_acc, "betas", "Mean Accuracy", log_x=False, plt_name="
    Validation_Accuracy_vs_betas_for_{}.png".format(dataset_name))
451 plot_fig(betas, proc_time, "betas", "Processing Time", log_x=False, plt_name="
    Processing_Time_vs_betas_for_{}.png".format(dataset_name))
```