HW3_Problem4-3

May 5, 2020

[0]:
```python
import json
import pandas as pd
import numpy as np
import time
import math
import string, re
import matplotlib.pyplot as plt
import sys
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from scipy.sparse import csr_matrix
from sklearn.svm import LinearSVC
from sklearn.linear_model import SGDClassifier
```

[2]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[0]:
```python
f = open('/content/drive/My Drive/HW3/labeled_small.json','r')
data = json.load(f)
```

[0]:
```python
beer = pd.DataFrame.from_dict(data)
```

[5]:
```python
type(beer)
```

[5]:
```
pandas.core.frame.DataFrame
```

[6]:
```python
beer
```

[6]:
```
      style  palate  …                              beer_name  beer_id
0        17     3.0  …                   John Harvards Simcoe IPA    45842
1        17     4.0  …                   John Harvards Simcoe IPA    45842
2        33     3.0  …              John Harvards Cristal Pilsner    95213
3        33     2.0  …          John Harvards Fancy Lawnmower Beer    65957
4        58     4.0  …   John Harvards Vanilla Black Velvet Stout    41336
```

```
…       …      …   …                                …       …
99995      69      2.0   …                    Mission Street Pale Ale    68983
99996      69      2.0   …                    Mission Street Pale Ale    68983
99997      69      3.0   …                    Mission Street Pale Ale    68983
99998      69      3.0   …                    Mission Street Pale Ale    68983
99999      69      2.0   …                    Mission Street Pale Ale    68983

[100000 rows x 11 columns]
```

[0]:
```
with open('/content/drive/My Drive/HW3/vocab_30.json', 'r') as f:
    vocab = json.load(f)
```

[8]:
```
len(vocab)
```

[8]:
```
41346
```

[0]:
```
# Part 1: Data Inspection
```

[10]:
```
beer.describe()
```

[10]:
```
               style         palate  ...          aroma        beer_id
count  100000.000000  100000.000000  ...  100000.000000  100000.00000
mean       36.464290       3.277750  ...       6.447190   55650.48179
std        22.538597       0.773156  ...       1.439254   33327.57236
min         0.000000       1.000000  ...       1.000000       1.00000
25%        16.000000       3.000000  ...       6.000000   26244.00000
50%        37.000000       3.000000  ...       7.000000   56100.00000
75%        58.000000       4.000000  ...       7.000000   86041.00000
max        73.000000       5.000000  ...      10.000000  110283.00000

[8 rows x 9 columns]
```

[0]:
```
# Mean: 13.396
# Median: 14.000
# Standard Deviation: 2.949
```

[0]:
```
# Now, do people have a similar taste? In order to answer this question,
# We can assume that if people do, they will leave similar ratings for
# the same kind of beers. Then, the standard deviation of ratings for
# a selected beer should be quite small compared to the overall ratings
# for all kinds of beers
```

[0]:
```
# Let's try three examples
```

[0]:
```
beer1 = beer[beer["beer_name"] == "Mission Street Pale Ale"]
beer2 = beer[beer["beer_name"] == "Burggraf Maibock"]
beer3 = beer[beer["beer_name"] == "Barley Island Barrel-Aged Count Hopula"]
```

[15]:
```python
beer1["overall"].std()
```

[15]: 2.1420781684525454

[16]:
```python
beer2["overall"].std()
```

[16]: 1.789114825239473

[17]:
```python
beer3["overall"].std()
```

[17]: 0.8997354108424372

[0]:
```python
# The standard deviation of the overall rating of all beers was 2.949.
# We can see that the overall ratings of the above three beers have standard
# deviations lower than this threshold, but some are much lower than others.
# We can argue that people could have similar tastes for only some types of␣
↪beer
```

[0]:
```python
# Part 2
```

[0]:
```python
# (a) Generating Features
```

[0]:
```python
# Splitting data into training, validation, and testing
```

[0]:
```python
# But First, create a function that gives binary labels
```

[0]:
```python
label = np.array(beer["overall"] >= 14).astype(int)
```

[0]:
```python
train_data, test_data, train_label, test_label = train_test_split(beer, label,␣
↪test_size = 0.3, random_state =2)
val_data, test_data, val_label, test_label = train_test_split(test_data,␣
↪test_label, test_size = 0.5, random_state =2)
```

[0]:
```python
# function that normalize the text
```

[0]:
```python
vocab_index = {}
vocab_lst = list(vocab.keys())
for i, vocab in enumerate(vocab_lst):
    vocab_index[vocab] = i
```

[0]:
```python
def normalize_txt(data):
    r = re.compile("[" + re.escape(string.punctuation) + "]")
    normal = []
    for i, row in data.iterrows():
        words = r.sub('', row['review'])
        split = words.split(' ')
        lst = []
```

```
        for s in split:
            if s in vocab_index:
                lst.append(s)
        normal.append(lst)
    return normal
```

[0]:
```
# function that creates sparse matrix
```

[0]:
```
def create_sparse(document, vocab_index_):
    indptr = [0]
    indices = []
    data = []
    for doc in document:
        terms = set(doc)
        for term in terms:
            index = vocab_index_[term]
            indices.append(index)
            data.append(1)
        indptr.append(len(indices))
    sparse = csr_matrix((data, indices, indptr), dtype = bool).astype(int)
    return sparse
```

[30]:
```
time_start = time.time()
norm_doc = normalize_txt(train_data)
print(time.time() - time_start)
```

```
9.474142074584961
```

[31]:
```
time_start = time.time()
sparse = create_sparse(norm_doc, vocab_index)
print(time.time() - time_start)
```

```
1.0818650722503662
```

[0]:
```
# It takes about 1.117 seconds to go over the entire training data set, which␣
↪is
# 70,000 documents long
```

[0]:
```
# part (b): Logistic Regression
```

[0]:
```
sparse_test = create_sparse(normalize_txt(test_data), vocab_index)
```

[0]:
```
sparse_val = create_sparse(normalize_txt(val_data), vocab_index)
```

[36]:
```
start = time.time()
lg = LogisticRegression(penalty = "l2", C = 1/10, solver = 'newton-cg')
lg.fit(sparse, train_label)
```

```python
print(time.time() - start)
```

```
3.860454559326172
```

[37]:
```python
score = accuracy_score(val_label, lg.predict(sparse_val))
score
```

[37]: 0.7605333333333333

[0]:
```python
# selecting the optimal lambda_ by tring different values on the validation set
```

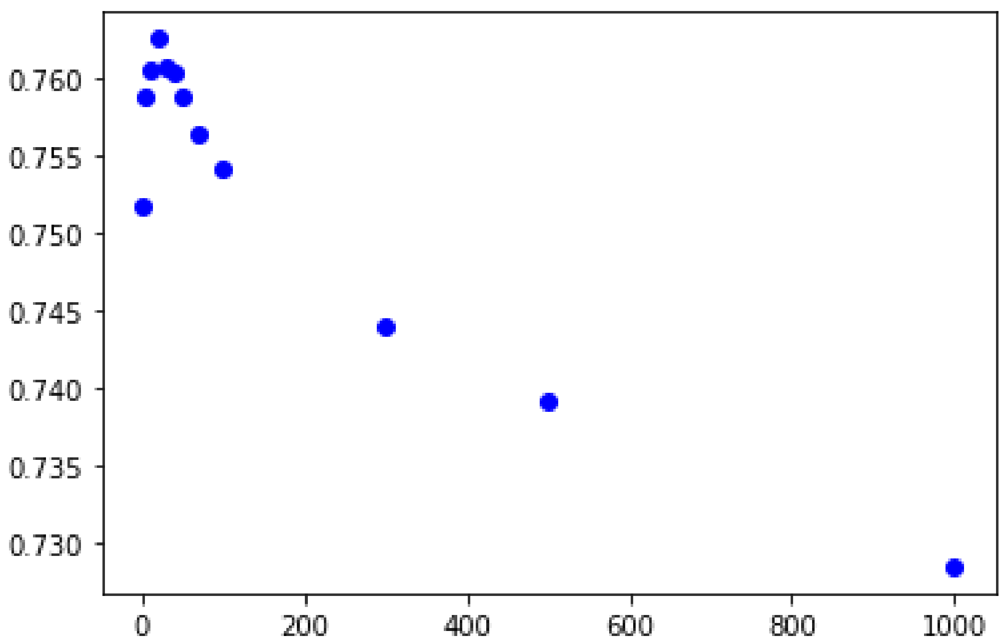
[39]:
```python
lambda_set1 = [1, 5, 10, 20, 30, 40, 50, 70, 100, 300, 500, 1000]
accuracy1 = []
for lam in lambda_set1:
    print("lambda: {} | Penalty C: {}".format(lam, 1/lam))
    lg = LogisticRegression(penalty = "l2", C = 1/lam, solver = 'newton-cg')
    start = time.time()
    lg.fit(sparse, train_label)
    score = accuracy_score(val_label, lg.predict(sparse_val))
    accuracy1.append(score)
    print("operation time: %s" %(time.time() - start))
    print("accuracy: %s" %(score))
```

```
lambda: 1 | Penalty C: 1.0
operation time: 7.5562450885772705
accuracy: 0.7518
lambda: 5 | Penalty C: 0.2
operation time: 4.4831624031066895
accuracy: 0.7587333333333334
lambda: 10 | Penalty C: 0.1
operation time: 3.943840503692627
accuracy: 0.7605333333333333
lambda: 20 | Penalty C: 0.05
operation time: 3.605893135070801
accuracy: 0.7625333333333333
lambda: 30 | Penalty C: 0.03333333333333333
operation time: 3.516540288925171
accuracy: 0.7606666666666667
lambda: 40 | Penalty C: 0.025
operation time: 3.1036739349365234
accuracy: 0.7603333333333333
lambda: 50 | Penalty C: 0.02
operation time: 2.9787139892578125
accuracy: 0.7588
lambda: 70 | Penalty C: 0.014285714285714285
operation time: 2.881065607070923
accuracy: 0.7563333333333333
lambda: 100 | Penalty C: 0.01
```

```
operation time: 2.623732566833496
accuracy: 0.7542
lambda: 300 | Penalty C: 0.0033333333333333335
operation time: 2.144583225250244
accuracy: 0.744
lambda: 500 | Penalty C: 0.002
operation time: 2.358748435974121
accuracy: 0.7391333333333333
lambda: 1000 | Penalty C: 0.001
operation time: 1.7104160785675049
accuracy: 0.7284666666666667
```

[40]:
```
plt.plot(lambda_set1, accuracy1, 'bo')
```

[40]:
```
[<matplotlib.lines.Line2D at 0x7f0ad94d3f28>]
```



[0]:
```
# The accuracy rate was the highest when lambda = 20.
# With lambda = 20, it took about 3.5 seconds to run the algorithm in order to
# attain accuracy rate of 0.7625
```

[0]:
```
# Moving on to the LinearSVC class
```

[43]:
```
lambda_set2 = [1, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100]
accuracy2 = []
for lam in lambda_set2:
    print("lambda: {} | penalty C: {} ".format(lam, 1 / lam))
```

```
    lsvc = LinearSVC(penalty = 'l2', loss = 'hinge', C = 1/lam)
    start = time.time()
    lsvc.fit(sparse, train_label)
    score = accuracy_score(val_label, lsvc.predict(sparse_val))
    accuracy2.append(score)
    print("operation time: %s " % (time.time() - start))
    print("accuracy: %s"%(score))
```

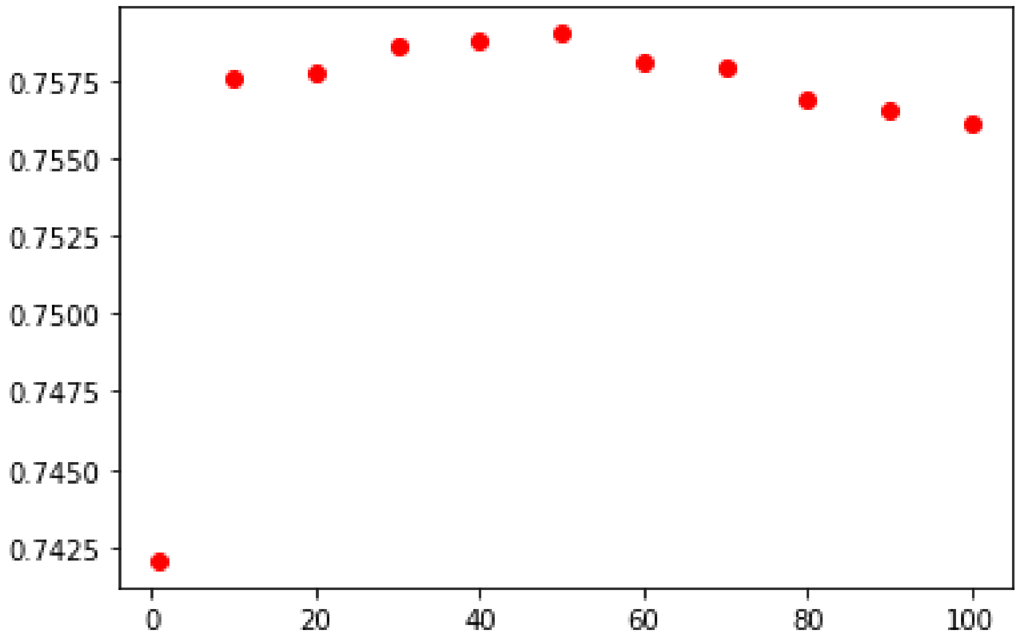
```
lambda: 1 | penalty C: 1.0
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/svm/_base.py:947:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  "the number of iterations.", ConvergenceWarning)
```

```
operation time: 5.048051595687866
accuracy: 0.7420666666666667
lambda: 10 | penalty C: 0.1
operation time: 1.37498140335083
accuracy: 0.7575333333333333
lambda: 20 | penalty C: 0.05
operation time: 0.6204280853271484
accuracy: 0.7577333333333334
lambda: 30 | penalty C: 0.03333333333333333
operation time: 0.5432126522064209
accuracy: 0.7586
lambda: 40 | penalty C: 0.025
operation time: 0.4545018672943115
accuracy: 0.7587333333333334
lambda: 50 | penalty C: 0.02
operation time: 0.33524274826049805
accuracy: 0.759
lambda: 60 | penalty C: 0.016666666666666666
operation time: 0.3623623847961426
accuracy: 0.7580666666666667
lambda: 70 | penalty C: 0.014285714285714285
operation time: 0.28708910942077637
accuracy: 0.7578666666666667
lambda: 80 | penalty C: 0.0125
operation time: 0.25193142890930176
accuracy: 0.7568666666666667
lambda: 90 | penalty C: 0.011111111111111112
operation time: 0.23581838607788086
accuracy: 0.7565333333333333
lambda: 100 | penalty C: 0.01
operation time: 0.2680075168609619
accuracy: 0.7561333333333333
```

```
[44]: plt.plot(lambda_set2, accuracy2, 'ro')
```

```
[44]: [<matplotlib.lines.Line2D at 0x7f0ad9452550>]
```




```
[0]: # Using hinge loss instead of logistic loss, lambda = 50 seems to be close to
# the optimal lambda value. It provided an accuracy rate of 0.759 with
# operation time of about 0.26 seconds. We can conclude that under the given
# circumstances, the logistic Regression model showed slightly higher (very␣
↪small
# difference) accuracy, but the lsvc model computed the algorithms faster.
```

```
[0]: # part (c): Stochastic gradient descent
```

```
[0]: def yield_batches(x, y, epochs):
    np.random.shuffle(x)
    for e in range(epochs):
        interval = x.shape[0] // epochs
        yield x[int(e*interval): int((e + 1)*interval)], np.
↪array(y[int(e*interval): int((e + 1)*interval)])[:, np.newaxis]
```

```
[0]: def compute_h(x, coef):
    return 1 /(1 + np.exp(-np.dot(x, coef)))
```

```
[0]: def compute_gradient(x, y, coef):
    h = compute_h(x, coef)
```

```
    return (h - y) * x
```

[0]:
```
def compute_error_rate(x, y, coef):
    pred = np.matmul(x, coef)
    y = np.array(y)[:, np.newaxis]
    return np.mean(1/2 * (np.power((pred - y), 2)))
```

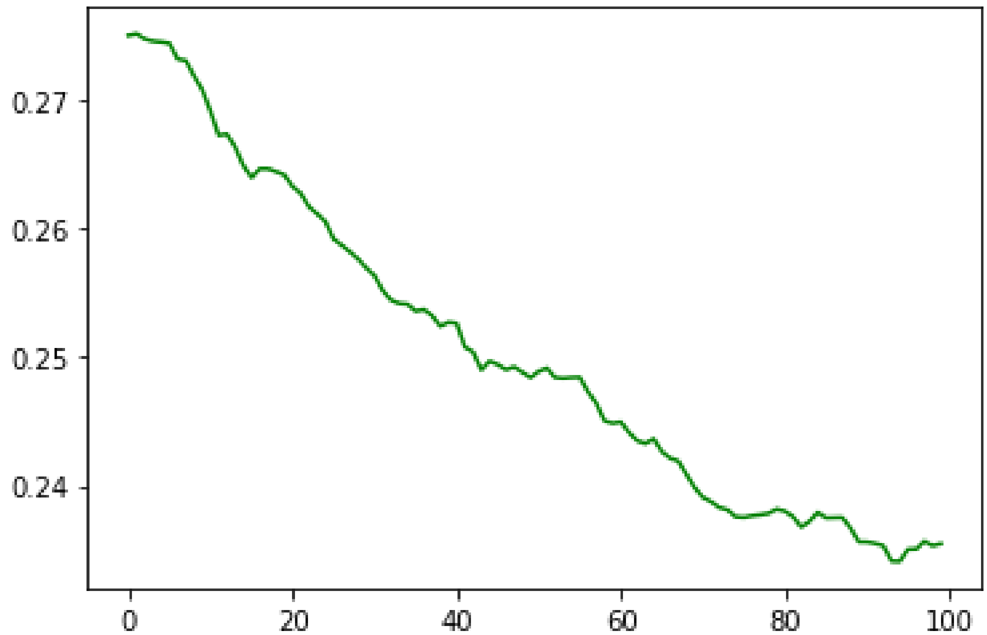
[0]:
```
def perform_sgd(x, y, learning_rate, lambda_, epochs, decrease = False, plot =␣
↪True):
    if type(x) != np.ndarray:
        x = x.toarray()
    x = np.concatenate((np.ones(len(x))[:, np.newaxis], x), axis = 1)
    coef = np.zeros((x.shape[1], 1))
    batches = yield_batches(x, y, epochs)
    er = []
    for i in range(epochs):
        x_b , y_b = next(batches)
        gradient = np.zeros((len(coef), 1))
        error = compute_error_rate(x, y, coef)
        er.append(error)
        for j in range(len(x_b)):
            gradient += (compute_gradient(x_b[j], y_b[j], coef)[:, np.newaxis])
        if decrease:
            coef = coef - learning_rate/(i+1) * (gradient / len(x_b) + lambda_␣
↪* coef)
        else:
            coef = coef - learning_rate * (gradient / len(x_b) + lambda_ * coef)

    if plot:
        plt.plot(er, "g")

    return coef
```

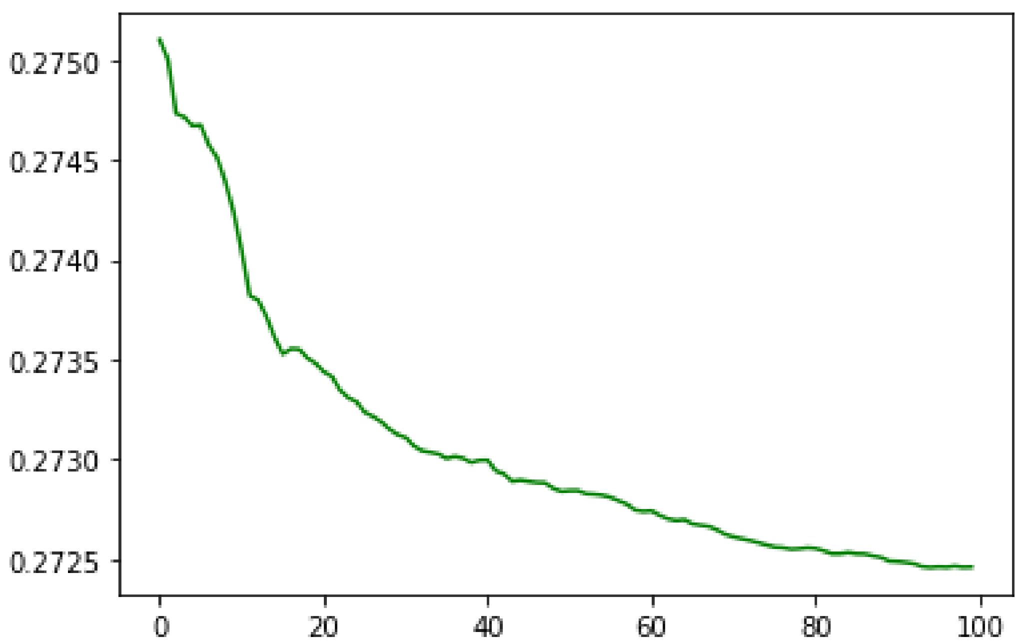
[0]:
```
# Performing Stochastic Gradient Descent without decreasing learning rate
```

[53]:
```
coef = perform_sgd(sparse[:10000], train_label[:10000], 0.01, 0.1, 100,␣
↪decrease = False, plot = True)
```




```
[0]: # Performing Stochastic Gradient Descent with decreasing learning rate
```

```
[55]: coef = perform_sgd(sparse[:10000], train_label[:10000], 0.01, 0.1, 100,␣
       ↪decrease = True, plot = True)
```



[0]:
```
# We can see that the error rate falls and converges as iterations proceed.
# When we use decreasing learning rate, we can erase most of the noise that
# causes oscillation and reach convergence much faster
```

[0]:
```
# compute accuracy of the model by adopting misclassificaiton threshold as 0.5
```

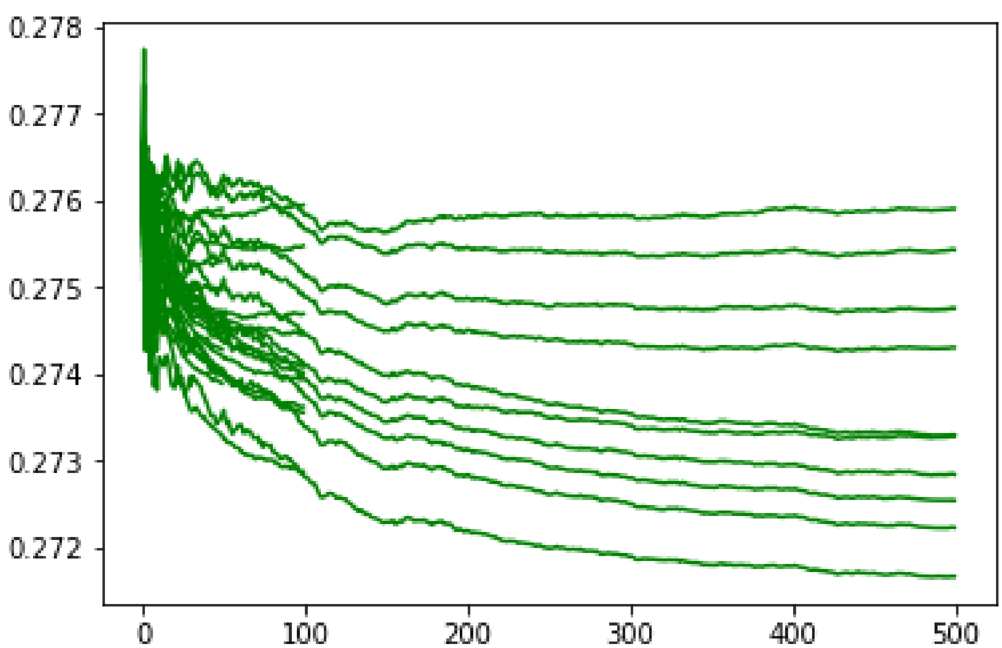
[0]:
```
def compute_mis(coef, x_n, y_n):
    x = np.concatenate((np.ones(len(x_n))[:,np.newaxis], x_n), axis = 1)
    eta = np.matmul(x, coef)
    c = 0
    for i in range(len(y_n)):
        if eta[i] > 0:
            if y_n[i] == 0:
                c +=1
        elif eta[i] < 0 :
            if y_n[i] == 1:
                c += 1
    return c / len(y_n)
```

[0]:
```
# now, let's test with different lambdas and number of iterations
```

[60]:
```
s = sparse_val.toarray()
lambda_s = [0.0001, 0.001, 0.01, 0.1, 1 , 10, 20, 30, 50, 100]
epochs = [10, 50, 100, 500]
for lam in lambda_s:
    for epoch in epochs:
        coef = perform_sgd(sparse[: 5000], train_label[: 5000], 0.01, lam,␣
↪epoch, decrease = True, plot = True)
        error = compute_mis(coef, s, val_label)
        print("lambda: {} | epoch: {} | error rate: {}".format(lam, epoch,␣
↪error))
```

```
lambda: 0.0001 | epoch: 10 | error rate: 0.4554
lambda: 0.0001 | epoch: 50 | error rate: 0.4554
lambda: 0.0001 | epoch: 100 | error rate: 0.4554666666666667
lambda: 0.0001 | epoch: 500 | error rate: 0.45586666666666664
lambda: 0.001 | epoch: 10 | error rate: 0.4554
lambda: 0.001 | epoch: 50 | error rate: 0.4554
lambda: 0.001 | epoch: 100 | error rate: 0.4554
lambda: 0.001 | epoch: 500 | error rate: 0.4554
lambda: 0.01 | epoch: 10 | error rate: 0.4554
lambda: 0.01 | epoch: 50 | error rate: 0.4554
lambda: 0.01 | epoch: 100 | error rate: 0.4554
lambda: 0.01 | epoch: 500 | error rate: 0.4554
lambda: 0.1 | epoch: 10 | error rate: 0.4554
lambda: 0.1 | epoch: 50 | error rate: 0.4554
lambda: 0.1 | epoch: 100 | error rate: 0.4554
```

```
lambda: 0.1 | epoch: 500 | error rate: 0.4552
lambda: 1 | epoch: 10 | error rate: 0.4554
lambda: 1 | epoch: 50 | error rate: 0.4554
lambda: 1 | epoch: 100 | error rate: 0.4554
lambda: 1 | epoch: 500 | error rate: 0.4554
lambda: 10 | epoch: 10 | error rate: 0.4554
lambda: 10 | epoch: 50 | error rate: 0.4554
lambda: 10 | epoch: 100 | error rate: 0.4554
lambda: 10 | epoch: 500 | error rate: 0.4554
lambda: 20 | epoch: 10 | error rate: 0.4554
lambda: 20 | epoch: 50 | error rate: 0.4554
lambda: 20 | epoch: 100 | error rate: 0.4554
lambda: 20 | epoch: 500 | error rate: 0.4554
lambda: 30 | epoch: 10 | error rate: 0.4554
lambda: 30 | epoch: 50 | error rate: 0.4554
lambda: 30 | epoch: 100 | error rate: 0.4554
lambda: 30 | epoch: 500 | error rate: 0.4554
lambda: 50 | epoch: 10 | error rate: 0.4554
lambda: 50 | epoch: 50 | error rate: 0.4554
lambda: 50 | epoch: 100 | error rate: 0.4554
lambda: 50 | epoch: 500 | error rate: 0.4554
lambda: 100 | epoch: 10 | error rate: 0.4554
lambda: 100 | epoch: 50 | error rate: 0.4554
lambda: 100 | epoch: 100 | error rate: 0.4554
lambda: 100 | epoch: 500 | error rate: 0.4554
```

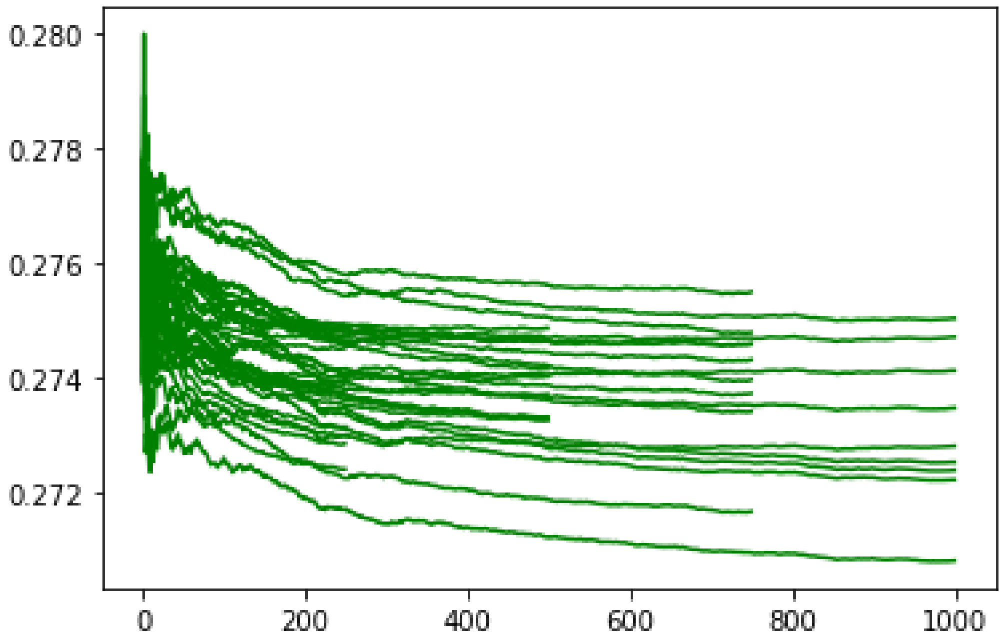


[0]:
```
# We can observe that the accuracy rate decreases as the size of batches
# increase. The optimal value of lambda seems to be between 10 and 30.
# We can narrow down the scope of optimal lambdas and number of iterations.
```

[65]:
```
lambda_s = [0.01, 0.05, 0.1, 1, 10, 15, 20, 25, 30]
epochs = [250, 500, 750, 1000]
error_rate = []
lambda_ = []
epoch_ = []
for epoch in epochs:
    for lam in lambda_s:
        coef = perform_sgd(sparse[:5000], train_label[:5000], 0.01, lam, epoch,␣
 ↪decrease = True)
        error = compute_mis(coef, s, val_label)
        print("lambda: {} | epoch: {} | error: {}".format(lam, epoch, error))
        error_rate.append(error)
```

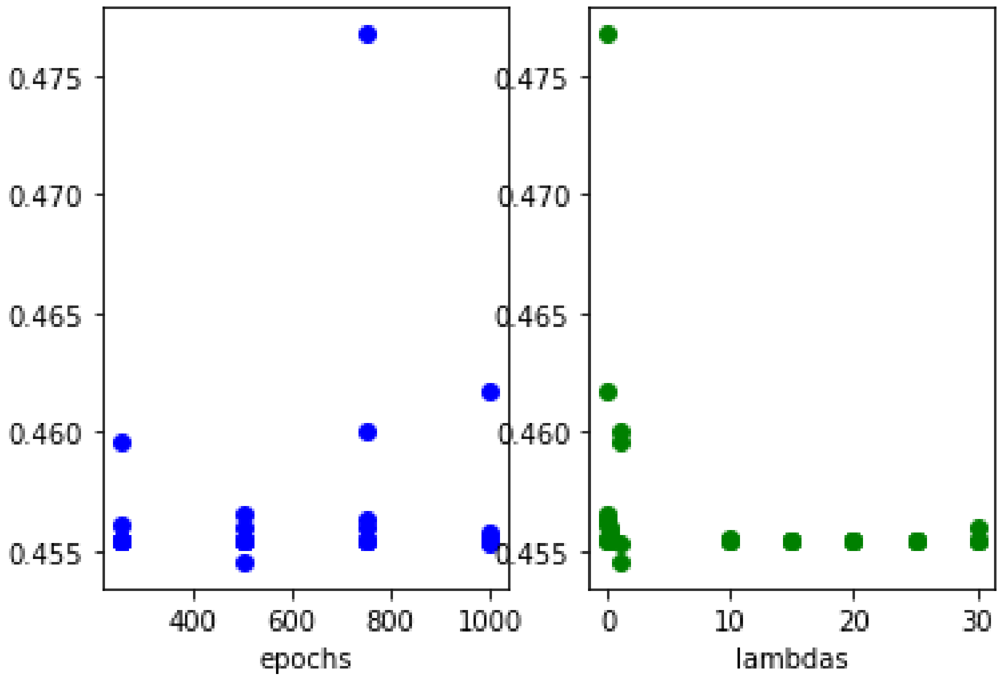
```
lambda: 0.01 | epoch: 250 | error: 0.4554
lambda: 0.05 | epoch: 250 | error: 0.4554
lambda: 0.1 | epoch: 250 | error: 0.4554
lambda: 1 | epoch: 250 | error: 0.4553333333333333
lambda: 10 | epoch: 250 | error: 0.4554
lambda: 15 | epoch: 250 | error: 0.4554
lambda: 20 | epoch: 250 | error: 0.4554
lambda: 25 | epoch: 250 | error: 0.4554
lambda: 30 | epoch: 250 | error: 0.4554
lambda: 0.01 | epoch: 500 | error: 0.45653333333333335
lambda: 0.05 | epoch: 500 | error: 0.45626666666666665
lambda: 0.1 | epoch: 500 | error: 0.4557333333333333
lambda: 1 | epoch: 500 | error: 0.45953333333333335
lambda: 10 | epoch: 500 | error: 0.4554
lambda: 15 | epoch: 500 | error: 0.4554
lambda: 20 | epoch: 500 | error: 0.4554
lambda: 25 | epoch: 500 | error: 0.4554
lambda: 30 | epoch: 500 | error: 0.4554
lambda: 0.01 | epoch: 750 | error: 0.47673333333333334
lambda: 0.05 | epoch: 750 | error: 0.46166666666666667
lambda: 0.1 | epoch: 750 | error: 0.4554
lambda: 1 | epoch: 750 | error: 0.45453333333333334
lambda: 10 | epoch: 750 | error: 0.4554
lambda: 15 | epoch: 750 | error: 0.4554666666666667
lambda: 20 | epoch: 750 | error: 0.4554
lambda: 25 | epoch: 750 | error: 0.4554
lambda: 30 | epoch: 750 | error: 0.45593333333333336
lambda: 0.01 | epoch: 1000 | error: 0.45553333333333335
lambda: 0.05 | epoch: 1000 | error: 0.45613333333333334
lambda: 0.1 | epoch: 1000 | error: 0.456
```

```
lambda: 1 | epoch: 1000 | error: 0.46
lambda: 10 | epoch: 1000 | error: 0.45553333333333335
lambda: 15 | epoch: 1000 | error: 0.4554
lambda: 20 | epoch: 1000 | error: 0.4554666666666667
lambda: 25 | epoch: 1000 | error: 0.4554
lambda: 30 | epoch: 1000 | error: 0.4554
```



[67]:
```
plt.subplot(121)
plt.plot(epochs * len(lambda_s) , error_rate,'bo')
plt.xlabel("epochs")
plt.subplot(122)
plt.plot(lambda_s * len(epochs), error_rate,'go')
plt.xlabel("lambdas")
```

[67]:
```
Text(0.5, 0, 'lambdas')
```



[0]:
```
# The results show that the optimal lambda value and the number of epochs are
# about 1 and 400 respectively(based on the sample of training data we used).
# We can use these figures to model the test data
# and compare the results with the Logistic Regression function
```

[0]:
```
st = sparse_test.toarray()
coef = perform_sgd(sparse[: 5000], train_label[: 5000], 0.01, 1, 750, decrease␣
↪= True, plot = False)
error = compute_mis(coef, st, test_label)
```

[69]:
```
print("test error: ", error)
```

```
test error:  0.45053333333333334
```

[0]:
```
# Although the speed of computation is much faster for the stoichastic
# gradient descent method, the logistic regression function in the previous
# item was slightly more accurate. When we implemented stoichastic gradient
# descent, the lowest error rate we could achieve on the test set was
# only 0.4497
```

[0]:
```
```

[0]:
```
# Part 3: Scores versus text
```

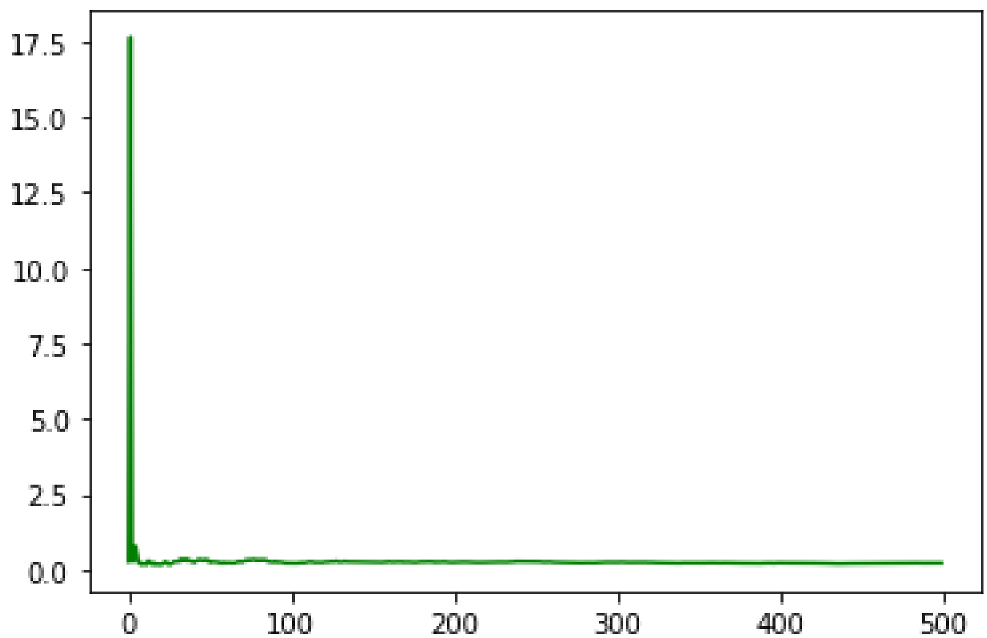
[0]:
```
# Function that compiles the scores for other criteria
```

[0]:
```python
def compile_scores(data):
    lst = []
    for i in range(len(data)):
        lst.append([data.iloc[i]['appearance'], data.iloc[i]['aroma'],\
        data.iloc[i]['palate'], data.iloc[i]['style'], data.iloc[i]['taste']])
    return np.array(lst)
```

[0]:
```python
train_scores = compile_scores(train_data)
```

[0]:
```python
test_scores = compile_scores(test_data)
val_scores = compile_scores(val_data)
```

[76]:
```python
coef = perform_sgd(val_scores[:5000], val_label[:5000], 0.01, 10, 500, decrease␣
↪= True, plot = True)
```



[0]:
```python
# The results show that the loss function converges much quicker than the model
# using only overall ratings
```

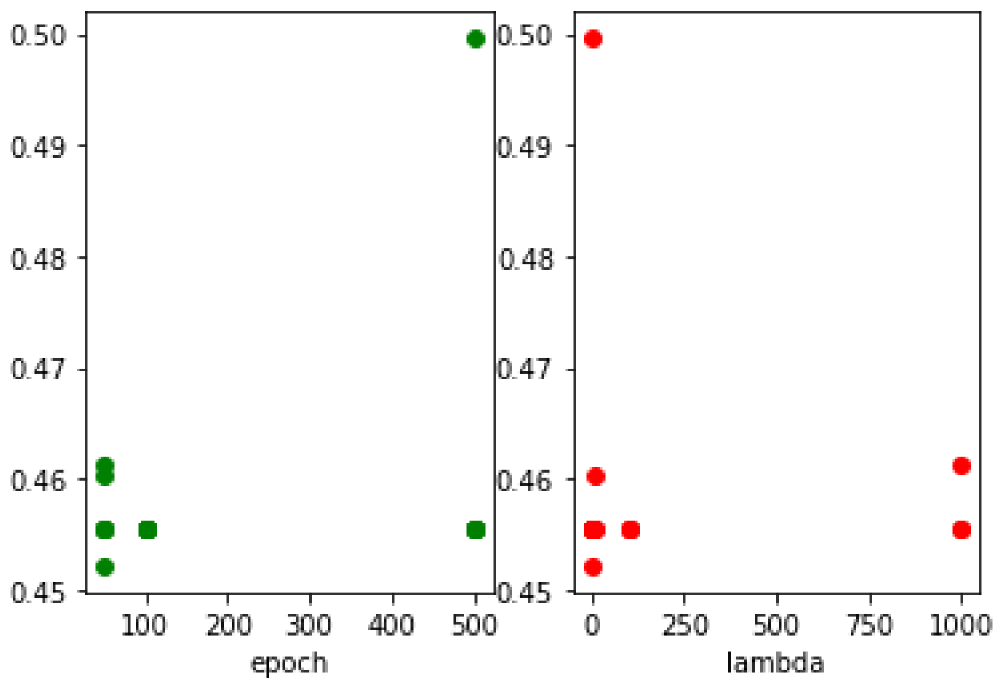
[78]:
```python
lambda_s = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
epochs = [50, 100, 500]
error = []
epoch_ = []
lambda_ = []
for epoch in epochs:
    for lam in lambda_s:
```

```python
        coef = perform_sgd(train_scores[:5000], train_label[:5000], 0.01, lam, \
                           epoch, decrease = True, plot = False)
        e = compute_mis(coef, val_scores, val_label)
        print("lambda: {} | epoch: {} | error:  {}".format(lam, epoch, e))
        epoch_.append(epoch)
        lambda_.append(lam)
        error.append(e)
```

```
lambda: 0.001 | epoch: 50 | error:  0.4554
lambda: 0.01 | epoch: 50 | error:  0.4554
lambda: 0.1 | epoch: 50 | error:  0.4554
lambda: 1 | epoch: 50 | error:  0.4554
lambda: 10 | epoch: 50 | error:  0.4554
lambda: 100 | epoch: 50 | error:  0.4554
lambda: 1000 | epoch: 50 | error:  0.4612
lambda: 0.001 | epoch: 100 | error:  0.4554
lambda: 0.01 | epoch: 100 | error:  0.4554
lambda: 0.1 | epoch: 100 | error:  0.4554
lambda: 1 | epoch: 100 | error:  0.4554
lambda: 10 | epoch: 100 | error:  0.4554
lambda: 100 | epoch: 100 | error:  0.4554
lambda: 1000 | epoch: 100 | error:  0.4554
lambda: 0.001 | epoch: 500 | error:  0.4996
lambda: 0.01 | epoch: 500 | error:  0.45213333333333333
lambda: 0.1 | epoch: 500 | error:  0.4554
lambda: 1 | epoch: 500 | error:  0.4554
lambda: 10 | epoch: 500 | error:  0.46026666666666666
lambda: 100 | epoch: 500 | error:  0.4554
lambda: 1000 | epoch: 500 | error:  0.4554
```

[79]:
```python
plt.subplot(121)
plt.plot(epochs * len(lambda_s), error,'go')
plt.xlabel("epoch")
plt.subplot(122)
plt.plot(lambda_s * len(epochs), error,'ro')
plt.xlabel("lambda")
```

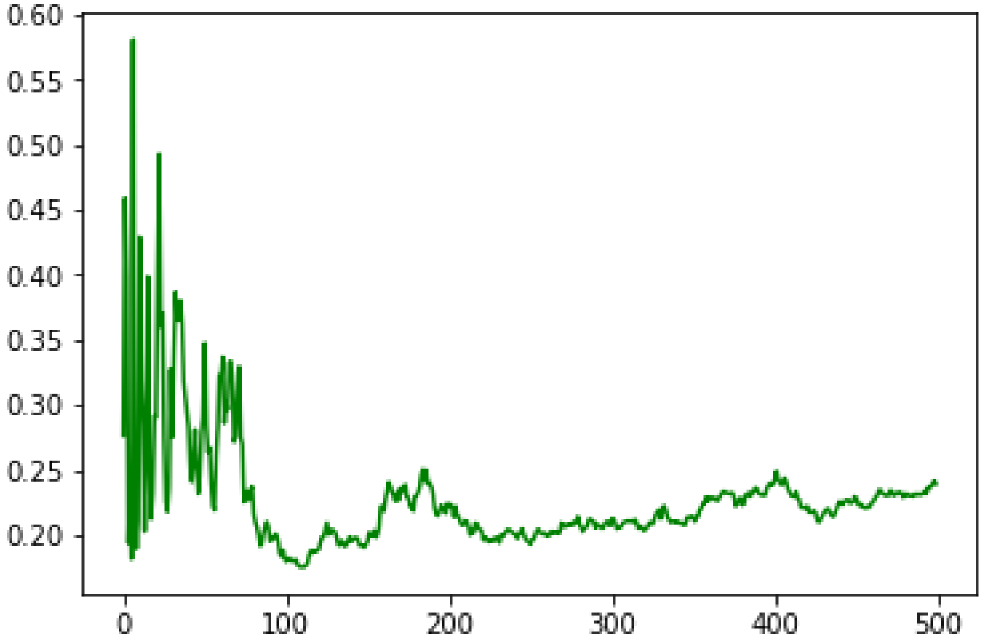
[79]:
```
Text(0.5, 0, 'lambda')
```



[0]:
```
# Computing the prediction error on the testing set
```

[80]:
```
coef2 = perform_sgd(train_scores[:5000], train_label[:5000], 0.01, 0.01, 500,␣
 ↪decrease = True, plot = True)
error2 = compute_mis(coef2, test_scores, test_label)
print("test error: ", error2)
```

```
test error:  0.4534
```



[0]:
```
# In general, the previous model to which we fed overall reviews is more
# effective because the score models have generated higher error rates. The
# results are acceptable considering the fact that texts provide more␣
↪information
# about ratings than mere numbers.
```

[0]:
```
```

[0]:
```
```

[0]:
```
```

[0]:
```
```