Homework3

September 19, 2019

This notebook uses the packages **pandas**(loads datasets and output tables), **numpy**(label formatting) and **matplotlib**(contains module for plotting graphs). In this project, the datasets used are the **gissette**, **madelon** and **dexter** datasets. The folders containing the three datasets must be in the same directory as this notebook.

In order to run the code for this project, the following packages must be imported first

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statistics import mean
```

The style and size used for graph and fonts were found in: https://www.kdnuggets.com/2019/04/data-visualization-python-matplotlib-seaborn.html

[2]:
```
# style and size for graph fonts
fontdict_title = {'fontsize': 24, 'weight': 'bold', 'horizontalalignment':␣
 ↪'center'}
fontdict_xlabel = {'fontsize': 18, 'weight': 'bold', 'horizontalalignment':␣
 ↪'center'}
fontdict_ylabel = {'fontsize': 16, 'weight': 'bold', 'horizontalalignment':␣
 ↪'center', 'verticalalignment': 'baseline'}
```

Helper functions defined below are part of logistic regression algorithm. ***sigmoid*** applies the sigmoid function to a numpy array. ***log_likelihood*** applies the log-likelihood function to a numpy array. This function is used as the **loss function** for this project. ***prediction*** returns a numpy array of the same size as the input numpy array with values assigned according to the threshold: assigns 1 if the value is more than or equal to 0.5 otherwise, 0. ***misclassification_error*** calculates the mean misclassification error by comparing the values predicted with the actual labels and counting how many were incorrectly misclassified. The output of this function is then *amount of misclassifications/amount of classifications*. Finally, ***normalize*** normalizes a dataset.

[3]:
```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))


def log_likelihood(x, y, w):
```

```
    z = np.dot(x, w)
    return np.sum(y * z - np.log(1 + np.exp(z))) / z.size


def prediction(probabilities, threshold=0.5):
    return np.where(probabilities >= threshold, 1, 0)


def misclassification_error(predictions, labels):
    return np.where(predictions != labels, 1, 0).mean()


def normalize(m, std, data):
    return (data - m) / std
```

Function for the logistic regression algorithm. This function returns the mean classification error for the training, all the loss values and the last updated weights after all the iterations. The intercept is set to 0.

[4]:
```
def log_regression(features, labels, learning_rate, iterations, shrinkage=0.
↪0001):
    misclassification_errors = []
    loss = []
    intercept = np.zeros((features.shape[0], 1))
    features = np.hstack((intercept, features))
    weights = np.zeros(features.shape[1])
    observation_num = features.size

    for iteration in range(1, iterations + 1):
        scores = np.dot(features, weights)
        probs = sigmoid(scores)
        pred = prediction(probs)
        error = misclassification_error(labels, pred)
        misclassification_errors.append(error)

        # Calculate gradient
        gradient = np.dot(features.T, labels - probs)
        # Update weights
        weights += -(learning_rate * shrinkage * weights) + ((learning_rate *␣
↪gradient) / observation_num)
        # Calculate log likelihood and store it in a list
        ll = np.mean(log_likelihood(features, labels, weights))
        loss.append(ll)
    mean_error = mean(misclassification_errors)
    return mean_error, loss, weights
```

Problem 1: Logistic Regression: Gisette Dataset

Load training and test set

[5]:
```
gisette_train_data = pd.read_csv("./Gisette/gisette_train.data", header=None,␣
 ↪sep=" ").dropna(axis=1).values
gisette_train_labels = np.where(np.ravel(
    pd.read_csv("./Gisette/gisette_train.labels", header=None, sep=" ").
 ↪dropna(axis=1).values) == -1, 0, 1)

gisette_test_data = pd.read_csv("./Gisette/gisette_valid.data", header=None,␣
 ↪sep=" ").dropna(axis=1).values

gisette_test_labels = np.where(np.ravel(
    pd.read_csv("./Gisette/gisette_valid.labels", header=None, sep=" ").
 ↪dropna(axis=1).values) == -1, 0, 1)
```

Normalize training and test set

[6]:
```
gisette_train_data_mean = gisette_train_data.mean(axis=0)
gisette_train_data_std = np.where(gisette_train_data.std(axis=0) == 0, 1,␣
 ↪gisette_train_data.std(axis=0))
normalized_gisette_train_data = normalize(gisette_train_data_mean,␣
 ↪gisette_train_data_std, gisette_train_data)
normalized_gisette_test_data = normalize(gisette_train_data_mean,␣
 ↪gisette_train_data_std, gisette_test_data)
```

Set learning rate and iterations

[7]:
```
iters = 1000
gisette_learning_rate = 900
```

Run logistic regression and store the train error, losses and weights

[8]:
```
gisette_train_error, gisette_train_loss, gisette_train_weights =␣
 ↪log_regression(normalized_gisette_train_data,
                                                                            ␣
 ↪gisette_train_labels,
                                                                            ␣
 ↪gisette_learning_rate, iters)
```

Add extra column to test set to account for the intercept.

[9]:
```
intercept_test = np.zeros((normalized_gisette_test_data.shape[0], 1))
normalized_gisette_test_data = np.hstack((intercept_test,␣
 ↪normalized_gisette_test_data))
```

Predict using the test set and calculate the test error

[10]:
```
gisette_test_scores = np.dot(normalized_gisette_test_data,␣
 ↪gisette_train_weights)
gisette_test_preds = prediction(sigmoid(gisette_test_scores))
gisette_test_error = misclassification_error(gisette_test_labels,␣
 ↪gisette_test_preds)
```

Creates figure object. This is in its own cell so that the plots appear in the correct size.

[11]:
```
fig = plt.figure()
```

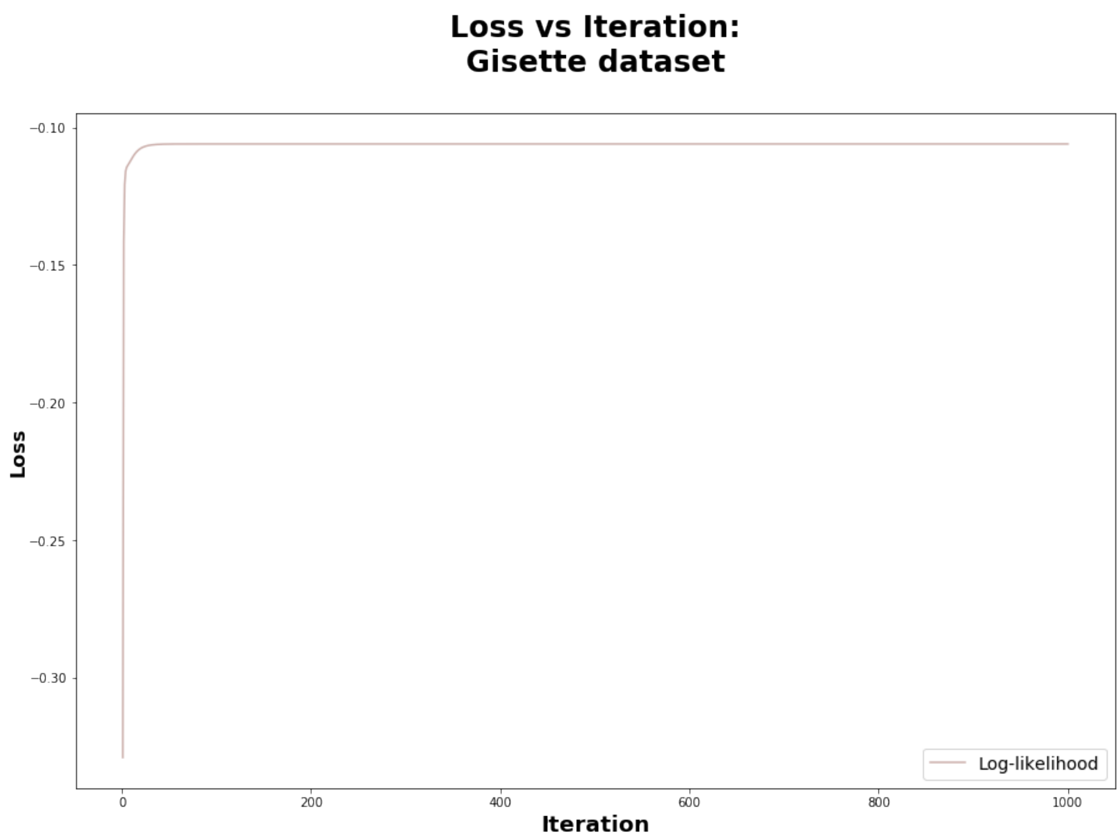
```
<Figure size 432x288 with 0 Axes>
```

Plot a graph of loss vs iteration number

[12]:
```
# size of graph
plt.rcParams['figure.figsize'] = [15, 10]  # size=15x10 inches

# labels
plt.title("Loss vs Iteration:\nGisette dataset\n", fontdict=fontdict_title)
plt.xlabel("Iteration", fontdict=fontdict_xlabel)
plt.ylabel("Loss", fontdict=fontdict_ylabel)

# plotting
plt.plot(list(range(1, iters + 1)), gisette_train_loss,
         color="#CDB1AD",
         linestyle="-",
         label="Log-likelihood")
plt.legend(fontsize=14);
```



Problem 2: Logistic Regression: Madelon Dataset

Load training and test set

[13]:
```
madelon_train_data = pd.read_csv("./madelon/madelon_train.data", header=None,␣
↪sep=" ").dropna(axis=1).values
madelon_train_labels = np.where(np.ravel(
    pd.read_csv("./madelon/madelon_train.labels", header=None, sep=" ").
↪dropna(axis=1).values) == -1, 0, 1)

madelon_test_data = pd.read_csv("./madelon/madelon_valid.data", header=None,␣
↪sep=" ").dropna(axis=1).values

madelon_test_labels = np.where(np.ravel(
    pd.read_csv("./madelon/madelon_valid.labels", header=None, sep=" ").
↪dropna(axis=1).values) == -1, 0, 1)
```

Normalize training and test set

```
[14]: madelon_train_data_mean = madelon_train_data.mean(axis=0)
madelon_train_data_std = np.where(madelon_train_data.std(axis=0) == 0, 1,␣
 ↪madelon_train_data.std(axis=0))
normalized_madelon_train_data = normalize(madelon_train_data_mean,␣
 ↪madelon_train_data_std, madelon_train_data)
normalized_madelon_test_data = normalize(madelon_train_data_mean,␣
 ↪madelon_train_data_std, madelon_test_data)
```

Set learning rate and iterations

```
[15]: iters = 1000
madelon_learning_rate = 660
```

Run logistic regression and store the train error, losses and weights

```
[16]: madelon_train_error, madelon_train_loss, madelon_train_weights =␣
 ↪log_regression(normalized_madelon_train_data,
                                                                              ␣
 ↪madelon_train_labels,
                                                                              ␣
 ↪madelon_learning_rate, iters)
```

Add extra column to test set to account for the intercept.

```
[17]: intercept_test = np.zeros((normalized_madelon_test_data.shape[0], 1))
normalized_madelon_test_data = np.hstack((intercept_test,␣
 ↪normalized_madelon_test_data))
```

Predict using the test set and calculate the test error

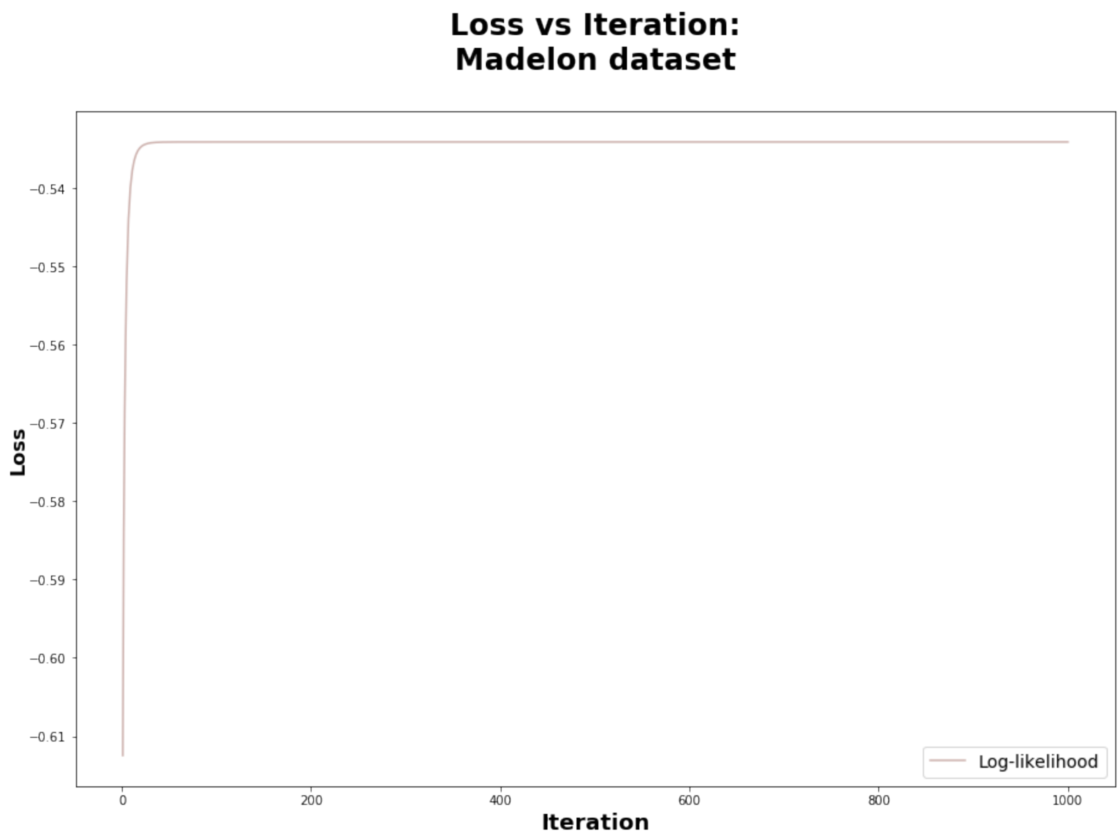
```
[18]: madelon_test_scores = np.dot(normalized_madelon_test_data,␣
 ↪madelon_train_weights)
madelon_test_preds = prediction(sigmoid(madelon_test_scores))
madelon_test_error = misclassification_error(madelon_test_labels,␣
 ↪madelon_test_preds)
```

Plot a graph of loss vs iteration number

```
[19]: fig = plt.figure()
# size of graph
plt.rcParams['figure.figsize'] = [15, 10]  # size=15x10 inches

# labels
plt.title("Loss vs Iteration:\nMadelon dataset\n", fontdict=fontdict_title)
plt.xlabel("Iteration", fontdict=fontdict_xlabel)
plt.ylabel("Loss", fontdict=fontdict_ylabel)
```

```
# plotting
plt.plot(list(range(1, iters + 1)), madelon_train_loss,
         color="#CDB1AD",
         linestyle="-",
         label="Log-likelihood")
plt.legend(fontsize=14);
```



Problem 3: Logistic Regression: Dexter Dataset

Create csv files from **dexter_train.data** and **dexter_test.data** in order to load it with pandas.

[20]:
```
def reformat_file(input_filepath, output_filepath, row_num, col_num):
    output_file = open(output_filepath, "w+")
    with open(input_filepath, "r") as fp:
        for obs in range(0, row_num):
            line = fp.readline()
```

```
            strs = line.split(" ")
            output_line = ["0" for col in range(0, col_num)]

            for s in strs:
                if s != "\n":
                    i, value = s.split(":")
                    output_line[int(i)] = value

            output_file.write(",".join(output_line) + "\n")

    output_file.close()

reformat_file("./dexter/dexter_train.data", "./dexter/dexter_train.csv", 300,␣
 ↪20000)
reformat_file("./dexter/dexter_valid.data", "./dexter/dexter_valid.csv", 300,␣
 ↪20000)
```

Load training and test set

[21]:
```
dexter_train_data = pd.read_csv("./dexter/dexter_train.csv", header=None).values
dexter_train_labels = np.where(np.ravel(pd.read_csv("./dexter/dexter_train.
 ↪labels", header=None).values) == -1, 0, 1)
dexter_test_data = pd.read_csv("./dexter/dexter_valid.csv", header=None).values
dexter_test_labels = np.where(np.ravel(pd.read_csv("./dexter/dexter_valid.
 ↪labels", header=None).values) == -1, 0, 1)
```

Normalize training and test set

[22]:
```
dexter_train_data_mean = dexter_train_data.mean(axis=0)
dexter_train_data_std = np.where(dexter_train_data.std(axis=0) == 0, 1,␣
 ↪dexter_train_data.std(axis=0))
normalized_dexter_train_data = normalize(dexter_train_data_mean,␣
 ↪dexter_train_data_std, dexter_train_data)
normalized_dexter_test_data = normalize(dexter_train_data_mean,␣
 ↪dexter_train_data_std, dexter_test_data)
```

Set learning rate and iterations. After several experimentation, 1000 was the largest learning rate value where it converges.

[23]:
```
iters = 1000
dexter_learning_rate = 19
```

Run logistic regression and store the train error, losses and weights

[24]:
```
dexter_train_error, dexter_train_loss, dexter_train_weights =␣
 ↪log_regression(normalized_dexter_train_data,
```

```
                                                                    ␣
↪dexter_train_labels,
                                                                    ␣
↪dexter_learning_rate, iters)
```

Add extra column to test set to account for the intercept.

[25]:
```
intercept_test = np.zeros((normalized_dexter_test_data.shape[0], 1))
normalized_dexter_test_data = np.hstack((intercept_test,␣
↪normalized_dexter_test_data))
```

Predict using the test set and calculate the test error

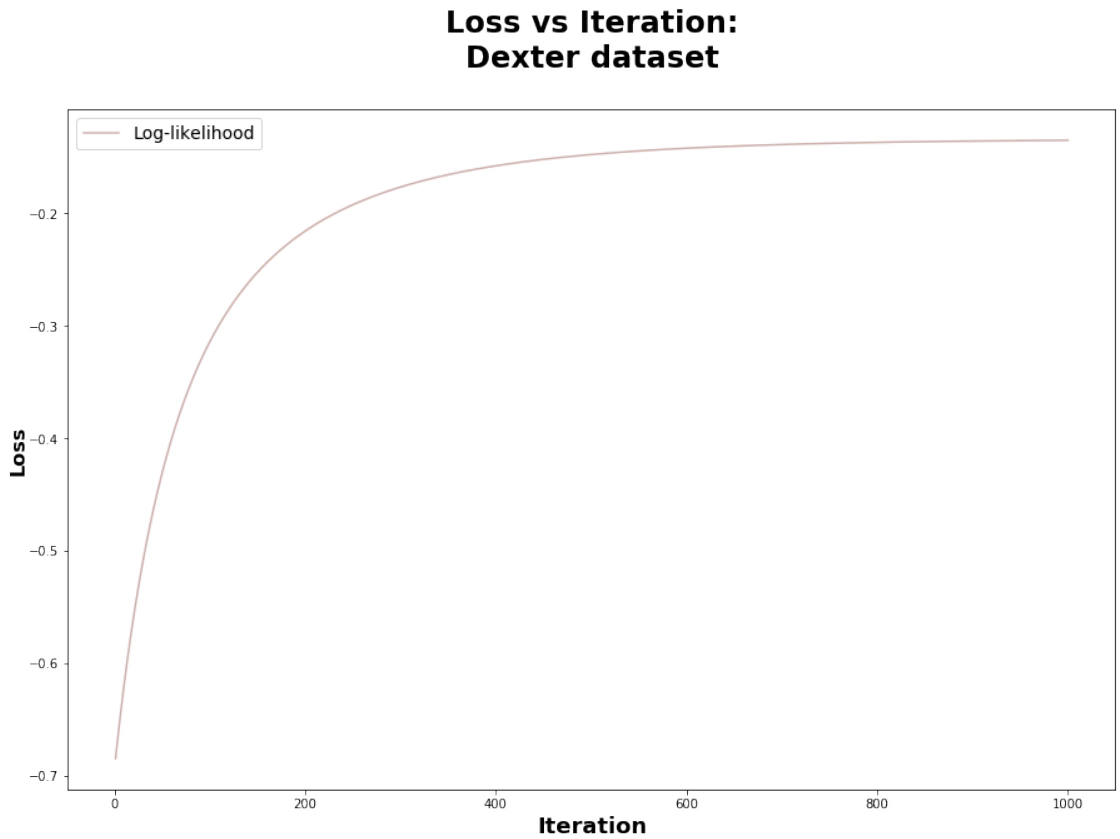
[26]:
```
dexter_test_scores = np.dot(normalized_dexter_test_data, dexter_train_weights)
dexter_test_preds = prediction(sigmoid(dexter_test_scores))
dexter_test_error = misclassification_error(dexter_test_labels,␣
↪dexter_test_preds)
```

Plot a graph of loss vs iteration number

[27]:
```
fig = plt.figure()
# size of graph
plt.rcParams['figure.figsize'] = [15, 10]  # size=15x10 inches

# labels
plt.title("Loss vs Iteration:\nDexter dataset\n", fontdict=fontdict_title)
plt.xlabel("Iteration", fontdict=fontdict_xlabel)
plt.ylabel("Loss", fontdict=fontdict_ylabel)

# plotting
plt.plot(list(range(1, iters + 1)), dexter_train_loss,
         color="#CDB1AD",
         linestyle="-",
         label="Log-likelihood")
plt.legend(fontsize=14);
```



Training and Test Misclassification Error Table

[28]:
```
# Create labels
rows_labels = ["Gisette","Madelon", "Dexter", ]
columns_labels = ["Dataset","Training Error","Test Error"]

# Store the misclassification error from each dataset for training and testing
misclassification_errors = {
    columns_labels[1]: [gisette_train_error, madelon_train_error,␣
 ↪dexter_train_error],
    columns_labels[2]: [gisette_test_error, madelon_test_error,␣
 ↪dexter_test_error]
}

# Create dataframe to output table
error_tabledf=pd.DataFrame(misclassification_errors, index=rows_labels)
error_tabledf.index.name = columns_labels[0]
```

```
error_tabledf
```

[28]:

```
         Training Error  Test Error
Dataset
Gisette        0.013211       0.023
Madelon        0.262941       0.420
Dexter         0.000500       0.130
```