exercise_2

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1 CSCI 416 - HW2

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2 Problem 2

3 Implement Logistic Regression for Book Classification

This notebook does the following:

- Loads a data set for predicting whether a book is hardcover or paperback from two input features: the thickness of the book and the weight of the book
- Normalizes the features
- Has a placeholder for your implementation of logistic regression
- Plots the data and the decision boundary of the learned model

Read below and follow instructions to complete the implementation.

3.1 Setup

Run the code below to import modules, etc.

[ ]:
```
%matplotlib inline
%reload_ext autoreload
%autoreload 2

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

from logistic_regression import logistic, cost_function, gradient_descent
```

[ ]:
```
def normalize_features( X, mu=None, sigma=None ):
    '''
    Feature normalization

    Inputs:
        X       m x n data matrix (either train or test)
        mu      vector of means (length n)
```

```
        sigma   vector of standard deviations (length n)

    Outputs:
        X_norm  normalized data matrix
        mu      vector of means
        sigma   vector of standard deviations

    IMPORTANT NOTE:
        When called for training data, mu and sigma should be computed
        from X and returned for later use. When called for test data,
        the mu and sigma should be passed in to the function and
        *not* computed from X.

    '''
    if mu is None:
        mu    = np.mean(X, axis=0)
        sigma = np.std (X, axis=0)

    # Don't normalize constant features
    mu   [sigma == 0] = 0
    sigma[sigma == 0] = 1
    X_norm = (X - mu)/sigma

    return (X_norm, mu, sigma)
```

3.2 Load and Prep Data

Read the code in the cell below and run it. This loads the book data from file and selects two features to set up the training data `X` (data matrix) and `y` (label vector). It then normalizes the training data.

[ ]:
```
data = pd.read_csv('book-data.csv', sep=',',header=None).values

# % Data columns
# %
# % 0 - width
# % 1 - thickness
# % 2 - height
# % 3 - pages
# % 4 - hardcover
# % 5 - weight

y = data[:,4]

# % Extract the normalized features into named column vectors
width     = data[:,0]
thickness = data[:,1]
```

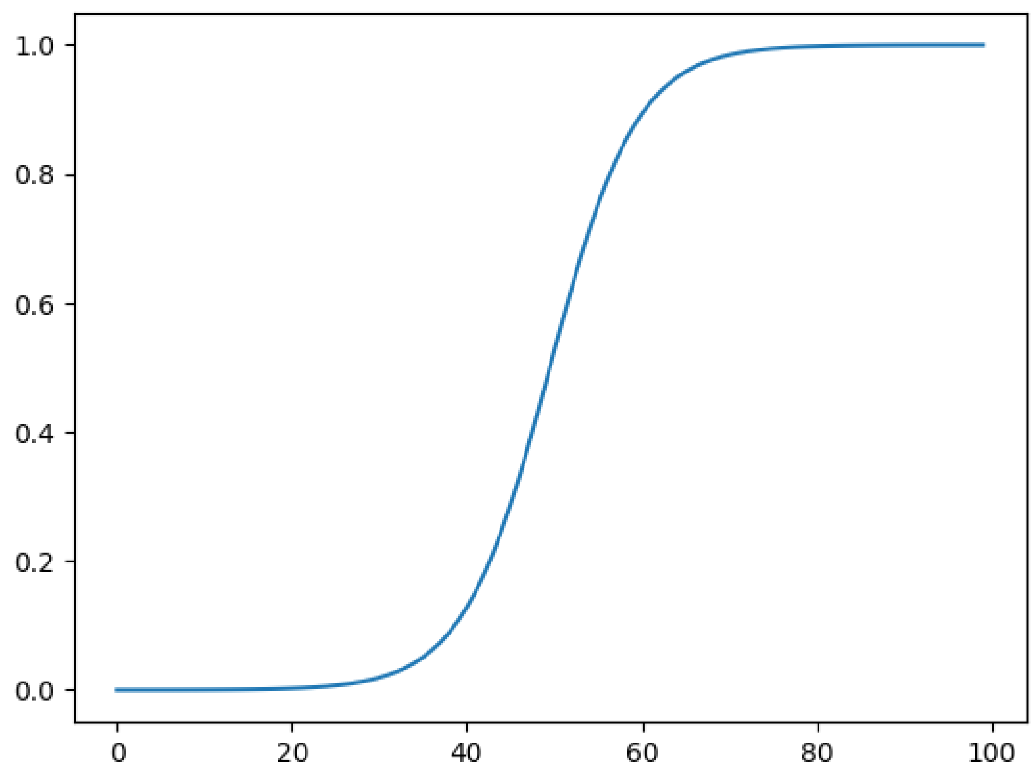
```
height    = data[:,2]
pages     = data[:,3]
weight    = data[:,5]

m = data.shape[0]
X = np.stack([np.ones(m), thickness, height], axis=1)
n = X.shape[1]

X, mu, sigma = normalize_features(X)
```

4 (1 point) Implement the `logistic` function

Open the file `logistic_regression.py` and complete the code for the function `logistic`. Then run the cell below to plot the logistic function for $-10 \leq z \leq 10$ to test your implementation — it should look like the logistic function!

[ ]:
```
z = np.linspace(-10, 10, 100)
#plt.plot(z, logistic(z))
#plt.plot(z)
#plt.show()
plt.plot(logistic(z))
```

[ ]: `[<matplotlib.lines.Line2D at 0x18860ce4280>]`



5 (2 points) Implement `cost_function`

Complete the code for `cost_function` in the file `logistic_regression.py` to implement the logistic regression cost function. Then test it with the code in the cell below.

[ ]:
```
theta = np.zeros(n)
print(cost_function(X, y, theta)) # prints 38.81624....
```

```
38.816242111356914
```

6 Setup for plotting a learned model

Run this cell and optionally read the code. It defines a function to help plot the data together with the decision boundary for the model we are about to learn.

[ ]:
```
def plot_model(X, y, theta):
    pos = y==1
    neg = y==0

    plt.scatter(X[pos,1], X[pos,2], marker='+', color='blue', label='Hardcover')
    plt.scatter(X[neg,1], X[neg,2], marker='o', color='red', facecolors='none',␣
 ↪label='Paperback')

    # plot the decision boundary
    x1_min = np.min(X[:,1]) - 0.5
    x1_max = np.max(X[:,1]) + 0.5

    x1 = np.array([x1_min, x1_max])
    x2 = (theta[0] + theta[1]*x1)/(-theta[2])
    plt.plot(x1, x2, label='Decision boundary')

    plt.xlabel('thickness (normalized)')
    plt.ylabel('height (normalized)')
    plt.legend(loc='lower right')
    plt.show()
```

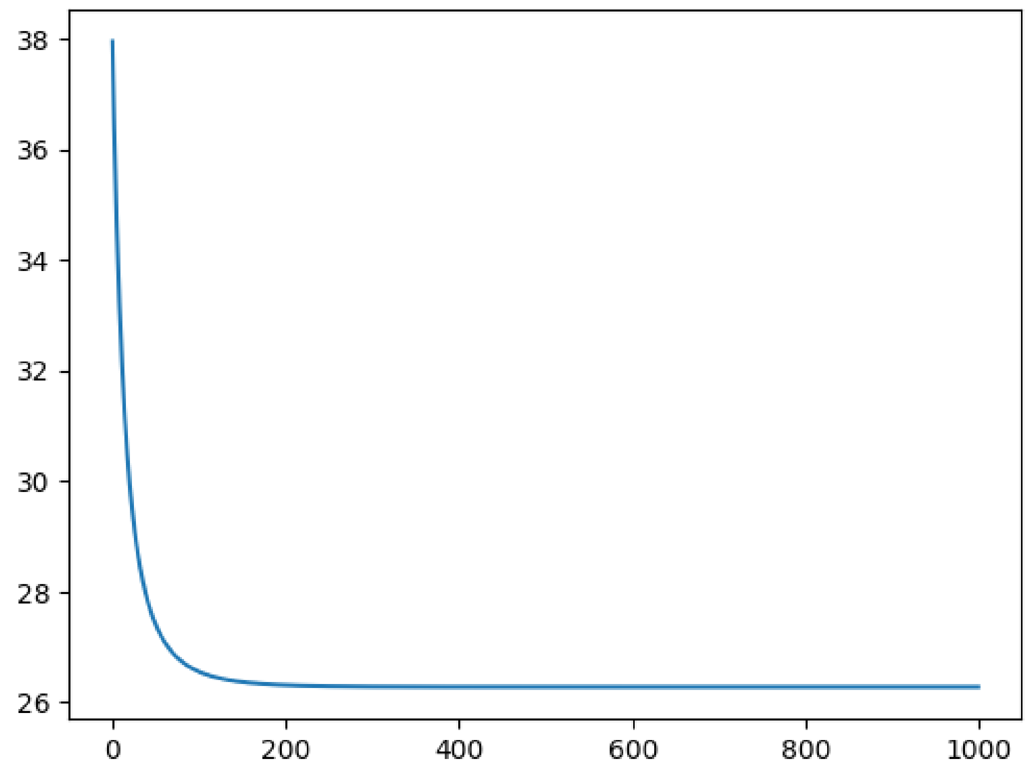
7 (7 points) Implement gradient descent for logistic regression

Now complete the code for `gradient_descent` in the file `logistic_regression.py`, which runs gradient descent to find the best parameters `theta`, and write code in the cell below to:

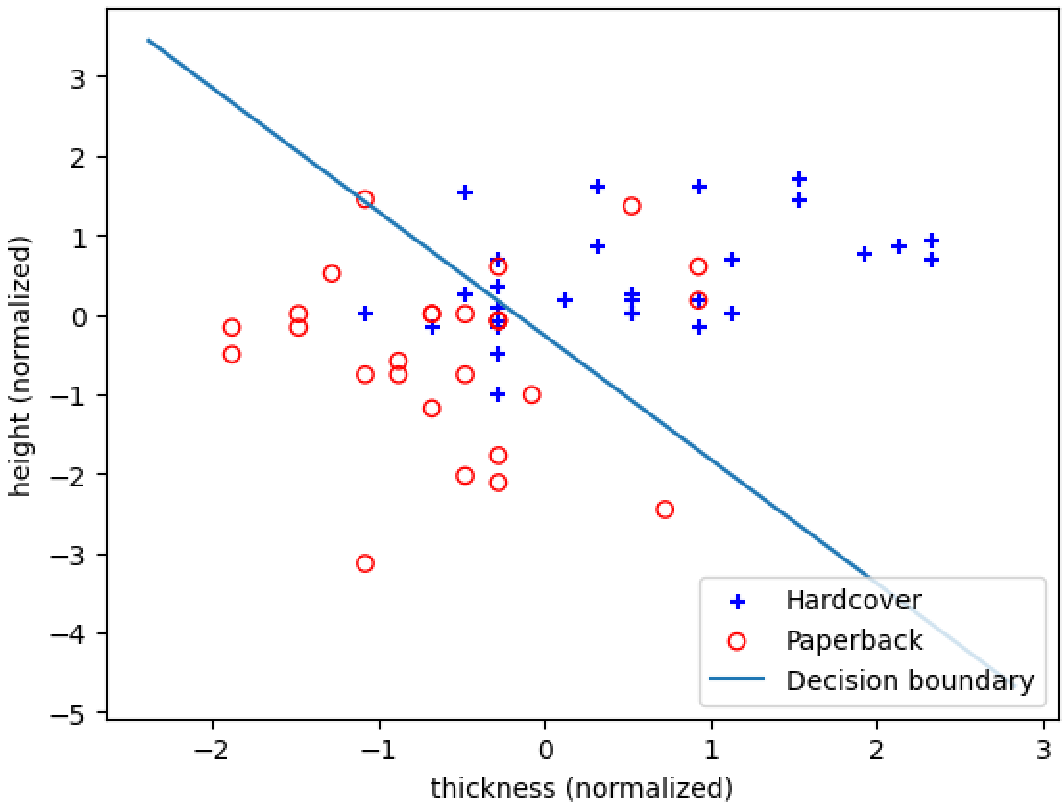
1. Call `gradient_descent` to learn `theta`
2. Print the final value of the cost function
3. Plot J_history to assess convergence
4. Tune the step size and number of iterations if needed until the algorithm converges and the decision boundary (see next cell) looks reasonable

5. Print the accuracy—the percentage of correctly classified examples in the training set

[ ]:
```
theta = np.zeros(n)

#
# YOUR CODE HERE
#

#setup alpha, iters
alpha = 2.25e-3
iters = 1000

theta, J_history = gradient_descent(X, y, theta, alpha, iters)

#print(J_history)

plt.plot(J_history)
plt.show()

# Plots data and decision boundary. If you have learned a good theta
# you will see a decision boundary that separates the data in a
# reasonable way.
plot_model(X, y, theta)

prediction = np.dot(X, theta)
acc = 0
for i in range(y.size):
    if prediction[i] < 0 and y[i] == 0 or prediction[i] > 0 and y[i] == 1:
        acc += 1

percent = (acc / y.size) * 100
print("Percentage Correct: ", percent)
```



38
36
34
32
30
28
26
0
200
400
600
800
1000




```
Percentage Correct:  76.78571428571429
```

8 Problem 3

9 Logistic regression for SMS spam classification

Each line of the data file `sms.txt` contains a label—either "spam" or "ham" (i.e. non-spam)—followed by a text message. Here are a few examples (line breaks added for readability):

```
ham     Ok lar... Joking wif u oni...
ham     Nah I don't think he goes to usf, he lives around here though
spam    Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005.
        Text FA to 87121 to receive entry question(std txt rate)
        T&C's apply 08452810075over18's
spam    WINNER!! As a valued network customer you have been
        selected to receivea £900 prize reward! To claim
        call 09061701461. Claim code KL341. Valid 12 hours only.
```

To create features suitable for logistic regression, code is provided to do the following (using tools from the `sklearn.feature_extraction.text`):

- Convert words to lowercase.

- Remove punctuation and special characters (but convert the $ and £ symbols to special tokens and keep them, because these are useful for predicting spam).
- Create a dictionary containing the 3000 words that appeared most frequently in the entire set of messages.
- Encode each message as a vector $\mathbf{x}^{(i)} \in \mathbb{R}^{3000}$. The entry $x_j^{(i)}$ is equal to the number of times the jth word in the dictionary appears in that message.
- Discard some ham messages to have an equal number of spam and ham messages.
- Split data into a training set of 1000 messages and a test set of 400 messages.

Follow the instructions below to complete the implementation. Your job will be to:

- Learn θ by gradient descent
- Plot the cost history
- Make predictions and report the accuracy on the test set
- Test out the classifier on a few of your own text messages

10 Load and prep data

This cell preps the data. Take a look to see how it works, and then run it.

[ ]:
```
%matplotlib inline
%reload_ext autoreload
%autoreload 2

import numpy as np
import re
import matplotlib.pyplot as plt
import codecs

from logistic_regression import logistic, cost_function, gradient_descent
from sklearn.feature_extraction.text import CountVectorizer

# Preprocess the SMS Spam Collection data set
#
#   https://archive.ics.uci.edu/ml/datasets/SMS+Spam+Collection
#
# From Dan Sheldon

numTrain    = 1000
numTest     = 494
numFeatures = 3000

np.random.seed(1)

# Open the file
f = codecs.open('sms.txt', encoding='utf-8')

labels = []    # list of labels for each message
```

```python
docs   = []    # list of messages

# Go through each line of file and extract the label and the message
for line in f:
    l, d= line.strip().split('\t', 1)
    labels.append(l)
    docs.append(d)

# This function will be called on each message to preprocess it
def preprocess(doc):
    # Replace all currency signs and some url patterns by special
    # tokens. These are useful features.
    doc = re.sub('[£$]', ' __currency__ ', doc)
    doc = re.sub('\://', ' __url__ ', doc)
    doc = doc.lower() # convert to lower
    return doc


# This is the object that does the conversion from text to feature vectors
vectorizer = CountVectorizer(max_features=numFeatures, preprocessor=preprocess)

# Do the conversion ("fit" the transform from text to feature vector.
#   later we will also "apply" the tranform on test messages)
X = vectorizer.fit_transform(docs)

# Convert labels to numbers: 1 = spam, 0 = ham
y = np.array([l == 'spam' for l in labels]).astype('int')

# The vectorizer returns sparse scipy arrays. Convert this back to a dense
#   numpy array --- not as efficient but easier to work with
X = X.toarray()
m,n = X.shape

# Add a column of ones
X = np.column_stack([np.ones(m), X])

#
# Now massage and split into test/train
#
pos = np.nonzero(y == 1)[0]   # indices of positive training examples
neg = np.nonzero(y == 0)[0]   # indices of negative training examples

npos = len(pos)

# Create a subset that has the same number of positive and negative examples
subset = np.concatenate([pos, neg[0:len(pos)] ])
```

```
# Randomly shuffle order of examples
np.random.shuffle(subset)

X = X[subset,:]
y = y[subset]

# Split into test and train
train = np.arange(numTrain)
test  = numTrain + np.arange(numTest)

X_train = X[train,:]
y_train = y[train]

X_test  = X[test,:]
y_test  = y[test]

# Extract the list of test documents
test_docs = [docs[i] for i in subset[test]]

# Extract the list of tokens (words) in the dictionary
tokens = vectorizer.get_feature_names()
```

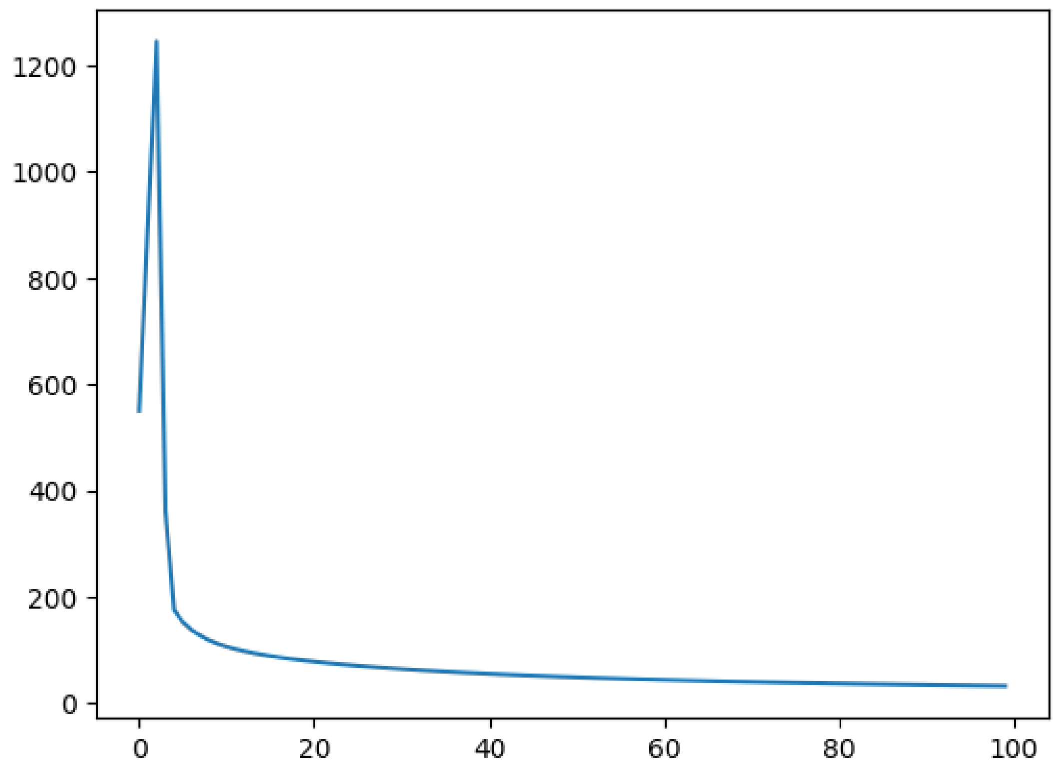
```
C:\Users\tankk\AppData\Roaming\Python\Python310\site-
packages\sklearn\utils\deprecation.py:87: FutureWarning: Function
get_feature_names is deprecated; get_feature_names is deprecated in 1.0 and will
be removed in 1.2. Please use get_feature_names_out instead.
  warnings.warn(msg, category=FutureWarning)
```

11 Train logistic regresion model

Now train the logistic regression model. The comments summarize the relevant variables created by the preprocessing.

[ ]:
```
# X_train     contains information about the words within the training
#             messages. the ith row represents the ith training message.
#             for a particular text, the entry in the jth column tells
#             you how many times the jth dictionary word appears in
#             that message
#
# X_test      similar but for test set
#
# y_train     ith entry indicates whether message i is spam
#
# y_test      similar
#

m, n = X_train.shape
```

```
theta = np.zeros(n)


# YOUR CODE HERE:
#  - learn theta by gradient descent
#  - plot the cost history
#  - tune step size and # iterations if necessary
alpha = 1e-2
iters = 100

#print(X_train.shape)
#print(X_train)
theta, J_history = gradient_descent(X_train, y_train, theta, alpha, iters)

#plot_model(X_test, y_test, theta)

#print(J_history)
plt.plot(J_history)
plt.show()
```



12 Make predictions on test set

Use the model fit in the previous cell to make predictions on the test set and compute the accuracy (percentage of messages in the test set that are classified correctly). You should be able to get accuracy above 95%.

[ ]:
```
m_test, n_test = X_test.shape

# YOUR CODE HERE
#  - use theta to make predictions for test set
#  - print the accuracy on the test set---i.e., the precent of messages␣
↪classified correctly
prediction = np.dot(X_test, theta)
#print(prediction)

acc = 0
for i in range(y_test.size):
    if (prediction[i] < 0 and y_test[i] == 0) or (prediction[i] > 0 and␣
↪y_test[i] == 1):
        acc += 1

percent = (acc / y_test.size) * 100
print("Percentage Correct: ", percent)
```

```
Percentage Correct:  95.95141700404858
```

13 Inspect model parameters

Run this code to examine the model parameters you just learned. These parameters assign a postive or negative value to each word — where positive values are words that tend to be spam and negative values are words that tend to be ham. Do they make sense?

[ ]:
```
token_weights = theta[1:]

def reverse(a):
    return a[::-1]

most_negative = np.argsort(token_weights)
most_positive = reverse(most_negative)

k = 10

print('Top %d spam words' % k)
for i in most_positive[0:k]:
    print('  %+.4f  %s' % (token_weights[i], tokens[i]))

print('\nTop %d ham words' % k)
for i in most_negative[0:k]:
```

```
    print('  %+.4f  %s' % (token_weights[i], tokens[i]))
```

```
Top 10 spam words
  +2.8841  __currency__
  +2.1622  call
  +1.9978  txt
  +1.9091  text
  +1.8525  reply
  +1.5877  mobile
  +1.5666  service
  +1.5328  stop
  +1.5227  150p
  +1.4712  from

Top 10 ham words
  -1.5016  my
  -1.3469  so
  -1.1881  ok
  -1.0924  me
  -0.9732  ll
  -0.9467  what
  -0.9375  come
  -0.9164  later
  -0.9136  he
  -0.8528  gt
```

13.1 Make a prediction on new messages

Type a few of your own messages in below and make predictions. Are they ham or spam? Do the predictions make sense?

[ ]:
```
def extract_features(msg):
    x = vectorizer.transform([msg]).toarray()
    x = np.insert(x, 0, 1)
    return x

msg = u'Write your own text here...'
x = extract_features(msg)  # this is the feature vector



# YOUR CODE HERE
#  - try a few texts of your own
#  - predict whether they are spam or non-spam
```

[ ]:
```
msg_arr = []

#spam
```

```
msg_arr.append(u'Battle Pass and Tier Skips, or equivalent versions, will be␣
 ↪accessible in Modern Warfare II once the Season 1 Battle Pass, or equivalent␣
 ↪system, is made available in game. Battle Pass redemption applies to one␣
 ↪season of Modern Warfare II Battle Pass, or equivalent system, only. For␣
 ↪more information, please visit https:// www . callofduty . com')
#spam
msg_arr.append(u'Make standout graphics, social media assets, and more with␣
 ↪thousands of beautiful templates in just a couple of clicks. Available on␣
 ↪web and mobile.')
#ham
msg_arr.append(u'Have yall tried discord activities yet poker is pog we should␣
 ↪do a wmas poker night the scrabble one is ok golf is pretty good')
#ham
msg_arr.append(u'Also just a PSA if anyone already knows what they want to␣
 ↪nominate for pirate night tonight, replay to this message with the anime␣
 ↪name and episode number.')

for str in msg_arr:
    temp = extract_features(str)
    print(np.dot(temp, theta))
```

```
5.400607778765326
0.46361914227146284
-3.056794018290266
-1.026780746612702
```

[ ]:

```

```

14 Problem 4

15 Hand-Written Digit Classification

In this assignment you will implement multi-class classification for hand-written digits and run a few experiments. The file `digits-py.mat` is a data file containing the data set, which is split into a training set with 4000 examples, and a test set with 1000 examples.

You can import the data as a Python dictionary like this:

```
data = scipy.io.loadmat('digits-py.mat')
```

The code in the cell below first does some setup and then imports the data into the following variables for training and test data:

- `X_train` - 2d array shape 4000 x 400
- `y_train` - 1d array shape 4000
- `X_test` - 2d array shape 1000 x 400
- `y_test` - 1d array shape 1000

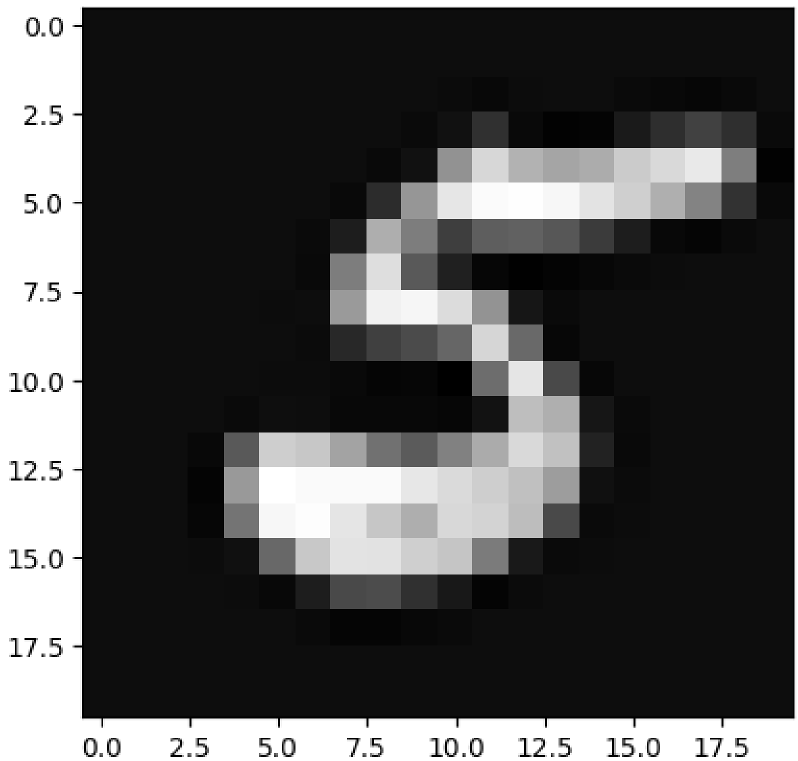
[ ]:
```python
%matplotlib inline
%reload_ext autoreload
%autoreload 2

import numpy as np
import matplotlib.pyplot as plt

# Load train and test data
import scipy.io
data = scipy.io.loadmat('digits-py.mat')
X_train = data['X_train']
y_train = data['y_train'].ravel()
X_test  = data['X_test']
y_test  = data['y_test'].ravel()
```

15.1 (2 points) Write code to visualize the data

Once you have loaded the data, it is helpful to understand how it represents images. Each row of `X_train` and `X_test` represents a 20 x 20 image as a vector of length 400 containing the pixel intensity values. To see the original image, you can reshape one row of the train or test data into a 20 x 20 matrix and then visualize it using the matlplotlib `imshow` command.

Write code using `np.reshape` and `plt.imshow` to display the 100th training example as an image. (Hint: use `cmap='gray'` in `plt.imshow` to view as a grayscale image.)

[ ]:
```python
# Write code here
test_image = X_train[100]
#print(test_image)
test_image = test_image.reshape((20, 20))
#print(test_image)
plt.imshow(test_image, cmap = 'gray')
plt.show()
```



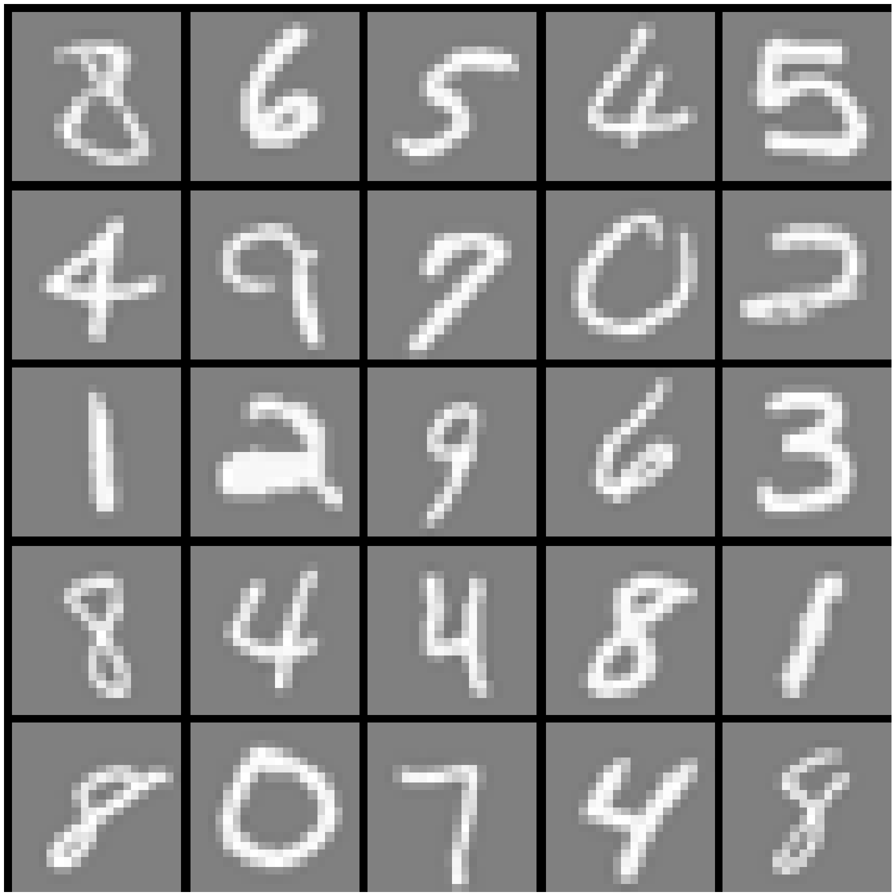
15.2 (2 points) Explore the data

A utility function `display_data` is provided for you to further visualize the data by showing a mosaic of many digits at the same time. For example, you can display the first 25 training examples like this:

`display_data( X_train[:25, :] )`

Go ahead and do this to visualize the first 25 training examples. Then print the corresponding labels to see if they match.

[ ]:
```
from one_vs_all import display_data

# Write code here
display_data(X_train[:25,:])

y_train_temp = y_train[:25].reshape((5, 5))
print(y_train_temp)#data.keys())
```



```
[[8 6 5 4 5]
 [4 9 7 0 2]
 [1 2 9 6 3]
 [8 4 4 8 1]
 [8 0 7 4 8]]
```

15.3 Alert: notation change!

Please read this carefully to understand the notation used in the assignment. We will use logistic regression to solve multi-class classification. For three reasons (ease of displaying parameters as images, compatibility with scikit learn, previewing notation for SVMs and neural networks), we will change the notation as described here.

15.3.1 Old notation

Previously we defined our model as

$$h_\theta(\mathbf{x}) = \text{logistic}(\theta_0 + \theta_1 x_1 + ... + \theta_n x_n) = \text{logistic}(\theta^T \mathbf{x})$$

where

- $\mathbf{x} = [1, x_1, \dots, x_n]$ was a feature vector with a 1 added in the first position
- $\theta = [\theta_0, \theta_1, \dots, \theta_n]$ was a parameter vector with the intercept parameter θ_0 in the first position

15.3.2 New notation

We will now define our model as

$$h_{\mathbf{w}}(\mathbf{x}) = \text{logistic}(b + w_1 x_1 + \dots + w_n x_n) = \text{logistic}(\mathbf{w}^T \mathbf{x} + b)$$

where

- $\mathbf{x} \in \mathbb{R}^n$ is the **original feature vector** with no 1 added
- $\mathbf{w} \in \mathbb{R}^n$ is a **weight vector** (equivalent to $\theta_1, \dots, \theta_n$ in the old notation)
- b is a scalar **intercept parameter** (equivalent to θ_0 in our old notation)

15.4 (10 points) One-vs-All Logistic Regression

Now you will implement one vs. all multi-class classification using logistic regression. Recall the method presented in class. Suppose we are solving a K class problem given training examples in the data matrix $X \in \mathbb{R}^{m \times n}$ and label vector $\mathbf{y} \in \mathbb{R}^m$ (the entries of $\mathbf{y}$ can be from 1 to K).

For each class $c = 1, \dots, K$, fit a logistic regression model to distinguish class c from the others using the labels

$$y_c^{(i)} = \begin{cases} 1 & \text{if } y^{(i)} = c \\ 0 & \text{otherwise.} \end{cases}$$

This training procedure will result in a weight vector $\mathbf{w}_c$ and an intercept parameter b_c that can be used to predict the probability that a new example $\mathbf{x}$ belongs to class c:

$$\text{logistic}(\mathbf{w}_c^T \mathbf{x} + b_c) = \text{probability that } \mathbf{x} \text{ belongs to class } c.$$

The overall training procedure will yield one weight vector for each class. To make the final prediction for a new example, select the class with highest predicted probability:

$$\text{predicted class} = \text{the value of } c \text{ that maximizes logistic}(\mathbf{w}_c^T \mathbf{x} + b_c).$$

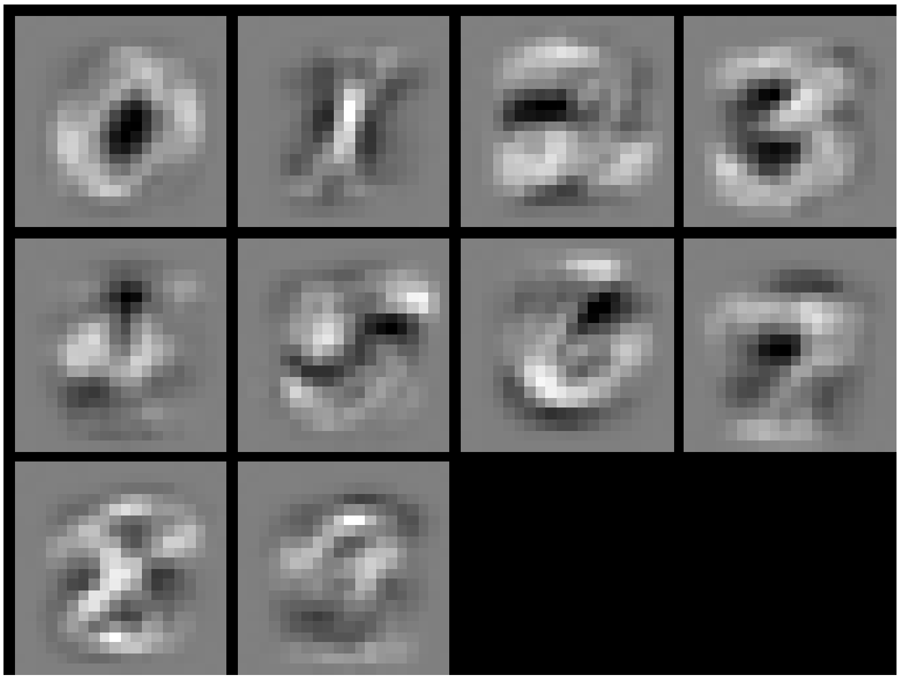
15.4.1 Training

Open the file `one_vs_all.py` and complete the function `train_one_vs_all` to train binary classifiers using the procedure outlined above. I have included a function for training a regularized logistic regression model, which you can call like this:

```
weight_vector, intercept = train_logistic_regression(X, y, lambda_val)
```

Follow the instructions in the file for more details. Once you are done, test your implementation by running the code below to train the model and display the weight vectors as images. You should see images that are recognizable as the digits 0 through 9 (some are only vague impressions of the digit).

[ ]:
```python
from one_vs_all import train_one_vs_all

lambda_val = 100
weight_vectors, intercepts = train_one_vs_all(X_train, y_train, 10, lambda_val)
display_data(weight_vectors.T) # display weight vectors as images
```



15.4.2 Predictions

Now complete the function `predict_one_vs_all` in `one_vs_all.py` and run the code below to make predictions on the train and test sets. You should see accuracy around 88% on the test set.

[ ]:
```python
from one_vs_all import predict_one_vs_all

pred_train = predict_one_vs_all(X_train, weight_vectors, intercepts)
pred_test  = predict_one_vs_all(X_test,  weight_vectors, intercepts)

print("Training Set Accuracy: %f" % (np.mean(pred_train == y_train) * 100))
print("    Test Set Accuracy: %f" % (np.mean( pred_test == y_test) * 100))
```

```
Training Set Accuracy: 90.400000
    Test Set Accuracy: 89.200000
```

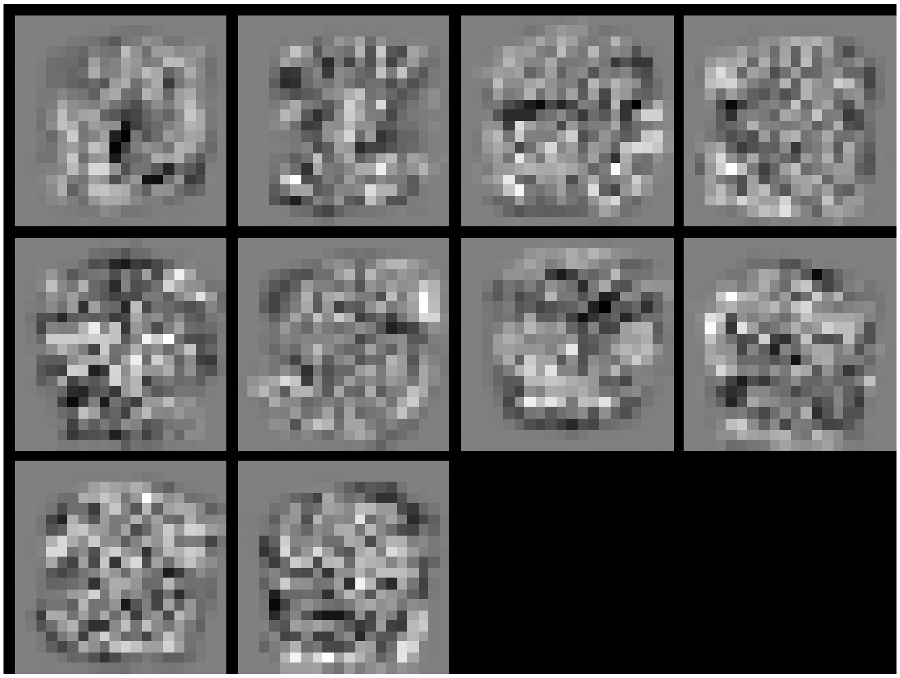
15.5 (5 points) Regularization Experiment

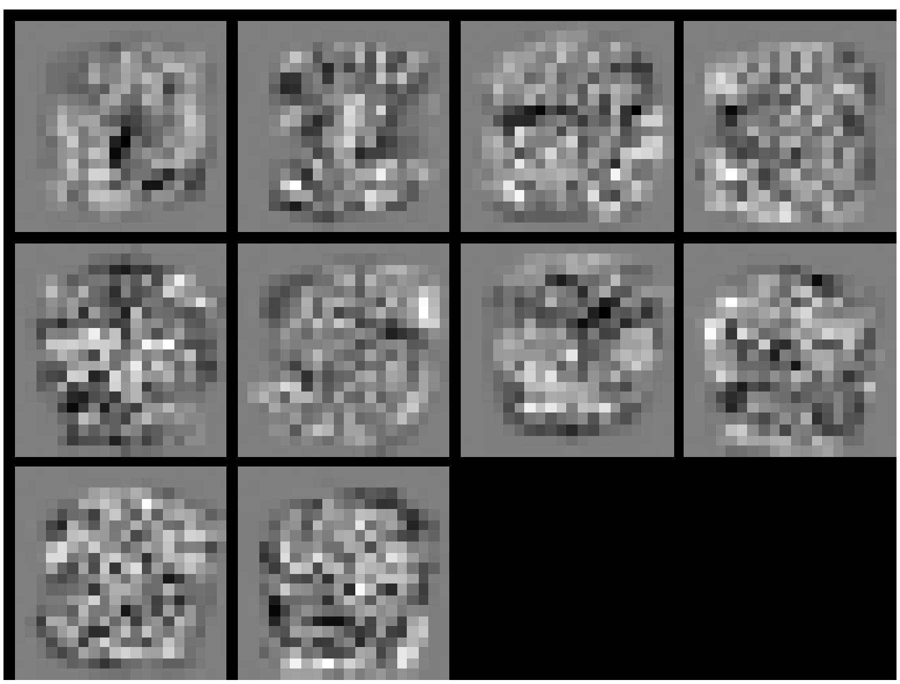
Now you will experiment with different values of the regularization parameter λ to control overfitting. Write code to measure the training and test accuracy for values of λ that are powers of 10 ranging from 10^{-3} to 10^5.

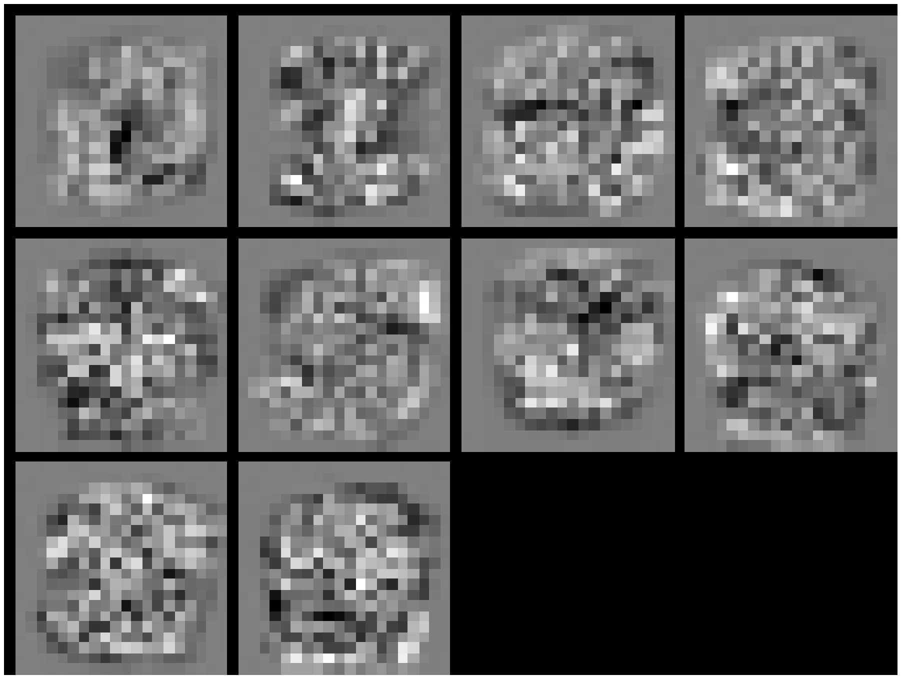
- Display the weight vectors for each value of λ as an image using the `display_data` function
- Save the training and test accuracy for each value of λ
- Plot training and test accuracy versus lambda (in one plot).

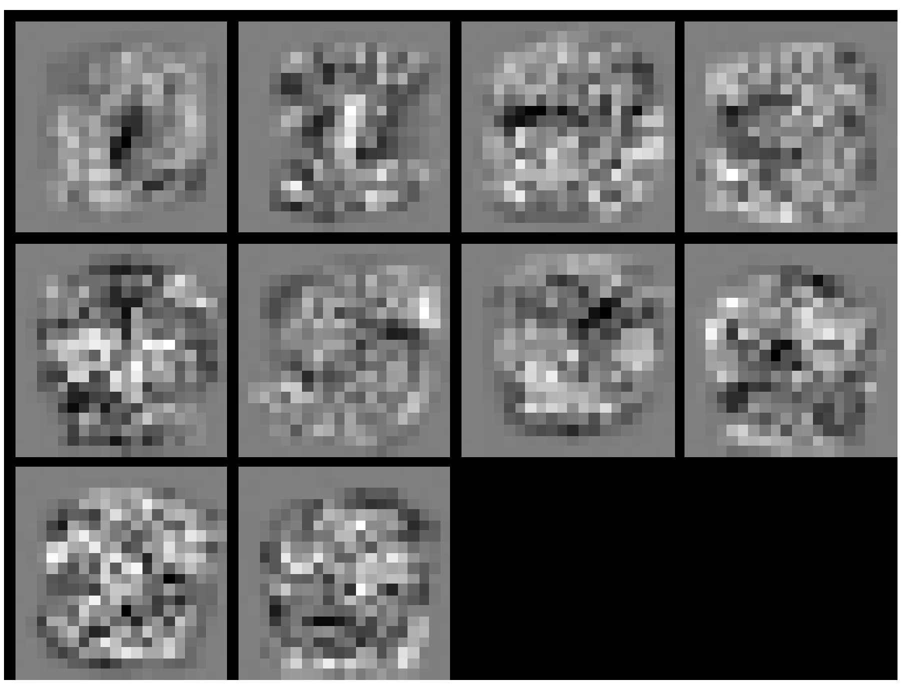
[ ]:
```
lambda_vals = 10**np.arange(-3., 5.)
num_classes = 10

# Write code here
from one_vs_all import train_one_vs_all
from one_vs_all import predict_one_vs_all

weight_vectors_list = []
intercepts_list = []
training_list = []
testing_list = []

#index = 0
for lm in lambda_vals:
    weights, intercepts = train_one_vs_all(X_train, y_train, num_classes, lm)

    weight_vectors_list.append(weights)
    intercepts_list.append(intercepts)

    display_data(weights.T)

    pred_train = predict_one_vs_all(X_train, weights, intercepts)
    pred_test  = predict_one_vs_all(X_test,  weights, intercepts)

    percent_train = np.mean(pred_train == y_train) * 100
    percent_test = np.mean(pred_test == y_test) * 100

    training_list.append(percent_train)
    testing_list.append(percent_test)
    #print(percent_train)

#plot1 = plt.subplot(2, 1, 1)
#plot2 = plt.subplot(2, 1, 2)

plt.plot(lambda_vals, training_list)
plt.plot(lambda_vals, testing_list)

# In your final plot, use these commands to provide a legend and set
# the horizontal axis to have a logarithmic scale so the value of lambda
# appear evenly spaced.

plt.legend(('train', 'test'))
```

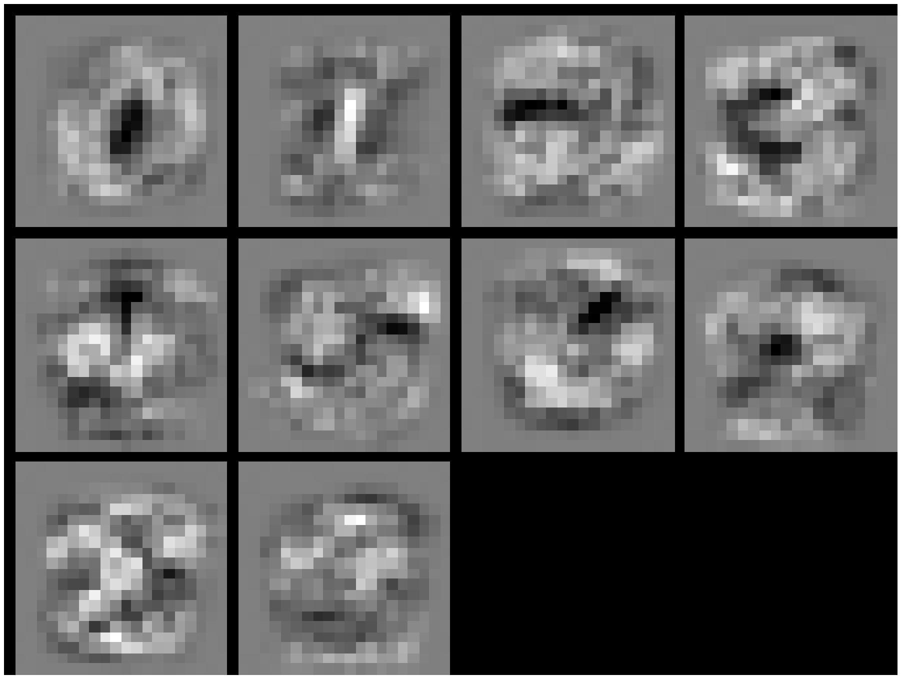
```
plt.xscale('log')
plt.xlabel('Amount of Training Data')
plt.ylabel('Lambda')
```

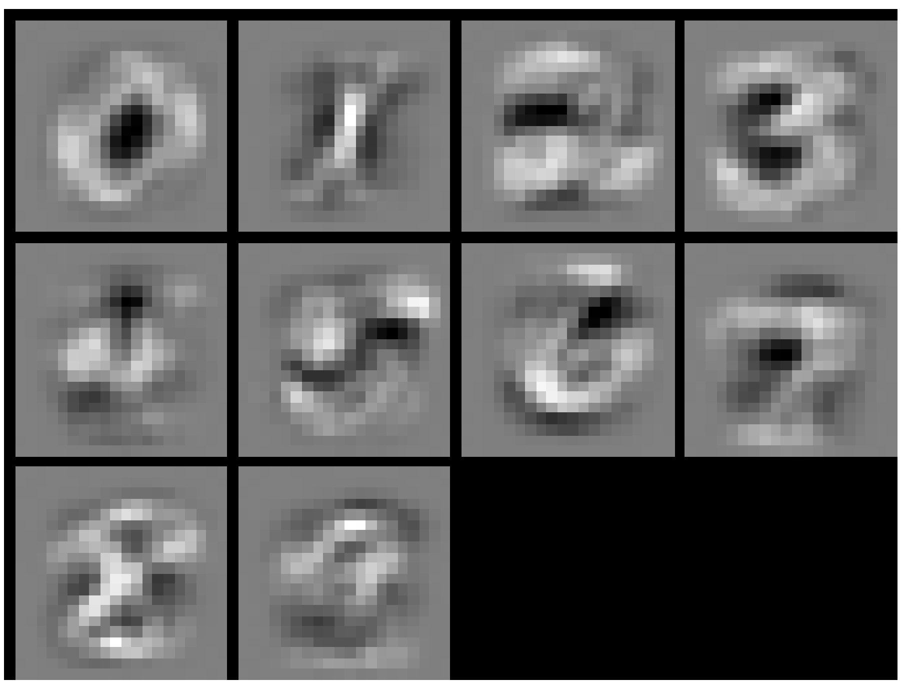


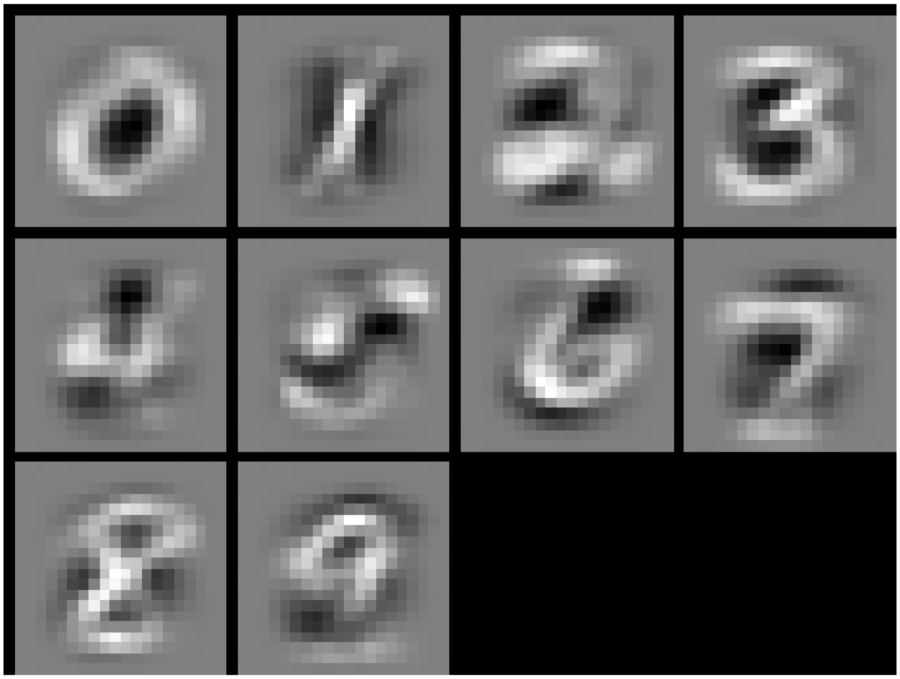


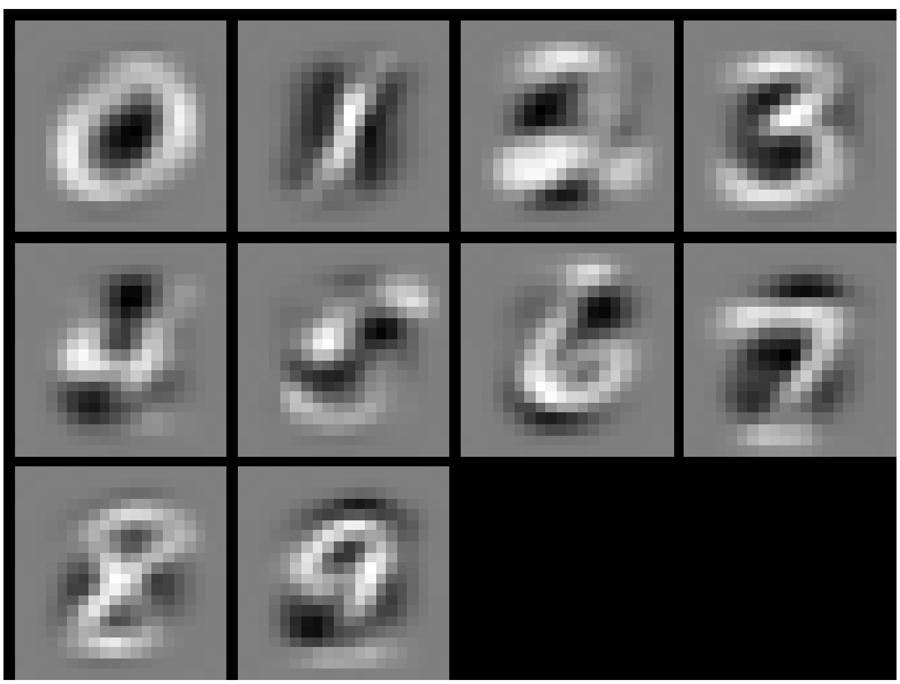




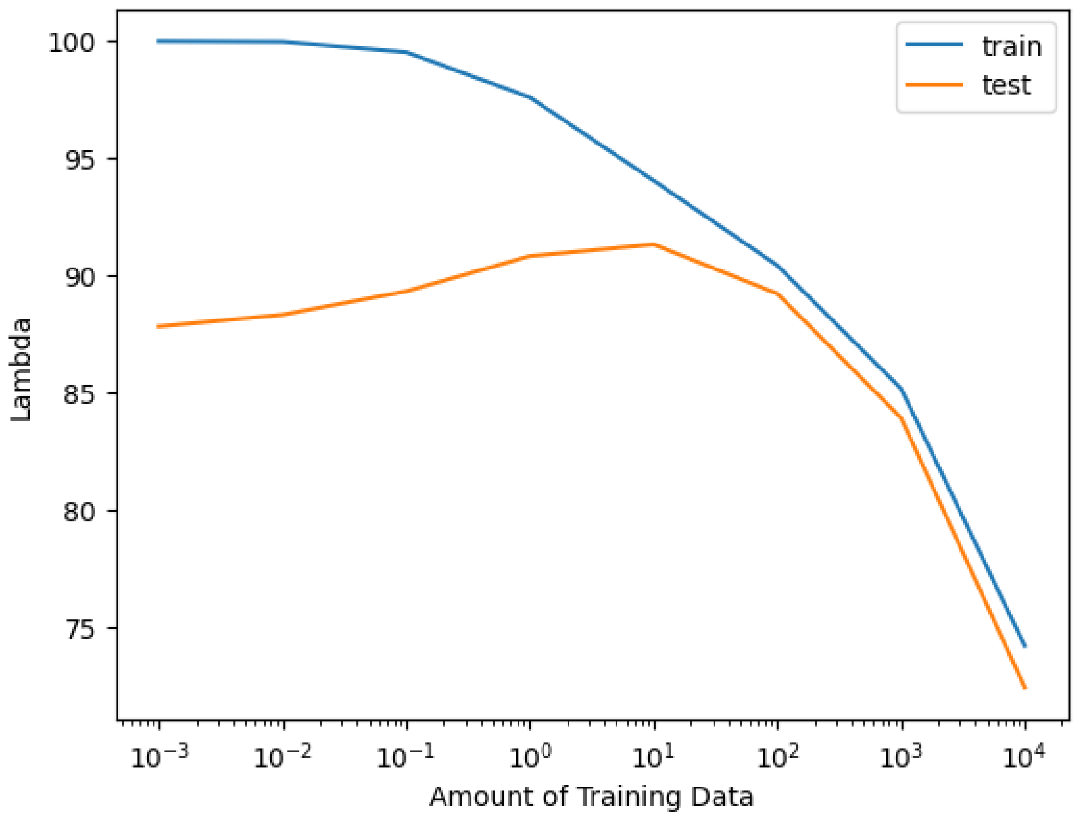








[ ]: Text(0, 0.5, 'Lambda')



15.6 (5 points) Regularization Questions

1. Does the plot show any evidence of overfitting? If so, for what range of values (roughly) is the model overfit? What do the images of the weight vectors look when the model is overfit?
2. Does the plot show any evidence of underfitting? For what range of values (roughly) is the model underfit? What do the images of the weight vectors look like when the model is underfit?
3. If you had to choose one value of , what would you select?
4. Would it make sense to run any additional experiments to look for a better value of . If so, what values would you try?

** *Your answers here* **

1. Yes. At lambdas 10^{-3} to 10^0, there exists high accuracy values for the training curve and very low accuracy values for testing curves. Images of weight vectors applied to input values at these lambdas would have very clear images at values which are in the training data and very noisy images for values not in training data.
2. Yes. At lambdas past 10^4, there exists very low accuracy values for both training and testing curves. The images of weight vectors applied to input values at these lambdas would have very noisy images for all input values.

3. 10^1, as the testing value was greatest at that lambda.
4. Yes. There exists a very clear curve in the testing accuracy chart. As such, we should test all values between 10^0 and 10^2 to find the absolute best possible accuracy.

15.7 (6 points) Learning Curve

A learning curve shows accuracy on the vertical axis vs. the amount of training data used to learn the model on the horizontal axis. To produce a learning curve, train a sequence of models using subsets of the available training data, starting with only a small fraction of the data and increasing the amount until all of the training data is used.

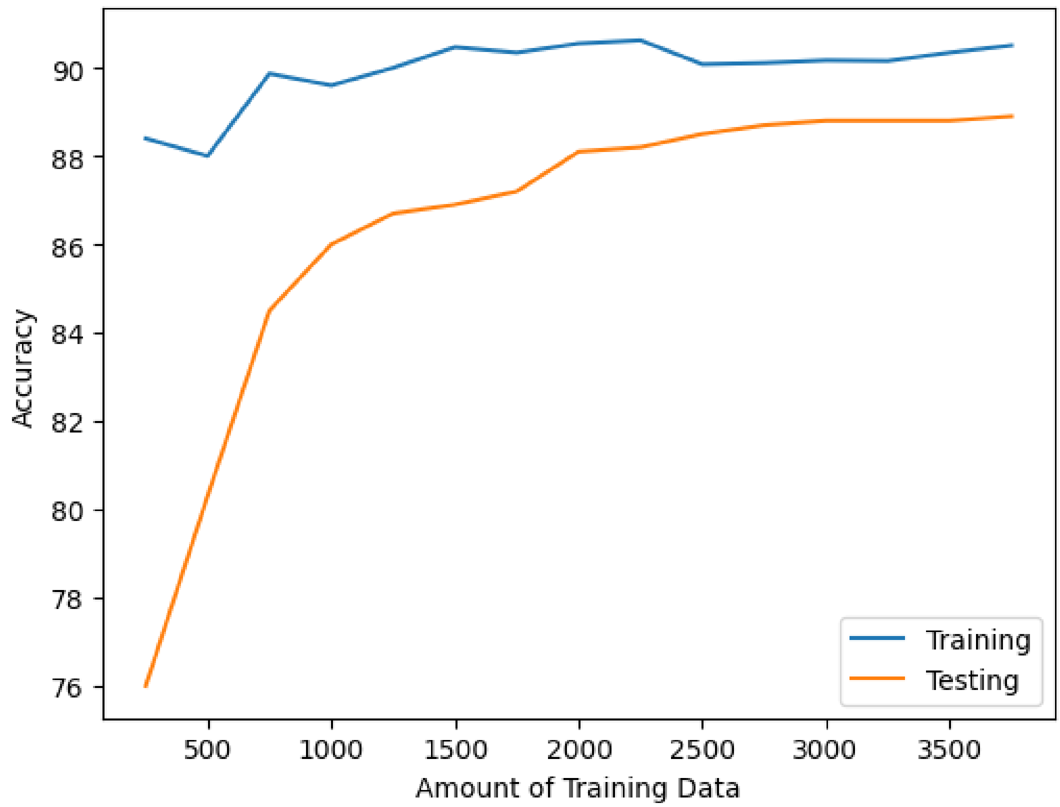
Write code below to train models on training sets of increasing size and then plot both training and test accuracy vs. the amount of training data used. (This time, you do not need to display the weight vectors as images and you will not set the horizontal axis to have log-scale.)

In this problem, please use the best value of λ you have found.

[ ]:
```
from one_vs_all import train_one_vs_all
from one_vs_all import predict_one_vs_all

m, n = X_train.shape

train_sizes = np.arange(250, 4000, 250)
nvals = len(train_sizes)

# Example: select a subset of 100 training examples
p = np.random.permutation(m)
selected_examples = p[0:100]
X_train_small = X_train[selected_examples,:]
y_train_small = y_train[selected_examples]

# Write your code here
lambda1 = 10e1

#print(train_sizes)
#weights, intercepts = train_one_vs_all(X_train_small, y_train_small,␣
↪num_classes, lambda1)

training = []
testing = []

for size in train_sizes:
    #print(size)
    selected_examples = p[0:size]
    X_train_small = X_train[selected_examples,:]
    y_train_small = y_train[selected_examples]
    #X_test_small = X_test[selected_examples, :]
    #y_test_small = y_test[selected_examples]
```

```
    weights, intercepts = train_one_vs_all(X_train_small, y_train_small,␣
 ↪num_classes, lambda1)

    pred_train = predict_one_vs_all(X_train_small, weights, intercepts)
    pred_test  = predict_one_vs_all(X_test,  weights, intercepts)

    percent_train = np.mean(pred_train == y_train_small) * 100
    percent_test = np.mean(pred_test == y_test) * 100

    training.append(percent_train)
    testing.append(percent_test)

#train_sizes.insert(0, 100)
#print(train_sizes.size, len(training))

#print(training)
#print(testing)
plt.plot(train_sizes, training)
plt.plot(train_sizes, testing)

plt.legend(('Training', 'Testing'))
plt.xlabel('Amount of Training Data')
plt.ylabel('Accuracy')
```

[ ]: Text(0, 0.5, 'Accuracy')



16 (4 points) Learning Curve Questions

1. Does the learning curve show evidence that additional training data might improve performance on the test set? Why or why not?
2. Is the any relationship between the amount of training data used and the propensity of the model to overfit? Explain what you can conclude from the plot.

** *Your answers here* **

1. Yes, as the testing accuracy clearly shows that by increasing the amount of training data, one is able to get better accuracy from prediction of testing data.
2. There is a relationship between the amount of training data and the overfitting of the model. Given that we have a static number of features, by using fewer data points, as can be seen on the graph, we have very good training prediction. However, as the weights are only trained on a small amount of training data, the testing data accuracy is very low due to the values in the testing data being different and that the weights are likely very large as to fit the majority of training data onto the model. As we increase the size of the training data set, we can see that overfitting becomes less of an issue despite training prediction accuracy decreasing as the greater amount of data begins to decrease the variance of the model between data points.