CSCI547 Machine Learning
Homework 2

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1 Logistic Regression

1A

```
import numpy as np
import pandas as pd


# The sigmoid function
def _sigmoid(w,X):
        z = np.dot(X,w)
        return 1./(1+np.exp(-z))


# The objective function
def _J_fun(w,X,y):
        return -sum(y*np.log(_sigmoid(w,X)) + (1-y)*np.log(1-_sigmoid(w,X)))


# The gradient of the objective function
def _gradient_fun(w,X,y):
        return np.dot(_sigmoid(w,X)-y,X)


class LogisticRegression:
        def __init__(self, eta=None, epochs=10000, w=None):
                self.eta= eta
                self.epochs = epochs
                self.w = w
                self.cost_over_epochs = []
```

```python
    def fit(self, x, y):
        N = len(y)

        for i in range(self.epochs):
        grad_w = _gradient_fun(self.w,x,y)    # Compute the gradient
             of the objective function
        self.w -= np.dot(self.eta,grad_w)
        self.cost_over_epochs.append(_J_fun(self.w,x,y))

        classification_error = sum((_sigmoid(self.w,x)>0.5)==y)/N
        return classification_error


    def score(self, x, y):
        N = len(y)

        classification_error = sum((_sigmoid(self.w,x)>0.5)==y)/N
        return classification_error
```

```python
import numpy as np
import pandas as pd

from logistic_regression import LogisticRegression


if __name__ == '__main__':
    DATAFILE = 'lobster_survive.dat'
    df = pd.read_csv(DATAFILE,header=0, sep=r"\s{2,}")
    x = df.iloc[:, 0].as_matrix().astype(float)
    y = df.iloc[:, 1].as_matrix().astype(float)
    x = np.vander(x,2,increasing=True)


    #learning rate, tensor
    eta = np.array([[0.000001,0],[0,0.000000001]])

    #number of iterations
    epochs = 200000

    #weights
    w = np.array([-1.,0.5])

    lr = LogisticRegression(eta=eta, epochs=epochs, w=w)
    error = lr.fit(x, y)
    print("classification error: {}".format(error))
```

classification error: 0.710691823899371

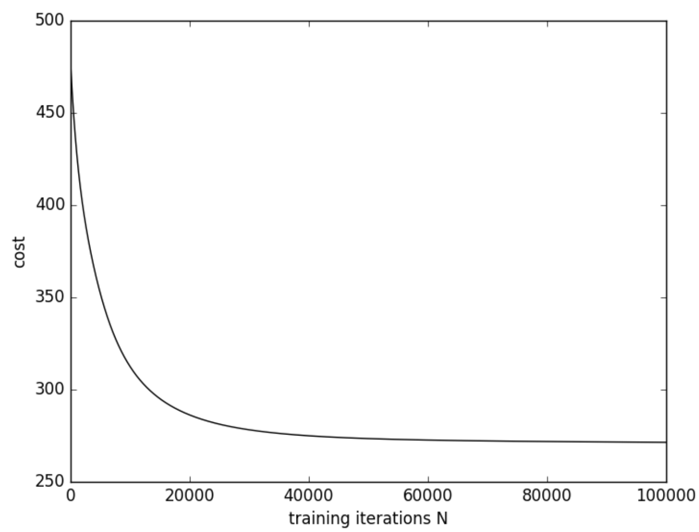
1B

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import zscore
```

```python
from logistic_regression import LogisticRegression


if __name__ == '__main__':
        TRAINFILE = 'titanic_train.csv'
        TESTFILE = 'titanic_test.csv'
        train_df = pd.read_csv(TRAINFILE,header=0)
        test_df = pd.read_csv(TESTFILE,header=0)

        x_data = train_df.iloc[:, 2:]

        # drop useless columns
        x_data.drop(['Cabin', 'Ticket', 'Name'], axis=1, inplace=True)

        # one hot sex and embarked
        x_data = pd.get_dummies(x_data, columns=['Sex', 'Embarked'])

        # fill missing age data with mean....
        x_data['Age'] = x_data['Age'].fillna(x_data['Age'].mean())

        # normalize with zscores
        numeric_cols = ['Parch', 'SibSp', 'Age', 'Fare']
        x_data[numeric_cols] = x_data[numeric_cols].apply(zscore)

        x = x_data.as_matrix().astype(float)
        y = train_df.iloc[:, 1].as_matrix().astype(float)


        x_data_test = test_df.iloc[:, 2:]

        # drop useless columns
        x_data_test.drop(['Cabin', 'Ticket', 'Name'], axis=1, inplace=True)

        # one hot sex and embarked
        x_data_test = pd.get_dummies(x_data_test, columns=['Sex', 'Embarked'
            ])

        # fill missing age data with mean....
        x_data_test['Age'] = x_data_test['Age'].fillna(x_data_test['Age'].
            mean())

        # normalize with zscores
        x_data_test[numeric_cols] = x_data_test[numeric_cols].apply(zscore)

        x_test = x_data_test.as_matrix().astype(float)
        y_test = test_df.iloc[:, 1].as_matrix().astype(float)

        #learning rate, tensor
        eta = np.eye(10) * np.array([0.000001] * 10)

        #number of iterations
        epochs = 200000

        #weights
        w = np.array([-1.,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5])
```

```
        lr = LogisticRegression(eta=eta, epochs=epochs, w=w)

        error = lr.fit(x, y)
        print("training error: {}".format(error))

        test_error = lr.score(x_test, y_test)
        print("test error: {}".format(test_error))

        iterations = len(lr.cost_over_epochs)
        print("training iterations: {}".format(iterations))

        plt.plot(lr.cost_over_epochs, 'k')
        plt.xlabel('training iterations N')
        plt.ylabel('cost')
        plt.show()
```

training error: 0.7962962962962963
test error: 0.8047138047138047
training iterations: 100000



1C*

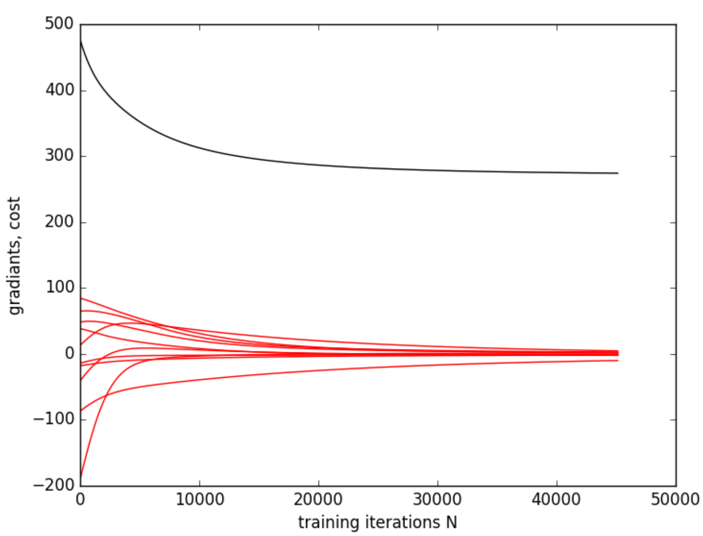
```
import numpy as np
import pandas as pd


# The sigmoid function
def _sigmoid(w,X):
        z = np.dot(X,w)
        return 1./(1+np.exp(-z))
```

```
# The objective function
def _J_fun(w,X,y):
        return -sum(y*np.log(_sigmoid(w,X)) + (1-y)*np.log(1-_sigmoid(w,X)))


# The gradient of the objective function
def _gradient_fun(w,X,y):
        return np.dot(_sigmoid(w,X)-y,X)


class LogisticRegression:
        def __init__(self, eta=None, epochs=10000, w=None, enable_early_stop
            =False, early_stop_tolerance=10):
                self.eta= eta
                self.epochs = epochs
                self.w = w
                self.cost_over_epochs = []
                self.gradiant_over_epochs = []

                self.enable_early_stop = enable_early_stop
                self.early_stop_tolerance = early_stop_tolerance


        def fit(self, x, y):
                N = len(y)

                for i in range(self.epochs):
                        grad_w = _gradient_fun(self.w,x,y)    # Compute the
                            gradient of the objective function
                        self.w -= np.dot(self.eta,grad_w)
                        self.cost_over_epochs.append(_J_fun(self.w,x,y))
                        self.gradiant_over_epochs.append(grad_w)

                        if(self.shouldTerminateEarly()):
                                break;

                classification_error = sum((_sigmoid(self.w,x)>0.5)==y)/N
                return classification_error


        def score(self, x, y):
                N = len(y)

                classification_error = sum((_sigmoid(self.w,x)>0.5)==y)/N
                return classification_error

        def shouldTerminateEarly(self):
                if(self.enable_early_stop == True):
                        grads = self.gradiant_over_epochs[-1]
                        return (all(g < self.early_stop_tolerance for g in
                            grads)
                        and all(g > -1 * self.early_stop_tolerance for g in
                            grads) )
                        return False
```

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import zscore

from logistic_regression import LogisticRegression


if __name__ == '__main__':
TRAINFILE = 'titanic_train.csv'
TESTFILE = 'titanic_test.csv'
train_df = pd.read_csv(TRAINFILE,header=0)
test_df = pd.read_csv(TESTFILE,header=0)

x_data = train_df.iloc[:, 2:]

# drop useless columns
x_data.drop(['Cabin', 'Ticket', 'Name'], axis=1, inplace=True)

# one hot sex and embarked
x_data = pd.get_dummies(x_data, columns=['Sex', 'Embarked'])

# fill missing age data with mean....
x_data['Age'] = x_data['Age'].fillna(x_data['Age'].mean())

# normalize with zscores
numeric_cols = ['Parch', 'SibSp', 'Age', 'Fare']
x_data[numeric_cols] = x_data[numeric_cols].apply(zscore)

x = x_data.as_matrix().astype(float)
y = train_df.iloc[:, 1].as_matrix().astype(float)


x_data_test = test_df.iloc[:, 2:]

# drop useless columns
x_data_test.drop(['Cabin', 'Ticket', 'Name'], axis=1, inplace=True)

# one hot sex and embarked
x_data_test = pd.get_dummies(x_data_test, columns=['Sex', 'Embarked'])

# fill missing age data with mean....
x_data_test['Age'] = x_data_test['Age'].fillna(x_data_test['Age'].mean())

# normalize with zscores
x_data_test[numeric_cols] = x_data_test[numeric_cols].apply(zscore)

x_test = x_data_test.as_matrix().astype(float)
y_test = test_df.iloc[:, 1].as_matrix().astype(float)

#learning rate, tensor
eta = np.eye(10) * np.array([0.000001] * 10)

#number of iterations
epochs = 100000
```

```
#weights
w = np.array([-1.,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5,0.5])

lr = LogisticRegression(eta=eta, epochs=epochs, w=w, enable_early_stop=True,
     early_stop_tolerance=10)

error = lr.fit(x, y)
print("training error: {}".format(error))

test_error = lr.score(x_test, y_test)
print("test error: {}".format(test_error))

iterations = len(lr.cost_over_epochs)
print("training iterations: {}".format(iterations))

plt.plot(lr.cost_over_epochs, 'k')
plt.plot(lr.gradiant_over_epochs, 'r')
plt.xlabel('training iterations N')
plt.ylabel('gradiants, cost')
plt.show()
```

training error: 0.7962962962962963
test error: 0.8080808080808081
training iterations: 45137
for this i plotted cost and gradients over iterations and noticed that when the gradients all converge towards 0 the cost is converging. seems sound, got similar results with less than 1/4 the iterations.



2 Neural Networks

2A

Ok, Done!

2B

```
from __future__ import division,print_function

import numpy as np

class Network(object):
"""
Neural network for softmax regression problems
"""

def __init__(self,layer_number_of_nodes,layer_activation_functions,
    layer_has_bias,layer_weight_means_and_stds=None):
        self.layer_number_of_nodes = layer_number_of_nodes          # Of
            nodes in each layer
        self.layer_activation_functions = [None]
        # Add an identity activation function here!
        for act in layer_activation_functions:
                if act=='softmax':
                        self.layer_activation_functions.append(self._softmax
                            )
                if act=='sigmoid':
                        self.layer_activation_functions.append(self._sigmoid
                            )
                if act=='leaky_relu':
                        self.layer_activation_functions.append(self.
                            _leaky_relu)
                if act=='gaussian':
                        self.layer_activation_functions.append(self.
                            _gaussian)
                if act=='identity':
                        self.layer_activation_functions.append(self.
                            _identity)

        self.layer_has_bias = layer_has_bias                          #
            Whether to add a bias node to each layer
        self.L = len(self.layer_number_of_nodes)                      #
            Number of layers

        self.weights = [np.array([])]

        # Create arrays to hold the weights, which are N_l(+1) by N_(l+1)
        for i in range(self.L-1):
                # if we have a normal distribution and standard deviation,
                    then generate random weights from that distribution,
                if layer_weight_means_and_stds is not None:
                        w = layer_weight_means_and_stds[i][1]*np.random.
                            randn(self.layer_number_of_nodes[i] + self.
```

```
                        layer_has_bias[i],self.layer_number_of_nodes[i
                        +1]) + layer_weight_means_and_stds[i][0]
                # Otherwise just initialize the weights to zero
                else:
                        w = np.zeros((self.layer_number_of_nodes[i] + self.
                        layer_has_bias[i],self.layer_number_of_nodes[i
                        +1]))
                self.weights.append(w)

def feed_forward(self,feature):
        # evaluate the neural network for a vector-valued input
        m = feature.shape[0]

        # Append a column of ones to the input if a bias is desired
        if self.layer_has_bias[0]:
                z = np.column_stack((np.ones((m)),feature))
        else:
                z = feature

        # Initialize lists to hold the node inputs and outputs, treating the
             input values as the output of the first node
        self.a_vals = [None]
        self.z_vals = [z]

        # Loop over the remaining layers
        for l in range(1,self.L):
                # Take the linear combination of the previous layers outputs
                     (z^(l-1)) and weights (w^(l)) to form a^(l)
                a = np.dot(self.z_vals[l-1],self.weights[l])
                # Run a through the activation function to form z^(l)
                z = self.layer_activation_functions[l](a)
                # If a bias is desired, append a column of ones to z
                if self.layer_has_bias[l]:
                z = np.column_stack((np.ones((m)),z))
                # Store these values (for computing the gradient later)
                self.a_vals.append(a)
                self.z_vals.append(z)
        return z

def _J_fun(self,feature,label):
        # Add your sum square error evaluation here!
        if self.layer_activation_functions[-1]==self._identity:
                cost_function_data = np.sum(np.sum((1/2) * np.power(label -
                    self.feed_forward(feature), 2), axis=1), axis=0)
        if self.layer_activation_functions[-1]==self._softmax:
                # Model objective function -- Cross-entropy
                cost_function_data = -np.sum(np.sum(label*np.log(self.
                    feed_forward(feature)),axis=1),axis=0)
        else:
                print('Only softmax supported for final layer')

        # Add regularization here!
        # TODO
        cost_function_reg = 0
        return cost_function_data + cost_function_reg

def _gradient_fun(self,feature,label):
```

```
# Compute the gradient via backpropagation
m = feature.shape[0]

# Initialize gradient arrays (same shape as the weights)
grads = [np.zeros_like(w) for w in self.weights]

# Compute dJ/da (aka the delta term) for the final layer.  This
    often involves
# Some algebraic simplification when cost function is selected
    judiciously, so
# this is coded by hand here.

l = self.L-1 #last layer

z = self.z_vals[l]              # Current layer out
z_previous = self.z_vals[l-1]   # Last layer out
a = self.a_vals[l]              # Current layer in
w = self.weights[l]             # Last layer weights
activation = self.layer_activation_functions[l]     #Current layer
    activation
if activation==self._softmax or activation==self._identity:
        delta_l = (z - label)                         # Current layer
            error
# Add gradient of SSE here!
else:
        print('Only softmax and identity supported for final layer')

grads[l] = np.dot(z_previous.T,delta_l)    # gradient due to data
    misfit

# Add gradient of regularization here!
model_norm_gradient = 0
grads[l] += model_norm_gradient                         # add gradient
    due to regularization

# Loop over the remaining layers
for l in range(self.L-2,0,-1):

        z_previous = self.z_vals[l-1]                       # last
            layer output
        a = self.a_vals[l]                                   # Current
            layer input

        w_next = self.weights[l+1][1:] # weights from the next layer
            , excluding bias weights
        activation = self.layer_activation_functions[l]  # Current
            layer activation

        delta_l = np.dot(delta_l,w_next.T)*activation(a,dx=1)   #
            Current layer error
        grads[l] = np.dot(z_previous.T,delta_l)  # Gradient due to
            data misfit

        # Add gradient of regularization here!
        model_norm_gradient = 0
        grads[l] += model_norm_gradient              # add gradient
            due to regularization
```

```
        return grads

@staticmethod
def _softmax(X,dx=0):
        if dx==0:
                return np.exp(X)/np.repeat(np.sum(np.exp(X),axis=1,keepdims=
                    True),X.shape[1],axis=1)
@staticmethod
def _sigmoid(X,dx=0):
        if dx==0:
                return 1./(1+np.exp(-X))
        if dx==1:
        s = 1./(1+np.exp(-X))
                return s*(1-s)

@staticmethod
def _leaky_relu(X,dx=0):
        if dx==0:
                return (X>0)*X + 0.01*(X<=0)*X
        if dx==1:
                return (X>0) + 0.01*(X<=0)

@staticmethod
def _gaussian(X,dx=0):
        if dx==0:
                return np.exp(-X**2)
        if dx==1:
                return -2*X*np.exp(-X**2)

# Add @staticmethod for identity here
@staticmethod
def _identity(X,dx=0):
        if dx == 0:
                return X
        return np.onelike(X)
```

```
import numpy as np
import matplotlib.pyplot as plt

from neural_network import Network


if __name__ == '__main__':
        n = 1
        m = 100
        N = 1
        X = np.random.rand(m, 1)
        y = np.exp(-np.sin(np.power(X, 3) * 4 * np.pi))

        X_test = np.random.rand(m, 1)
        y_test = np.exp(-np.sin(np.power(X_test, 3) * 4 * np.pi))

        nn = Network([n,20,N],[None,'sigmoid','identity'],[True,True,False],
            layer_weight_means_and_stds=[(0,0.1),(0,0.1)])

        eta = 0.001
```

```
        N_iterations = 10000

        T = y

        # Perform gradient descent
        for i in range(N_iterations):

                # For stochastic gradient descent, take random samples of X
                    and T

                # Run the features through the neural net (to compute a and
                    z)
                y_pred = nn.feed_forward(X)

                # Compute the gradient
                grad_w = nn._gradient_fun(X,T)

                # Update the neural network weight matrices
                for w,gw in zip(nn.weights,grad_w):
                        w -= eta*gw

                # Print some statistics every thousandth iteration
                if i%1000==0:
                        misclassified = sum(np.argmax(y_pred,axis=1)!=y.
                            ravel())
                        print ("Iteration: {0}, Objective Function Value:
                            {1:3f}, Misclassified: {2}".format(i,nn._J_fun(X
                            ,T), misclassified))

        # Predict the training data and classify
        y_pred = np.argmax(nn.feed_forward(X_test),axis=1)
        print ("Test data accuracy: {0:3f}".format(1-sum(y_pred!=y_test.
            ravel())/float(len(y_test))))
```

2C

```
from __future__ import division,print_function

import numpy as np

class Network(object):
"""
Neural network for softmax regression problems
"""

def __init__(self,layer_number_of_nodes,layer_activation_functions,
    layer_has_bias,layer_weight_means_and_stds=None, gama=0.1,
    regularization=None):
        self.layer_number_of_nodes = layer_number_of_nodes          # Of
            nodes in each layer
        self.layer_activation_functions = [None]
        # Add an identity activation function here!
        for act in layer_activation_functions:
```

```
            if act=='softmax':
                    self.layer_activation_functions.append(self._softmax
                        )
            if act=='sigmoid':
                    self.layer_activation_functions.append(self._sigmoid
                        )
            if act=='leaky_relu':
                    self.layer_activation_functions.append(self.
                        _leaky_relu)
            if act=='gaussian':
                    self.layer_activation_functions.append(self.
                        _gaussian)
            if act=='identity':
                    self.layer_activation_functions.append(self.
                        _identity)

    self.layer_has_bias = layer_has_bias                            #
        Whether to add a bias node to each layer
    self.L = len(self.layer_number_of_nodes)                        #
        Number of layers
    self.gama = gama

    self.weights = [np.array([])]
    self.regularization = regularization

    # Create arrays to hold the weights, which are N_l(+1) by N_(l+1)
    for i in range(self.L-1):
            # if we have a normal distribution and standard deviation,
                then generate random weights from that distribution,
            if layer_weight_means_and_stds is not None:
                    w = layer_weight_means_and_stds[i][1]*np.random.
                        randn(self.layer_number_of_nodes[i] + self.
                        layer_has_bias[i],self.layer_number_of_nodes[i
                        +1]) + layer_weight_means_and_stds[i][0]
            # Otherwise just initialize the weights to zero
            else:
                    w = np.zeros((self.layer_number_of_nodes[i] + self.
                        layer_has_bias[i],self.layer_number_of_nodes[i
                        +1]))
            self.weights.append(w)

def feed_forward(self,feature):
    # evaluate the neural network for a vector-valued input
    m = feature.shape[0]

    # Append a column of ones to the input if a bias is desired
    if self.layer_has_bias[0]:
            z = np.column_stack((np.ones((m)),feature))
    else:
            z = feature

    # Initialize lists to hold the node inputs and outputs, treating the
         input values as the output of the first node
    self.a_vals = [None]
    self.z_vals = [z]

    # Loop over the remaining layers
```

```
        for l in range(1,self.L):
                # Take the linear combination of the previous layers outputs
                    (z^(l-1)) and weights (w^(l)) to form a^(l)
                a = np.dot(self.z_vals[l-1],self.weights[l])
                # Run a through the activation function to form z^(l)
                z = self.layer_activation_functions[l](a)
                # If a bias is desired, append a column of ones to z
                if self.layer_has_bias[l]:
                        z = np.column_stack((np.ones((m)),z))
                # Store these values (for computing the gradient later)
                self.a_vals.append(a)
                self.z_vals.append(z)
        return z

def _J_fun(self,feature,label):
        # Add your sum square error evaluation here!
        if self.layer_activation_functions[-1]==self._identity:
                cost_function_data = np.sum(np.sum((1/2) * np.power(label -
                    self.feed_forward(feature), 2), axis=1), axis=0)
        if self.layer_activation_functions[-1]==self._softmax:
                # Model objective function -- Cross-entropy
                cost_function_data = -np.sum(np.sum(label*np.log(self.
                    feed_forward(feature)),axis=1),axis=0)
        else:
                print('Only softmax supported for final layer')

        # Add regularization here!
        # TODO
        cost_function_reg = 0
        if(self.regularization == 'L1'):
                for w in self.weights:
                        cost_function_reg = self.gama * np.sum(np.abs(w))
        if(self.regularization == 'L2'):
                for w in self.weights:
                        cost_function_reg = self.gama * np.sum(np.power(w,
                            2))

        return cost_function_data + cost_function_reg

def _gradient_fun(self,feature,label):
        # Compute the gradient via backpropagation
        m = feature.shape[0]

        # Initialize gradient arrays (same shape as the weights)
        grads = [np.zeros_like(w) for w in self.weights]

        # Compute dJ/da (aka the delta term) for the final layer.  This
            often involves
        # Some algebraic simplification when cost function is selected
            judiciously, so
        # this is coded by hand here.

        l = self.L-1 #last layer

        z = self.z_vals[l]                # Current layer out
        z_previous = self.z_vals[l-1]     # Last layer out
        a = self.a_vals[l]                # Current layer in
```

```
        w = self.weights[l]              # Last layer weights
        activation = self.layer_activation_functions[l]     #Current layer activation
        if activation==self._softmax or activation==self._identity:
            delta_l = (z - label)                          # Current layer error
        # Add gradient of SSE here!
        else:
            print('Only softmax and identity supported for final layer')

        grads[l] = np.dot(z_previous.T,delta_l)    # gradient due to data misfit

        # Add gradient of regularization here!
        model_norm_gradient = 0
        if(self.regularization == 'L1'):
            model_norm_gradient = self.gama * np.sign(w)
        if(self.regularization == 'L2'):
            model_norm_gradient = self.gama * w
        grads[l] += model_norm_gradient                    # add gradient due to regularization

        # Loop over the remaining layers
        for l in range(self.L-2,0,-1):

            z_previous = self.z_vals[l-1]                      # last layer output
            a = self.a_vals[l]                                 # Current layer input

            w_next = self.weights[l+1][1:] # weights from the next layer, excluding bias weights
            activation = self.layer_activation_functions[l]  # Current layer activation

            delta_l = np.dot(delta_l,w_next.T)*activation(a,dx=1)   # Current layer error
            grads[l] = np.dot(z_previous.T,delta_l)  # Gradient due to data misfit

            # Add gradient of regularization here!
            model_norm_gradient = 0
            if(self.regularization == 'L1'):
                model_norm_gradient = self.gama * np.sign(self.weights[l])
            if(self.regularization == 'L2'):
                model_norm_gradient = self.gama * self.weights[l]
            grads[l] += model_norm_gradient               # add gradient due to regularization

        return grads

    @staticmethod
    def _softmax(X,dx=0):
        if dx==0:
            return np.exp(X)/np.repeat(np.sum(np.exp(X),axis=1,keepdims=True),X.shape[1],axis=1)
```

```
@staticmethod
def _sigmoid(X,dx=0):
        if dx==0:
                return 1./(1+np.exp(-X))
        if dx==1:
                s = 1./(1+np.exp(-X))
                return s*(1-s)

@staticmethod
def _leaky_relu(X,dx=0):
        if dx==0:
                return (X>0)*X + 0.01*(X<=0)*X
        if dx==1:
                return (X>0) + 0.01*(X<=0)

@staticmethod
def _gaussian(X,dx=0):
        if dx==0:
                return np.exp(-X**2)
        if dx==1:
                return -2*X*np.exp(-X**2)

# Add @staticmethod for identity here
@staticmethod
def _identity(X,dx=0):
        if dx == 0:
                return X
        return np.onelike(X)
```

2D

I overextended my schedule this week and did not get to complete 2D or 2E.

2E*

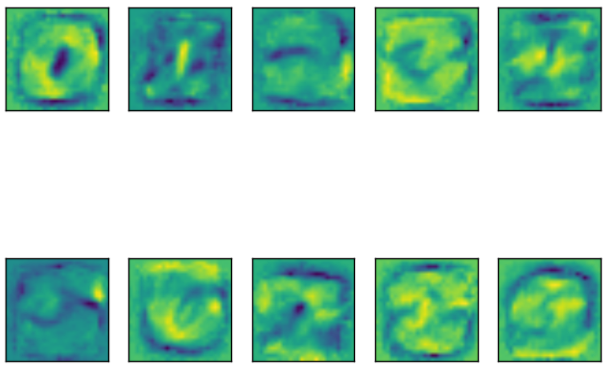
...

3 TensorFlow

3A

```
import matplotlib.pyplot as plt

...

# You can acquire the values of your layer weights with
w = sess.run(W_0)
w = w.reshape(10, 28, 28)
```

```
fig, axes = plt.subplots(2, 5, subplot_kw={'xticks': [], 'yticks': []})

for ax, x in zip(axes.flat, w):
ax.imshow(x, interpolation=None, cmap='viridis')

plt.show()
```



3B

```
import argparse
import sys
import matplotlib.pyplot as plt

from tensorflow.examples.tutorials.mnist import input_data

import tensorflow as tf


# Tensorflow has the mnist data builtin
data_dir = '/tmp/tensorflow/mnist/input_data'

# Import data
mnist = input_data.read_data_sets(data_dir,one_hot=True)

n = 784  # Number of input features
N = 10   # Number of classes

# X is the vector of inputs (though it's just a placeholder until a
    tensorflow session is started)
X = tf.placeholder("float", [None, n])
```

```
# y is the vector of targets
y = tf.placeholder("float", [None, N])

# Create the model
# layer 1 weights and biases
W_0 = tf.Variable(tf.random_normal([n,N],stddev=0.01))
b_0 = tf.Variable(tf.random_normal([N],stddev=0.01))

# Create neural network
def multilayer_perceptron(x):
        out_layer = tf.add(tf.matmul(x,W_0),b_0)
        hidden_layer = tf.layers.dense(inputs=out_layer, units=300,
            activation=tf.nn.sigmoid)
        logits = tf.layers.dense(inputs=hidden_layer, units=10)
        return logits

# define prediction object
y_pred = multilayer_perceptron(X)

# Define loss function (combined softmax and cross-entropy output)
loss_op = tf.reduce_sum(tf.nn.softmax_cross_entropy_with_logits(logits=
    y_pred, labels=y))

# Specify learning rate
learning_rate = 0.001

# Define optimization step
optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate)

# The optimization procedure (minimizing the softmax cross_entropy)
train_op = optimizer.minimize(loss_op)

# Initialize all the variables
# (tensorflow doesn't compute variable values unless run by as session)
sess = tf.InteractiveSession()
init  = tf.global_variables_initializer().run()

# Train
N_iterations = 200000
sample_size = 10

for i in range(N_iterations):

        # Pull a sample from the training set
        batch_xs, batch_ys = mnist.train.next_batch(sample_size)

        # Run tensor flow objects: train_op updates the weights, loss_op
            compute the cost function
        _,c = sess.run([train_op,loss_op], feed_dict={X: batch_xs, y:
            batch_ys})

        # Print statistics every 1000 steps
        if i%1000==0:
                # Test trained model
                pred = tf.nn.softmax(y_pred)
```

```
                correct_prediction = tf.equal(tf.argmax(pred, 1), tf.argmax(
                    y,1))
                accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.
                    float32))
                print("Accuracy:", accuracy.eval({X: mnist.test.images, y:
                    mnist.test.labels}),c)

# You can acquire the values of your layer weights with
# w = sess.run(W_0)
# w = w.reshape(10, 28, 28)

# fig, axes = plt.subplots(2, 5, subplot_kw={'xticks': [], 'yticks': []})

# for ax, x in zip(axes.flat, w):
#     ax.imshow(x, interpolation=None, cmap='viridis')

# plt.show()
```