

Module1v2

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you hit this button, it will run tests cases for the lab that aren't hidden. It is good to use the validate button before submitting the lab. Do know that the labs in the course contain hidden test cases. The validate button will not let you know whether these test cases pass. After submitting your lab, you can see more information about these hidden test cases in the Grader Output.

Cells with longer execution times will cause the validate button to time out and freeze. Please know that if you run into Validate time-outs, it will not affect the final submission grading.

Homework 1. Neural Networks

This assignment has mixed types of theoretical and code implementation questions on multilayer perceptron and neural network training.

In [1]:

```
import math
import pickle
import gzip
import numpy as np
import pandas
import matplotlib.pyplot as plt
import pytest
%matplotlib inline
```

[Peer Review] Problem 1 - Single-Layer and Multilayer Perceptron Learning

Part A : Answer this question in this week's Peer Review assignment. Consider learning the following concepts with either a single-layer or multilayer perceptron where all hidden and output neurons utilize *indicator* activation functions. For each of the following concepts, state whether the concept can be learned by a single-layer perceptron. Briefly justify your response by providing weights and biases as applicable:

- NOT x_1
- x_1 NOR x_2
- x_1 XNOR x_2 (output 1 when $x_1 = x_2$ and 0 otherwise)

Part B : Determine an architecture and specific values of the weights and biases in a single-layer or multilayer perceptron with *indicator* activation functions that can learn x_1 XNOR x_2 .
In this week's Peer Review, describe your architecture and state your weight matrices and bias vectors.

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In [2]:

```
Student's answer (Top)

# implement forward propagation for network
# show that it correctly produces the correct boolean output values
# for each of the four possible combinations of x1 and x2

# Initialize x with the 4 possible combinations of 0 and 1 to generate 4 values for y(output)

# your code here
# Activation function (indicator function)
def indicator(x):
    return 1 if x > 0 else 0

# Define weights and biases
w1 = w2 = 1
b1 = -0.5
w3 = 1
b2 = -1

# Define input values
inputs = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])

# Forward propagation
for x1, x2 in inputs:
    # Layer 1 (Input Layer)
    neuron1 = x1
    neuron2 = x2

    # Layer 2 (Hidden Layer)
    hidden_neuron1 = indicator(w1 * neuron1 + w2 * neuron2 + b1)
    hidden_neuron2 = indicator(w1 * neuron1 + w2 * neuron2 + b1)

    # Layer 3 (Output Layer)
    output = indicator(w3 * hidden_neuron1 + w3 * hidden_neuron2 + b2)

# Print the result
print(f"x1={x1}, x2={x2} => Output={output}")
```

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Grader Output

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In [3]: Student's answer (Top)

```
import math

def relu(x):
    # your code here
    return np.maximum(0, x)

def sigmoid(x):
    # your code here
    return 1 / (1 + np.exp(-x))

def soft_max(x):
    # your code here
    exp_x = np.exp(x - np.max(x)) # Subtracting max(x) for numerical stability
    return exp_x / exp_x.sum(axis=0, keepdims=True)
```

In [4]: Grade cell: cell-abe86f4d2a055610 Score: 5.26 / 5.26 (Top)

```
# Activation function tests
# PLEASE NOTE: These sample tests are only indicative and are added to help you debug your code
# and there are additional hidden test cases on which your notebook will be evaluated upon submission

# Test Relu function
assert int(relu(-6.5)) == 0, "Check relu function"

# Test Sigmoid function
assert pytest.approx(sigmoid(0.3), 0.00001) == 0.574442516811659, "Check sigmoid function"

# Test Softmax function
assert pytest.approx(soft_max([5,7]), 0.00001) == [0.11920292, 0.88079708], "Check softmax function"
```

Congratulations! All test cases in this cell passed.

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In [5]: Grade cell: cell-0193f7345d99339c Score: 26.32 / 26.32 (Top)

```
# tests relu, sigmoid, and softmax functions
Hidden Tests Redacted
```

Congratulations! All test cases in this cell passed.

PART D Implement the following Loss functions:

Formulas for activation functions

- Mean squared error
Formula: $MSE = (1/n) \cdot \sum (y_i - \hat{y}_i)^2$
- Mean absolute error
Formula: $MAE = (1/n) \cdot \sum |y_i - \hat{y}_i|$
- Hinge Loss
Formula: $L = \max(0, 1 - y_i \cdot \hat{y}_i)$

In [6]: Student's answer (Top)

```
def mean_squared_error(yhat,y):
    # your code here
    n = len(yhat)
```

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Module1v2

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In [6]:

```
def mean_squared_error(yhat,y):  
    # your code here  
    n = len(yhat)  
    return (1/n) * np.sum((yhat - y)**2)  
  
def mean_absolute_error(yhat,y):  
    # your code here  
    n = len(yhat)  
    return (1/n) * np.sum(np.abs(yhat - y))  
  
def hinge(yhat,y):  
    # your code here  
    n = len(yhat)  
    loss = np.maximum(0, 1 - yhat * y)  
    return np.mean(loss)
```

In [7]:

```
# Error function tests  
# PLEASE NOTE: These sample tests are only indicative and are added to help you debug your code  
# and there are additional hidden test cases on which your notebook will be evaluated upon submission  
  
y_true = np.array([2, 3, -0.45])  
y_pred = np.array([1.5, 3, 0.2])  
  
# Test mean squared error function  
assert pytest.approx(mean_squared_error(y_pred,y_true), 0.00001) == 0.224166666666667, "Check mean_squared_error function"
```

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In [7]:

```
return np.mean(loss)
```

In [7]:

```
# Error function tests  
# PLEASE NOTE: These sample tests are only indicative and are added to help you debug your code  
# and there are additional hidden test cases on which your notebook will be evaluated upon submission  
  
y_true = np.array([2, 3, -0.45])  
y_pred = np.array([1.5, 3, 0.2])  
  
# Test mean squared error function  
assert pytest.approx(mean_squared_error(y_pred,y_true), 0.00001) == 0.224166666666667, "Check mean_squared_error function"  
  
# Test mean absolute error function  
assert pytest.approx(mean_absolute_error(y_pred,y_true), 0.00001) == 0.3833333333333333, "Check mean_absolute_error function"  
  
# Test hinge loss function  
assert pytest.approx(hinge(y_pred,y_true), 0.00001) == 0.36333333333333334, "Check hinge loss function"
```

Congratulations! All test cases in this cell passed.

In [8]:

```
# tests mean_squared_error, mean_absolute_error, and hinge  
Hidden Tests Redacted
```

Congratulations! All test cases in this cell passed.

[Peer Review] Problem 3 - Build a feed-forward neural network

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code is indicated as "TODO" in the code. Please do not modify other parts of the code.

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In [9]: Student's answer (Top)

```
import numpy as np
from sklearn import datasets
import matplotlib.pyplot as plt
from matplotlib.colors import colorConverter, ListedColormap
%matplotlib inline

class Network:
    def __init__(self, sizes):
        """
        Initialize the neural network

        :param sizes: a list of the number of neurons in each layer
        """
        # save the number of layers in the network
        self.L = len(sizes)

        # store the list of layer sizes
        self.sizes = sizes

        # initialize the bias vectors for each hidden and output layer
        self.b = [np.random.randn(n, 1) for n in self.sizes[1:]]

        # initialize the matrices of weights for each hidden and output layer
        self.W = [np.random.randn(n, m) for (m, n) in zip(self.sizes[:-1], self.sizes[1:])]

        # initialize the derivatives of biases for backprop
        self.db = [np.zeros((n, 1)) for n in self.sizes[1:]]

        # initialize the derivatives of weights for backprop
        self.dW = [np.zeros((n, m)) for (m, n) in zip(self.sizes[:-1], self.sizes[1:])]

        # initialize the activities on each hidden and output layer
        self.z = [np.zeros((n, 1)) for n in self.sizes]

        # initialize the activations on each hidden and output layer
        self.a = [np.zeros((n, 1)) for n in self.sizes]
```

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code is indicated as "TODO" in the code. Please do not modify other parts of the code.

Grader Output

Module1v2

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```
# initialize the activities on each hidden and output layer
self.z = [np.zeros((n, 1)) for n in self.sizes]

# initialize the activations on each hidden and output layer
self.a = [np.zeros((n, 1)) for n in self.sizes]

# initialize the deltas on each hidden and output layer
self.delta = [np.zeros((n, 1)) for n in self.sizes]

def g(self, z):
    """
    sigmoid activation function

    :param z: vector of activities to apply activation to
    """
    return 1.0 / (1.0 + np.exp(-z))

def g_prime(self, z):
    """
    derivative of sigmoid activation function

    :param z: vector of activities to apply derivative of activation to
    """
    return self.g(z) * (1.0 - self.g(z))

def grad_loss(self, a, y):
    """
    evaluate gradient of cost function for squared-loss C(a,y) = (a-y)^2/2

    :param a: activations on output layer
    :param y: vector-encoded label
    """
    return (a - y)

def forward_prop(self, x):
    """
    take a feature vector and propagate it through the network

    :param x: input feature vector
    """
    if len(x.shape) == 1:
```

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```
:param a: activations on output layer
:param y: vector-encoded label
"""
return (a - y)

def forward_prop(self, x):
    """
    take a feature vector and propagate it through the network

    :param x: input feature vector
    """
    if len(x.shape) == 1:
        x = x.reshape(-1, 1)
    # TODO: Step 1. Initialize activation on the initial layer to x
    self.a[0] = x # Initialize the input layer activation with x

    # TODO: Step 2-4. Loop over layers and compute activities and activations
    # Use the Sigmoid activation function defined above
    for l in range(1, self.L):
        self.z[l] = np.dot(self.w[l-1], self.a[l-1]) + self.b[l-1]
        self.a[l] = self.g(self.z[l])

def back_prop(self, x, y):
    """
    Back propagation to get derivatives of C wrt weights and biases for given training example

    :param x: training features
    :param y: vector-encoded label
    """
    if len(y.shape) == 1:
        y = y.reshape(-1, 1)

    # TODO: step 1. forward prop training example to fill in activities and activations
    # your code here
    self.forward_prop(x)

    # TODO: step 2. compute deltas on output layer (Hint: python index numbering starts from 0 ends at N-
```

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```
# Use the Sigmoid activation function defined above
for l in range(1, self.L):
    self.z[l] = np.dot(self.w[l-1], self.a[l-1]) + self.b[l-1]
    self.a[l] = self.g(self.z[l])

def back_prop(self, x, y):
    """
    Back propagation to get derivatives of C wrt weights and biases for given training example

    :param x: training features
    :param y: vector-encoded label
    """
    if len(y.shape) == 1:
        y = y.reshape(-1, 1)

    # TODO: step 1. forward prop training example to fill in activities and activations
    # your code here
    self.forward_prop(x)

    # TODO: step 2. compute deltas on output layer (Hint: python index numbering starts from 0 ends at N-
1)

    # Correction in Instructions: From the instructions mentioned below for backward propagation,
    # Use normal product instead of dot product in Step 2 and 6
    # The derivative and gradient functions have already been implemented for you
    # your code here
    self.delta[-1] = self.grad_loss(self.a[-1], y) * self.g_prime(self.z[-1])

    # TODO: step 3-6. Loop backward through layers, backprop deltas, compute dws and dbs
    # your code here

    # Corrected code to avoid out of index range errors
    for l in range(self.L-2, -1, -1):
        self.delta[l] = np.dot(self.w[l].T, self.delta[l+1]) * self.g_prime(self.z[l])
        self.dw[l] = np.dot(self.delta[l+1], self.a[l].T)
        self.db[l] = self.delta[l+1]
```

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```
self.dw[l] = np.dot(self.delta[l+1], self.a[l].T)
self.db[l] = self.delta[l+1]

def train(self, X_train, y_train, X_valid=None, y_valid=None, eta=0.25, num_epochs=10, isPrint=True, isVisible=False):
    """
    Train the network with SGD
    :param X_train: matrix of training features
    :param y_train: matrix of vector-encoded Labels
    """
    # Initialize shuffled indices
    shuffled_inds = list(range(X_train.shape[0]))

    # Loop over training epochs (step 1.)
    for ep in range(num_epochs):
        np.random.shuffle(shuffled_inds)
        for ind in shuffled_inds:
            # back prop to get derivatives
            self.back_prop(X_train[ind], y_train[ind])
            # update all weights and biases for all layers
            for l in range(self.L - 1):
                self.w[l] -= eta * self.dw[l]
                self.b[l] -= eta * self.db[l]

def compute_loss(self, X, y):
    """
    compute average loss for given data set
    :param X: matrix of features
    :param y: matrix of vector-encoded Labels
    """
    loss = 0
    if len(X.shape) == 1:
        X = X[np.newaxis, :]
    if len(y.shape) == 1:
        y = y[np.newaxis, :]
    for x, t in zip(X, y):
        self.forward_prop(x)
        if len(t.shape) == 1:
            t = t.reshape(-1, 1)
        loss += 0.5 * np.sum((self.a[-1] - t) ** 2)
    return loss / X.shape[0]
```

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```
def compute_loss(self, X, y):
    """
    compute average loss for given data set
    :param X: matrix of features
    :param y: matrix of vector-encoded Labels
    """
    loss = 0
    if len(X.shape) == 1:
        X = X[np.newaxis, :]
    if len(y.shape) == 1:
        y = y[np.newaxis, :]
    for x, t in zip(X, y):
        self.forward_prop(x)
        if len(t.shape) == 1:
            t = t.reshape(-1, 1)
        loss += 0.5 * np.sum((self.a[-1] - t) ** 2)
    return loss / X.shape[0]

def gradient_check(self, x, y, h=1e-5):
    """
    check whether the gradient is correct for X, y
    Assuming that back_prop has finished.
    """
    for l1 in range(self.L - 1):
        oldw = self.w[l1].copy()
        oldb = self.b[l1].copy()
        for i in range(self.w[l1].shape[0]):
            for j in range(self.w[l1].shape[1]):
                self.w[l1][i, j] = oldw[i, j] + h
                lxph = self.compute_loss(x, y)
                self.w[l1][i, j] = oldw[i, j] - h
                lxmh = self.compute_loss(x, y)
                grad = (lxph - lxmh) / (2 * h)
                assert abs(self.dw[l1][i, j] - grad) < 1e-5
                self.w[l1][i, j] = oldw[i, j]
            for i in range(self.b[l1].shape[0]):
                self.b[l1][i] = oldb[i] + h
                lxph = self.compute_loss(x, y)
                self.b[l1][i] = oldb[i] - h
                lxmh = self.compute_loss(x, y)
                grad = (lxph - lxmh) / (2 * h)
                assert abs(self.db[l1][i] - grad) < 1e-5
                self.b[l1][i] = oldb[i]
```

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Grader Output

Module1v2

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6 / 6 autograded cells passed

Graded Cells

Cell 4 (cell-abe86f4d2a055610)
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Cell 5 (cell-0193f7345d99339c)
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Cell 7 (cell-d9363ea4e62e2041)
Passed | 5.26 / 5.26 points
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Cell 8 (cell-503845f9fe0eb3d2)
Passed | 52.64 / 52.64 points
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Cell 14 (cell-87b6b4d4b5259351)
Passed | 5.26 / 5.26 points
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Cell 15 (cell-ad565ceb6c1c4f33)
Passed | 5.26 / 5.26 points
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```
loss += 0.5 * np.sum((self.a[-1] - t) ** 2)
return loss / X.shape[0]

def gradient_check(self, x, y, h=1e-5):
    """
    check whether the gradient is correct for X, y

    Assuming that back_prop has finished.
    """
    for ll in range(self.L - 1):
        oldw = self.w[ll].copy()
        oldb = self.b[ll].copy()
        for i in range(self.w[ll].shape[0]):
            for j in range(self.w[ll].shape[1]):
                self.w[ll][i, j] = oldw[i, j] + h
                lxph = self.compute_loss(x, y)
                self.w[ll][i, j] = oldw[i, j] - h
                lxmh = self.compute_loss(x, y)
                grad = (lxph - lxmh) / (2 * h)
                assert abs(self.dw[ll][i, j] - grad) < 1e-5
                self.w[ll][i, j] = oldw[i, j]
        for i in range(self.b[ll].shape[0]):
            j = 0
            self.b[ll][i, j] = oldb[i, j] + h
            lxph = self.compute_loss(x, y)
            self.b[ll][i, j] = oldb[i, j] - h
            lxmh = self.compute_loss(x, y)
            grad = (lxph - lxmh) / (2 * h)
            assert abs(self.db[ll][i, j] - grad) < 1e-5
            self.b[ll][i, j] = oldb[i, j]

def pretty_pictures(self, X, y, decision_boundary=False, epoch=None):
    """
    Function to plot data and neural net decision boundary

    :param X: matrix of features
    :param y: matrix of vector-encoded labels
    :param decision_boundary: whether or not to plot decision
    :param epoch: epoch number for printing
    """
```

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Grader Output

Module1v2

100.00 / 100.00 points earned
6 / 6 autograded cells passed

Graded Cells

Cell 4 (cell-abe86f4d2a055610)
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Passed | 5.26 / 5.26 points
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Cell 15 (cell-ad565ceb6c1c4f33)
Passed | 5.26 / 5.26 points
[View feedback](#)

```
assert abs(self.db[ll][i, j] - grad) < 1e-5
self.b[ll][i, j] = oldb[i, j]

def pretty_pictures(self, X, y, decision_boundary=False, epoch=None):
    """
    Function to plot data and neural net decision boundary

    :param X: matrix of features
    :param y: matrix of vector-encoded labels
    :param decision_boundary: whether or not to plot decision
    :param epoch: epoch number for printing
    """

    mycolors = {"blue": "steelblue", "red": "#a76c6e"}
    colorlist = [c for (n,c) in mycolors.items()]
    colors = [colorlist[np.argmax(yk)] for yk in y]

    fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(8,8))

    if decision_boundary:
        xx, yy = np.meshgrid(np.linspace(-1.25,1.25,300), np.linspace(-1.25,1.25,300))
        grid = np.column_stack((xx.ravel(), yy.ravel()))
        grid_pred = np.zeros_like(grid[:,0])
        for ii in range(len(grid_pred)):
            self.forward_prop(grid[ii,:])
            grid_pred[ii] = np.argmax(self.a[-1])
        grid_pred = grid_pred.reshape(xx.shape)
        cmap = ListedColormap([
            colorConverter.to_rgba('steelblue', alpha=0.30),
            colorConverter.to_rgba('#a76c6e', alpha=0.30)])
        plt.contourf(xx, yy, grid_pred, cmap=cmap)
        if epoch is not None:
            plt.text(-1.23,1.15, "epoch = {}".format(epoch), fontsize=16)

    plt.scatter(X[:,0], X[:,1], color=colors, s=100, alpha=0.9)
    plt.axis('off')

def generate_data(N, config="checkerboard"):
    X = np.zeros((N,2))
    y = np.zeros((N,2)).astype(int)

    if config=="checkerboard":
```

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Grader Output

Module1v2

100.00 / 100.00 points earned
6 / 6 autograded cells passed

Graded Cells

Cell 4 (cell-abe86f4d2a055610)
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Passed | 5.26 / 5.26 points
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Cell 15 (cell-ad565ceb6c1c4f33)
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```
def generate_data(N, config="checkerboard"):\n    X = np.zeros((N,2))\n    y = np.zeros((N,2)).astype(int)\n\n    if config=="checkerboard":\n        nps, sqlen = N//8, 2/3\n        ctr = 0\n        for ii in range(3):\n            for jj in range(3):\n                X[ctr * nps : (ctr + 1) * nps, :] = np.column_stack(\n                    (np.random.uniform(ii * sqlen + .05 - 1, (ii + 1) * sqlen - .05 - 1, size=nps),\n                     np.random.uniform(jj * sqlen + .05 - 1, (jj + 1) * sqlen - .05 - 1, size=nps)))\n                y[ctr * nps : (ctr + 1) * nps, (3 * ii + jj) % 2] = 1\n                ctr += 1\n\n    if config=="blobs":\n        X, yflat = datasets.make_blobs(n_samples=N, centers=[[-.5,.5],[.5,-.5]],\n                                       cluster_std=[.20,.20],n_features=2)\n        for kk, yk in enumerate(yflat):\n            y[kk,:] = np.array([1,0]) if yk else np.array([0,1])\n\n    if config=="circles":\n        kk=0\n        while kk < N / 2:\n            sample = 2 * np.random.rand(2) - 1\n            if np.linalg.norm(sample) <= .45:\n                X[kk,:] = sample\n                y[kk,:] = np.array([1,0])\n                kk += 1\n        while kk < N:\n            sample = 2 * np.random.rand(2) - 1\n            dist = np.linalg.norm(sample)\n            if dist < 0.9 and dist > 0.55:\n                X[kk,:] = sample\n                y[kk,:] = np.array([0,1])\n                kk += 1\n\n    if config=="moons":\n        X, yflat = datasets.make_moons(n_samples=N, noise=.05)
```

Grader Output

Module1v2

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Graded Cells

Cell 4 (cell-abe86f4d2a055610)
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Passed | 5.26 / 5.26 points
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Cell 15 (cell-ad565ceb6c1c4f33)
Passed | 5.26 / 5.26 points
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```
X, yflat = datasets.make_blobs(n_samples=N, centers=[[-.5,.5],[.5,-.5]],\n                               cluster_std=[.20,.20],n_features=2)\nfor kk, yk in enumerate(yflat):\n    y[kk,:] = np.array([1,0]) if yk else np.array([0,1])\n\nif config=="circles":\n    kk=0\n    while kk < N / 2:\n        sample = 2 * np.random.rand(2) - 1\n        if np.linalg.norm(sample) <= .45:\n            X[kk,:] = sample\n            y[kk,:] = np.array([1,0])\n            kk += 1\n    while kk < N:\n        sample = 2 * np.random.rand(2) - 1\n        dist = np.linalg.norm(sample)\n        if dist < 0.9 and dist > 0.55:\n            X[kk,:] = sample\n            y[kk,:] = np.array([0,1])\n            kk += 1\n\nif config=="moons":\n    X, yflat = datasets.make_moons(n_samples=N, noise=.05)\n    X[:,0] = .5 * (X[:,0] - .5)\n    X[:,1] = X[:,1] - .25\n    for kk, yk in enumerate(yflat):\n        y[kk,:] = np.array([1,0]) if yk else np.array([0,1])\n\nreturn X, y\n\nfrom IPython.core.display import HTML\nHTML("""\n<style>\n.MathJax nobr>span.math>span{border-left-width:0 !important};\n</style>\n""")
```

We'll be using our network to do binary classification of two-dimensional feature vectors. Scroll down to the **Helper Functions** and examine the function `generate_data`. Then move around with the following cell to look at the random data sets available.

Module1v2

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Graded Cells

Cell 4 (cell-abe96f4d2a055610)
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Cell 5 (cell-0193f7345d99339c)
Passed | 26.32 / 26.32 points
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Passed | 5.26 / 5.26 points
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Cell 8 (cell-503845fcfe0eb3d2)
Passed | 52.64 / 52.64 points
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Cell 14 (cell-87b6bd4db5259351)
Passed | 5.26 / 5.26 points
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Cell 15 (cell-ad565ceb6c1c4f33)
Passed | 5.26 / 5.26 points
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Check that your indexing was correct by making sure that all of the activations are now non-zero (remember, we initialized them to vectors of zeros).

What other things could we check?
Answer the question about this section in this week's Peer Review assignment.

```
In [11]: # test your forward_prop function
nn = Network([2,3,2])
nn.forward_prop(X_train[0])
nn.z
```

PART B. Implementing Back Propagation

OK, now it's time to implement back propagation. Complete the function `back_prop` in the `Network` class to use a single training example to compute the derivatives of the loss function with respect to the weights and the biases. Remember, the pseudocode for back-prop was as follows:

- Forward propagate the training example \mathbf{x} , \mathbf{y}
- Compute the $\delta^L = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^L} \odot g'(\mathbf{z}^L)$
- For $\ell = L - 1, \dots, 1$:
- $\frac{\partial \mathcal{L}}{\partial W^\ell} = \delta^{\ell+1} (\mathbf{a}^\ell)^T$
- $\frac{\partial \mathcal{L}}{\partial \mathbf{b}^\ell} = \delta^{\ell+1}$
- $\delta^\ell = (W^{\ell+1})^T \delta^{\ell+1} \odot g'(\mathbf{z}^\ell)$

When you think you're done, instantiate a small `Network` and call back-prop for a single training example.

Check that it's likely working by checking that the derivative matrices `dwl` and `dbl` are nonzero.
Answer the question about this section in this week's Peer Review assignment.

```
In [12]: # test back_prop
nn = Network([2,3,2])
nn.back_prop(X_train[0,:], y_train[0,:])
print(nn.W[0])
```

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Grader Output

Module1v2

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6 / 6 autograded cells passed

Graded Cells

Cell 4 (cell-abe86f4d2a055610)

Passed | 5.26 / 5.26 points
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Cell 5 (cell-0193f7345d99339c)

Passed | 26.32 / 26.32 points
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Cell 7 (cell-d9363ea4e62e2041)

Passed | 5.26 / 5.26 points
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Cell 8 (cell-503845f9e0eb3d2)

Passed | 52.64 / 52.64 points
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Cell 14 (cell-87b6b4d4b5259351)

Passed | 5.26 / 5.26 points
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Cell 15 (cell-ad565ceb6c1c4f33)

Passed | 5.26 / 5.26 points
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$$u_i = \sum_j w_{ij} v_j + b_i$$

When you think you're done, instantiate a small `Network` and call back-prop for a single training example.

Check that it's likely working by checking that the derivative matrices `dw` and `db` are nonzero.

Answer the question about this section in this week's Peer Review assignment.

In [12]:

test back_prop
nn = Network([2,3,2])
nn.back_prop(X_train[0,:], y_train[0,:])
print(nn.W[0])

In [13]:

test gradient_check
nn.gradient_check(X_train[0, :], y_train[0, :])
print(nn.W[0])

The below test cells are to help you validate your forward and backward propagation functions better and help you identify problem areas

In [14]:

Grade cell: cell-87b6b4d4b5259351 Score: 5.26 / 5.26 (Top)

Neural Network Tests - Forward Propagation
PLEASE NOTE: These sample tests are only indicative and are added to help you debug your code

mock_X = np.array([[-0.4838731, 0.88083195], [0.93456167, -0.50316134]])
np.random.seed(42) ## DO NOT CHANGE THE SEED VALUE HERE
nn1 = Network([2,3,2])
nn1.forward_prop(mock_X)

a = np.array([[0.],[0.]])
b = np.array([[2.08587849, -0.31681043],[-0.94835809, 0.15999031],[-0.04793409, 0.92471859]])
c = np.array([[0.24259536, 0.0874714],[-2.41978734, -1.98990137]])
forward_z = [a, b, c]

for pred, true in zip(nn1.z, forward_z):
 assert pytest.approx(pred, 0.01) == true, "Check forward function"

Congratulations! All test cases in this cell passed.

Type here to search

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