Neural Network

Logistic Regression
&
Planar Data Classification with One Hidden Layer

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Logistic Regression with a Neural Network mindset

- Goal: building a logistic regression classifier to **recognize cats**
- Building general architecture of a learning algorithm:
  - Initializing parameters
  - Calculating the cost function and its gradient
  - Using an optimization algorithm (gradient descent)

1. Packages

- numpy - fundamental package for scientific computing
- H5py - interact with a dataset that is stored on an H5 file
- Matplotlib - library to plot graphs in Python

```
import numpy as np
import copy
import matplotlib.pyplot as plt
import h5py
import scipy
from PIL import Image
from scipy import ndimage
from lr_utils import load_dataset
from public_tests import *

%matplotlib inline
%load_ext autoreload
%autoreload 2
```

2. Overview of the Problem set

- Problem Statement: You are given a dataset ("data.h5") containing:
  - a **training set of m_train images** labeled as **cat (y=1) or non-cat (y=0)**
  - a **test set of m_test images** labeled as **cat** or **non-cat**
  - each image is of **shape (num_px, num_px, 3)** where 3 is for the 3 channels (RGB). Thus, each image is **square** (height = num_px) and (width = num_px).

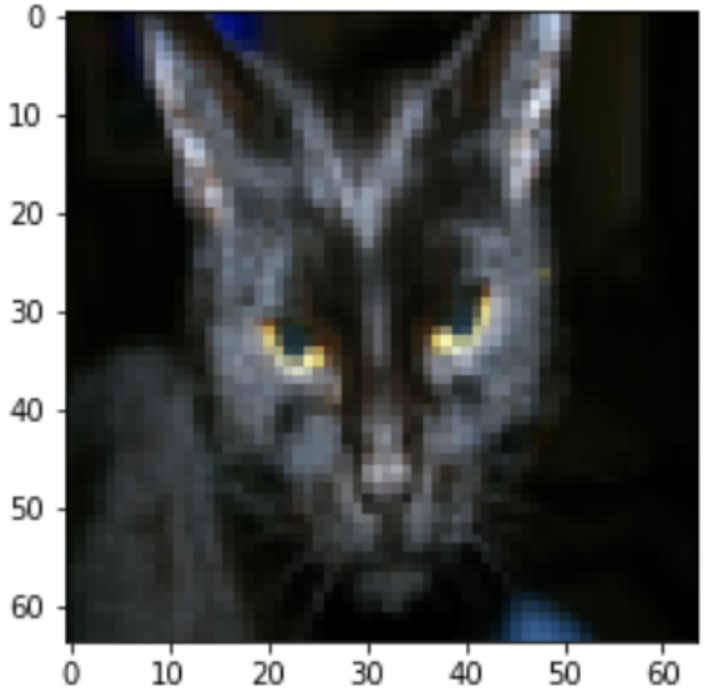
```
# Loading the data (cat/non-cat)
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes = load_dataset()
```

"_orig" at the end of image datasets -> preprocess
After preprocessing, end up with train_set_x and test_set_x

3. Visualization of Image

```
# Example of a picture
index = 25
plt.imshow(train_set_x_orig[index])
print ("y = " + str(train_set_y[:, index]) + ", it's a '" + classes[np.squeeze(train_set_y[:, index])].decode("utf-8")
```

```
y = [1], it's a 'cat' picture.
```



4. Values for m_train, m_test, num_px

Find the values for:

- `m_train` (number of training examples)
- `m_test` (number of test examples)
- `num_px` (= height = width of a training image)

Remember that `train_set_x_orig` is a numpy-array of shape (m_train, num_px, num_px, 3). For instance, you can access `m_train` by writing `train_set_x_orig.shape[0]`.

```
m_train = train_set_x_orig.shape[0]
m_test = test_set_x_orig.shape[0]
num_px = test_set_x_orig.shape[2]


print ("Number of training examples: m_train = " + str(m_train))
print ("Number of testing examples: m_test = " + str(m_test))
print ("Height/Width of each image: num_px = " + str(num_px))
print ("Each image is of size: (" + str(num_px) + ", " + str(num_px) + ", 3)")
print ("train_set_x shape: " + str(train_set_x_orig.shape))
print ("train_set_y shape: " + str(train_set_y.shape))
print ("test_set_x shape: " + str(test_set_x_orig.shape))
print ("test_set_y shape: " + str(test_set_y.shape))
```

```
Number of training examples: m_train = 209
Number of testing examples: m_test = 50
Height/Width of each image: num_px = 64
Each image is of size: (64, 64, 3)
train_set_x shape: (209, 64, 64, 3)
train_set_y shape: (1, 209)
test_set_x shape: (50, 64, 64, 3)
test_set_y shape: (1, 50)
```

5. Reshaping the training and test data sets

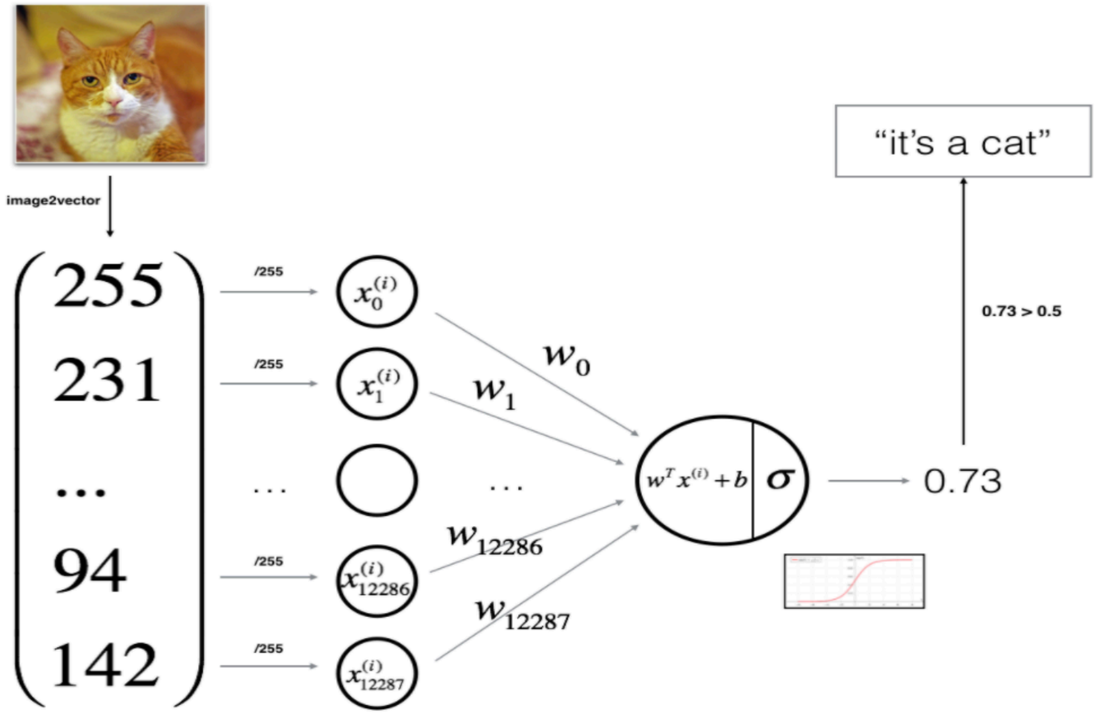
```
# Reshape the training and test examples

train_set_x_flatten = train_set_x_orig.reshape(train_set_x_orig.shape[0], -1).T
test_set_x_flatten = test_set_x_orig.reshape(test_set_x_orig.shape[0], -1).T

# Check that the first 10 pixels of the second image are in the correct place
assert np.alltrue(train_set_x_flatten[0:10, 1] == [196, 192, 190, 193, 186, 182, 188, 179, 174, 213]), "Wrong solution. Use (X.shape[0], -1).T."
assert np.alltrue(test_set_x_flatten[0:10, 1] == [115, 110, 111, 137, 129, 129, 155, 146, 145, 159]), "Wrong solution. Use (X.shape[0], -1).T."

print ("train_set_x_flatten shape: " + str(train_set_x_flatten.shape))
print ("train_set_y shape: " + str(train_set_y.shape))
print ("test_set_x_flatten shape: " + str(test_set_x_flatten.shape))
print ("test_set_y shape: " + str(test_set_y.shape))
```

```
train_set_x_flatten shape: (12288, 209)
train_set_y shape: (1, 209)
test_set_x_flatten shape: (12288, 50)
test_set_y shape: (1, 50)
```

Standardizing our dataset

```
train_set_x = train_set_x_flatten / 255.
test_set_x = test_set_x_flatten / 255.
```

General Architecture of the learning algorithm



Mathematical expression of the algorithm:

For one example $x^{(i)}$:

$$z^{(i)} = w^T x^{(i)} + b \tag{1}$$

$$\hat{y}^{(i)} = a^{(i)} = sigmoid(z^{(i)}) \tag{2}$$

$$\mathcal{L}(a^{(i)}, y^{(i)}) = -y^{(i)} \log(a^{(i)}) - (1 - y^{(i)}) \log(1 - a^{(i)}) \tag{3}$$

The cost is then computed by summing over all training examples:

$$J = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(a^{(i)}, y^{(i)}) \tag{6}$$

Key steps: In this exercise, you will carry out the following steps:

- Initialize the parameters of the model
- Learn the parameters for the model by minimizing the cost
- Use the learned parameters to make predictions (on the test set)
- Analyse the results and conclude

Loss: Calculated at every instance
Cost: Calculated as an average of loss functions

Explanation for Cost Function

Logistic Regression Cost Function

$\hat{y} = \sigma(w^T x + b)$ where $\sigma(z) = \frac{1}{1+e^{-z}}$

Interpret $\hat{y} = p(y=1|x)$

If $y=1$: $p(y|x) = \hat{y}$

If $y=0$: $p(y|x) = 1-\hat{y}$

$p(y|x) = \hat{y}^y (1-\hat{y})^{(1-y)}$

If $y=1$: $\hat{y}$ $(1-\hat{y})^0 = 1$ $p(y|x) = 1$

If $y=0$: 1 $(1-\hat{y})$ $p(y|x) = 1-\hat{y}$

∴ Correct definition

$\uparrow \log p(y|x) = \log \hat{y}^y (1-\hat{y})^{(1-y)} = y \log \hat{y} + (1-y)\log(1-\hat{y})$

$= -\mathcal{L}(\hat{y}, y) \downarrow$

Minus sign b/c usually when training an algorithm, you want to make Probability large whereas in the logistic function, minimizing the loss function.

Cost on m examples

$\log P(\text{labels in training set}) = \log \prod_{i=1}^{m} p(y^{(i)}|x^{(i)})$

Maximum Likelihood Estimation

Find the parameters that maximizes the chance of your observations and training set

Same as maximizing log of it.

$\log p(\text{labels in training set}) = \sum_{i=1}^{m} \log \underbrace{P(y^{(i)}|x^{(i)})}_{-\mathcal{L}(\hat{y}^{(i)}, y^{(i)})}$

$= -\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$

Cost: $J(w,b) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$

(minimize)

↑ Adding a scaling factor to make quantities a better scale

By minimizing the cost function $J(w,b)$, carrying out maximum likelihood estimation with the logistic regression model, under the assumption that our training examples are I.I.d. (identically independently distributed)

Cross-Entropy Loss Function

- Entropy of a random variable X is the level of uncertainty inherent in the variables possible outcome

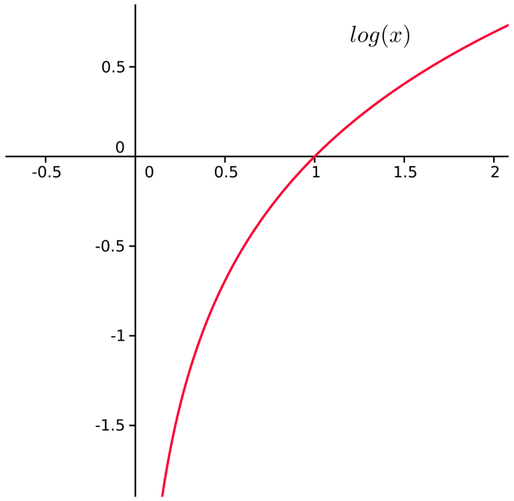
- p(x) - probability distribution and a random variable X, entropy defined:

$$H(X) = \begin{cases} -\int_x p(x) \log p(x), & \text{if } X \text{ is continous} \\ \sum_x p(x) \log p(x), & \text{if } X \text{ is discrete} \end{cases}$$

- Reason for negative sign: log(p(x)) < 0 for all p(x) in (0, 1)

- p(x) is a probability distribution and therefore the values must range between 0 and 1

- The greater the value of entropy, H(x), the greater the uncertainty for probability distribution and the smaller the value the less the uncertainty



Cross-Entropy Loss Function

- Each predicted class probability is compared to the actual class desired output 0 or 1 and a score/loss is calculated that penalizes the probability based on how far it is from the actual expected value

$$L_{\text{CE}} = -\sum_{i=1}^{n} t_i \log(p_i), \text{ for n classes,}$$

where t_i is the truth label and p_i is the Softmax probability for the i^{th} class.

Binary Cross-Entropy Loss

$$
\begin{aligned}
L &= -\sum_{i=1}^{2} t_i \log(p_i) \\
&= -\left[t \log(p) + (1-t) \log(1-p)\right]
\end{aligned}
$$

where t_i is the truth value taking a value 0 or 1 and p_i is the Softmax probability for the i^{th} class.

Binary cross-entropy is often calculated as the average cross-entropy across all data examples

$$
L = -\frac{1}{N}\left[\sum_{j=1}^{N} \left[t_j \log(p_j) + (1-t_j) \log(1-p_j)\right]\right]
$$

for N data points where t_i is the truth value taking a value 0 or 1 and p_i is the Softmax probability for the i^{th} data point.

6. Sigmoid Function

Exercise 3 - sigmoid

Using your code from "Python Basics", implement `sigmoid()`. As you've seen in the figure above, you need to compute $sigmoid(z) = \frac{1}{1+e^{-z}}$ for $z = w^T x + b$ to make predictions. Use np.exp().

```
# GRADED FUNCTION: sigmoid

def sigmoid(z):
    """
    Compute the sigmoid of z

    Arguments:
    z -- A scalar or numpy array of any size.

    Return:
    s -- sigmoid(z)
    """

    #(≈ 1 line of code)
    # s = ...
    # YOUR CODE STARTS HERE
    s = 1/(1+np.exp(-z))

    # YOUR CODE ENDS HERE

    return s
```

```
print ("sigmoid([0, 2]) = " + str(sigmoid(np.array([0,2]))))

sigmoid_test(sigmoid)
```

```
sigmoid([0, 2]) = [0.5        0.88079708]
All tests passed!
```

```
x = np.array([0.5, 0, 2.0])
output = sigmoid(x)
print(output)
```

```
[0.62245933 0.5        0.88079708]
```

7. Initializing parameters

Exercise 4 - initialize_with_zeros

Implement parameter initialization in the cell below. You have to initialize w as a vector of zeros. If you don't know what numpy function to use, look up np.zeros() in the Numpy library's documentation.

```
# GRADED FUNCTION: initialize_with_zeros

def initialize_with_zeros(dim):
    """
    This function creates a vector of zeros of shape (dim, 1) for w and initializes b to 0.

    Argument:
    dim -- size of the w vector we want (or number of parameters in this case)

    Returns:
    w -- initialized vector of shape (dim, 1)
    b -- initialized scalar (corresponds to the bias) of type float
    """

    # (≈ 2 lines of code)
    # w = ...
    # b = ...
    # YOUR CODE STARTS HERE
    w = np.zeros((dim, 1))
    b = 0.0

    # YOUR CODE ENDS HERE

    return w, b
```

<- two dimensional array with dim(dimension) number of rows and 1 column

```
dim = 2
w, b = initialize_with_zeros(dim)

assert type(b) == float
print ("w = " + str(w))
print ("b = " + str(b))

initialize_with_zeros_test(initialize_with_zeros)
```

```
w = [[0.]
 [0.]]
b = 0.0
All tests passed!
```

8. Forward and Back Propagation

Forward Propagation:

- You get X
- You compute $A = \sigma(w^T X + b) = (a^{(1)}, a^{(2)}, \ldots, a^{(m-1)}, a^{(m)})$
- You calculate the cost function: $J = -\frac{1}{m}\sum_{i=1}^{m}(y^{(i)}\log(a^{(i)}) + (1-y^{(i)})\log(1-a^{(i)}))$

Here are the two formulas you will be using:

$$\frac{\partial J}{\partial w} = \frac{1}{m}X(A-Y)^T \tag{7}$$

$$\frac{\partial J}{\partial b} = \frac{1}{m}\sum_{i=1}^{m}(a^{(i)} - y^{(i)}) \tag{8}$$

```
# GRADED FUNCTION: propagate

def propagate(w, b, X, Y):
    """
    Implement the cost function and its gradient for the propagation explained above

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of size (num_px * num_px * 3, number of examples)
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat) of size (1, number of examples

    Return:
    cost -- negative log-likelihood cost for logistic regression
    dw -- gradient of the loss with respect to w, thus same shape as w
    db -- gradient of the loss with respect to b, thus same shape as b

    Tips:
    - Write your code step by step for the propagation. np.log(), np.dot()
    """

    m = X.shape[1]

    # FORWARD PROPAGATION (FROM X TO COST)
    # compute activation
    # compute cost using np.dot. Don't use loops for the sum.
    # YOUR CODE STARTS HERE
    A = sigmoid(np.dot(w.T, X) + b)
    cost = -1/m *np.sum((Y * np.log(A))+(1-Y)*np.log(1-A))
    # YOUR CODE ENDS HERE

    # BACKWARD PROPAGATION (TO FIND GRAD)
    # YOUR CODE STARTS HERE
    dw = 1/m * np.dot(X, (A-Y).T)
    db = 1/m * np.sum(A-Y)
    # YOUR CODE ENDS HERE
    cost = np.squeeze(np.array(cost))
    grads = {"dw": dw,
             "db": db}

    return grads, cost
```

```
w =  np.array([[1.], [2.]])
b = 2.
X =np.array([[1., 2., -1.], [3., 4., -3.2]])
Y = np.array([[1, 0, 1]])
grads, cost = propagate(w, b, X, Y)

assert type(grads["dw"]) == np.ndarray
assert grads["dw"].shape == (2, 1)
assert type(grads["db"]) == np.float64


print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
print ("cost = " + str(cost))

propagate_test(propagate)
```

```
dw = [[0.99845601]
 [2.39507239]]
db = 0.001455578136784208
cost = 5.801545319394553
All tests passed!
```

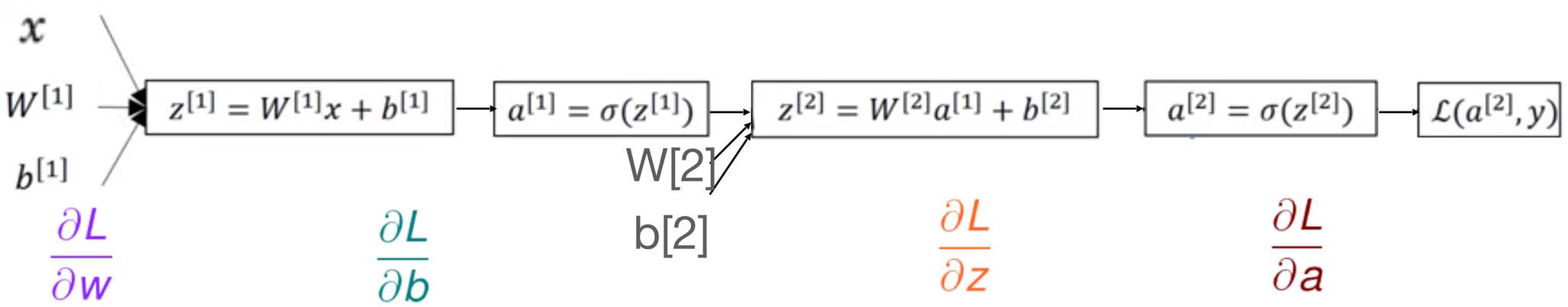
Explanation

Forward Propagation

$$Z^{[1]} = W^{[1]}X + b^{[1]}$$
$$A^{[1]} = g^{[1]}(Z^{[1]})$$
$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$$
$$A^{[2]} = g^{[2]}(Z^{[2]})$$
$$\vdots$$
$$A^{[L]} = g^{[L]}(Z^{[L]}) = \hat{Y}$$

Backward Propagation

$$dZ^{[L]} = A^{[L]} - Y$$
$$dW^{[L]} = \frac{1}{m} dZ^{[L]} A^{[L]^T}$$
$$db^{[L]} = \frac{1}{m} np.\text{sum}(\text{d}Z^{[L]}, axis = 1, keepdims = True)$$
$$dZ^{[L-1]} = W^{[L]^T} dZ^{[L]} g'^{[L]}(Z^{[L-1]})$$
$$\vdots$$
$$dZ^{[1]} = W^{[L]^T} dZ^{[2]} g'^{[1]}(Z^{[1]})$$
$$dW^{[1]} = \frac{1}{m} dZ^{[1]} A^{[1]^T}$$
$$db^{[1]} = \frac{1}{m} np.\text{sum}(\text{d}Z^{[1]}, axis = 1, keepdims = True)$$



Cross Entropy / Negative Log Likelihood

$$\mathcal{L}(a,y) = -\frac{1}{m}\left[\sum_{i=1}^{m} y\ln(a) + (1-y)\ln(1-a)\right]$$

$\frac{\partial L}{\partial a}$ $\frac{\partial L}{\partial z}$ $\frac{\partial L}{\partial w}$ $\frac{\partial L}{\partial b}$

① Derivation w.r.t activation Function $\frac{\partial L}{\partial a}$

$\frac{\partial L}{\partial a}$ $-[y\ln(a) + (1-y)\ln(1-a)]$ - Expanded

$[-y\ln(a) - (1-y)\ln(1-a)]$

differentiate $\left[\frac{-y}{\ln(a)} - (-)\frac{(1-y)}{(1-a)}\right]$ $\frac{d}{dx}[\ln g(x)] = \frac{1}{g(x)}g'(x)$

$$\frac{\partial L}{\partial a} = \left[-\frac{y}{a} + \frac{(1-y)}{(1-a)}\right]$$

② Derivative of Sigmoid

$\frac{\partial a}{\partial z}$ $\quad \text{sigmoid} = \frac{1}{1+e^{-z}} = (1+e^{-z})^{-1} = -(1+e^{-z})^{-2}\cdot[e^{-z}\cdot -1] = \frac{e^{-z}}{(1+e^{-z})^2} = \frac{1}{1+e^{-z}}\cdot\frac{1+(e^{-z})-1}{(1+e^{-z})}$

$$= \left[1 - \frac{1}{1+e^{-z}}\right]$$

$$= (1-\text{sig}(z))$$

$$= \text{sig}(z)\cdot(1-\text{sig}(z))$$

$$= a(1-a)$$

③ Derivative w.r.t linear Function $\frac{\partial L}{\partial z}$

$$\frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial z} = -\left[\frac{y}{a} - \frac{(1-y)}{(1-a)}\right]\cdot a(1-a)$$

$$= -\left[\frac{y(1-a)}{a(1-a)} - \frac{(a)(1-y)}{(a)(1-a)}\right]\cdot a(1-a)$$

$$= -\left[\frac{y(1-a)+(a)(1-y)}{a(1-a)}\right]\cdot a(1-a)$$

$$= -y(1-a) + (a)(1-y)$$

$$= -y + ya + a - ay$$

$$= -y + a$$

$$= a - y$$

④ Derivative w.r.t weights $\frac{\partial z}{\partial w}$

$w^T x + b = x$

derivative of 'z' w.r.t 'w'

⑤ Derivative w.r.t weights II $\frac{\partial L}{\partial w}$

$$\frac{\partial L}{\partial z} = \frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial z}$$

$$\frac{\partial L}{\partial z}\cdot\frac{\partial z}{\partial w} = \frac{\partial L}{\partial z}\cdot x = x(a-y)$$

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial a}\cdot\frac{\partial a}{\partial z}\cdot\frac{\partial z}{\partial w}$$ 'chain rule'

computing dw directly:

take cost function

$$-\sum[y\ln(a) + (1-y)\ln(1-a)]$$

$$\ln(1+e^{-z})^{-1}$$

$$= -\ln(1+e^{-z})$$

$$= \ln\frac{e^{-z}}{(1+e^{-z})}$$

$$= -z - \ln(1+e^{-z})$$

log of numerator

rule of logs: $\log\frac{p}{q} = \log p - \log q$

$$= \sum -y\ln(1+e^{-z}) - (1-y)(-z - \ln(1+e^{-z}))$$

$$= \sum -y\ln(1+e^{-z}) - z - \ln(1+e^{-z}) + yz + y\ln(1+e^{-z})$$

$$= -z - \ln(1+e^{-z}) + yz$$

$$= yz - [z + \ln(1+e^{-z})]$$

$$= yz - [\ln(e^z) + \ln(1+e^{-z})]$$

$$= yz - [\ln(e^z\cdot(1+e^{-z}))]$$

$$= yz - [\ln(1+e^z)]$$

$$= [yz - \ln(1+e^z)]$$

$$\frac{\partial L}{\partial w} = \frac{\partial}{\partial w}[yz - \ln(1+e^z)]$$

$$= yx - \frac{x\cdot e^{wx}}{1+e^{wx}}$$

$*z = wx + b$ ∴ taking derivative of w

$$= x\cdot\text{sig}(z)$$

$$= -[yx - x\cdot\text{sig}(z)]$$

$$= -x[y - \text{sig}(z)]$$

$$\frac{\partial L}{\partial w} = x[a-y]$$

Calculating dz directly

$[yz - \ln(1+e^z)]$

$*\ z = wx + b$

w.r.t b from both terms yz and $\ln(1+e^z)$

$$\frac{\partial L}{\partial b}y(wx+b) - \frac{\partial L}{\partial b}\ln(1+e^{wx+b})$$

$$\frac{e^{wx+b}}{1+e^{wx+b}}$$

$$= a$$

$$= [a-y]$$

⑥ Derivative w.r.t bias $\frac{\partial L}{\partial b}$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial z}\cdot\frac{\partial z}{\partial b}$$

derive $z = wx + b$ w.r.t b $= 1$

$$= a - y\cdot 1 = a - y$$

9. Optimization

```python
# GRADED FUNCTION: optimize

def optimize(w, b, X, Y, num_iterations=100, learning_rate=0.009, print_cost=False):
    """
    This function optimizes w and b by running a gradient descent algorithm

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of shape (num_px * num_px * 3, number of examples)
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat), of shape (1, number of examples)
    num_iterations -- number of iterations of the optimization loop
    learning_rate -- learning rate of the gradient descent update rule
    print_cost -- True to print the loss every 100 steps

    Returns:
    params -- dictionary containing the weights w and bias b
    grads -- dictionary containing the gradients of the weights and bias with respect to the cost function
    costs -- list of all the costs computed during the optimization, this will be used to plot the learning curve.

    Tips:
    You basically need to write down two steps and iterate through them:
        1) Calculate the cost and the gradient for the current parameters. Use propagate().
        2) Update the parameters using gradient descent rule for w and b.
    """

    w = copy.deepcopy(w)
    b = copy.deepcopy(b)

    costs = []

    for i in range(num_iterations):
        # Cost and gradient calculation
        # YOUR CODE STARTS HERE
        grads, cost = propagate(w, b, X, Y)
        # YOUR CODE ENDS HERE

        # Retrieve derivatives from grads
        dw = grads["dw"]
        db = grads["db"]

        # YOUR CODE STARTS HERE
        w = w - learning_rate * dw
        b = b - learning_rate * db
        # YOUR CODE ENDS HERE

        # Record the costs
        if i % 100 == 0:
            costs.append(cost)

            # Print the cost every 100 training iterations
            if print_cost:
                print ("Cost after iteration %i: %f" %(i, cost))

    params = {"w": w,
              "b": b}

    grads = {"dw": dw,
             "db": db}

    return params, grads, costs
```

```python
params, grads, costs = optimize(w, b, X, Y, num_iterations=100, learning_rate=0.009, print_cost=False)

print ("w = " + str(params["w"]))
print ("b = " + str(params["b"]))
print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
print("Costs = " + str(costs))

optimize_test(optimize)
```

```
w = [[0.19033591]
 [0.12259159]]
b = 1.9253598300845747
dw = [[0.67752042]
 [1.41625495]]
db = 0.21919450454067652
Costs = [array(5.80154532)]
All tests passed!
```

10. Predicting

```
# GRADED FUNCTION: predict

def predict(w, b, X):
    '''
    Predict whether the label is 0 or 1 using learned logistic regression parameters (w, b)

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of size (num_px * num_px * 3, number of examples)

    Returns:
    Y_prediction -- a numpy array (vector) containing all predictions (0/1) for the examples in X
    '''

    m = X.shape[1]
    Y_prediction = np.zeros((1, m))
    w = w.reshape(X.shape[0], 1)

    # Compute vector "A" predicting the probabilities of a cat being present in the picture
    #(≈ 1 line of code)
    # A = ...
    # YOUR CODE STARTS HERE
    A = sigmoid(np.dot(w.T, X) + b)
    # YOUR CODE ENDS HERE

    for i in range(A.shape[1]):

        # Convert probabilities A[0,i] to actual predictions p[0,i]
        #(≈ 4 lines of code)
        # if A[0, i] > ____ :
        #     Y_prediction[0,i] =
        # else:
        #     Y_prediction[0,i] =
        # YOUR CODE STARTS HERE
        if A[0, i] > 0.5 :
            Y_prediction[0,i] = 1
        else:
            Y_prediction[0,i] = 0

        # YOUR CODE ENDS HERE

    return Y_prediction
```

```
w = np.array([[0.1124579], [0.23106775]])
b = -0.3
X = np.array([[1., -1.1, -3.2],[1.2, 2., 0.1]])
print ("predictions = " + str(predict(w, b, X)))

predict_test(predict)
```

```
predictions = [[1. 1. 0.]]
All tests passed!
```

11. Merge all functions into a model

```
# GRADED FUNCTION: model

def model(X_train, Y_train, X_test, Y_test, num_iterations=2000, learning_rate=0.5, print_cost=False):
    """
    Builds the logistic regression model by calling the function you've implemented previously

    Arguments:
    X_train -- training set represented by a numpy array of shape (num_px * num_px * 3, m_train)
    Y_train -- training labels represented by a numpy array (vector) of shape (1, m_train)
    X_test -- test set represented by a numpy array of shape (num_px * num_px * 3, m_test)
    Y_test -- test labels represented by a numpy array (vector) of shape (1, m_test)
    num_iterations -- hyperparameter representing the number of iterations to optimize the parameters
    learning_rate -- hyperparameter representing the learning rate used in the update rule of optimize()
    print_cost -- Set to True to print the cost every 100 iterations

    Returns:
    d -- dictionary containing information about the model.
    """
    # (≈ 1 line of code)
    # initialize parameters with zeros
    # w, b = ...
    w, b = initialize_with_zeros(X_train.shape[0])
    #(≈ 1 line of code)
    # Gradient descent
    # parameters, grads, costs = ...
    parameters, grads, costs = optimize(w, b, X_train, Y_train, num_iterations, learning_rate, print_cost)
    # Retrieve parameters w and b from dictionary "parameters"
    # w = ...
    # b = ...
    w = parameters["w"]
    b = parameters["b"]
    # Predict test/train set examples (≈ 2 lines of code)
    # Y_prediction_test = ...
    # Y_prediction_train = ...
    Y_prediction_test = predict(w, b, X_test)
    Y_prediction_train = predict(w, b, X_train)
    # YOUR CODE STARTS HERE


    # YOUR CODE ENDS HERE

    # Print train/test Errors
    if print_cost:
        print("train accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_train - Y_train)) * 100))
        print("test accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_test - Y_test)) * 100))


    d = {"costs": costs,
         "Y_prediction_test": Y_prediction_test,
         "Y_prediction_train" : Y_prediction_train,
         "w" : w,
         "b" : b,
         "learning_rate" : learning_rate,
         "num_iterations": num_iterations}

    return d
```

```
model_test(model)
```

```
All tests passed!
```

```
logistic_regression_model = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations=2000, learning_rate=
```

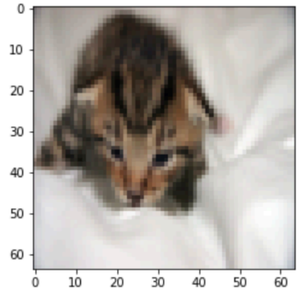
```
Cost after iteration 0: 0.693147
Cost after iteration 100: 0.584508
Cost after iteration 200: 0.466949
Cost after iteration 300: 0.376007
Cost after iteration 400: 0.331463
Cost after iteration 500: 0.303273
Cost after iteration 600: 0.279880
Cost after iteration 700: 0.260042
Cost after iteration 800: 0.242941
Cost after iteration 900: 0.228004
Cost after iteration 1000: 0.214820
Cost after iteration 1100: 0.203078
Cost after iteration 1200: 0.192544
Cost after iteration 1300: 0.183033
Cost after iteration 1400: 0.174399
Cost after iteration 1500: 0.166521
Cost after iteration 1600: 0.159305
Cost after iteration 1700: 0.152667
Cost after iteration 1800: 0.146542
Cost after iteration 1900: 0.140872
train accuracy: 99.04306220095694 %
test accuracy: 70.0 %
```

Comment: Training accuracy is close to 100%. This is a good sanity check: your model is working and has high enough capacity to fit the training data. Test accuracy is 70%. It is actually not bad for this simple model, given the small dataset we used and that logistic regression is a linear classifier. But no worries, you'll build an even better classifier next week!

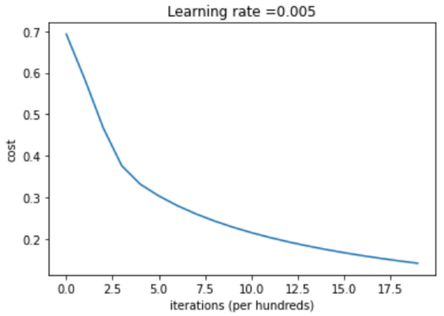
Also, you see that the model is clearly overfitting the training data. Later in this specialization you will learn how to reduce overfitting, for example by using regularization. Using the code below (and changing the `index` variable) you can look at predictions on pictures of the test set.

```
# Example of a picture that was wrongly classified.
index = 1
plt.imshow(test_set_x[:, index].reshape((num_px, num_px, 3)))
print ("y = " + str(test_set_y[0,index]) + ", you predicted that it is a \"" + classes[int(logistic_regression_model['Y
```

```
y = 1, you predicted that it is a "cat" picture.
```




```
# Plot learning curve (with costs)
costs = np.squeeze(logistic_regression_model['costs'])
plt.plot(costs)
plt.ylabel('cost')
plt.xlabel('iterations (per hundreds)')
plt.title("Learning rate =" + str(logistic_regression_model["learning_rate"]))
plt.show()
```

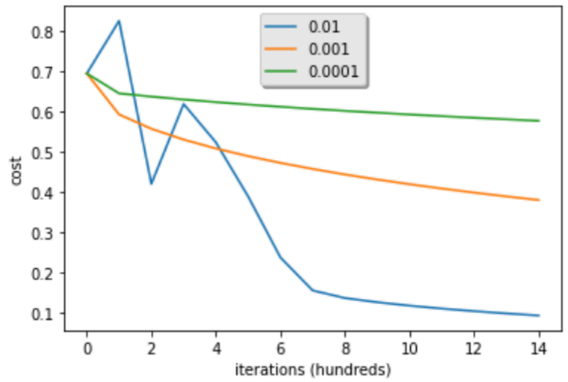


Interpretation: You can see the cost decreasing. It shows that the parameters are being learned. However, you see that you could train the model even more on the training set. Try to increase the number of iterations in the cell above and rerun the cells. You might see that the training set accuracy goes up, but the test set accuracy goes down. This is called overfitting.

13. Further analysis

```
learning_rates = [0.01, 0.001, 0.0001]
models = {}

for lr in learning_rates:
    print ("Training a model with learning rate: " + str(lr))
    models[str(lr)] = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations=1500, learning_rate=lr, pr
    print ('\n' + "-------------------------------------------------------" + '\n')

for lr in learning_rates:
    plt.plot(np.squeeze(models[str(lr)]["costs"]), label=str(models[str(lr)]["learning_rate"]))

plt.ylabel('cost')
plt.xlabel('iterations (hundreds)')

legend = plt.legend(loc='upper center', shadow=True)
frame = legend.get_frame()
frame.set_facecolor('0.90')
plt.show()
```

```
Training a model with learning rate: 0.01

-------------------------------------------------------

Training a model with learning rate: 0.001

-------------------------------------------------------

Training a model with learning rate: 0.0001

-------------------------------------------------------
```



Planar Data Classification with One Hidden Layer

- Implement a 2-class classification neural network with a single hidden layer
- Use units with a non-linear activation function, such as tanh
- Compute the cross entropy loss
- Implement forward and backward propagation

1. Packages

1 - Packages

First import all the packages that you will need during this assignment.

- numpy is the fundamental package for scientific computing with Python.
- sklearn provides simple and efficient tools for data mining and data analysis.
- matplotlib is a library for plotting graphs in Python.
- testCases provides some test examples to assess the correctness of your functions
- planar_utils provide various useful functions used in this assignment

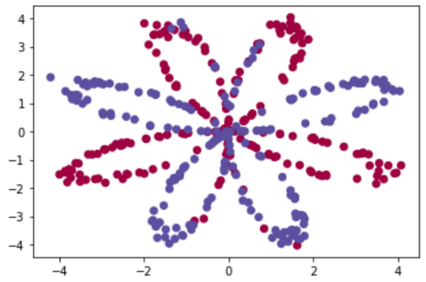
```
# Package imports
import numpy as np
import matplotlib.pyplot as plt
from testCases_v2 import *
from public_tests import *
import sklearn
import sklearn.datasets
import sklearn.linear_model
from planar_utils import plot_decision_boundary, sigmoid, load_planar_dataset, load_extra_datasets

%matplotlib inline

np.random.seed(2) # set a seed so that the results are consistent

%load_ext autoreload
%autoreload 2
```

2. Load the Dataset

```
X, Y = load_planar_dataset()
```

Visualize the dataset using matplotlib. The data looks like a "flower" with some red (label y=0) and some blue (y=1) points. Your goal is to build a model to fit this data. In other words, we want the classifier to define regions as either red or blue.

```
# Visualize the data:
plt.scatter(X[0, :], X[1, :], c=Y, s=40, cmap=plt.cm.Spectral);
```



You have:

- a numpy-array (matrix) X that contains your features (x1, x2)
- a numpy-array (vector) Y that contains your labels (red:0, blue:1).

First, get a better sense of what your data is like.

Exercise 1

How many training examples do you have? In addition, what is the `shape` of the variables `X` and `Y`?

Hint: How do you get the shape of a numpy array? (help)

```
# (≈ 3 lines of code)
# shape_X = ...
# shape_Y = ...
# training set size
# m = ...
# YOUR CODE STARTS HERE
shape_X = X.shape
shape_Y = Y.shape
m = shape_X[1]

# YOUR CODE ENDS HERE

print ('The shape of X is: ' + str(shape_X))
print ('The shape of Y is: ' + str(shape_Y))
print ('I have m = %d training examples!' % (m))
```

```
The shape of X is: (2, 400)
The shape of Y is: (1, 400)
I have m = 400 training examples!
```

3. Simple Logistic Regression

3 - Simple Logistic Regression

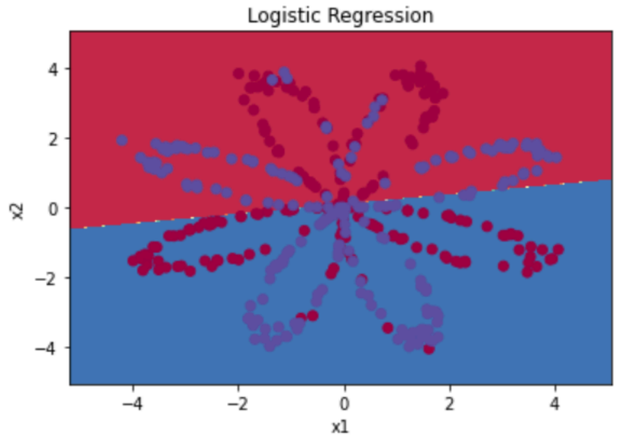
Before building a full neural network, let's check how logistic regression performs on this problem. You can use sklearn's built-in functions for this. Run the code below to train a logistic regression classifier on the dataset.

```
# Train the logistic regression classifier
clf = sklearn.linear_model.LogisticRegressionCV();
clf.fit(X.T, Y.T);
```

You can now plot the decision boundary of these models! Run the code below.

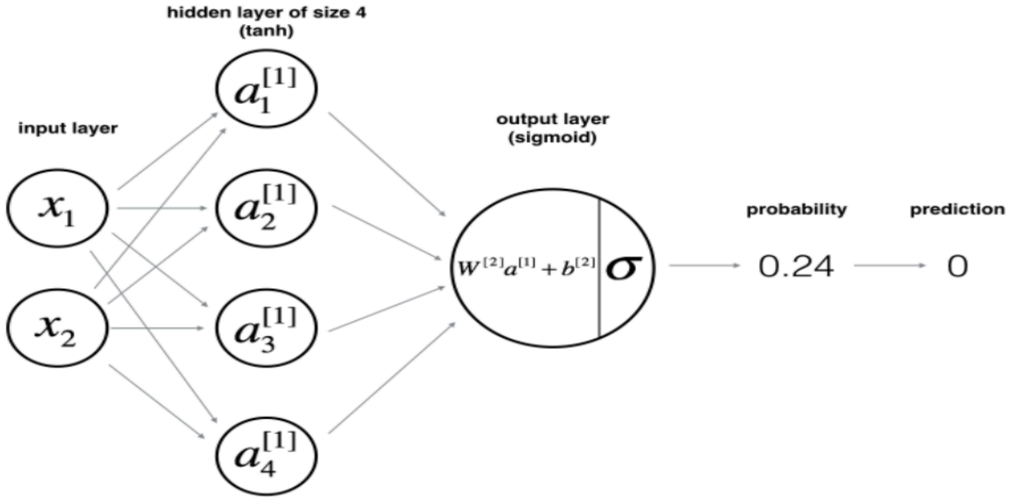
```
# Plot the decision boundary for logistic regression
plot_decision_boundary(lambda x: clf.predict(x), X, Y)
plt.title("Logistic Regression")

# Print accuracy
LR_predictions = clf.predict(X.T)
print ('Accuracy of logistic regression: %d ' % float((np.dot(Y,LR_predictions) + np.dot(1-Y,1-LR_predictions))/float(Y
       '% ' + "(percentage of correctly labelled datapoints)")
```

```
Accuracy of logistic regression: 47 % (percentage of correctly labelled datapoints)
```



4. Neural Network model

The model:



Mathematically:

For one example $x^{(i)}$:

$$z^{[1](i)} = W^{[1]}x^{(i)} + b^{[1]} \tag{1}$$
$$a^{[1](i)} = \tanh(z^{[1](i)}) \tag{2}$$
$$z^{[2](i)} = W^{[2]}a^{[1](i)} + b^{[2]} \tag{3}$$
$$\hat{y}^{(i)} = a^{[2](i)} = \sigma(z^{[2](i)}) \tag{4}$$
$$y^{(i)}_{prediction} = \begin{cases} 1 & \text{if } a^{[2](i)} > 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Given the predictions on all the examples, you can also compute the cost J as follows:

$$J = -\frac{1}{m}\sum_{i=0}^{m}\left(y^{(i)}\log\left(a^{[2](i)}\right) + (1-y^{(i)})\log\left(1-a^{[2](i)}\right)\right) \tag{6}$$

4.1 Defining the neural network structure - layer sizes

Exercise 2 - layer_sizes

Define three variables:

- n_x: the size of the input layer
- n_h: the size of the hidden layer (set this to 4)
- n_y: the size of the output layer

Hint: Use shapes of X and Y to find n_x and n_y. Also, hard code the hidden layer size to be 4.

```
# GRADED FUNCTION: layer_sizes

def layer_sizes(X, Y):
    """
    Arguments:
    X -- input dataset of shape (input size, number of examples)
    Y -- labels of shape (output size, number of examples)

    Returns:
    n_x -- the size of the input layer
    n_h -- the size of the hidden layer
    n_y -- the size of the output layer
    """
    # YOUR CODE STARTS HERE
    n_x = X.shape[0]
    n_h = 4
    n_y = Y.shape[0]
    # YOUR CODE ENDS HERE
    return (n_x, n_h, n_y)
```

```
t_X, t_Y = layer_sizes_test_case()
(n_x, n_h, n_y) = layer_sizes(t_X, t_Y)
print("The size of the input layer is: n_x = " + str(n_x))
print("The size of the hidden layer is: n_h = " + str(n_h))
print("The size of the output layer is: n_y = " + str(n_y))

layer_sizes_test(layer_sizes)
```

```
The size of the input layer is: n_x = 5
The size of the hidden layer is: n_h = 4
The size of the output layer is: n_y = 2
 All tests passed.
```

4.2 Initialize parameters

```python
# GRADED FUNCTION: initialize_parameters

def initialize_parameters(n_x, n_h, n_y):
    """
    Argument:
    n_x -- size of the input layer
    n_h -- size of the hidden layer
    n_y -- size of the output layer

    Returns:
    params -- python dictionary containing your parameters:
                    W1 -- weight matrix of shape (n_h, n_x)
                    b1 -- bias vector of shape (n_h, 1)
                    W2 -- weight matrix of shape (n_y, n_h)
                    b2 -- bias vector of shape (n_y, 1)
    """

    np.random.seed(2) # we set up a seed so that your output matches ours although the initialization is random.

    #(≈ 4 lines of code)
    # W1 = ...
    # b1 = ...
    # W2 = ...
    # b2 = ...
    # YOUR CODE STARTS HERE
    W1 = np.random.randn(n_h, n_x) * 0.01
    b1 = np.zeros(shape=(n_h, 1))
    W2 = np.random.randn(n_y, n_h) * 0.01
    b2 = np.zeros(shape=(n_y, 1))
    # YOUR CODE ENDS HERE

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return parameters
```

```python
n_x, n_h, n_y = initialize_parameters_test_case()
parameters = initialize_parameters(n_x, n_h, n_y)

print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))

initialize_parameters_test(initialize_parameters)
```

```
W1 = [[-0.00416758 -0.00056267]
 [-0.02136196  0.01640271]
 [-0.01793436 -0.00841747]
 [ 0.00502881 -0.01245288]]
b1 = [[0.]
 [0.]
 [0.]
 [0.]]
W2 = [[-0.01057952 -0.00909008  0.00551454  0.02292208]]
b2 = [[0.]]
 All tests passed.
```

4.3 Forward Propagation

Exercise 4 - forward_propagation

Implement `forward_propagation()` using the following equations:

$$Z^{[1]} = W^{[1]} X + b^{[1]} \tag{1}$$
$$A^{[1]} = \tanh(Z^{[1]}) \tag{2}$$
$$Z^{[2]} = W^{[2]} A^{[1]} + b^{[2]} \tag{3}$$
$$\hat{Y} = A^{[2]} = \sigma(Z^{[2]}) \tag{4}$$

```
# GRADED FUNCTION:forward_propagation

def forward_propagation(X, parameters):
    """
    Argument:
    X -- input data of size (n_x, m)
    parameters -- python dictionary containing your parameters (output of initialization function)

    Returns:
    A2 -- The sigmoid output of the second activation
    cache -- a dictionary containing "Z1", "A1", "Z2" and "A2"
    """
    # Retrieve each parameter from the dictionary "parameters"
    # YOUR CODE STARTS HERE
    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']

    # YOUR CODE ENDS HERE

    # Implement Forward Propagation to calculate A2 (probabilities)
    # YOUR CODE STARTS HERE
    Z1 = np.dot(W1, X) + b1
    A1 = np.tanh(Z1)
    Z2 = np.dot(W2, A1) + b2
    A2 = sigmoid(Z2)
    # YOUR CODE ENDS HERE

    assert(A2.shape == (1, X.shape[1]))

    cache = {"Z1": Z1,
             "A1": A1,
             "Z2": Z2,
             "A2": A2}

    return A2, cache
```

```
t_X, parameters = forward_propagation_test_case()
A2, cache = forward_propagation(t_X, parameters)
print("A2 = " + str(A2))

forward_propagation_test(forward_propagation)
```

```
A2 = [[0.21292656 0.21274673 0.21295976]]
 All tests passed.
```

4.4 Compute the Cost

4.4 - Compute the Cost

Now that you've computed $A^{[2]}$ (in the Python variable "`A2`"), which contains $a^{[2](i)}$ for all examples, you can compute the cost function as follows:

$$J = -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\log\left(a^{[2](i)}\right) + (1-y^{(i)})\log\left(1-a^{[2](i)}\right)\right) \tag{13}$$

Exercise 5 - compute_cost

Implement `compute_cost()` to compute the value of the cost J.

```
# GRADED FUNCTION: compute_cost

def compute_cost(A2, Y):
    """
    Computes the cross-entropy cost given in equation (13)

    Arguments:
    A2 -- The sigmoid output of the second activation, of shape (1, number of examples)
    Y -- "true" labels vector of shape (1, number of examples)

    Returns:
    cost -- cross-entropy cost given equation (13)

    """

    m = Y.shape[1] # number of examples

    # Compute the cross-entropy cost
    # YOUR CODE STARTS HERE
    logprobs = np.multiply(np.log(A2),Y) + np.multiply((1-Y), np.log(1-A2))
    cost = -np.sum(logprobs)/m

    # YOUR CODE ENDS HERE

    cost = float(np.squeeze(cost))  # makes sure cost is the dimension we expect.
                                    # E.g., turns [[17]] into 17

    return cost
```

```
A2, t_Y = compute_cost_test_case()
cost = compute_cost(A2, t_Y)
print("cost = " + str(compute_cost(A2, t_Y)))

compute_cost_test(compute_cost)
```

```
cost = 0.6930587610394646
 All tests passed.
```

4.5 Implement Backpropagation

Summary of gradient descent

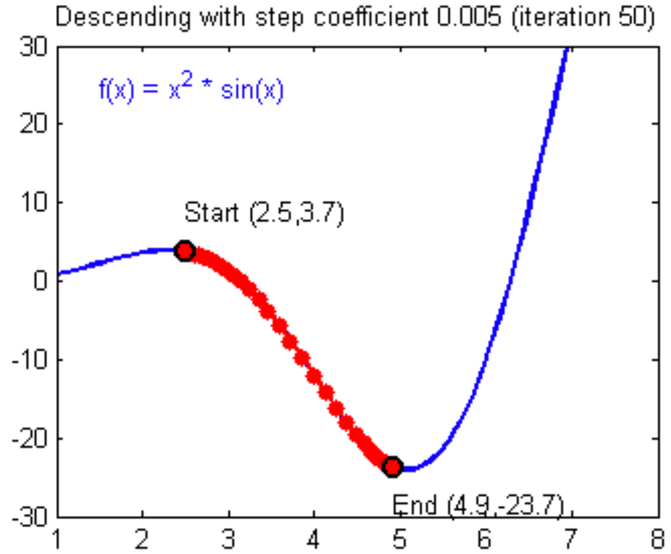
$dz^{[2]} = a^{[2]} - y$	$dZ^{[2]} = A^{[2]} - Y$
$dW^{[2]} = dz^{[2]} a^{[1]T}$	$dW^{[2]} = \frac{1}{m} dZ^{[2]} A^{[1]T}$
$db^{[2]} = dz^{[2]}$	$db^{[2]} = \frac{1}{m} np.sum(dZ^{[2]}, axis = 1, keepdims = True)$
$dz^{[1]} = W^{[2]T} dz^{[2]} * g^{[1]\prime}(z^{[1]})$	$dZ^{[1]} = W^{[2]T} dZ^{[2]} * g^{[1]\prime}(Z^{[1]})$
$dW^{[1]} = dz^{[1]} x^T$	$dW^{[1]} = \frac{1}{m} dZ^{[1]} X^T$
$db^{[1]} = dz^{[1]}$	$db^{[1]} = \frac{1}{m} np.sum(dZ^{[1]}, axis = 1, keepdims = True)$

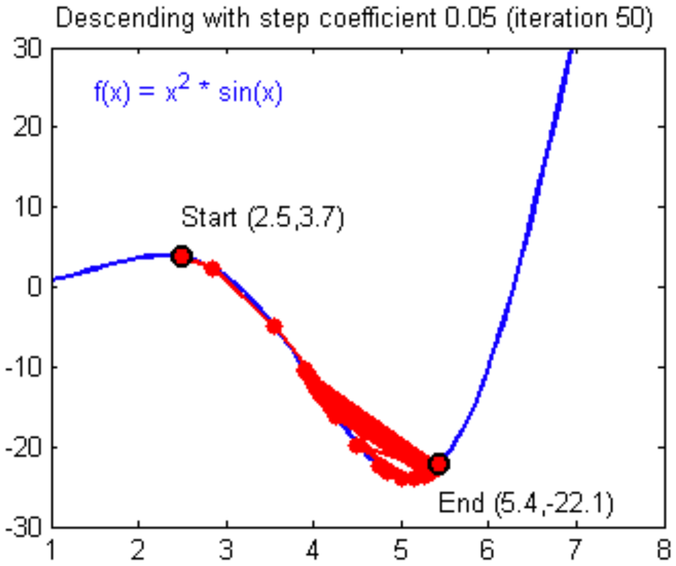
```
parameters, cache, t_X, t_Y = backward_propagation_test_case()

grads = backward_propagation(parameters, cache, t_X, t_Y)
print ("dW1 = "+ str(grads["dW1"]))
print ("db1 = "+ str(grads["db1"]))
print ("dW2 = "+ str(grads["dW2"]))
print ("db2 = "+ str(grads["db2"]))

backward_propagation_test(backward_propagation)
```

```
dW1 = [[ 0.00301023 -0.00747267]
 [ 0.00257968 -0.00641288]
 [-0.00156892  0.003893  ]
 [-0.00652037  0.01618243]]
db1 = [[ 0.00176201]
 [ 0.00150995]
 [-0.00091736]
 [-0.00381422]]
dW2 = [[ 0.00078841  0.01765429 -0.00084166 -0.01022527]]
db2 = [[-0.16655712]]
 All tests passed.
```

```
# GRADED FUNCTION: backward_propagation

def backward_propagation(parameters, cache, X, Y):
    """
    Implement the backward propagation using the instructions above.

    Arguments:
    parameters -- python dictionary containing our parameters
    cache -- a dictionary containing "Z1", "A1", "Z2" and "A2".
    X -- input data of shape (2, number of examples)
    Y -- "true" labels vector of shape (1, number of examples)

    Returns:
    grads -- python dictionary containing your gradients with respect to different parameters
    """
    m = X.shape[1]

    # First, retrieve W1 and W2 from the dictionary "parameters".
    # YOUR CODE STARTS HERE
    W1 = parameters['W1']
    W2 = parameters['W2']
    # YOUR CODE ENDS HERE

    # Retrieve also A1 and A2 from dictionary "cache".
    # YOUR CODE STARTS HERE
    A1 = cache['A1']
    A2 = cache['A2']

    # YOUR CODE ENDS HERE

    # Backward propagation: calculate dW1, db1, dW2, db2.
    # YOUR CODE STARTS HERE
    dZ2 = A2 - Y
    dW2 = np.dot(dZ2, A1.T) * (1/m)
    db2 = np.sum(dZ2, axis = 1, keepdims = True) * (1/m)
    dZ1 = np.multiply(np.dot(W2.T, dZ2), 1-np.power(A1, 2))
    dW1 = np.dot(dZ1, X.T)*(1/m)
    db1 = np.sum(dZ1, axis = 1, keepdims = True) * (1/m)
    # YOUR CODE ENDS HERE

    grads = {"dW1": dW1,
             "db1": db1,
             "dW2": dW2,
             "db2": db2}

    return grads
```

4.6 Update Parameters






```python
# GRADED FUNCTION: update_parameters

def update_parameters(parameters, grads, learning_rate = 1.2):
    """
    Updates parameters using the gradient descent update rule given above

    Arguments:
    parameters -- python dictionary containing your parameters
    grads -- python dictionary containing your gradients

    Returns:
    parameters -- python dictionary containing your updated parameters
    """
    # Retrieve each parameter from the dictionary "parameters"
    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']
    # Retrieve each gradient from the dictionary "grads"
    dW1 = grads['dW1']
    db1 = grads['db1']
    dW2 = grads['dW2']
    db2 = grads['db2']
    # Update rule for each parameter
    W1 = W1 - learning_rate * dW1
    b1 = b1 - learning_rate * db1
    W2 = W2 - learning_rate * dW2
    b2 = b2 - learning_rate * db2

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return parameters
```

```python
parameters, grads = update_parameters_test_case()
parameters = update_parameters(parameters, grads)

print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))

update_parameters_test(update_parameters)
```

```
W1 = [[-0.00643025  0.01936718]
 [-0.02410458  0.03978052]
 [-0.01653973 -0.02096177]
 [ 0.01046864 -0.05990141]]
b1 = [[-1.02420756e-06]
 [ 1.27373948e-05]
 [ 8.32996807e-07]
 [-3.20136836e-06]]
W2 = [[-0.01041081 -0.04463285  0.01758031  0.04747113]]
b2 = [[0.00010457]]
 All tests passed.
```

4.7 Integration

```python
# GRADED FUNCTION: nn_model

def nn_model(X, Y, n_h, num_iterations = 10000, print_cost=False):
    """
    Arguments:
    X -- dataset of shape (2, number of examples)
    Y -- labels of shape (1, number of examples)
    n_h -- size of the hidden layer
    num_iterations -- Number of iterations in gradient descent loop
    print_cost -- if True, print the cost every 1000 iterations

    Returns:
    parameters -- parameters learnt by the model. They can then be used to predict.
    """

    np.random.seed(3)
    n_x = layer_sizes(X, Y)[0]
    n_y = layer_sizes(X, Y)[2]

    # Initialize parameters
    parameters = initialize_parameters(n_x, n_h, n_y)

    # Loop (gradient descent)
    for i in range(0, num_iterations):
        A2, cache = forward_propagation(X, parameters)

        cost = compute_cost(A2, Y)

        grads = backward_propagation(parameters, cache, X, Y)

        parameters = update_parameters(parameters, grads)

        # Print the cost every 1000 iterations
        if print_cost and i % 1000 == 0:
            print ("Cost after iteration %i: %f" %(i, cost))

    return parameters
```

```python
t_X, t_Y = nn_model_test_case()
parameters = nn_model(t_X, t_Y, 4, num_iterations=10000, print_cost=True)

print("W1 = " + str(parameters["W1"]))
print("b1 = " + str(parameters["b1"]))
print("W2 = " + str(parameters["W2"]))
print("b2 = " + str(parameters["b2"]))

nn_model_test(nn_model)
```

```
Cost after iteration 0: 0.692739
Cost after iteration 1000: 0.000218
Cost after iteration 2000: 0.000107
Cost after iteration 3000: 0.000071
Cost after iteration 4000: 0.000053
Cost after iteration 5000: 0.000042
Cost after iteration 6000: 0.000035
Cost after iteration 7000: 0.000030
Cost after iteration 8000: 0.000026
Cost after iteration 9000: 0.000023
W1 = [[-0.65848169  1.21866811]
 [-0.76204273  1.39377573]
 [ 0.5792005  -1.10397703]
 [ 0.76773391 -1.41477129]]
b1 = [[ 0.287592  ]
 [ 0.3511264 ]
 [-0.2431246 ]
 [-0.35772805]]
W2 = [[-2.45566237 -3.27042274  2.00784958  3.36773273]]
b2 = [[0.20459656]]
 All tests passed.
```

5.1 Test the Model - Predict

Exercise 9 - predict

Predict with your model by building `predict()`. Use forward propagation to predict results.

Reminder: predictions = $y_{prediction} = \mathbb{1}\{\text{activation} > 0.5\} = \begin{cases} 1 & \text{if } activation > 0.5 \\ 0 & \text{otherwise} \end{cases}$

As an example, if you would like to set the entries of a matrix X to 0 and 1 based on a threshold you would do: `X_new = (X > threshold)`

```
# GRADED FUNCTION: predict

def predict(parameters, X):
    """
    Using the learned parameters, predicts a class for each example in X

    Arguments:
    parameters -- python dictionary containing your parameters
    X -- input data of size (n_x, m)

    Returns
    predictions -- vector of predictions of our model (red: 0 / blue: 1)
    """

    # Computes probabilities using forward propagation, and classifies to 0/1 using 0.5 as the threshold.
    #(≈ 2 lines of code)
    # A2, cache = ...
    # predictions = ...
    # YOUR CODE STARTS HERE
    A2, cache = forward_propagation(X, parameters)
    predictions = A2 > 0.5

    # YOUR CODE ENDS HERE

    return predictions
```

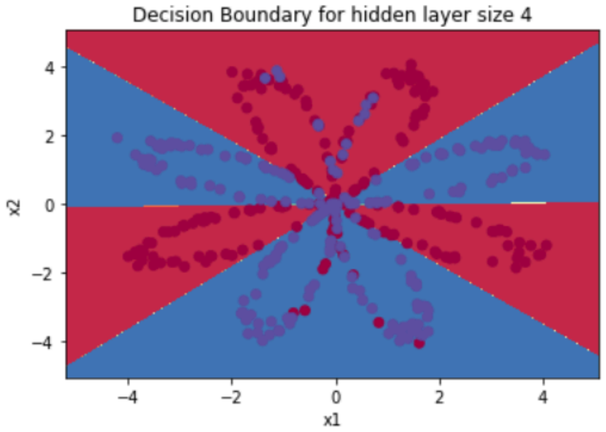
```
parameters, t_X = predict_test_case()

predictions = predict(parameters, t_X)
print("Predictions: " + str(predictions))

predict_test(predict)
```

```
Predictions: [[ True False  True]]
 All tests passed.
```

5.2 Test the Model on the Planar Dataset

```
# Build a model with a n_h-dimensional hidden layer
parameters = nn_model(X, Y, n_h = 4, num_iterations = 10000, print_cost=True)

# Plot the decision boundary
plot_decision_boundary(lambda x: predict(parameters, x.T), X, Y)
plt.title("Decision Boundary for hidden layer size " + str(4))
```

```
Cost after iteration 0: 0.693048
Cost after iteration 1000: 0.288083
Cost after iteration 2000: 0.254385
Cost after iteration 3000: 0.233864
Cost after iteration 4000: 0.226792
Cost after iteration 5000: 0.222644
Cost after iteration 6000: 0.219731
Cost after iteration 7000: 0.217504
Cost after iteration 8000: 0.219430
Cost after iteration 9000: 0.218551

Text(0.5, 1.0, 'Decision Boundary for hidden layer size 4')
```



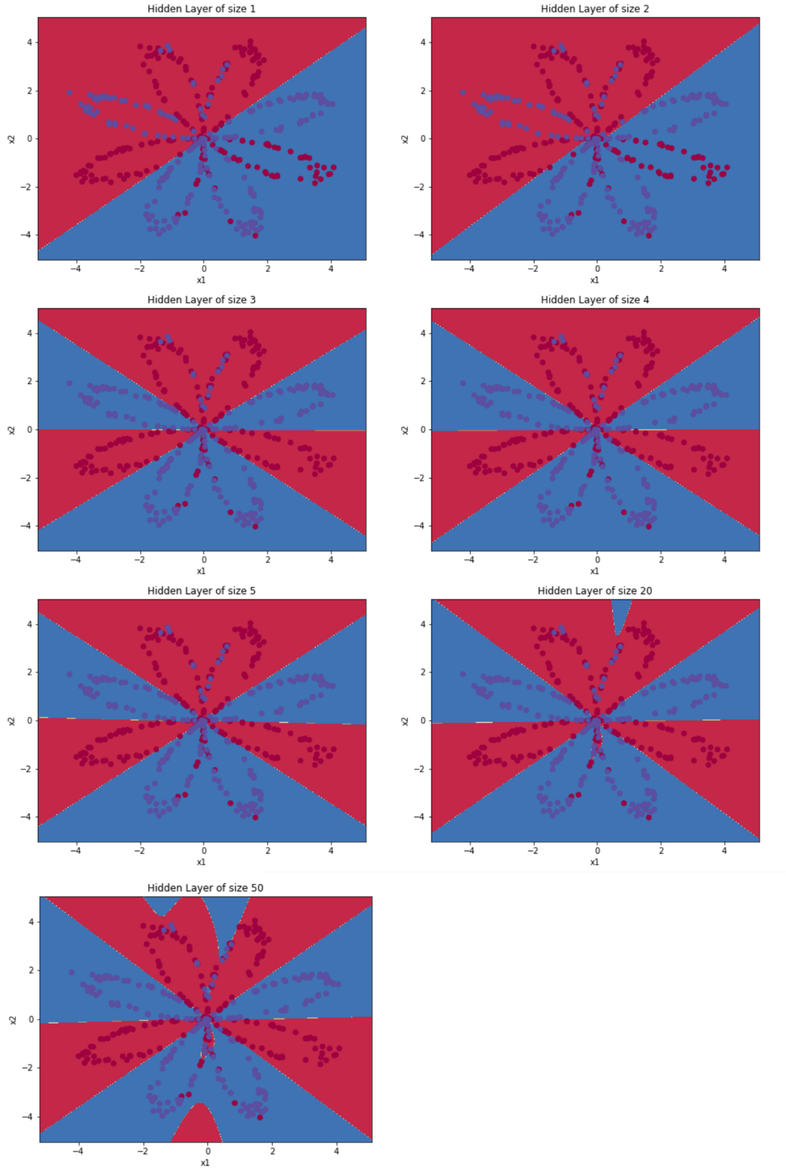

```
# Print accuracy
predictions = predict(parameters, X)
print ('Accuracy: %d' % float((np.dot(Y, predictions.T) + np.dot(1 - Y, 1 - predictions.T)) / float(Y.size) * 100) + '%
```

```
Accuracy: 90%
```

6. Tuning hidden layer size

```
# This may take about 2 minutes to run

plt.figure(figsize=(16, 32))
hidden_layer_sizes = [1, 2, 3, 4, 5, 20, 50]
for i, n_h in enumerate(hidden_layer_sizes):
    plt.subplot(5, 2, i+1)
    plt.title('Hidden Layer of size %d' % n_h)
    parameters = nn_model(X, Y, n_h, num_iterations = 5000)
    plot_decision_boundary(lambda x: predict(parameters, x.T), X, Y)
    predictions = predict(parameters, X)
    accuracy = float((np.dot(Y,predictions.T) + np.dot(1 - Y, 1 - predictions.T)) / float(Y.size)*100)
    print ("Accuracy for {} hidden units: {} %".format(n_h, accuracy))
```

```
Accuracy for 1 hidden units: 67.5 %
Accuracy for 2 hidden units: 67.25 %
Accuracy for 3 hidden units: 90.75 %
Accuracy for 4 hidden units: 90.5 %
Accuracy for 5 hidden units: 91.25 %
Accuracy for 20 hidden units: 90.0 %
Accuracy for 50 hidden units: 90.25 %
```



7. Performance on other datasets

```
# Datasets
noisy_circles, noisy_moons, blobs, gaussian_quantiles, no_structure = load_extra_datasets()

datasets = {"noisy_circles": noisy_circles,
            "noisy_moons": noisy_moons,
            "blobs": blobs,
            "gaussian_quantiles": gaussian_quantiles}

### START CODE HERE ### (choose your dataset)
dataset = "noisy_moons"
### END CODE HERE ###

X, Y = datasets[dataset]
X, Y = X.T, Y.reshape(1, Y.shape[0])

# make blobs binary
if dataset == "blobs":
    Y = Y%2

# Visualize the data
plt.scatter(X[0, :], X[1, :], c=Y, s=40, cmap=plt.cm.Spectral);
```