Python Basics with Numpy (optional assignment)

Welcome to your first assignment. This exercise gives you a brief introduction to Python. Even if you've used Python before, this will help familiarize you with the functions we'll need.

Instructions:

- You will be using Python 3.
- Avoid using for-loops and while-loops, unless you are explicitly told to do so.
- After coding your function, run the cell right below it to check if your result is correct.

After this assignment you will:

- Be able to use iPython Notebooks
- Be able to use numpy functions and numpy matrix/vector operations
- Understand the concept of "broadcasting"
- Be able to vectorize code

Let's get started!

Important Note on Submission to the AutoGrader

Before submitting your assignment to the AutoGrader, please make sure you are not doing the following:

1. You have not added any *extra* `print` statement(s) in the assignment.
2. You have not added any *extra* code cell(s) in the assignment.
3. You have not changed any of the function parameters.
4. You are not using any global variables inside your graded exercises. Unless specifically instructed to do so, please refrain from it and use the local variables instead.
5. You are not changing the assignment code where it is not required, like creating *extra* variables.

If you do any of the following, you will get something like, `Grader Error: Grader feedback not found` (or similarly unexpected) error upon submitting your assignment. Before asking for help/debugging the errors in your assignment, check for these first. If this is the case, and you don't remember the changes you have made, you can get a fresh copy of the assignment by following these [instructions (https://www.coursera.org/learn/neural-networks-deep-learning/supplement/iLwon/h-ow-to-refresh-your-workspace)](https://www.coursera.org/learn/neural-networks-deep-learning/supplement/iLwon/h-ow-to-refresh-your-workspace).

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About iPython Notebooks

iPython Notebooks are interactive coding environments embedded in a webpage. You will be using iPython notebooks in this class. You only need to write code between the # your code here comment. After writing your code, you can run the cell by either pressing "SHIFT"+"ENTER" or by clicking on "Run Cell" (denoted by a play symbol) in the upper bar of the notebook.

We will often specify "(≈ X lines of code)" in the comments to tell you about how much code you need to write. It is just a rough estimate, so don't feel bad if your code is longer or shorter.

```
In [ ]: ### v1.2
```

Exercise 1

Set test to "Hello World" in the cell below to print "Hello World" and run the two cells below.

```
In [1]: # (≈ 1 line of code)
        # test =
        # YOUR CODE STARTS HERE
        test = "Hello World"

        # YOUR CODE ENDS HERE
```

```
In [2]: print ("test: " + test)
```

```
test: Hello World
```

Expected output: test: Hello World

What you need to remember :

- Run your cells using SHIFT+ENTER (or "Run cell")
- Write code in the designated areas using Python 3 only
- Do not modify the code outside of the designated areas

1 - Building basic functions with numpy

Numpy is the main package for scientific computing in Python. It is maintained by a large community ([www.numpy.org (http://www.numpy.org)](http://www.numpy.org)). In this exercise you will learn several key numpy functions such as `np.exp`, `np.log`, and `np.reshape`. You will need to know how to use these functions for future assignments.

1.1 - sigmoid function, np.exp()

Before using `np.exp()`, you will use `math.exp()` to implement the sigmoid function. You will then see why `np.exp()` is preferable to `math.exp()`.

Exercise 2 - basic_sigmoid

Build a function that returns the sigmoid of a real number x. Use `math.exp(x)` for the exponential function.

Reminder: $sigmoid(x) = \dfrac{1}{1+e^{-x}}$ is sometimes also known as the logistic function. It is a non-linear function used not only in Machine Learning (Logistic Regression), but also in Deep Learning.
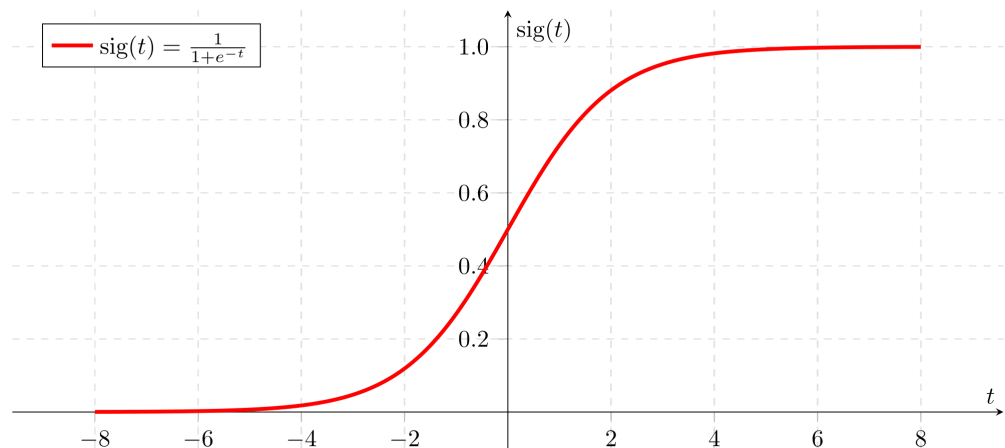
To refer to a function belonging to a specific package you could call it using `package_name.function()`. Run the code below to see an example with `math.exp()`.

```python
In [3]:  import math
         from public_tests import *

         # GRADED FUNCTION: basic_sigmoid
         def basic_sigmoid(x):
             """
             Compute sigmoid of x.

             Arguments:
             x -- A scalar

             Return:
             s -- sigmoid(x)
             """
             # YOUR CODE STARTS HERE
             s = 1 / (1 + math.exp(-x))
             # YOUR CODE ENDS HERE
             return s

         print("basic_sigmoid(1) = " + str(basic_sigmoid(1)))
         basic_sigmoid_test(basic_sigmoid)
```

```
basic_sigmoid(1) = 0.7310585786300049
 All tests passed.
```

```python
In [4]:  print("basic_sigmoid(1) = " + str(basic_sigmoid(1)))

         basic_sigmoid_test(basic_sigmoid)
```

```
basic_sigmoid(1) = 0.7310585786300049
 All tests passed.
```

Actually, we rarely use the "math" library in deep learning because the inputs of the functions are real numbers. In deep learning we mostly use matrices and vectors. This is why numpy is more useful.

```python
In [7]:  import numpy as np

         def basic_sigmoid(x):
             return 1 / (1 + np.exp(-x))

         x = np.array([1, 2, 3])
         print(basic_sigmoid(x))  # ✅ Works fine, returns a vector
```

```
[0.73105858 0.88079708 0.95257413]
```

In fact, if $x = (x_1, x_2, \ldots, x_n)$ is a row vector then `np.exp(x)` will apply the exponential function to every element of x. The output will thus be: `np.exp(x) = (e^{x_1}, e^{x_2}, ..., e^{x_n})`

```
In [8]: import numpy as np

        # example of np.exp
        t_x = np.array([1, 2, 3])
        print(np.exp(t_x)) # result is (exp(1), exp(2), exp(3))
```

```
[ 2.71828183  7.3890561  20.08553692]
```

Furthermore, if x is a vector, then a Python operation such as $s = x + 3$ or $s = \dfrac{1}{x}$ will output s as a vector of the same size as x.

```
In [9]: # example of vector operation
        t_x = np.array([1, 2, 3])
        print (t_x + 3)
```

```
[4 5 6]
```

Any time you need more info on a numpy function, we encourage you to look at [the official documentation (https://docs.scipy.org/doc/numpy-1.10.1/reference/generated/numpy.exp.html)](https://docs.scipy.org/doc/numpy-1.10.1/reference/generated/numpy.exp.html).

You can also create a new cell in the notebook and write `np.exp?` (for example) to get quick access to the documentation.

Exercise 3 - sigmoid

Implement the sigmoid function using numpy.

Instructions: x could now be either a real number, a vector, or a matrix. The data structures we use in numpy to represent these shapes (vectors, matrices...) are called numpy arrays. You don't need to know more for now.

$$\text{For } x \in \mathrm{R}^n, sigmoid(x) = sigmoid\begin{pmatrix} x_1 \\ x_2 \\ \ldots \\ x_n \end{pmatrix} = \begin{pmatrix} \dfrac{1}{1+e^{-x_1}} \\ \dfrac{1}{1+e^{-x_2}} \\ \ldots \\ \dfrac{1}{1+e^{-x_n}} \end{pmatrix}$$

```python
In [10]:  import numpy as np

          # GRADED FUNCTION: sigmoid
          def sigmoid(x):
              """
              Compute the sigmoid of x

              Arguments:
              x -- A scalar or numpy array of any size

              Return:
              s -- sigmoid(x)
              """
              # YOUR CODE STARTS HERE
              s = 1 / (1 + np.exp(-x))
              # YOUR CODE ENDS HERE
              return s

          t_x = np.array([1, 2, 3])
          print("sigmoid(t_x) = " + str(sigmoid(t_x)))
          sigmoid_test(sigmoid)
```

```
sigmoid(t_x) = [0.73105858 0.88079708 0.95257413]
 All tests passed.
```

```python
In [11]:  t_x = np.array([1, 2, 3])
          print("sigmoid(t_x) = " + str(sigmoid(t_x)))

          sigmoid_test(sigmoid)
```

```
sigmoid(t_x) = [0.73105858 0.88079708 0.95257413]
 All tests passed.
```

1.2 - Sigmoid Gradient

As you've seen in lecture, you will need to compute gradients to optimize loss functions using backpropagation. Let's code your first gradient function.

Exercise 4 - sigmoid_derivative

Implement the function sigmoid_grad() to compute the gradient of the sigmoid function with respect to its input x. The formula is:

$$sigmoid\_derivative(x) = \sigma^{'}(x) = \sigma(x)(1 - \sigma(x))$$

You often code this function in two steps:

1. Set s to be the sigmoid of x. You might find your sigmoid(x) function useful.
2. Compute $\sigma^{'}(x) = s(1 - s)$

In [12]:
```python
# GRADED FUNCTION: sigmoid_derivative
def sigmoid_derivative(x):
    """
    Compute the gradient (also called the slope or derivative) of the sigmoid

    Arguments:
    x -- A scalar or numpy array

    Return:
    ds -- Your computed gradient.
    """
    # YOUR CODE STARTS HERE
    s = sigmoid(x)
    ds = s * (1 - s)
    # YOUR CODE ENDS HERE
    return ds


t_x = np.array([1, 2, 3])
print("sigmoid_derivative(t_x) = " + str(sigmoid_derivative(t_x)))
sigmoid_derivative_test(sigmoid_derivative)
```

```
sigmoid_derivative(t_x) = [0.19661193 0.10499359 0.04517666]
 All tests passed.
```

In [13]:
```python
t_x = np.array([1, 2, 3])
print ("sigmoid_derivative(t_x) = " + str(sigmoid_derivative(t_x)))

sigmoid_derivative_test(sigmoid_derivative)
```

```
sigmoid_derivative(t_x) = [0.19661193 0.10499359 0.04517666]
 All tests passed.
```

1.3 - Reshaping arrays

Two common numpy functions used in deep learning are np.shape (https://docs.scipy.org/doc/numpy/reference/generated/numpy.ndarray.shape.html) and np.reshape() (https://docs.scipy.org/doc/numpy/reference/generated/numpy.reshape.html).

- X.shape is used to get the shape (dimension) of a matrix/vector X.
- X.reshape(...) is used to reshape X into some other dimension.

For example, in computer science, an image is represented by a 3D array of shape $(length, height, depth = 3)$. However, when you read an image as the input of an algorithm you convert it to a vector of shape $(length * height * 3, 1)$. In other words, you "unroll", or reshape, the 3D array into a 1D vector.
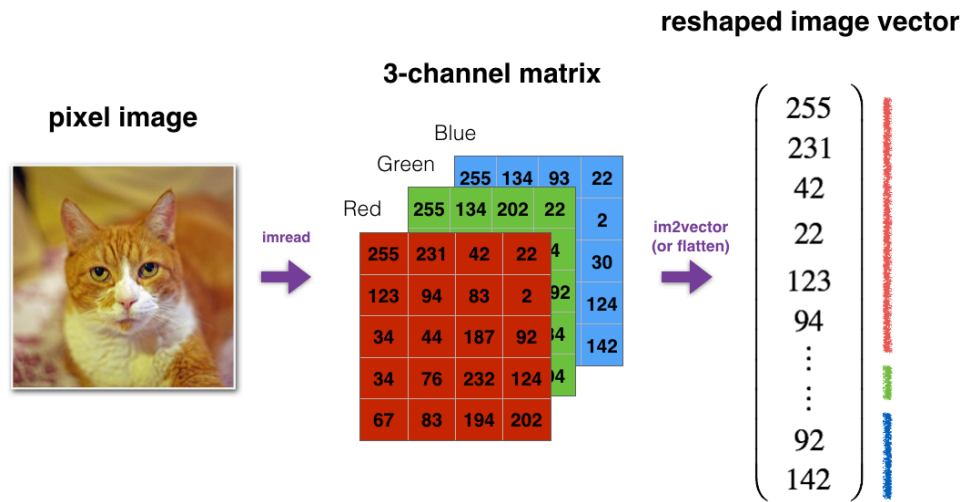
Exercise 5 - image2vector

Implement `image2vector()` that takes an input of shape (length, height, 3) and returns a vector of shape (length*height*3, 1). For example, if you would like to reshape an array v of

```python
In [30]: import numpy as np

# GRADED FUNCTION: image2vector
def image2vector(image):
    """
    Argument:
    image -- a numpy array of shape (length, height, depth)

    Returns:
    v -- a vector of shape (length*height*depth, 1)
    """
    # Flatten the image array and reshape it into a vector of shape (length*he
    v = image.reshape(-1, 1)  # This reshapes the image into a column vector

    return v
```

```
In [31]:  # This is a 3 by 3 by 2 array, typically images will be (num_px_x, num_px_y,3)
          t_image = np.array([[[ 0.67826139,  0.29380381],
                               [ 0.90714982,  0.52835647],
                               [ 0.4215251 ,  0.45017551]],

                              [[ 0.92814219,  0.96677647],
                               [ 0.85304703,  0.52351845],
                               [ 0.19981397,  0.27417313]],

                              [[ 0.60659855,  0.00533165],
                               [ 0.10820313,  0.49978937],
                               [ 0.34144279,  0.94630077]]])

          print ("image2vector(image) = " + str(image2vector(t_image)))

          image2vector_test(image2vector)
```

```
image2vector(image) = [[0.67826139]
 [0.29380381]
 [0.90714982]
 [0.52835647]
 [0.4215251 ]
 [0.45017551]
 [0.92814219]
 [0.96677647]
 [0.85304703]
 [0.52351845]
 [0.19981397]
 [0.27417313]
 [0.60659855]
 [0.00533165]
 [0.10820313]
 [0.49978937]
 [0.34144279]
 [0.94630077]]
All tests passed.
```

1.4 - Normalizing rows

Another common technique we use in Machine Learning and Deep Learning is to normalize our data. It often leads to a better performance because gradient descent converges faster after normalization. Here, by normalization we mean changing x to $\frac{x}{\|x\|}$ (dividing each row vector of x by its norm).

For example, if

$$x = \begin{bmatrix} 0 & 3 & 4 \\ 2 & 6 & 4 \end{bmatrix}$$

then

$$\|x\| = np.linalg.norm(x, axis=1, keepdims=True) = \begin{bmatrix} 5 \\ \sqrt{56} \end{bmatrix}$$

and

$$x\_normalized = \frac{x}{\|x\|} = \begin{bmatrix} 0 & \frac{3}{5} & \frac{4}{5} \\ \frac{2}{\sqrt{56}} & \frac{6}{\sqrt{56}} & \frac{4}{\sqrt{56}} \end{bmatrix}$$

Note that you can divide matrices of different sizes and it works fine: this is called broadcasting and you're going to learn about it in part 5.

With `keepdims=True` the result will broadcast correctly against the original x.

`axis=1` means you are going to get the norm in a row-wise manner. If you need the norm in a column-wise way, you would need to set `axis=0`.

numpy.linalg.norm has another parameter `ord` where we specify the type of normalization to be done (in the exercise below you'll do 2-norm). To get familiar with the types of normalization you can visit [numpy.linalg.norm (https://numpy.org/doc/stable/reference/generated/numpy.linalg.norm.html)](https://numpy.org/doc/stable/reference/generated/numpy.linalg.norm.html)

In [20]:
```python
import numpy as np

# GRADED FUNCTION: normalize_rows
def normalize_rows(x):
    """
    Normalize each row of the matrix x to have unit length.

    Argument:
    x -- A numpy matrix of shape (n, m)

    Returns:
    x -- The normalized (by row) numpy matrix. You are allowed to modify x.
    """
    # Compute the L2 norm of each row (axis=1) and keep dimensions for broadca
    x_norm = np.linalg.norm(x, ord=2, axis=1, keepdims=True)

    # Divide each row by its corresponding norm
    x = x / x_norm

    return x
```

```
In [21]: x = np.array([[0., 3., 4.],
                       [1., 6., 4.]])
         print("normalizeRows(x) = " + str(normalize_rows(x)))

         normalizeRows_test(normalize_rows)
```

```
normalizeRows(x) = [[0.          0.6         0.8        ]
 [0.13736056 0.82416338 0.54944226]]
 All tests passed.
```

Note: In normalize_rows(), you can try to print the shapes of x_norm and x, and then rerun the assessment. You'll find out that they have different shapes. This is normal given that x_norm takes the norm of each row of x. So x_norm has the same number of rows but only 1 column. So how did it work when you divided x by x_norm? This is called broadcasting and we'll talk about it now!

Exercise 7 - softmax

Implement a softmax function using numpy. You can think of softmax as a normalizing function used when your algorithm needs to classify two or more classes. You will learn more about softmax in the second course of this specialization.

Instructions:

- for $x \in R^{1 \times n}$,

$$softmax(x) = softmax\left(\begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}\right)$$

$$= \begin{bmatrix} \dfrac{e^{x_1}}{\sum_j e^{x_j}} & \dfrac{e^{x_2}}{\sum_j e^{x_j}} & \cdots & \dfrac{e^{x_n}}{\sum_j e^{x_j}} \end{bmatrix}$$

- for a matrix $x \in R^{m \times n}$, x_{ij} maps to the element in the ith row and j^{th} column of x, thus we have:

$$softmax(x) = softmax \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{bmatrix}$$

Notes: Note that later in the course, you'll see "m" used to represent the "number of training examples", and each training example is in its own column of the matrix. Also, each feature will be in its own row (each row has data for the same feature).
Softmax should be performed for all features of each training example, so softmax would be performed on the columns (once we switch to that representation later in this course).

However, in this coding practice, we're just focusing on getting familiar with Python, so we're using the common math notation $m \times n$
where m is the number of rows and n is the number of columns.

In [22]:
```python
# GRADED FUNCTION: softmax

import numpy as np

def softmax(x):
    """
    Calculates the softmax for each row of the input x.

    Arguments:
    x -- A numpy matrix of shape (m, n)

    Returns:
    s -- A numpy matrix equal to the softmax of x, of shape (m, n)
    """

    # YOUR CODE STARTS HERE
    # Step 1: Compute the exponential of all elements
    x_exp = np.exp(x)

    # Step 2: Sum the exponentials for each row
    x_sum = np.sum(x_exp, axis=1, keepdims=True)

    # Step 3: Divide the exponentials by the sum (broadcasting)
    s = x_exp / x_sum
    # YOUR CODE ENDS HERE

    return s
```

```
In [23]: t_x = np.array([[9, 2, 5, 0, 0],
                         [7, 5, 0, 0 ,0]])
         print("softmax(x) = " + str(softmax(t_x)))

         softmax_test(softmax)
```

```
softmax(x) = [[9.80897665e-01 8.94462891e-04 1.79657674e-02 1.21052389e-04
  1.21052389e-04]
 [8.78679856e-01 1.18916387e-01 8.01252314e-04 8.01252314e-04
  8.01252314e-04]]
 All tests passed.
```

Notes

- If you print the shapes of x_exp, x_sum and s above and rerun the assessment cell, you will see that x_sum is of shape (2,1) while x_exp and s are of shape (2,5). **x_exp/x_sum** works due to python broadcasting.

Congratulations! You now have a pretty good understanding of python numpy and have implemented a few useful functions that you will be using in deep learning.

What you need to remember:

- np.exp(x) works for any np.array x and applies the exponential function to every coordinate
- the sigmoid function and its gradient
- image2vector is commonly used in deep learning
- np.reshape is widely used. In the future, you'll see that keeping your matrix/vector dimensions straight will go toward eliminating a lot of bugs.
- numpy has efficient built-in functions
- broadcasting is extremely useful

2 - Vectorization

In deep learning, you deal with very large datasets. Hence, a non-computationally-optimal function can become a huge bottleneck in your algorithm and can result in a model that takes ages to run. To make sure that your code is computationally efficient, you will use vectorization. For example, try to tell the difference between the following implementations of the dot/outer/elementwise product.

In [24]:
```python
import time
import numpy as np

# Input vectors
x1 = [9, 2, 5, 0, 0, 7, 5, 0, 0, 0, 9, 2, 5, 0, 0]
x2 = [9, 2, 2, 9, 0, 9, 2, 5, 0, 0, 9, 2, 5, 0, 0]

# --- CLASSIC DOT PRODUCT ---
tic = time.process_time()
dot = 0
for i in range(len(x1)):
    dot += x1[i] * x2[i]
toc = time.process_time()
print("Classic dot = " + str(dot) + "\n----- Computation time = " + str(1000 *

# --- CLASSIC OUTER PRODUCT ---
tic = time.process_time()
outer = np.zeros((len(x1), len(x2)))
for i in range(len(x1)):
    for j in range(len(x2)):
        outer[i, j] = x1[i] * x2[j]
toc = time.process_time()
print("Classic outer =\n" + str(outer) + "\n----- Computation time = " + str(1

# --- CLASSIC ELEMENTWISE MULTIPLICATION ---
tic = time.process_time()
mul = np.zeros(len(x1))
for i in range(len(x1)):
    mul[i] = x1[i] * x2[i]
toc = time.process_time()
print("Classic elementwise = " + str(mul) + "\n----- Computation time = " + st

# --- CLASSIC GENERAL DOT PRODUCT ---
W = np.random.rand(3, len(x1))  # Random 3×len(x1) matrix
tic = time.process_time()
gdot = np.zeros(W.shape[0])
for i in range(W.shape[0]):
    for j in range(len(x1)):
        gdot[i] += W[i, j] * x1[j]
toc = time.process_time()
print("Classic general dot = " + str(gdot) + "\n----- Computation time = " + s

# --- VECTORIZED DOT PRODUCT ---
tic = time.process_time()
dot = np.dot(x1, x2)
toc = time.process_time()
print("Vectorized dot = " + str(dot) + "\n----- Computation time = " + str(100

# --- VECTORIZED OUTER PRODUCT ---
tic = time.process_time()
outer = np.outer(x1, x2)
toc = time.process_time()
print("Vectorized outer =\n" + str(outer) + "\n----- Computation time = " + st

# --- VECTORIZED ELEMENTWISE MULTIPLICATION ---
tic = time.process_time()
mul = np.multiply(x1, x2)
toc = time.process_time()
print("Vectorized elementwise = " + str(mul) + "\n----- Computation time = " +

# --- VECTORIZED GENERAL DOT PRODUCT ---
```

```python
tic = time.process_time()
gdot = np.dot(W, x1)
toc = time.process_time()
print("Vectorized general dot = " + str(gdot) + "\n----- Computation time = "
```

```
Classic dot = 278
----- Computation time = 0.09315800000009311ms
Classic outer =
[[81. 18. 18. 81.  0. 81. 18. 45.  0.  0. 81. 18. 45.  0.  0.]
 [18.  4.  4. 18.  0. 18.  4. 10.  0.  0. 18.  4. 10.  0.  0.]
 [45. 10. 10. 45.  0. 45. 10. 25.  0.  0. 45. 10. 25.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [63. 14. 14. 63.  0. 63. 14. 35.  0.  0. 63. 14. 35.  0.  0.]
 [45. 10. 10. 45.  0. 45. 10. 25.  0.  0. 45. 10. 25.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [81. 18. 18. 81.  0. 81. 18. 45.  0.  0. 81. 18. 45.  0.  0.]
 [18.  4.  4. 18.  0. 18.  4. 10.  0.  0. 18.  4. 10.  0.  0.]
 [45. 10. 10. 45.  0. 45. 10. 25.  0.  0. 45. 10. 25.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.]]
----- Computation time = 0.21317200000003922ms
Classic elementwise = [81.  4. 10.  0.  0. 63. 10.  0.  0.  0. 81.  4. 25.
0.  0.]
----- Computation time = 0.12181199999994341ms
Classic general dot = [24.57587188 24.55476983 25.38210614]
----- Computation time = 0.5183980000000865ms
Vectorized dot = 278
----- Computation time = 0.4629410000001055ms
Vectorized outer =
[[81 18 18 81  0 81 18 45  0  0 81 18 45  0  0]
 [18  4  4 18  0 18  4 10  0  0 18  4 10  0  0]
 [45 10 10 45  0 45 10 25  0  0 45 10 25  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [63 14 14 63  0 63 14 35  0  0 63 14 35  0  0]
 [45 10 10 45  0 45 10 25  0  0 45 10 25  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [81 18 18 81  0 81 18 45  0  0 81 18 45  0  0]
 [18  4  4 18  0 18  4 10  0  0 18  4 10  0  0]
 [45 10 10 45  0 45 10 25  0  0 45 10 25  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]]
----- Computation time = 0.1176859999998392ms
Vectorized elementwise = [81  4 10  0  0 63 10  0  0  0 81  4 25  0  0]
----- Computation time = 0.06806099999989712ms
Vectorized general dot = [24.57587188 24.55476983 25.38210614]
----- Computation time = 0.2488050000000186ms
```

In [25]:
```python
x1 = [9, 2, 5, 0, 0, 7, 5, 0, 0, 0, 9, 2, 5, 0, 0]
x2 = [9, 2, 2, 9, 0, 9, 2, 5, 0, 0, 9, 2, 5, 0, 0]

### VECTORIZED DOT PRODUCT OF VECTORS ###
tic = time.process_time()
dot = np.dot(x1,x2)
toc = time.process_time()
print ("dot = " + str(dot) + "\n ----- Computation time = " + str(1000 * (toc

### VECTORIZED OUTER PRODUCT ###
tic = time.process_time()
outer = np.outer(x1,x2)
toc = time.process_time()
print ("outer = " + str(outer) + "\n ----- Computation time = " + str(1000 * (

### VECTORIZED ELEMENTWISE MULTIPLICATION ###
tic = time.process_time()
mul = np.multiply(x1,x2)
toc = time.process_time()
print ("elementwise multiplication = " + str(mul) + "\n ----- Computation time

### VECTORIZED GENERAL DOT PRODUCT ###
tic = time.process_time()
dot = np.dot(W,x1)
toc = time.process_time()
print ("gdot = " + str(dot) + "\n ----- Computation time = " + str(1000 * (toc
```

```
dot = 278
 ----- Computation time = 0.08912699999985563ms
outer = [[81 18 18 81  0 81 18 45  0  0 81 18 45  0  0]
 [18  4  4 18  0 18  4 10  0  0 18  4 10  0  0]
 [45 10 10 45  0 45 10 25  0  0 45 10 25  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [63 14 14 63  0 63 14 35  0  0 63 14 35  0  0]
 [45 10 10 45  0 45 10 25  0  0 45 10 25  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [81 18 18 81  0 81 18 45  0  0 81 18 45  0  0]
 [18  4  4 18  0 18  4 10  0  0 18  4 10  0  0]
 [45 10 10 45  0 45 10 25  0  0 45 10 25  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]]
 ----- Computation time = 0.1681800000001843ms
elementwise multiplication = [81  4 10  0  0 63 10  0  0  0 81  4 25  0  0]
 ----- Computation time = 0.08376000000009931ms
gdot = [24.57587188 24.55476983 25.38210614]
 ----- Computation time = 0.08270899999995862ms
```

As you may have noticed, the vectorized implementation is much cleaner and more efficient. For bigger vectors/matrices, the differences in running time become even bigger.

Note that `np.dot()` performs a matrix-matrix or matrix-vector multiplication. This is different from `np.multiply()` and the `*` operator (which is equivalent to `.*` in Matlab/Octave), which performs an element-wise multiplication.

2.1 Implement the L1 and L2 loss functions

Exercise 8 - L1

Implement the numpy vectorized version of the L1 loss. You may find the function abs(x) (absolute value of x) useful.

Reminder:

- The loss is used to evaluate the performance of your model. The bigger your loss is, the more different your predictions ($\hat{y}$) are from the true values (y). In deep learning, you use optimization algorithms like Gradient Descent to train your model and to minimize the cost.
- L1 loss is defined as:

$$L_1(\hat{y}, y) = \sum_{i=0}^{m-1} |y^{(i)} - \hat{y}^{(i)}|$$

```python
In [26]: import numpy as np

# GRADED FUNCTION: L1
def L1(yhat, y):
    """
    Arguments:
    yhat -- vector of size m (predicted labels)
    y -- vector of size m (true labels)

    Returns:
    loss -- the value of the L1 loss function defined above
    """
    # YOUR CODE STARTS HERE
    loss = np.sum(np.abs(y - yhat))
    # YOUR CODE ENDS HERE

    return loss

# Example Test
yhat = np.array([.9, 0.2, 0.1, .4, .9])
y = np.array([1, 0, 0, 1, 1])
print("L1 = " + str(L1(yhat, y)))
```

```
L1 = 1.1
```

```python
In [27]: yhat = np.array([.9, 0.2, 0.1, .4, .9])
y = np.array([1, 0, 0, 1, 1])
print("L1 = " + str(L1(yhat, y)))

L1_test(L1)
```

```
L1 = 1.1
 All tests passed.
```

Exercise 9 - L2

Implement the numpy vectorized version of the L2 loss. There are several way of implementing the L2 loss but you may find the function np.dot() useful. As a reminder, if $x = [x_1, x_2, \ldots, x_n]$, then `np.dot(x,x)` $= \sum_{j=1}^{n} x_j^2$.

- L2 loss is defined as

$$\sum_{i=0}^{m-1}$$

In [28]:
```python
import numpy as np

# GRADED FUNCTION: L2
def L2(yhat, y):
    """
    Arguments:
    yhat -- vector of size m (predicted labels)
    y -- vector of size m (true labels)

    Returns:
    loss -- the value of the L2 loss function defined above
    """
    # YOUR CODE STARTS HERE
    loss = np.sum((y - yhat) ** 2)
    # YOUR CODE ENDS HERE

    return loss

# Example Test
yhat = np.array([.9, 0.2, 0.1, .4, .9])
y = np.array([1, 0, 0, 1, 1])
print("L2 = " + str(L2(yhat, y)))
```

```
L2 = 0.43
```

In [29]:
```python
yhat = np.array([.9, 0.2, 0.1, .4, .9])
y = np.array([1, 0, 0, 1, 1])

print("L2 = " + str(L2(yhat, y)))

L2_test(L2)
```

```
L2 = 0.43
 All tests passed.
```

Congratulations on completing this assignment. We hope that this little warm-up exercise helps you in the future assignments, which will be more exciting and interesting!

What to remember:

- Vectorization is very important in deep learning. It provides computational efficiency and clarity.
- You have reviewed the L1 and L2 loss.
- You are familiar with many numpy functions such as np.sum, np.dot, np.multiply, np.maximum, etc...