## Solution to Assignment 1, Problem 1(a)

Akash Rana

**Softmax** Prove that *softmax* is invariant to constant offsets in the input, that is, for any input vector x and any constant c,

$$softmax(\mathbf{x}) = softmax(\mathbf{x} + c), \tag{1}$$

where  $(\mathbf{x} + c)$  means adding the constant c to every dimension of  $\mathbf{x}$ .

$$\operatorname{softmax}(\mathbf{x})_j = \frac{e^{x_j}}{\sum_{k=1}^{\infty} e^{x_k}}$$
 (2)

Solution:

softmax(
$$\mathbf{x} + c$$
)<sub>j</sub> =  $\frac{e^{(x_j + c)}}{\sum_{k=1} e^{(x_k + c)}}$  (3)  
=  $\frac{e^c}{e^c} \frac{e^{(x_j)}}{sum_{k=1} e^{(x_j)}}$ 

$$= \frac{e^c}{e^c} \frac{e^{(x_j)}}{sum_{k-1}e^{(x_j)}} \tag{4}$$

$$= \operatorname{softmax}(\mathbf{x})_j \tag{5}$$

## Solution to Assignment 1, Problem 1(b)

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Given an input matrix of N-rows and d-columns, compute the softmax prediction for each row. Write your implementation in q1\_softmax.py. You may test by executing python q1\_softmax.py.

**Note:** The provided tests are not exhaustive. Later parts of the assignment will reference this code so it is important to have a correct implementation. Your implementation should also be efficient and vectorized whenever possible. A non-vectorized implementation will not receive full credit!

```
import numpy as np
def softmax(x):
#x.shape by default gives column value
    if len(x.shape) > 1:
        # Matrix
        ### YOUR CODE HERE
        c = np.max(x, axis=1).reshape(-1,1) #-1 here means, internally
numpy is just calculating, to get the missing dimension.
        x = np.exp(x-c) / np.sum(np.exp(x-c), axis=1).reshape(-1,1)
        print (np.shape(x))
        ### END YOUR CODE
    else:
        # Vector
        ### YOUR CODE HERE
        c = np.max(x)
        x = np.exp(x-c) / np.sum(np.exp(x-c))
        ### END YOUR CODE
    assert x.shape == orig_shape
    return x
```

## Solution to Assignment 1, Problem 2(a)

Akash Rana

Derive the gradients of the sigmoid function and show that it can be rewritten as a function of the function value (i.e. in some expression where only  $\sigma(x)$ , but not x, is present). Assume that the input x is a scalar for this question.

Denote the sigmoid function as  $\sigma(z)$ ,

$$\sigma(z) = \frac{1}{1 + e^{-z}},\tag{6}$$

Using chain rule,

$$\sigma'(z) = \frac{-1}{(1+e^{-z})^2} \times (-e^{-z})$$

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

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

$$= \sigma(z) - \sigma^2(z)$$

$$= \sigma(z)(1 - \sigma(z))$$