

## Homework 1 – Deep Neural Networks (CS525 191N, Whitehill, Spring 2017)

This homework is intended to help you learn (or refresh your understanding of) how to implement linear algebraic operations in Python using `numpy`.

For each of the problems below, write a method (e.g., `problem1`) that returns the answer for the corresponding problem. Put all your methods in one file called `homework1_WPIUSERNAME.py` (e.g., `homework1_jrwhitehill.py`). See the starter file `homework1_template.py`. In all problems, you may assume that the dimensions of the matrices and/or vectors are compatible for the requested mathematical operations.

1. Given matrices  $\mathbf{A}$  and  $\mathbf{B}$ , compute and return an expression for  $\mathbf{A} + \mathbf{B}$ . [ 2 pts ]
2. Given matrices  $\mathbf{A}$ ,  $\mathbf{B}$ , and  $\mathbf{C}$ , compute and return  $\mathbf{AB} - \mathbf{C}$  (i.e., right-multiply matrix  $\mathbf{A}$  by matrix  $\mathbf{B}$ , and then subtract  $\mathbf{C}$ ). Use `dot` or `numpy.dot`. [ 2 pts ]
3. Given matrices  $\mathbf{A}$ ,  $\mathbf{B}$ , and  $\mathbf{C}$ , return  $\mathbf{A} \odot \mathbf{B} + \mathbf{C}^\top$ , where  $\odot$  represents the element-wise (Hadamard) product and  $\top$  represents matrix transpose. In `numpy`, the element-wise product is obtained simply with `*`. [ 2 pts ]
4. Given column vectors  $\mathbf{x}$  and  $\mathbf{y}$ , compute the inner product of  $\mathbf{x}$  and  $\mathbf{y}$  (i.e.,  $\mathbf{x}^\top \mathbf{y}$ ). [ 2 pts ]
5. Given matrix  $\mathbf{A}$ , return a matrix with the same dimensions as  $\mathbf{A}$  but that contains all zeros. Use `numpy.zeros`. [ 2 pts ]
6. Given matrix  $\mathbf{A}$ , return a vector with the same number of rows as  $\mathbf{A}$  but that contains all ones. Use `numpy.ones`. [ 2 pts ]
7. Given (invertible) matrix  $\mathbf{A}$ , compute  $\mathbf{A}^{-1}$ . [ 2 pts ]  

(Now that you know how to compute the inverse of a matrix, you should **almost never need to do so ever again**. The reasons are that (1) in most numerical algorithms, you are not interested in the matrix inverse itself but rather in the inverse **multiplied** by something else (e.g., a vector); and (2) computing the matrix inverse explicitly is numerically unstable.)
8. Given square matrix  $\mathbf{A}$  and column vector  $\mathbf{x}$ , use `numpy.linalg.solve` to compute  $\mathbf{A}^{-1}\mathbf{x}$ . [ 2 pts ]
9. Given square matrix  $\mathbf{A}$  and row vector  $\mathbf{x}$ , use `numpy.linalg.solve` to compute  $\mathbf{x}\mathbf{A}^{-1}$ . Hint:  $\mathbf{AB} = (\mathbf{B}^\top \mathbf{A}^\top)^\top$ . [ 3 pts ]
10. Given square matrix  $\mathbf{A}$  and (scalar)  $\alpha$ , compute  $\mathbf{A} + \alpha \mathbf{I}$ , where  $\mathbf{I}$  is the identity matrix with the same dimensions as  $\mathbf{A}$ . Use `numpy.eye`. [ 2 pts ]
11. Given matrix  $\mathbf{A}$  and integers  $i, j$ , return the  $j$ th column of the  $i$ th row of  $\mathbf{A}$ , i.e.,  $\mathbf{A}_{ij}$ . [ 2 pts ]
12. Given matrix  $\mathbf{A}$  and integer  $i$ , return the sum of all the entries in the  $i$ th row, i.e.,  $\sum_j \mathbf{A}_{ij}$ . Do **not** use a loop, which in Python is very slow. Instead use the `numpy.sum` function. [ 4 pts ]
13. Given matrix  $\mathbf{A}$  and scalars  $c, d$ , compute the arithmetic mean over all entries of  $\mathbf{A}$  that are between  $c$  and  $d$  (inclusive). In other words, if  $\mathcal{S} = \{(i, j) : c \leq \mathbf{A}_{ij} \leq d\}$ , then compute  $\frac{1}{|\mathcal{S}|} \sum_{(i,j) \in \mathcal{S}} \mathbf{A}_{ij}$ . Use `numpy.nonzero` along with `numpy.mean`. [ 4 pts ]
14. Given an  $(n \times n)$  matrix  $\mathbf{A}$  and integer  $k$ , return an  $(n \times k)$  matrix containing the right-eigenvectors of  $\mathbf{A}$  corresponding to the  $k$  largest eigenvalues of  $\mathbf{A}$ . Use `numpy.linalg.eig` to compute eigenvectors. [ 4 pts ]
15. Given a  $n$ -dimensional column vector  $\mathbf{x}$ , an integer  $k$ , and positive scalars  $m, s$ , return an  $(n \times k)$  matrix, each of whose columns is a sample from multidimensional Gaussian distribution  $\mathcal{N}(\mathbf{x} + m\mathbf{z}, s\mathbf{I})$ , where  $\mathbf{z}$  is an  $n$ -dimensional column vector containing all ones and  $\mathbf{I}$  is the identity matrix. Use either `numpy.random.multivariate_normal` or `numpy.random.randn`. [ 5 pts ]