

# IIT Kanpur Intensive Training School (ITS) on PYTHON for Machine Learning, Neural Networks and Deep Learning

2nd to 22nd December 2023

## Assignment #2

1. The centroid of the  $i$ th cluster in  $l$ th iteration, denoted by  $\bar{\mu}_i^{(l)}$ , is

a.  $\frac{\sum_{j=1}^M \alpha_i^{(l)}(j) \bar{x}(j)}{\sum_{j=1}^M \bar{x}(j)}$   
b.  $\frac{\sum_{j=1}^M \bar{x}(j)}{M}$   
c.  $\frac{\sum_{j=1}^M \bar{x}(j)}{\sum_{j=1}^M \alpha_i^{(l)}(j)}$   
d.  $\frac{\sum_{j=1}^M \alpha_i^{(l)}(j) \bar{x}(j)}{\sum_{j=1}^M \alpha_i^{(l)}(j)}$

2. The **entropy**  $H(X)$  of a source is defined as

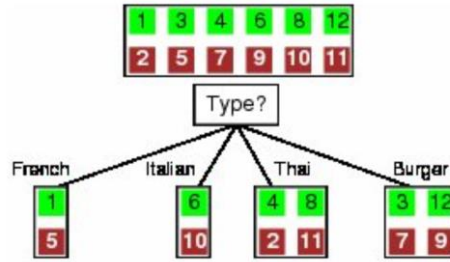
a.  $-\sum_{i=1}^n p(x_i) \log_2 \frac{1}{p(x_i)}$   
b.  $\sum_{i=1}^n \frac{1}{p(x_i)} \log_2 \frac{1}{p(x_i)}$   
c.  $-\sum_{i=1}^n \frac{1}{p(x_i)} \log_2 \frac{1}{p(x_i)}$   
d.  $\sum_{i=1}^n p(x_i) \log_2 \frac{1}{p(x_i)}$

3. Consider the table below showing *joint probabilities* of  
 $X = \{IC, \bar{IC}\}$ ,  $Y = \{CHOC, \bar{CHOC}\}$

|              | IC            | $\bar{IC}$    |
|--------------|---------------|---------------|
| CHOC         | $\frac{1}{6}$ | $\frac{1}{3}$ |
| $\bar{CHOC}$ | $\frac{1}{6}$ | $\frac{1}{3}$ |

The quantity  $H(Y|X = \bar{IC})$  is given as

- a. 0.92  
b. 1  
c. 0.73  
d. 0.65
4. Consider the example



The quantity  $H(Y|\text{Italian}) =$

- 1
  - $\frac{1}{2}$
  - $\frac{1}{4}$
  - 0
- The size of a typical neuron is
    - 4 microns to 100 picometres**
    - 4 microns to 100 nanometres**
    - 4 microns to 100 micrometres**
    - 4 microns to 100 femtometres**
  - There are approximately \_\_\_\_\_ neurons in the human brains
    - 10 billion
    - 10 million
    - 10 thousand
    - 10 trillion
  - In comparison to silicon logic gates, *Neurons* \_\_\_\_\_
    - Have an equal speed of operation
    - Depends on the type of Neuron
    - Are Much faster
    - Are Much slower
  - The activation function employed in the *McCulloch–Pitts model* of a neural network is
    - Sigmoid function
    - ReLU function
    - Linear function
    - Threshold function
  - Consider the loss function of a single neuron neural net given as

$$L(\bar{\mathbf{w}}_k) = \frac{1}{2} \left( y_k - \psi \left( \underbrace{\sum_{j=1}^m w_{kj} x_j + b_k}_{u_k} \right) \right)^2$$

The corresponding update rule for the weight vector is

- $\bar{\mathbf{w}}_k(n+1) = \bar{\mathbf{w}}_k(n) - \eta_k (y - \psi(u_k(n))) \psi'(u_k(n)) \bar{\mathbf{x}}$
- $\bar{\mathbf{w}}_k(n+1) = \bar{\mathbf{w}}_k(n) + \eta_k (y - \psi(u_k(n))) \bar{\mathbf{x}}$
- $\bar{\mathbf{w}}_k(n+1) = \bar{\mathbf{w}}_k(n) + \eta_k (y - \psi(u_k(n))) \psi'(u_k(n)) \bar{\mathbf{x}}$
- $\bar{\mathbf{w}}_k(n+1) = \bar{\mathbf{w}}_k(n) + \eta_k \psi'(u_k(n)) \bar{\mathbf{x}}$

10. The **ReLU function**  $f(x)$  is defined as

- a.  $x$
- b.  $\begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases}$
- c.  $\frac{1}{1+e^{-x}}$
- d.  $\begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$

11. In a two layer deep neural network, the gradient to update the weights of layer 1 during backpropagation is determined as

- a.  $\frac{\partial}{\partial \mathbf{W}^{[1]}} L = \left( (\mathbf{W}^{[2]})^T \phi^{[2]} \right) \times (\bar{\mathbf{x}}^{[0]})^T$
- b.  $\frac{\partial}{\partial \mathbf{W}^{[1]}} L = \left( (\mathbf{W}^{[2]})^T \phi^{[2]} \odot (\psi^{[1]})'(\bar{\mathbf{z}}^{[1]}) \right) \times (\bar{\mathbf{x}}^{[0]})^T$
- c.  $\frac{\partial}{\partial \mathbf{W}^{[1]}} L = \left( (\mathbf{W}^{[2]})^T \phi^{[2]} \odot (\psi^{[1]})'(\bar{\mathbf{z}}^{[1]}) \right) \times \bar{\mathbf{x}}^{[0]}$
- d.  $\frac{\partial}{\partial \mathbf{W}^{[1]}} L = \left( (\mathbf{W}^{[2]})^T \odot (\psi^{[1]})'(\bar{\mathbf{z}}^{[1]}) \right) \times (\bar{\mathbf{x}}^{[0]})^T$

12. In a  $K$  layer neural network, the size of the matrix  $\mathbf{W}^{[l]}$  for one of the inner layers is  $m \times n$ , where  $m, n$  are respectively

- a. Number of neurons in layers  $l, l - 1$
- b. Number of neurons in layers  $l - 1, l$
- c. Number of neurons in layers  $l$  and number of inputs in layer 0
- d. Number of neurons in layers  $l$  and number of outputs in layer  $K$

13. Convolutional neural nets are primarily suited for

- a. Gaussian datasets
- b. Purchase datasets
- c. Random datasets
- d. Images/ video datasets

14. Consider the simple image below

|   |   |   |   |
|---|---|---|---|
| 2 | 2 | 3 | 1 |
| 4 | 3 | 4 | 2 |
| 2 | 2 | 1 | 1 |
| 3 | 5 | 2 | 3 |

Max pooling with  $2 \times 2$  filters and stride 2 leads to

- a. 

|   |   |
|---|---|
| 3 | 4 |
| 5 | 3 |

- b. 

|   |   |
|---|---|
| 4 | 2 |
| 5 | 3 |

- c. 

|   |   |
|---|---|
| 4 | 4 |
| 5 | 3 |

- d. 

|   |   |
|---|---|
| 4 | 4 |
|---|---|

|   |   |
|---|---|
| 4 | 4 |
|---|---|

15. Consider the simple image below

|   |   |   |   |
|---|---|---|---|
| 2 | 2 | 3 | 1 |
| 4 | 3 | 4 | 2 |
| 2 | 2 | 1 | 1 |
| 3 | 5 | 2 | 3 |

Average pooling with  $2 \times 2$  filters and stride 2 leads to

a.

|      |      |
|------|------|
| 2.75 | 2.25 |
| 3    | 1.75 |

b.

|      |      |
|------|------|
| 2.75 | 2.5  |
| 3    | 1.75 |

c.

|      |      |
|------|------|
| 2.75 | 2.5  |
| 3.25 | 1.75 |

d.

|      |     |
|------|-----|
| 2.75 | 2.5 |
| 3    | 1.5 |

