

# Deep Learning

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Fri, 18<sup>th</sup> Sept 2020

# Perceptron

## Preliminaries

- Let the following hold for these classes:

$$\mathbf{w}^T \mathbf{x} > 0 \quad \forall \mathbf{x} \in \mathcal{C}_1$$

$$\mathbf{w}^T \mathbf{x} \leq 0 \quad \forall \mathbf{x} \in \mathcal{C}_2$$

- The case that if  $\mathbf{w}^T \mathbf{x} = 0$  then  $\mathbf{x} \in \mathcal{C}_2$

# Perceptron

## Update Rule 02

- If the following is violated then there is no change in  $\mathbf{w}$

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \eta(n)\mathbf{x}(n) \quad \text{if } \mathbf{w}^T(n)\mathbf{x}(n) > 0 \quad \mathbf{x}(n) \in \mathcal{C}_2$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \eta(n)\mathbf{x}(n) \quad \text{if } \mathbf{w}^T(n)\mathbf{x}(n) \leq 0 \quad \mathbf{x}(n) \in \mathcal{C}_1$$

- The case that if  $\mathbf{w}^T \mathbf{x} = 0$  then  $\mathbf{x} \in \mathcal{C}_2$

# Perceptron

## Initialization

- Let  $\mathbf{w} = \mathbf{0}$
- Let  $\eta(n) = 1$

## Assumption

- Suppose  $\mathbf{w}^T(n)\mathbf{x}(n) < 0$  for  $n = 1, 2, \dots$
- $\mathbf{x}(n) \in \mathcal{C}_1$  for  $n = 1, 2, \dots$
- Classes  $\mathcal{C}_1$  and  $\mathcal{C}_2$  are linearly separable
- Update  $\mathbf{w}(n+1)$

$$\begin{aligned}\mathbf{w}(n+1) &= \mathbf{w}(n) + \eta(n)\mathbf{x}(n) & \text{if } \mathbf{w}^T(n)\mathbf{x}(n) \leq 0 & \quad \mathbf{x}(n) \in \mathcal{C}_1 \\ \mathbf{w}(n+1) &= \mathbf{0} + \mathbf{x}(n) & \text{if } \mathbf{w}^T(n)\mathbf{x}(n) \leq 0 & \quad \mathbf{x}(n) \in \mathcal{C}_1\end{aligned}$$

# Applying Perceptron Update Rule

## Iterate

- $\mathbf{x}(1) \in \mathcal{C}_1$
- $\mathbf{w}^T(1)\mathbf{x}(1) = 0$
- Update Rule is:  $\mathbf{w}(2) = \mathbf{w}(1) + \mathbf{x}(1) = \mathbf{x}(1)$

# Applying Perceptron Update Rule

## Iterate

- $\mathbf{x}(2) \in \mathcal{C}_1$
- $\mathbf{w}^T(2)\mathbf{x}(2) \leq 0$
- Update Rule is:  $\mathbf{w}(3) = \mathbf{w}(2) + \mathbf{x}(2)$
- That is  $\mathbf{w}(3) = \mathbf{x}(1) + \mathbf{x}(2)$

# Applying Perceptron Update Rule

## Iterate

- $\mathbf{x}(3) \in \mathcal{C}_1$
- $\mathbf{w}^T(3)\mathbf{x}(3) \leq 0$
- Update Rule is:  $\mathbf{w}(4) = \mathbf{w}(3) + \mathbf{x}(3)$
- That is  $\mathbf{w}(4) = \mathbf{x}(1) + \mathbf{x}(2) + \mathbf{x}(3)$

# Applying Perceptron Update Rule

## Iterate

- $\mathbf{x}(4) \in \mathcal{C}_1$
- $\mathbf{w}^T(4)\mathbf{x}(4) \leq 0$
- Update Rule is:  $\mathbf{w}(5) = \mathbf{w}(4) + \mathbf{x}(4)$
- That is  $\mathbf{w}(5) = \mathbf{x}(1) + \mathbf{x}(2) + \mathbf{x}(3) + \mathbf{x}(4)$



# Applying Perceptron Update Rule

## Iterate

- $\mathbf{x}(n) \in \mathcal{C}_1$
- $\mathbf{w}^T(n)\mathbf{x}(n) \leq 0$
- Update Rule is:  $\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{x}(n)$
- That is  $\mathbf{w}(n+1) = \mathbf{x}(1) + \mathbf{x}(2) + \mathbf{x}(3) + \mathbf{x}(4) \cdots + \mathbf{x}(n)$

# Linearly Separable Assumption

## Make use of assumption

- As  $\mathcal{C}_1$  and  $\mathcal{C}_2$  are linearly separable
- There exists a  $\mathbf{w}_o$
- For which  $\mathbf{w}_o^T(n)\mathbf{x}(n) > 0$  for  $\mathbf{x}(1), \mathbf{x}(2), \dots, \mathbf{x}(n) \in \mathcal{C}_1$

# Linearly Separable Assumption

## Compute the norm of $\mathbf{w}(n)$

- We want to understand what is the norm (length of vector) of  $\mathbf{w}(n)$
- Why? Does  $\mathbf{w}(n)$  keeps on added with  $\mathbf{x}(n)$ ? Will the norm be unbounded?
- However,  $\mathcal{C}_1$  and  $\mathcal{C}_2$  are linearly separable

# Linearly Separable Assumption

## Minimum value of inner product

- Let the  $\alpha$  be a quantity defined as:

$$\alpha = \min \{ \mathbf{w}_o^T \mathbf{x}(1), \mathbf{w}_o^T \mathbf{x}(2), \mathbf{w}_o^T \mathbf{x}(3), \dots, \mathbf{w}_o^T \mathbf{x}(n) \}$$

- That is

$$\alpha = \min_{\mathbf{x}(n) \in \mathcal{C}_1} \mathbf{w}_o^T(n) \mathbf{x}(n)$$

# Linearly Separable Assumption

## Update rule as per mis-classification

- $\mathbf{w}(n+1) = \mathbf{x}(1) + \mathbf{x}(2) + \mathbf{x}(3) + \mathbf{x}(4) \cdots + \mathbf{x}(n)$
- To compute norm of  $\mathbf{w}(n)$
- Multiply both sides of this equation with  $\mathbf{w}_o^T$
- $\mathbf{w}_o^T \mathbf{w}(n+1) = \mathbf{w}_o^T \mathbf{x}(1) + \mathbf{w}_o^T \mathbf{x}(2) + \mathbf{w}_o^T \mathbf{x}(3) + \mathbf{w}_o^T \mathbf{x}(4) \cdots + \mathbf{w}_o^T \mathbf{x}(n)$
- Replace every term  $\mathbf{w}_o^T \mathbf{x}(n)$  with  $\alpha$
- $\mathbf{w}_o^T \mathbf{w}(n+1) \geq \alpha + \alpha + \alpha + \alpha + \cdots + \alpha$
- $\mathbf{w}_o^T \mathbf{w}(n+1) \geq n\alpha$

# Linearly Separable Assumption

Key equation

$$\mathbf{w}_o^T \mathbf{w}(n+1) \geq n\alpha$$

# Linearly Separable Assumption

## Cauchy-Bunyakovsky-Schwarz inequality

- For all  $\mathbf{u}$  and  $\mathbf{v}$
- $|\mathbf{u}^T \mathbf{u}| \cdot |\mathbf{v}^T \mathbf{v}| \geq |\mathbf{u}^T \mathbf{v}|$

## Apply Cauchy-Bunyakovsky-Schwarz inequality

- Given two vectors  $\mathbf{w}_o$  and  $\mathbf{w}(n+1)$
- $\|\mathbf{w}_o\|^2 \cdot \|\mathbf{w}(n+1)\|^2 \geq [\mathbf{w}_o^T \mathbf{w}(n+1)]^2$
- We have obtained  $\mathbf{w}_o^T \mathbf{w}(n+1) \geq n\alpha$
- That is  $[\mathbf{w}_o^T \mathbf{w}(n+1)]^2 \geq n^2 \alpha^2$
- $\|\mathbf{w}_o\|^2 \cdot \|\mathbf{w}(n+1)\|^2 \geq [\mathbf{w}_o^T \mathbf{w}(n+1)]^2 \geq n^2 \alpha^2$
- $\|\mathbf{w}_o\|^2 \cdot \|\mathbf{w}(n+1)\|^2 \geq n^2 \alpha^2$

# Linearly Separable Assumption

Norm of  $\mathbf{w}(n+1)$

Norm of  $\mathbf{w}(n+1)$  is:  $\|\mathbf{w}(n+1)\|^2 \geq \frac{n^2 \alpha^2}{\|\mathbf{w}_o\|^2}$



# Alternate: Norm

## Norm of $\mathbf{w}(n+1)$

$$\begin{aligned}\mathbf{w}(k+1) &= \mathbf{w}(k) + \mathbf{x}(k) \text{ for } k = 1, 2, \dots, n \\ \|\mathbf{w}(k+1)\|^2 &= (\mathbf{w}(k) + \mathbf{x}(k))^2 \\ \|\mathbf{w}(k+1)\|^2 &= \|\mathbf{w}(k)\|^2 + \|\mathbf{x}(k)\|^2 + 2\mathbf{w}^T(k)\mathbf{x}(k) \\ \|\mathbf{w}(k+1)\|^2 &\leq \|\mathbf{w}(k)\|^2 + \|\mathbf{x}(k)\|^2\end{aligned}$$

## Alternate: Norm

Norm of  $\mathbf{w}(n+1)$

$$\|\mathbf{w}(k+1)\|^2 - \|\mathbf{w}(k)\|^2 \leq \|\mathbf{x}(k)\|^2 \text{ for } k = 1, 2, \dots, n$$

# Alternate: Norm

Norm of  $\mathbf{w}(n+1)$

$$\begin{aligned} \|\mathbf{w}(2)\|^2 - \|\mathbf{w}(1)\|^2 &\leq \|\mathbf{x}(1)\|^2 \\ + \\ \|\mathbf{w}(3)\|^2 - \|\mathbf{w}(2)\|^2 &\leq \|\mathbf{x}(2)\|^2 \\ + \\ \|\mathbf{w}(4)\|^2 - \|\mathbf{w}(3)\|^2 &\leq \|\mathbf{x}(3)\|^2 \\ + \\ \|\mathbf{w}(n)\|^2 - \|\mathbf{w}(n-1)\|^2 &\leq \|\mathbf{x}(n-1)\|^2 \\ + \\ &\vdots \\ + \\ \|\mathbf{w}(n+1)\|^2 - \|\mathbf{w}(n)\|^2 &\leq \|\mathbf{x}(n)\|^2 \end{aligned}$$

## Alternate: Norm

Norm of  $\mathbf{w}(n+1)$

$$\begin{aligned}\|\mathbf{w}(n+1)\|^2 &\leq \sum_{k=1}^n \|\mathbf{x}(k)\|^2 \\ \|\mathbf{w}(n+1)\|^2 &\leq n\beta \\ \text{where } \beta &= \max_{\mathbf{x}(k) \in \mathcal{C}_1} \|\mathbf{x}(k)\|^2\end{aligned}$$

# Alternate: Norm

Norm of  $\mathbf{w}(n+1)$

$$\begin{aligned}\|\mathbf{w}(n+1)\|^2 &\geq \frac{n^2\alpha^2}{\|\mathbf{w}_o\|^2} \\ \text{and} \\ \|\mathbf{w}(n+1)\|^2 &\leq n\beta \\ \frac{n_{\max}^2\alpha^2}{\|\mathbf{w}_o\|^2} &= n_{\max}\beta \\ n_{\max} &= \frac{\beta\|\mathbf{w}_o\|^2}{\alpha^2}\end{aligned}$$

Norm of  $\mathbf{w}(n+1)$

That is maximum number of iterations are bounded. Perceptron should converge.

# Algorithm

## Incremental

**Initialization** Set  $\mathbf{w}(0) = \mathbf{0}$ ; Perform following computations for  $n = 1, 2, \dots$

**Activation** At time step  $n$ , provide the input vector  $\mathbf{x}(n)$  and desired response  $d(n)$

**Response**  $\text{sgn}(\mathbf{w}^T(n)\mathbf{x}(n))$  Output is  $\{-1, +1\}$

**Adaptation**  $\mathbf{w}(n+1) = \mathbf{w}(n) + \eta [d(n) - y(n)] \mathbf{x}(n)$   
Where

$$d(n) = \begin{cases} +1 & \text{if } \mathbf{x}(n) \in \mathcal{C}_1 \\ -1 & \text{if } \mathbf{x}(n) \in \mathcal{C}_2 \end{cases}$$

**Iterate** Increment  $n$  and go to activation step

# Batch Algorithm

## Objective (Cost) Function

- Compute:  $\mathbf{w}^T(n)\mathbf{x}(n)$
- Treat the above quantity as the objective function
- With the modification  $\mathbf{w}^T(n)\mathbf{x}(n)d(n)$
- For one  $\mathbf{x}(n)$  the above objective function is used:
- For many  $\mathbf{x}(n)$ 's we have:

$$J(\mathbf{w}) = \sum_{\mathbf{x}(n) \in \mathcal{H}} \left( -(\mathbf{w}^T(n)\mathbf{x}(n)d(n)) \right)$$

- The above objective function should be **minimized**

# Batch Algorithm

## Objective Function - Intuition

- We have to minimize or maximize a given objective function
- Perceptron rule:  $\mathbf{w}^T(n)\mathbf{x}(n) > 0 \quad \mathbf{x}(n) \in \mathcal{C}_1$
- $\mathbf{w}^T(n)\mathbf{x}(n)$  quantity for  $\mathcal{C}_1$  is positive,  $d(n) = +1$ . Decrease it by multiplying it -1
- Perceptron rule:  $\mathbf{w}^T(n)\mathbf{x}(n) \leq 0 \quad \mathbf{x}(n) \in \mathcal{C}_1$
- $\mathbf{w}^T(n)\mathbf{x}(n)$  quantity for  $\mathcal{C}_1$  is negative,  $d(n) = -1$ . Decrease it by multiplying it -1
- That is for any  $\mathbf{x}(n)$ , the quantity  $-(\mathbf{w}^T(n)\mathbf{x}(n)d(n))$  to be **minimized**



# Batch Algorithm

## Apply Gradient Descent Rule

- Compute direction:  $\nabla J(\mathbf{w}) = \sum_{\mathbf{x}(n) \in \mathcal{H}} (-\mathbf{x}(n)d(n))$
- Update  $\mathbf{w}(n+1) = \mathbf{w}(n) - \eta(n) \nabla J(\mathbf{w})$
- That is  $\mathbf{w}(n+1) = \mathbf{w}(n) - \eta(n) \sum_{\mathbf{x}(n) \in \mathcal{H}} (-\mathbf{x}(n)d(n))$