## CS344: Introduction to Artificial

Intelligence (associated lab: CS386)

## Pushpak Bhattacharyya

CSE Dept., IIT Bombay
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## The Perceptron Model

A perceptron is a computing element with input lines having associated weights and the cell having a threshold value. The perceptron model is motivated by the biological neuron.



# Step function / Threshold function 

$y \quad=1$ for $\Sigma w_{i} x_{i} \quad>=\boldsymbol{\theta}$
$=0$ otherwise

## Features of Perceptron

- Input output behavior is discontinuous and the derivative does not exist at $\boldsymbol{\Sigma} \mathbf{w}_{\mathbf{i}} \mathbf{x}_{\mathbf{i}}=\boldsymbol{\theta}$
- $\boldsymbol{\Sigma} \mathbf{w}_{\mathbf{i}} \mathbf{x}_{\mathbf{i}} \boldsymbol{- \theta}$ is the net input denoted as net
- Referred to as a linear threshold element - linearity because of $\mathbf{x}$ appearing with power $\mathbf{1}$
- $\mathbf{y}=\mathbf{f}($ net $)$ : Relation between y and net is nonlinear


## Perceptron Training Algorithm (PTA)

Preprocessing:

1. The computation law is modified to

$$
\begin{aligned}
& y=1 \text { if } \sum w_{i} x_{i}>\theta \\
& y=0 \text { if } \sum w_{i} x_{i}<\theta
\end{aligned}
$$



## PTA - preprocessing cont...

2. Absorb $\theta$ as a weight

3. Negate all the zero-class examples

## Example to demonstrate preprocessing

- OR perceptron

1-class <1,1>, <1,0>, <0,1>
0 -class <0,0>

Augmented $x$ vectors:-
1-class $<-1,1,1\rangle,<-1,1,0\rangle,<-1,0,1\rangle$
0-class <-1,0,0>

Negate 0-class:- < 1,0,0>

## Example to demonstrate preprocessing cont..

Now the vectors are

\[

\]

## Perceptron Training Algorithm

1. Start with a random value of $w$ ex: <0,0,0...>
2. Test for $w x_{i}>0$

If the test succeeds for $i=1,2, \ldots n$ then return w
3. Modify $\mathrm{w}, \mathrm{w}_{\text {next }}=\mathrm{w}_{\text {prev }}+\mathrm{X}_{\text {fail }}$

## PTA on NAND



Converted To


$$
X_{2} \quad X_{1} \quad X_{0=-1}
$$

## Preprocessing

NAND Augmented:

$$
\begin{array}{llll}
X_{2} & X_{1} & X_{0} & Y \\
0 & 0 & -1 & 1 \\
0 & 1 & -1 & 1
\end{array}
$$

$$
\begin{array}{llll}
1 & 0 & -1 & 1 \\
1 & 1 & -1 & 0
\end{array}
$$

NAND-0 class Negated

$$
\begin{array}{rrrr} 
& \mathrm{X}_{2} & \mathrm{X}_{1} & \mathrm{X}_{0} \\
\mathrm{~V}_{0}: & 0 & 0 & -1 \\
\mathrm{~V}_{1}: & 0 & 1 & -1
\end{array}
$$

$$
\begin{array}{lrlr}
\text { V2: }_{2} & 1 & 0 & -1 \\
\text { V }_{3} & -1 & 1 & -1
\end{array}
$$

Vectors for which
W=<W2 W1 W0> has to be found such that W. Vi > 0

## PTA Algo steps

Algorithm:

1. Initialize and Keep adding the failed vectors until W. Vi > 0 is true.

$$
\begin{aligned}
& \text { Step 0: } \mathrm{W}=<0,0,0\rangle \\
& W_{1}=\langle 0,0,0\rangle+\langle 0,0,-1\rangle \quad\left\{V_{0} \text { Fails }\right\} \\
& =<0,0,-1> \\
& W_{2}=\langle 0,0,-1\rangle+\langle-1,-1,1\rangle\left\{V_{3} \text { Fails }\right\} \\
& =\langle-1,-1,0\rangle \\
& \mathrm{W}_{3}=\langle-1,-1,0\rangle+\langle 0,0,-1\rangle \quad\left\{\mathrm{V}_{0} \text { Fails }\right\} \\
& =\langle-1,-1,-1\rangle \\
& \mathrm{W}_{4}=\langle-1,-1,-1\rangle+\langle 0,1,-1\rangle\left\{\mathrm{V}_{1} \text { Fails }\right\} \\
& =\langle-1,0,-2\rangle
\end{aligned}
$$

## Trying convergence

$$
\begin{aligned}
& \mathrm{W}_{5}=\langle-1,0,-2\rangle+\langle-1,-1,-1\rangle \quad\left\{\mathrm{V}_{3} \text { Fails }\right\} \\
& =\langle-2,-1,-1\rangle \\
& \mathrm{W}_{6}=\langle-2,-1,-1\rangle+\langle 0,1,-1\rangle \quad\left\{\mathrm{V}_{1} \text { Fails }\right\} \\
& =\langle-2,0,-2\rangle \\
& \mathrm{W}_{7}=\langle-2,0,-2\rangle+\langle 1,0,-1\rangle \quad\left\{\mathrm{V}_{0} \text { Fails }\right\} \\
& =\langle-1,0,-3\rangle \\
& \mathrm{W}_{8}=\langle-1,0,-3\rangle+\langle-1,-1,-1\rangle \quad\{\mathrm{V} 3 \text { Fails }\} \\
& =\langle-2,-1,-2\rangle \\
& \mathrm{W}_{9}=\langle-2,-1,-2\rangle+\langle 1,0,-1\rangle \quad\left\{\mathrm{V}_{2} \text { Fails }\right\} \\
& =\langle-1,-1,-3\rangle
\end{aligned}
$$

## Trying convergence

$$
\begin{aligned}
& W_{10}=\langle-1,-1,-3\rangle+\langle-1,-1,-1\rangle \quad\left\{V_{3} \text { Fails }\right\} \\
& =\langle-2,-2,-2\rangle \\
& \mathrm{W}_{11}=\langle-2,-2,-2\rangle+\langle 0,1,-1\rangle \quad\left\{\mathrm{V}_{1} \text { Fails }\right\} \\
& =\langle-2,-1,-3\rangle \\
& W_{12}=\langle-2,-1,-3\rangle+\langle-1,-1,-1\rangle \quad\left\{V_{3} \text { Fails }\right\} \\
& =\langle-3,-2,-2\rangle \\
& \mathrm{W}_{13}=\langle-3,-2,-2\rangle+\langle 0,1,-1\rangle \quad\left\{\mathrm{V}_{1} \text { Fails }\right\} \\
& =\langle-3,-1,-3\rangle \\
& \mathrm{W}_{14}=\langle-3,-1,-3\rangle+\langle 0,1,-1\rangle \quad\{\mathrm{V} 2 \text { Fails }\} \\
& =\langle-2,-1,-4\rangle
\end{aligned}
$$

## Converged!

$$
\begin{aligned}
& \mathrm{W}_{15}=\langle-2,-1,-4\rangle+\langle-1,-1,-1\rangle \quad\{\mathrm{V} 3 \text { Fails }\} \\
& =\langle-3,-2,-3\rangle \\
& \mathrm{W}_{16}=\langle-3,-2,-3\rangle+\langle 1,0,-1\rangle \quad\{\mathrm{V} 2 \text { Fails }\} \\
& =\langle-2,-2,-4\rangle \\
& W_{17}=\langle-2,-2,-4\rangle+\langle-1,-1,-1\rangle \quad\left\{V_{3} \text { Fails }\right\} \\
& =\langle-3,-3,-3\rangle \\
& \mathrm{W}_{18}=\langle-3,-3,-3\rangle+\langle 0,1,-1\rangle \quad\left\{\mathrm{V}_{1} \text { Fails }\right\} \\
& =\langle-3,-2,-4\rangle \\
& W_{2}=-3, \quad W_{1}=-2, \quad W 0=\Theta=-4
\end{aligned}
$$

PTA convergence

## Statement of Convergence of PTA

- Statement:

Whatever be the initial choice of weights and whatever be the vector chosen for testing, PTA converges if the vectors are from a linearly separable function.

## Proof of Convergence of PTA

- Suppose $\mathrm{w}_{\mathrm{n}}$ is the weight vector at the $\mathrm{n}^{\text {th }}$ step of the algorithm.
- At the beginning, the weight vector is $w_{0}$
- Go from $w_{i}$ to $w_{i+1}$ when a vector $X_{j}$ fails the test $w_{i} X_{j}>0$ and update $w_{i}$ as

$$
w_{i+1}=w_{i}+x_{j}
$$

- Since Xjs form a linearly separable function,
$\exists w^{*}$ s.t. $w^{*} X_{j}>0 \forall j$


## Proof of Convergence of PTA

 (cntd.)- Consider the expression

$$
\mathrm{G}\left(\mathrm{w}_{\mathrm{n}}\right)=\frac{\mathrm{w}_{\mathrm{n}} \cdot \mathrm{w}^{*}}{\left|\mathrm{w}_{\mathrm{n}}\right|}
$$

where $w_{n}=$ weight at nth iteration
$-\mathrm{G}\left(\mathrm{w}_{\mathrm{n}}\right)=\left\lfloor\mathrm{w}_{\mathrm{n}}\right\rfloor \cdot\left|\mathrm{w}^{*}\right| \cdot \cos \theta$
$\left|w_{n}\right|$
where $\theta=$ angle between $\mathrm{w}_{\mathrm{n}}$ and $\mathrm{w}^{*}$

- $\mathrm{G}\left(\mathrm{w}_{\mathrm{n}}\right)=\left|\mathrm{w}^{*}\right| \cdot \cos \theta$
- $\mathrm{G}\left(\mathrm{w}_{\mathrm{n}}\right) \leq\left|\mathrm{w}^{*}\right| \quad(\mathrm{as}-1 \leq \cos \theta \leq 1)$


## Behavior of Numerator of G

$$
\begin{aligned}
& w_{n} \cdot w^{*}=\left(w_{n-1}+X^{n-1} \text { fail }\right) \cdot w^{*} \\
& =W_{n-1} \cdot W^{*}+X^{n-1} \text { fail } \cdot W^{*} \\
& =\left(w_{n-2}+X^{n-2} \text { fail }\right) \cdot W^{*}+X^{n-1} \text { fail } \cdot W^{*} \ldots . \\
& =W_{0} \cdot W^{*}+\left(X_{\text {fail }}^{0}+X_{\text {fail }}^{1}+\ldots .+X^{n-1} \text { fail }\right) \cdot W^{*} \\
& W^{*} . X_{\text {fail }}^{i} \text { is always positive: note } \\
& \text { carefully } \\
& \text { - Suppose }\left|X_{j}\right| \geq \delta \text {, where } \delta \text { is the } \\
& \text { minimum magnitude. } \\
& \text { - Num of } G \geq\left|w_{0} \cdot w^{*}\right|+n \delta .\left|w^{*}\right| \\
& \text { - So, numerator of } G \text { grows with } n \text {. }
\end{aligned}
$$

## Behavior of Denominator of G

- $\left|w_{n}\right|=\sqrt{ } w_{n} \cdot w_{n}$
$=\sqrt{ }\left(w_{n-1}+X^{n-1}{ }_{\text {fail }}\right)^{2}$
$=\sqrt{ }\left(w_{n-1}\right)^{2}+2 \cdot w_{n-1} . X^{n-1}$ fail $+\left(X^{n-1} \text { fail }\right)^{2}$
$\leq \sqrt{ }\left(w_{n-1}\right)^{2}+\left(X^{n-1} \text { fail }\right)^{2} \quad$ (as $w_{n-1} . X^{n-1}$ fail $\leq 0$ )
$\leq \sqrt{ }\left(w_{0}\right)^{2}+\left(X_{\text {fail }}^{0}\right)^{2}+\left(X_{\text {fail }}^{1}\right)^{2}+\ldots .+\left(X^{n-1}\right.$ fail $)^{2}$
- $\left|\mathrm{X}_{\mathrm{j}}\right| \leq \rho$ (max magnitude)
- So, Denom $\leq \sqrt{ }\left(w_{0}\right)^{2}+n \rho^{2}$


## Some Observations

- Numerator of G grows as n
- Denominator of $G$ grows as $\sqrt{ } n$
=> Numerator grows faster than denominator
- If PTA does not terminate, $\mathrm{G}\left(\mathrm{w}_{\mathrm{n}}\right)$ values will become unbounded.


## Some Observations contd.

- But, as $\left|G\left(w_{n}\right)\right| \leq\left|w^{*}\right|$ which is finite, this is impossible!
- Hence, PTA has to converge.
- Proof is due to Marvin Minsky.


## Convergence of PTA proved

- Whatever be the initial choice of weights and whatever be the vector chosen for testing, PTA converges if the vectors are from a linearly separable function.

