

A)

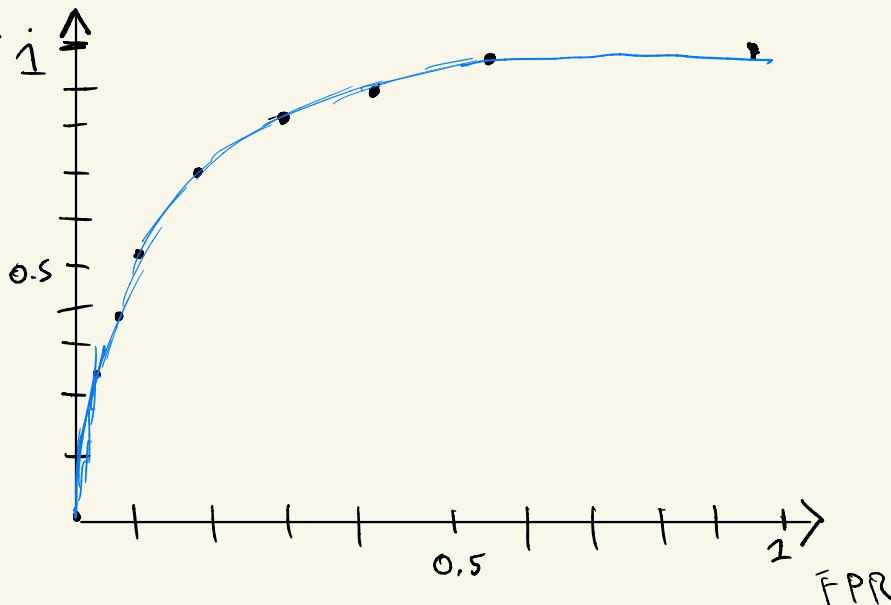
| Threshold | True Positives (TP) | False Positives (FP) | True Negatives (TN) | False Negatives (FN) | TPR | FPR |
|-----------|---------------------|----------------------|---------------------|----------------------|------|--------|
| 0.95 | 10 | 2 | 58 | 30 | .25 | .03333 |
| 0.85 | 15 | 4 | 56 | 25 | .375 | .06666 |
| 0.75 | 22 | 8 | 52 | 18 | .55 | .13333 |
| 0.65 | 28 | 12 | 48 | 12 | .7 | .2 |
| 0.55 | 32 | 18 | 42 | 8 | .815 | .3 |
| 0.45 | 35 | 25 | 35 | 5 | .95 | .41666 |
| 0.35 | 38 | 35 | 25 | 2 | | .88889 |

i) For each threshold: Calculate the True Positive Rate (TPR) and False Positive Rate (FPR).

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

B) TPR



$$c) A_{Rec} = \sum \frac{1}{2}(FPR_{i+1} - FPR_i) \times (FPR_{i+1} + TPR_i)$$

$$A_1 = \frac{1}{2}(0.667 - 0.33) \times (0.25 + 0.375) = 0.0104$$

$$A_2 = \frac{1}{2}(0.33 - 0.667) \times (0.375 + 0.55) = 0.0302$$

$$A_3 = \frac{1}{2}(0.200 - 0.33) \times (0.55 + 0.7) = 0.0417$$

$$A_4 = \frac{1}{2}(-0.3 - 0.2) \times (0.7 + 0.8) = 0.075$$

$$A_5 = \frac{1}{2}(-0.4167 - 0.3) \times (0.8 + 0.875) = 0.0927$$

$$A_6 = \frac{1}{2}(-0.5833 - 0.4167) \times (0.875 + 0.95) = 0.1577$$

$$A_7 = \frac{1}{2}(0.033 - 0) \times (0.25 + 0) = 0.0042$$

$$A_8 = \frac{1}{2}(1 - 0.583) \times (0.95 + 1) = 0.4115$$

$$AVC = \sum_{i=1}^8 A$$

$$\begin{aligned} AVC &= 0.0104 + 0.0302 + 0.0417 + 0.075 + \\ &\quad 0.0927 + 0.1577 + 0.0042 + 0.4115 \end{aligned}$$

$$= 0.7239$$

$$\boxed{\approx 0.823}$$

2)

A) $\times (1, 1, 0, 1, 0, 1) \rightarrow \text{BCFF}$

1011

bias = 1

$$1 + (1 \cdot 1) * (0 \cdot 0) + (0 \cdot -1) + (1 \cdot 1) = 3$$

$$\text{sign}(3) = 1$$

so A is 1

B) $\times (0, 1, 0, 1, 0, 1) \rightarrow \text{CDEF}$

$0-312$

bias = 1

$$1 + (1 \cdot 0) + (1 \cdot -1) + (1 \cdot 0) + (1 \cdot 2) = 0$$

$$\text{sign}(0) = -1$$

so b is -1

since Sign 0 = -1

3) Linear threshold $\rightarrow w_0 \sum_{i=1}^n w_i x_i > 0$
positive class based off w_0 being true
Separates linear hyperplane
 $n \geq 4$ proves this, as $n \geq 2$ will create a non-linear boundary because the sum of weights won't identify when w_0 inputs are false versus other

$$n=4$$

Positive: $(0, 0, 1, 1)$, $(0, 1, 0, 1)$, $(0, 1, 1, 0)$, etc
with 2 zeros

Negative: Any other combination

This shows you can't distinguish using a linear boundary because the false cases have fewer or more than 2 zeros. They cannot be separated solely on a weight sum.

Perceptrons cannot handle parity functions, on an east count being true or false

9)

| x_1 | x_2 | x_3 | y |
|-------|-------|-------|-----|
| 0 | 0 | 0 | 1 |
| 0 | 0 | 1 | -1 |
| 0 | 1 | 0 | 1 |
| 0 | 1 | 1 | 1 |
| 1 | 0 | 0 | 1 |
| 1 | 0 | 1 | -1 |
| 1 | 1 | 0 | 1 |
| 1 | 1 | 1 | 1 |

conflicting outputs

conflicting outputs

The data is not linearly separable

since there is no single set of weights that can consistently separate positive and negative classes. It lacks linear separability in the feature space.

$$x_1, x_2, x_3 = 0, 0, 1 \rightarrow y = -1$$

$$x_1, x_2, x_3 = 0, 1, 1 \rightarrow y = 1$$

Positive Class $\rightarrow (0, 0, 0), (0, 1, 0), (0, 1, 1), (1, 0, 0), (1, 1, 0)$
 $y=1$ $(1, 1, 1)$

Negative Class $\rightarrow (0, 0, 1) (1, 0, 1)$
 $y=-1$

these cannot be linearly separable as since $\beta = -1$
is scattered across $y=1$ or the positive class.

Examples

$(0, 0, 1)$ and $(0, 0, 0)$ adjacent
but have different labels

Same with $(1, 0, 1)$ and $(1, 0, 0)$
which are adjacent but
have diff labels

Since the data is not linearly
separable it cannot be represented
with a linear threshold function