

## Exercise 1.

### part 1

- a) Overfitting occurs when a model learns the training data too well, capturing noise & fluctuations rather than the underlying pattern, leading to poor performance on new data. It is detected when the training error is very low, but the validation/test error is high.
- b) Bias is the error introduced by approximating a real-world problem with a simplified model. High bias causes underfitting.
- \* Variance refers to the model's sensitivity to fluctuations in the training set. High variance causes overfitting.

c) Regularization adds a penalty term to the loss function to discourage complex Models. Its purpose is to reduce overfitting & variance, improving generalization.

d) Precision is more important. In spam detection, a FP is much worse than FN. We want to be very sure as what we classify as spam is actual spam.

### part 2

- a) True
- b) True

## Exercise 2:

1.)  $H(Y) = - \sum_{p_{(mc)}} \log_2(p_{(mc)}) = -\left(\frac{3}{4} \log_2\left(\frac{3}{4}\right) + \frac{1}{4} \log_2\left(\frac{1}{4}\right)\right) \approx \underline{\underline{0.811}}$

\* Splitting on  $X_1$ :

•  $X_1 = 0$  (rows 1, 2):  $Y = \{0, 1\}$ .  $H(Y|X_1=0) = -\left(\frac{1}{2} \log_2\left(\frac{1}{2}\right) + \frac{1}{2} \log_2\left(\frac{1}{2}\right)\right) = \underline{\underline{1}}$

•  $X_1 = 1$  (rows 3, 4):  $Y = \{1, 1\}$ .  $H(Y|X_1=1) = \underline{\underline{0}}$  (pure Node)

$$\Rightarrow E(X_1) = \frac{2}{4}(1) + \frac{2}{4}(0) = 0.5$$

$$\Rightarrow IG(X_1) = 0.811 - 0.5 = 0.311$$

\* Splitting on  $X_2$ :

// the data is symmetric, calculations will be the same

$$\Rightarrow IG(X_2) = \underline{\underline{0.311}}$$

2) we can choose randomly. But the reduce entropy by the exact same amount.

### Exercise 3:

Binary cross-entropy loss formula:  $-\frac{1}{N} \sum [y_i \ln(g_i) + (1-y_i) \ln(1-g_i)]$

1). sample 1:  $-\ln(0.9) \approx 0.105$

. sample 2:  $-\ln(1-0.2) \approx 0.223$

. sample 3:  $-\ln(0.7) \approx 0.357$

. sample 4:  $-\ln(1-0.6) \approx 0.916$

$$\Rightarrow \frac{\sum \dots}{N} = \frac{1.604}{4} \approx \underline{0.4}$$

2) 1:  $0.9 \geq 0.5 \rightarrow 1 \Rightarrow \text{correct}$

2:  $0.2 \geq 0.5 \rightarrow 0 \Rightarrow \text{correct}$

3:  $0.7 \geq 0.5 \rightarrow 1 \Rightarrow \text{correct}$

4:  $0.6 \geq 0.5 \rightarrow 1 \Rightarrow \text{incorrect!}$

		predicted 0	predicted 1	Accuracy = $\frac{TP+TN}{Total} = 0.75$
Actual 0	1 (TN)	1 (FP)		
Actual 1	0 (FN)	2 (TP)	Precision = $\frac{TP}{TP+FP} \approx 0.67$	
			Recall = $\frac{TP}{TP+FN} = 1.0$	
			F1-Score = $\frac{2 \times \frac{Precision \times Recall}{Precision + Recall}}{Precision + Recall} = 0.8$	

4) Lowering the threshold make it easier to predict "1" (positive).

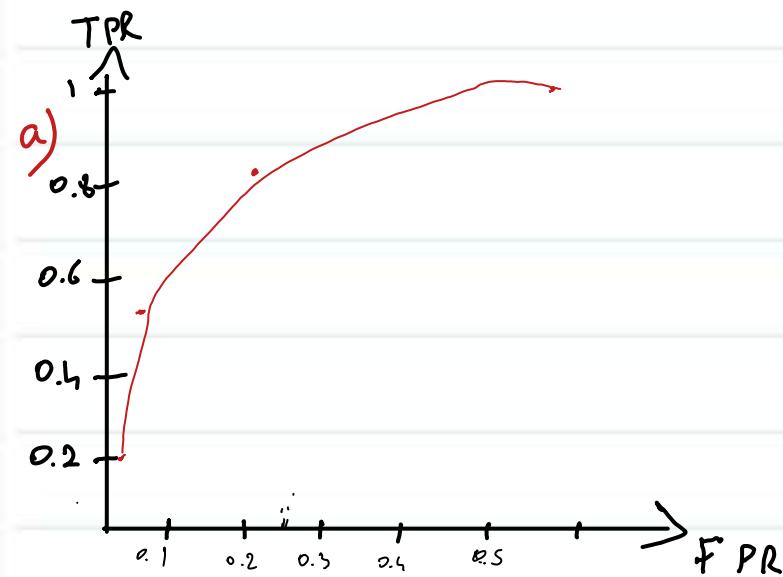
$\Rightarrow$  Recall stays 1.0 (or increase), Precision will likely decreases.

## Exercise 4:

- a) \* Expected prediction: Mean of predictions = 0.95  
\* Bias<sup>2</sup>:  $(\text{Expected predictions} - \text{True})^2 = (1-1)^2 = 0$   
\* Variance  $\approx 0.00034$

$$\text{Total Error} = \text{Bias}^2 + \text{Variance} + \text{Irreducible}$$
$$\approx 0.1038$$

## Exercise 5:



- b) FPR is smaller for threshold 0.5 while Keeping TPR  $> 0.8$ .  
c) We cannot tolerate False Negatives. we need to maximize recall (TPR), we choose threshold 0.3.