

Assignment 1

Bratadeep Sarkar - 240285 - EEG SPELLER

SECTION A

- | | | |
|---------|----------|----------|
| 1) True | 5) True | 9) True |
| 2) True | 6) False | 10) True |
| 3) True | 7) False | |
| 4) True | 8) True | |

SECTION B

Model	Loss fn	Regularization
SVM	$\max(0, 1 - y(n \cdot w + b))$	$\text{loss fn} + \lambda \sum_{i=1}^n w_i^2$
LASSO	$(y - \hat{y})^2$	$\text{loss fn} + \lambda \sum_{i=1}^n w_i $
RIDGE	$(y - \hat{y})^2$	$\text{loss fn} + \lambda \sum_{i=1}^n w_i^2$

3)

a) Loss fn that are differentiable. eg: Logistic loss
Δ (convex)

(b) Loss fn that are twice differentiable eg: Squared loss

4)

- 1) Underfitting - model is too simple to capture str of data (high bias) occurs when
- 2) If both training error & test error remain high \Leftrightarrow Model is underfitting
- 3) Bagging reduce variance by training multiple models independently on different subsets of data & averaging their predictions. Averaging helps smooth out \rightarrow remove noise by individual models.
- 4) Boosting primarily reduces bias by training models sequentially, where each new model focus on correcting errors made by previous combination of models. \rightarrow ~~reduce variance~~.

Section D

~~1) Steps to reduce KNN time:~~ Not done till now
 ~~\rightarrow Approx nearest.~~

Section E

- 1) To minimise sum of squared errors

$$\therefore \text{loss} = \sum_1^n (y_i - c)^2$$

$$\therefore \frac{\partial \text{loss}}{\partial c} = \sum_1^n 2(y_i - c) \cdot (-1) = -2 \sum_1^n (y_i - c) = 0$$

$$\Rightarrow \sum_1^n y_i = \sum_1^n c \Rightarrow \sum_1^n y_i = n c$$

$$\therefore c = \frac{1}{n} \sum_1^n y_i \rightarrow \text{optimal prediction is mean of targets in the leaf}$$

2) Gini impurity $\Rightarrow 1 - \sum_i p_i^2 \rightarrow \text{Min} = 0$

\rightarrow This occurs when node is pure (all samples belong to one class $(0, 0, 1)$)

$\therefore \text{Min gini} = 1 - 1 = 0$

Max \Rightarrow perfect impure node $\rightarrow \therefore p = (1, 1, 1)$

$$G_{\text{max}} = 1 - \left(\frac{1}{3}\right)^2 - \left(\frac{1}{3}\right)^2 - \left(\frac{1}{3}\right)^2 = \frac{2}{3}$$

3) becoz at each step, then choose to split that best maximises info gain locally at that node, without considering how this split will affect future splits deeper in the tree.

4) Two methods to avoid overfitting

\rightarrow limiting maximum depth

\rightarrow Remove features \rightarrow simplify model \rightarrow improve generalization

Section F

2) Done in section C 344

1) -