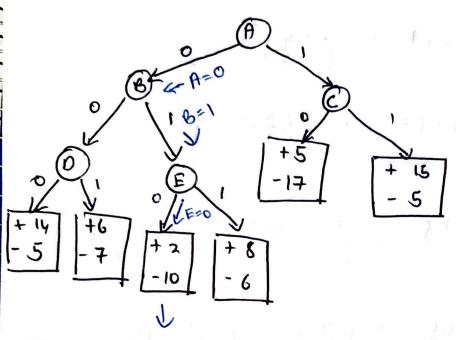


(I



Test T goes to this instance, where it will be clossified

$$= \left(1 - \left(\frac{16}{100} + \frac{36}{100}\right)\right) = 0.48$$

For splitting on A:

For A

Crini (T) = 1 -
$$\left(\left(\frac{4}{3}\right)^{2} + \left(\frac{3}{3}\right)^{2}\right) = 0.489$$

For A

+ - ((
$$\frac{4}{7}$$
)² + ($\frac{3}{7}$)²) = 0.4898

F 0 3

Crini(F) = 1 - (($\frac{4}{7}$)² + ($\frac{3}{7}$)²) = 0.

T 4 3

Grini (T)= 1-
$$((\frac{1}{4})^2 + (\frac{3}{4})^2) = 0.4898$$

F 0 3

Grini (F) = 1- $((\frac{1}{4})^2 + (\frac{3}{4})^2) = 0$

$$G_{1}(G) = (-(\frac{1}{3})^{2} + (\frac{3}{3})^{2}) = 0$$

F 0 3

Crini(F) =
$$1 - ((3)^2 + (3)^2) = 0$$

Crini Tripurity

Other Politics

Gini (F) =
$$(-(\frac{1}{3})^{-1}(\frac{3}{3})) = 0$$

Gini Tripurity
Glar splitting on $A = 6.48 - (\frac{7}{10})(0.4898) - (\frac{3}{10})(0)$

For 8

Crini (T) = 1- (
$$\frac{3}{4}$$
)²+($\frac{1}{4}$)²)

T 3 1

Crini (T) = 1 - (
$$\frac{3}{4}$$
)² + ($\frac{1}{4}$)²)

= 1 - ($\frac{3}{16}$ + $\frac{1}{16}$) = 0.375

Crini (F) = 1 - ($\frac{3}{16}$ + $\frac{1}{16}$) = 0.375

Gini
$$(F) = 1 - \left(\frac{1}{6}\right)^2 + \left(\frac{5}{6}\right)^2$$

$$= 1 - \frac{26}{36} = 0.277$$

Gini Toponity

Ghr splitting on $B = 0.48 - \left(\frac{1}{10}\right)(0.375) - \left(\frac{6}{10}\right)(0.277)$

Crain = 0.1633

THE SHOOT 4) we choose the attribute that gives us more information gain, so splitting over atthibut B would be more beneficial for our tree. @ Task-4 OI_ Decision thees are non-linear in nature. Unlike linear classifiers that create linear boundaries, decision thee partitions the Jeature Space into an inverse tree like Structure. These splik are board on values of indivud features at one node, allowing to gind non linear relations in data. Miss classification ever and Crini both have their own Denegits. > we can use missclassification evour to heduce the overall classification everous especially for both balanced classes - Gin; Index can be used to cheate balanced thees to handle imbalanced datasets more esectently. -) But we preger Orini the due to its lower sensitivity to noise

@ Task -5

Jeature selection.

Bagging - we hardomly form DT using multiple predictors, it helps heduce variance, thus prevents over fitting but it leads to

(3)

1 Lack of interphetability 2 Focuses on variance reduction but not on bas.

Random Jonest: - we do sampling on bootstrap we Start developing more DTs, using random

The add nesses bagging weaknesses by

Distribution of Jeature Selection

2) we we able to make decorrelated thees through handom feature selection.

The difference can impossive model interphetability and help reduce varionce and bias.

Inputs > [-1, -1] [-1,+1] [+1, -1] [+1,+1] Now we he map the data point as: [x1; x2 x2] d, → [-1,+1] d2 -> [-1,-1] d3 > [+1,-17 d2C+1,-1) d3C+1,-1) $d_{\gamma} \rightarrow [+1,+1]$ Now we can have 2 classes -> Class CAX+1) -> olg and dy Class (B)(-1) >d, and d2 Now the seperator would the line in between the points, the midpoint between two of the necessit new generated data points. The maximal margin separator is a vertical line at 221,=0 The margin is perpendicular distance Juan this line to the nearest data points on either side. (1,1)C1,-1)

of Task-6

$$\frac{|ab|x-7}{2}$$

$$\frac{|ab|x-7}{2$$

circular equation in this scalure space is

linear deperable

Task-8 $= (x_1-a)^2 + d(x_2-b)^2 - 1=0$ $K(u,v) = (1+u,v)^2 \text{ in the Jeanure Space}$ $C(1,x_1,x_2, \alpha_1^2, \alpha_2^2, x_1\alpha_2)$ we expand equation

we expand equation
$$C(x_1^2 + q^2 - 2ax_1) + d(x_2^2 + b^2 - 2bx_2) - 1 = 0$$

$$Cx_1^2 + dx_2^2 - 2acx_1 - 2bdx_2 + Ca^2c + b^2d - 1) = 0$$

$$Weights \Rightarrow (2ac, 2bd, a^2(1b^2d)0)$$
intercept $\Rightarrow a^2 + b^2 - 4^2$

The colliptical boundary looks linearly separable in this Jeature space