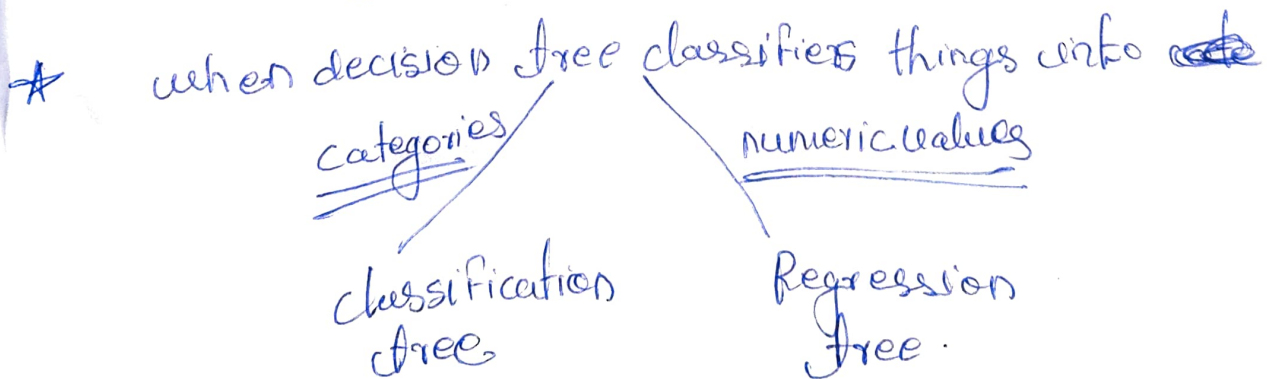
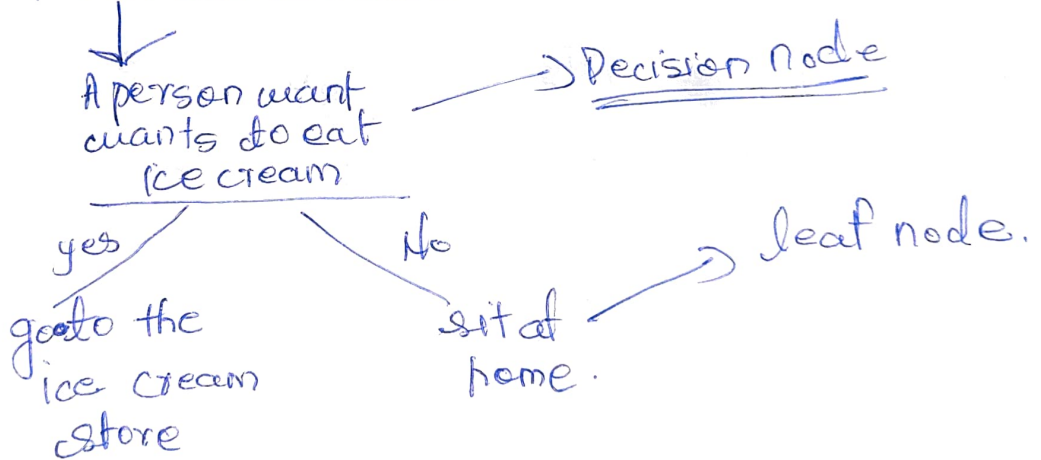
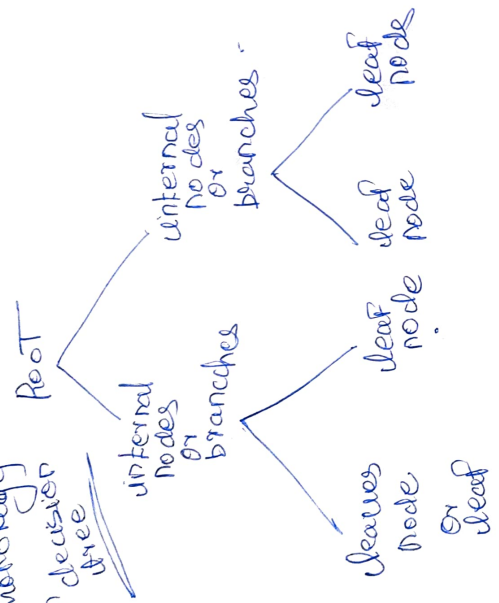


simple example of decision tree



we will focus on decision trees (classification or regression)

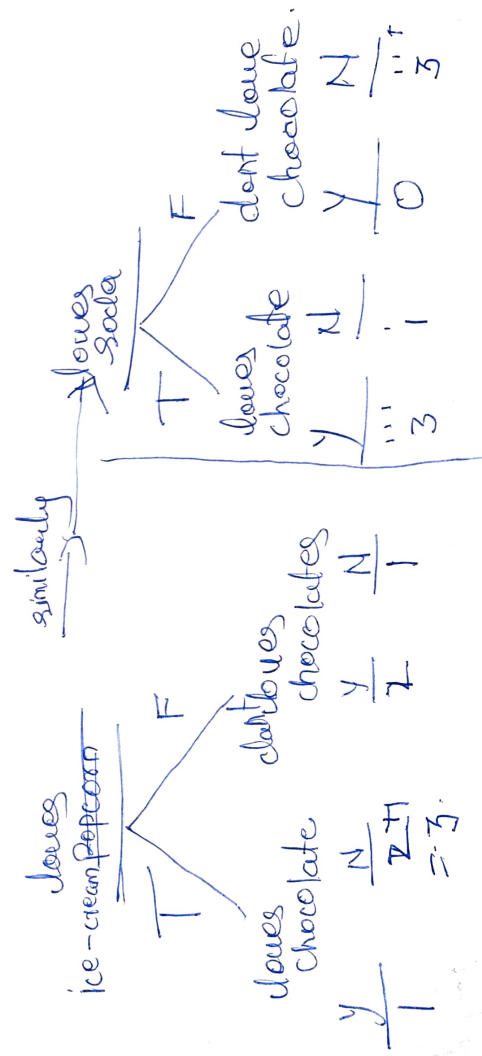
terminology  
or decision tree



\* Lets take an example for decision tree.

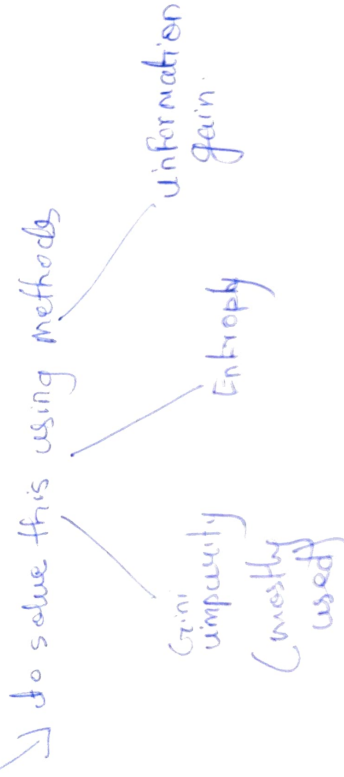
| likes ice cream | likes Soda | Age | likes chocolate |
|-----------------|------------|-----|-----------------|
| y               | y          | 7   | N               |
| y               | N          | 12  | N               |
| N               | y          | 18  | y               |
| No              | y          | 35  | y               |
| ye              | N          | 38  | N               |
| y               | N          | 50  | N               |
| N               | N          | 83  | N               |

y - yes  
N - No



Q.2  
★ how to identify Root nodes  
⇒ by checking independent variable.

★ in previous example you can see the split has not happened into equal parts (yes or no) these splits are called impurity.



### Gini impurity

how to calculate gini impurity

$$\star \text{Gini impurity for a leaf} = 1 - (\text{the probability of yes})^2 - (\text{the probability of No})^2$$

take previous example  
of ICE = cream  
(left side)

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

$$= 0.375$$

and calculate similarly for right side.  
 $= 0.444$ .

Now calculating the gini impurity

Total Gini = weighted average of Gini impurities for the  
the leaves

$$= \left( \frac{4}{4+3} \right) 0.575 + \left( \frac{3}{4+3} \right) 0.444$$

$$\left( \frac{\text{total impurity in leave on left}}{\text{total impurity in both leave}} \right)$$

Gini impurity + ("similarly" for right) Gini impurity

Conclusion is

Gini impurity for leaves

$$\text{ice cream} = 0.405$$



this is we have done

Just for categories what about numeric data?

from the previous example we will take age column

step 1 calculate average of adjacent data  
step 2 then calculate Gini impurity for each value.

Age

$$7 \rightarrow \frac{7+12}{2} = 9.5 \quad \text{for example}$$

$$12 \rightarrow 15 \rightarrow 0.429$$

$$18 \rightarrow 25.5 \rightarrow 0.476$$

$$35 \rightarrow 36.5 \rightarrow 0.476$$

$$38 \rightarrow 44.5 \rightarrow 0.343$$

$$50 \rightarrow 66.5 \rightarrow 0.429$$

83

Age eg. 5

|      |   |    |   |
|------|---|----|---|
| soda | 4 | N. | 1 |
|      | 0 |    | 3 |
|      |   |    | 3 |

$$\% \text{ total gini impurity} = 0.429$$

So the conclusion is 0.343 is lowest So

there are two 0.343 we will pick any one.

Similarly we took out gini impurity for age. So we we take out ice-cream and soda and we have found out soda has the lowest Gini impurity values.

is 0.214

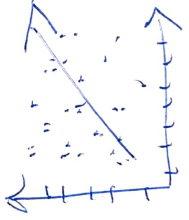
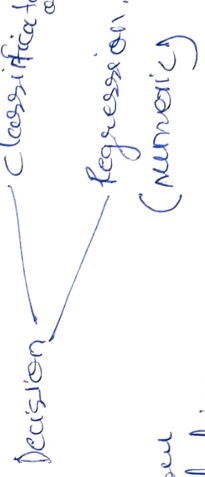
so likewise we will put Soda on the top and according to gini impurity we will distribute categories and whoever got the highest impurity ~~soda~~ will be the leaf node and

those who got the highest majority values will win  
Example

|           |      |                 |      |    |
|-----------|------|-----------------|------|----|
| 4         | Soda | 14              | Soda | 14 |
| 1         | 0    | 0               | 0    | 1  |
| <hr/>     |      | <hr/>           |      |    |
| love Soda |      | don't love Soda |      |    |

## problem statement (regression tree)

what if data is not linear and we have to predict the values.



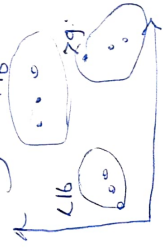
How  
Solution

is regression tree

## So How regression work?

lets say we have an example.

so you can see there is three part in graph. each has threshold value. so we will plot tree on the basis of this



average of this

average of 16 and 29

16 + 29 = 45

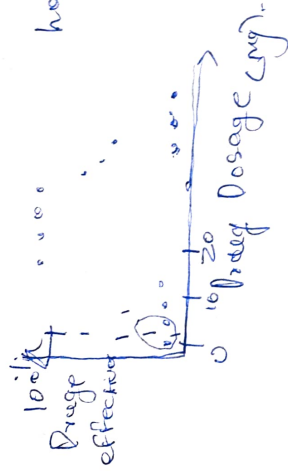
45 / 2 = 22.5

average of 29 and 29

29 + 29 = 58

58 / 2 = 29





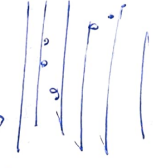
how to build tree for regression.

in above graph we have look only two data point (circles) the line is average values on that basis we can build a tree

Dosage < average (circle)

average = 0%

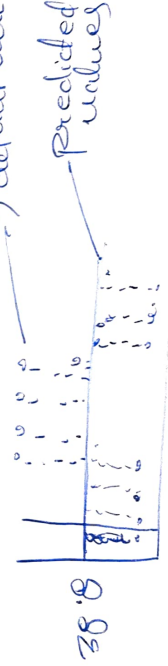
average = 38%



at the data point

and if the values come (dosage 20) ~~are~~ so according graph it showing 100% but according to Decision tree it showing 38%. So it really a poor prediction

★ So we can use visualize the predicted values and actual values.



\* what the solution then?

→ we can ~~not~~ be creative. best we can improve the decision tree.

to improve.

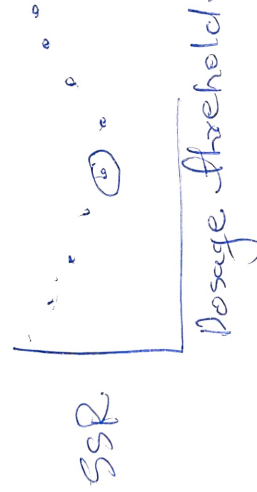
threshold.

(1) take any datapoint and ~~subtract~~ <sup>subtract</sup> it to all datapoint by square, like this.

$$(\text{datapoint} - \text{datapoint}_1)^2 + (\text{datapoint} - \text{datapoint}_2)^2 + (\text{datapoint} - \text{datapoint}_3)^2$$

= Ans.

whatever you get, and plot this in graph.



So whoever gets the lowest SSR that threshold we win. because it has lowest SSR.

So that threshold will be the root.

for example

Postage. 14.5

what about  
next

↓

do the same process to calculate threshold values again.

So do split until the Degree effectiveness it's same or you don't have data point to split.

but this process can lead to model variance  
cluster not by data point. what we have are not 1 there many independent variable.

- 1) step calculate threshold for every column.
- 2) and pick that threshold (column) whoever got the lowest values.
- 3) then make branch ascending to descending on the basis of threshold.

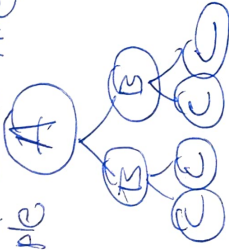
Decision tree

(work on

Divide and conquer technique (Yandl)

every Node is purely homogeneous region.

at the root node it represent the all the data set and so on for example





You can check Accuracy of Decision tree by Holdout method.

Decision tree (C5.0).

in C5.0 to select feature at branch it uses something called entropy.

data with high entropy



diverse, little information

↓ low entropy



homogeneous region

most important feature will determine by entropy score.

$$\text{entropy}(S) = \sum_{i=1}^c -p_i \log_2(p_i)$$

$p$  = proportion.

$i$  = features.

To calculate entropy we have to create random split for example. (ABCD)

(subset)

① (ABC)

② (CDB)

③ (CDB)

② then take 1<sup>st</sup> random and calculate entropy soon.  
just say

play

$\begin{vmatrix} y \\ y \\ y \end{vmatrix}$

$$\frac{3}{4} - \log_2(3/4)$$

$$= 0.4$$

③ calculate entropy for another random also

for purely homogeneous region = Entropy will always be 0.

Now we will calculate Entropy before by calculating complete dataset.

before continuing we should understand why we picking up important features by entropy method or any method

① if don't select the decision tree will have nodes so much.

② if don't select the decision tree will not predict values properly. (impurity will increase)

entropy: - measures the purity of split.

worst entropy  $\begin{matrix} N \\ 50\% \end{matrix} \left| \begin{matrix} Y \\ 50\% \end{matrix} \right. = 1 \text{ bits}$

best entropy  $\begin{matrix} \\ 100\% \end{matrix} \left| \begin{matrix} \\ 0\% \end{matrix} \right. = 0 \text{ bits}$

entropy ranges to 0-1 and entropy unit is bits

\* the split will go on till the leaf node is purely homogeneous subset.

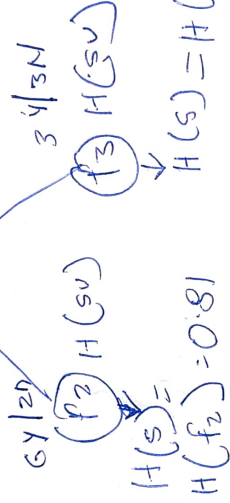
information gain.

that will give the ~~low~~ which split is best.

$$= \text{Gain}(S, A) = H(S) - \sum_{v \in \text{VAL}} \frac{|S_v|}{|S|} H(S_v)$$

$H(S)$  = entropy for particular subset (after split what is the split.)

Example  $f_1$   $H(f_1)$



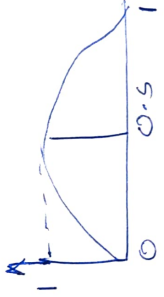
$$\begin{aligned} \text{Gain}(S, f_1) &= H(S) - 8/14 H(f_2) - \frac{6}{14} H(f_3) \\ &= 0.91 - 8/14 \times 0.81 - \frac{6}{14} \times 1 \\ &= 0.049 \end{aligned}$$

$= 0.049$

↓ what this value indicate.

if this value is high it means this structure is best to use the machine algorithm will use different Decision tree structure to identify which one is the best

to calculate ~~imp~~  
 to calculate purity in set we use Entropy  
Gini impurity



① entropy =

② Gini impurity,

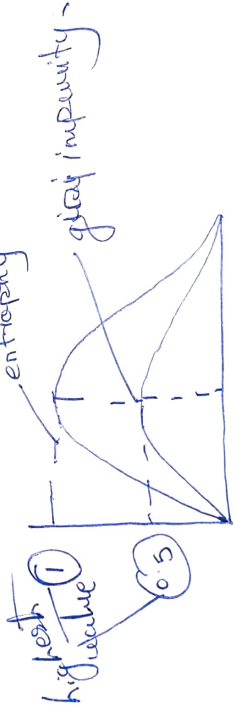
$$= 1 - \sum_{i=1}^n (p_i)^2$$

$$= 1 - [(P)^2 + (P)^2]$$

but we are using both to calculate impurity then which one to use and what is the different.

graph for

entropy and gini impurity



Gini impurity takes less time to do operation.

\* entropy before (after creating random set) original dataset  
before

\* information gain (lies in 1 to 0)

$$= \cancel{(P)} * \cancel{\text{entropy}} - \text{entropy before} - \text{entropy after}$$

\* information gain (How useful is split).

0 - worst

1 - best.

\* To avoid overfitting issue we will use pruning.

Decision tree: C5.0

(alpha near zero)  
↓  
research paper on decision tree.

\* How long Decision tree  
= it will go indefinitely until algorithm haven't got homogeneous region.

\* CART (Classification and Regression tree)