

Classification and Regression

- Decision Trees can be used for both

X1	X2	Y
0.268	0.266	Bad
0.219	0.372	Bad
0.517	0.573	Bad
0.269	0.908	Good
0.181	0.202	Bad
0.519	0.898	Good
0.563	0.945	Bad
0.179	0.661	Bad

Classification

- Spam / not Spam
- Admit to ICU /not
- Lend money / deny
- Intrusion detections

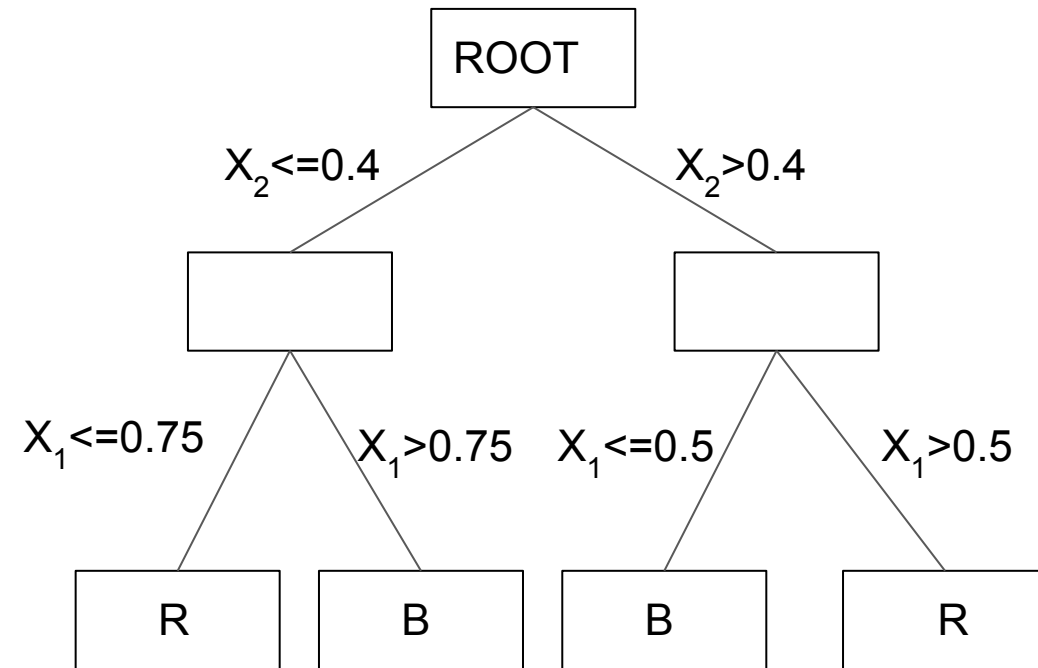
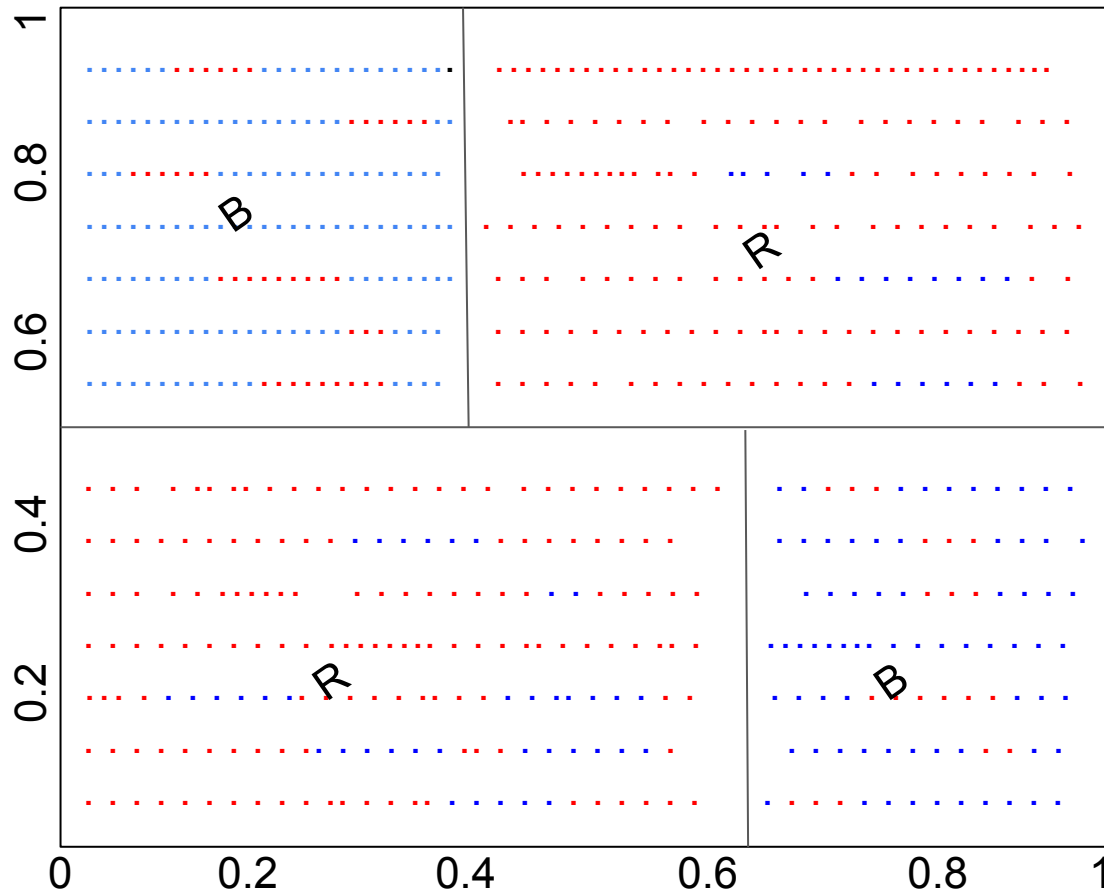
CART

Regression

- Predict stock returns
- Pricing a house or a car
- Weather predictions (temp, rain fall etc)
- Economic growth predictions
- Predicting sports scores

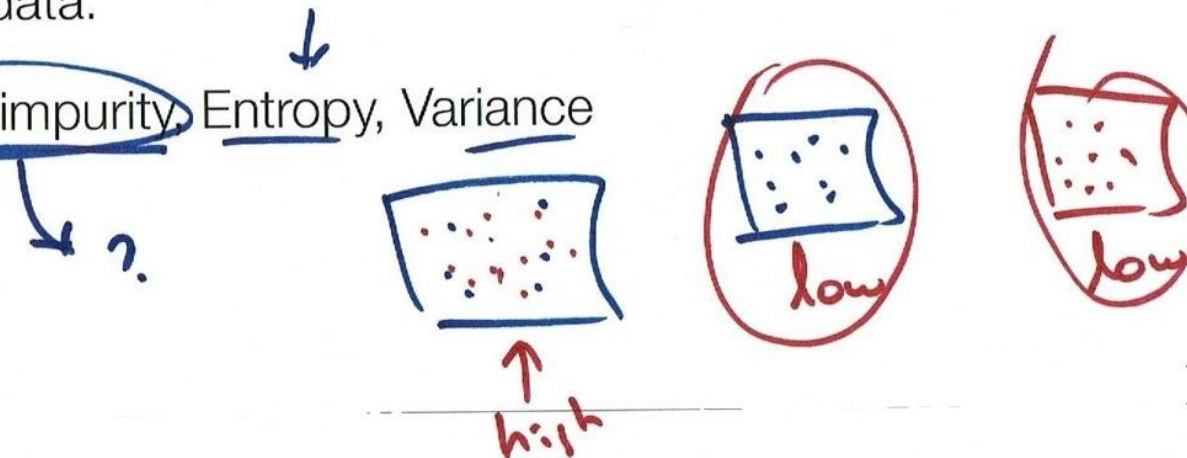
X1	X2	Y
0.268	0.266	64.41
0.219	0.372	28.08
0.517	0.573	95.76
0.269	0.908	15.84
0.181	0.202	41.83
0.519	0.898	25.20
0.563	0.945	9.44
0.179	0.661	82.77

Visualizing Classification as a Tree



Metrics

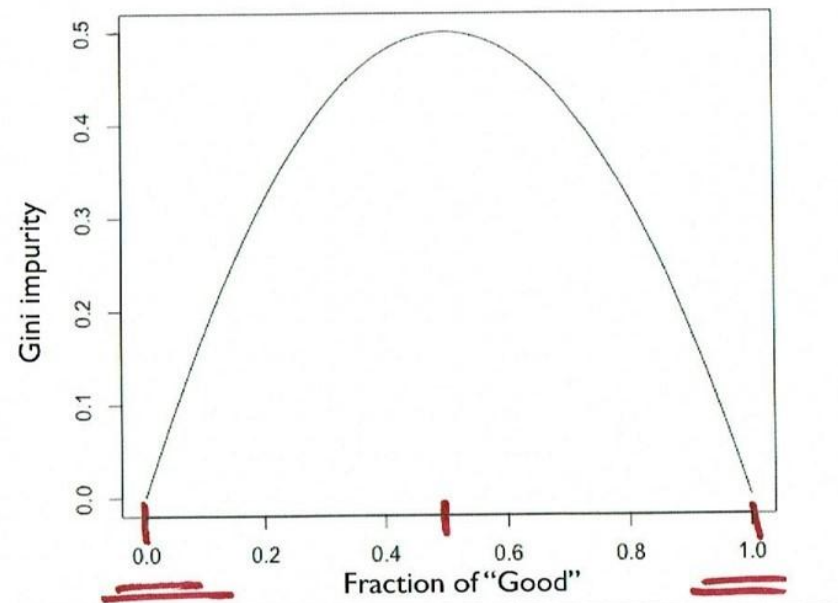
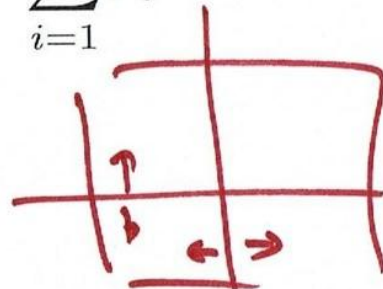
- Algorithms for constructing decision trees usually work top-down, by choosing a variable at each step that best splits the set of items.
- Different algorithms use different metrics for measuring "best"
- These metrics measure how similar a region or a node is. They are said to measure the impurity of a region.
- Larger these impurity metrics the larger the "dissimilarity" of a nodes/regions data.
- Examples. Gini impurity, Entropy, Variance



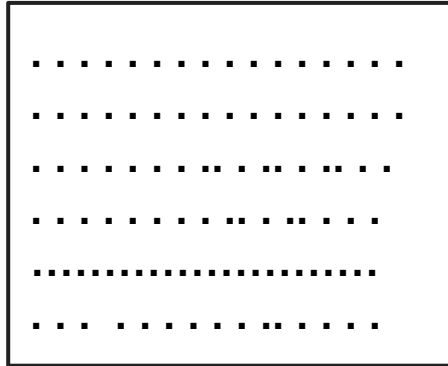
Gini impurity

- Used by the CART
- { Is a measure of how often a randomly chosen element from the set would be incorrectly labeled if it was randomly labeled according to the distribution of labels in the subset.
- Can be computed by summing the probability of an item with label i being chosen (p_i), times the probability of a mistake ($1 - p_i$) in categorizing that item.
- Simplifying gives, the Gini impurity of a set:

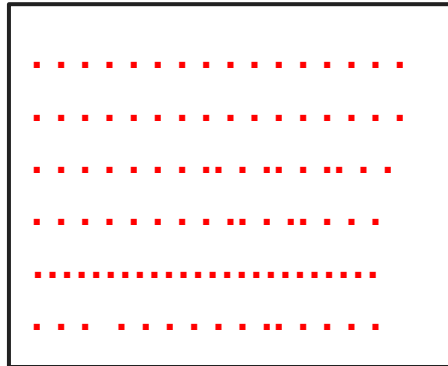
$$1 - \sum_{i=1}^J p_i^2$$



P1	P2	P3
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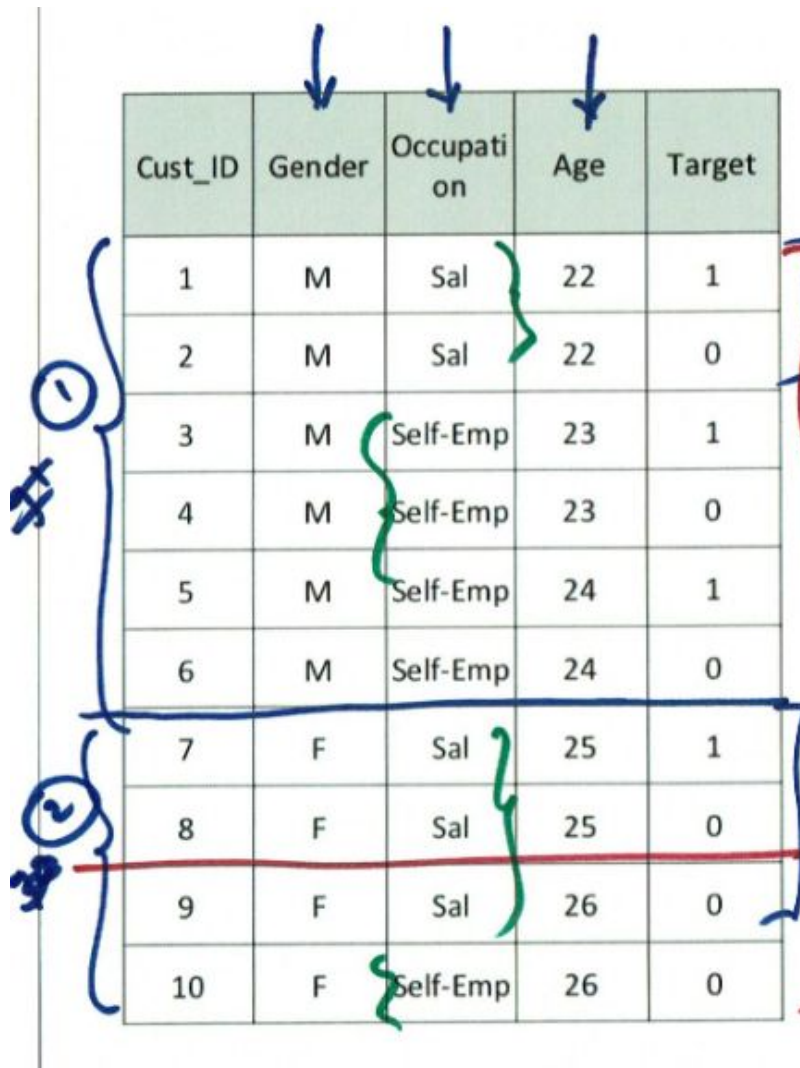


$$\begin{array}{lcl}
 \begin{array}{c} \nearrow \\ \rightarrow \\ \searrow \end{array} & \begin{array}{c} P1 \\ P2 \\ P3 \end{array} & \begin{array}{l} P1(1-P1) = P1P2 + P1P3 \\ P2(1-P2) = P2P1 + P2P3 \\ P3(1-P3) = P3P1 + P3P2 \end{array}
 \end{array}$$

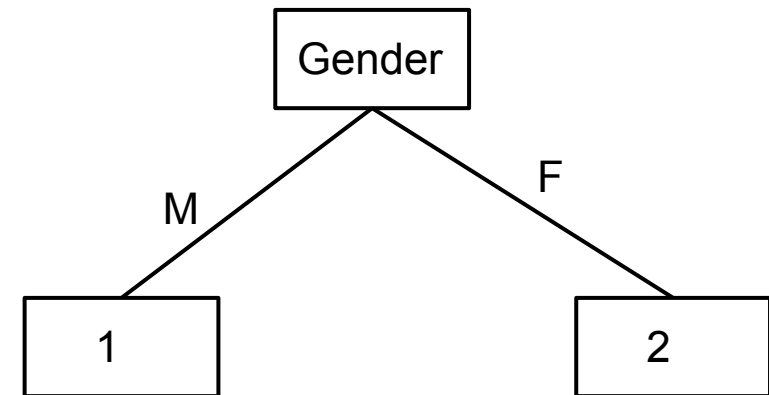


$$\sum P_i(1-P_i) = \sum P_i - \sum P_i^2 = 1 - \sum P_i^2$$

CART: An Example



Cust_ID	Gender	Occupation	Age	Target
1	M	Sal	22	1
2	M	Sal	22	0
3	M	Self-Emp	23	1
4	M	Self-Emp	23	0
5	M	Self-Emp	24	1
6	M	Self-Emp	24	0
7	F	Sal	25	1
8	F	Sal	25	0
9	F	Sal	26	0
10	F	Self-Emp	26	0



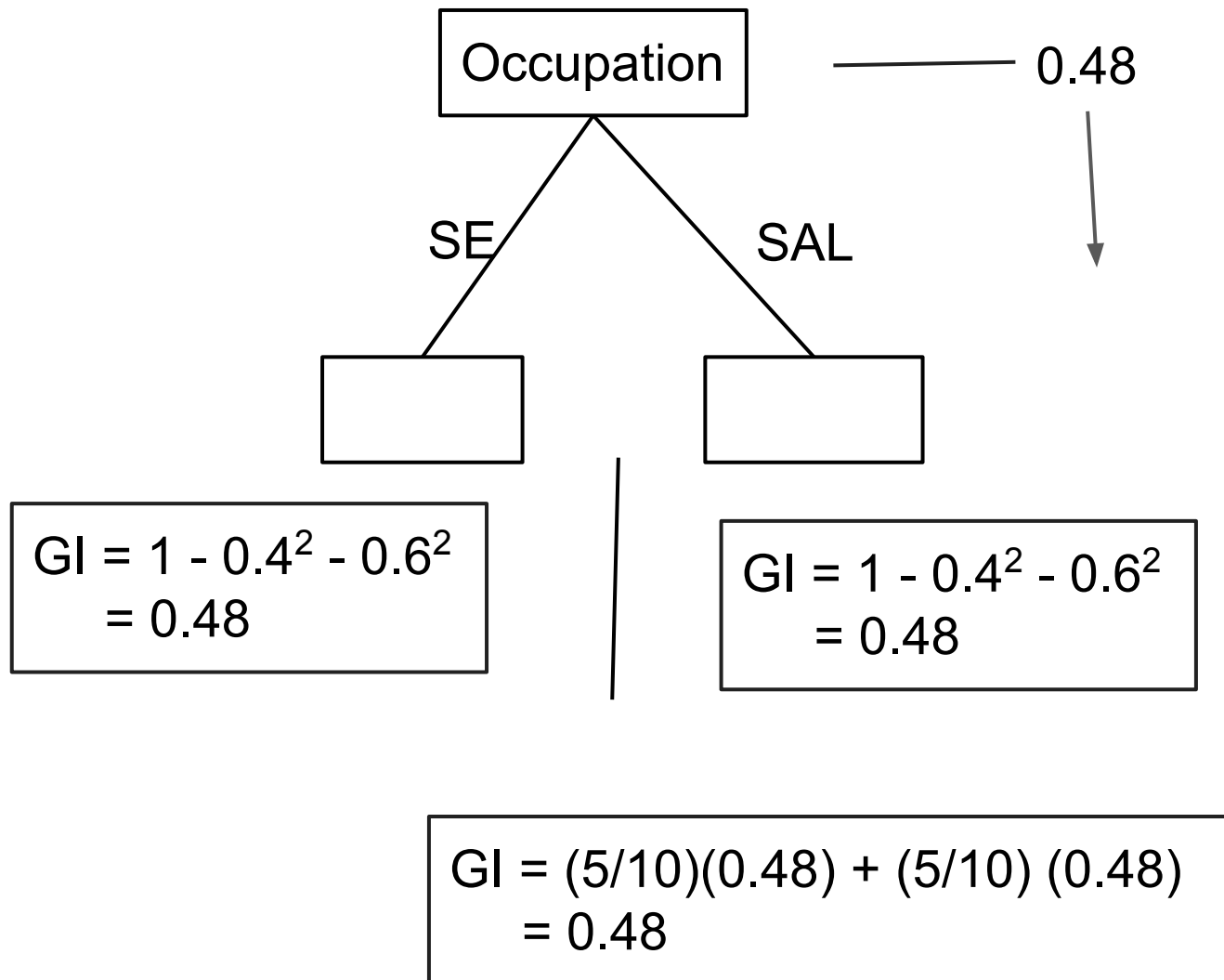
Root node : $P1=0.4$, $P2=0.6$

$$GI = 1 - (0.6)^2 - (0.6)^2 = 0.48$$

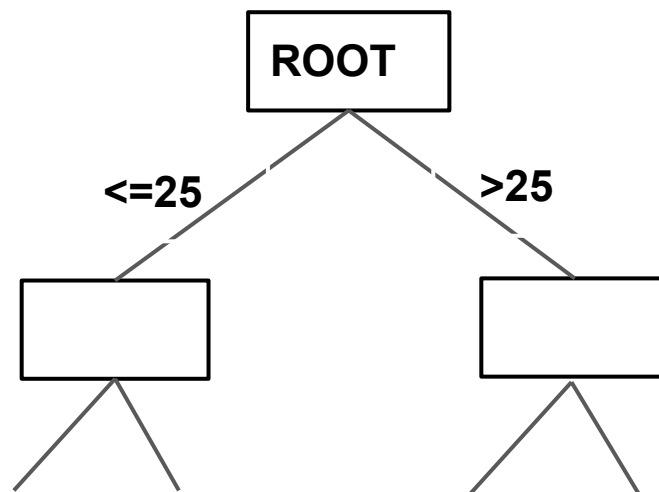
1. $P1=0.3$
 $P2=0.5$
 $1 - 0.5^2 - 0.3^2 = 0.5$

2. $P1=0.25$
 $P2=0.75$
 $1 - 0.25^2 - 0.75^2 = 0.375$

$$GI = (6/10)(0.5) + (4/10)(0.375) = 0.45$$



	Left	Right	Gini Split
$\leq 22, > 22$	0.5	0.47	0.48
$\leq 23, > 23$	0.5	0.44	0.47
$\leq 24, > 24$	0.5	0.38	0.45
$\leq 25, > 25$	0.5	0	0.40



0.48



0.40

$$\text{Gini Gain} = 0.48 - 0.40 = 0.08$$