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Decision Tree - Handson Theory

* In Supervised Learning → Regression, Regression, Logistic Regression.

* if output variable is yes or not mean two only it is called binary classification.

→ if output is more than two its called multi classification.

→ The benefit of Decision Tree is it can handle both numerical and categorical data.

For example

Age → Numerical
Salary → Numerical & continuous value.
Gender → Classification.
Occupation → Classification

→ Note :-
Output here is binary classification.

formula of entropy :-

$$= \sum_{i=1}^{2} -Pi \log_2 Pi$$

how to calculate entropy values.

$$-[0.5 \log_2 0.5 + 0.5 \log_2 0.5]$$

→ In Machine learning entropy exist as a measures of uncertainity.

For Classification data
↓
ML Model
→ (i) Logistic Regression
→ (ii) Decision Tree
→ (iii) Decision Tree Classifier.

Logistic Regression

Teaching Pace

→ Calculation Entropy

→ Decision Tree work on the Principal or homogeneity or purity.

→ Decision tree overcome the limitation of Logistic Regression.

↕ It is create only one decision boundary so Decision trees come into the picture. there are several data which need many decision boundary.

→ Graph of data is for Algorithm, and tree is for us.

→ ID3 (Iterative Dichomizer 3) → old
→ best for classification data.

→ if the less entrophy is there means in data more homogenity is there

→ if high then less homegenity is in the data

→ entropy is the measure of randomness or chaos, mixture.

53.54

→ one drawbacks of decision tree is it 90% stuck with overfitting.

And we have to control it.

→ Sparsity is very useful in case of imbalanced data.

→ Sectors/Box/ Decision boundary

→ overlearning is also known as overfitting.

→ We should always ensure that our training accuracy never ever be 100%.

→ whenever extra node added into the tree the it will be always bottom of tree

→ Confusion matrix

PREDICTED

ACTUAL	165	NO	Yes.
	NO	TN (50)	FP (10)
	Yes	FN (5)	TP (100)

Accuracy Score = $\frac{TP + TN}{Total}$

$= \frac{50+100}{165}$

$= 0.91$

Error Rate = 1 − accuracy

$= 1 - 0.91$

$= 0.09$

OR $= \frac{FP + FN}{TN+FP+FN+TP}$ (Total)

$= \frac{10+5}{165}$

$= 0.09$

Recall :- $\frac{TP}{\text{actual Yes}}$

$= \frac{100}{105}$

$= 0.95$

precision $= \frac{TP}{\text{predicted Yes}}$

$= \frac{100}{FP+TP}$

$= \frac{100}{10+100}$

$= \frac{100}{110}$

$= 0.64$

To develop such a model, the computed information gain (C, pitch) with respect to target is ....
(rounded off to two decimal places).

Match No	pitch	Format	Winner (Target)
1	S	T	Green
2	S	T	Blue
3	F	0	Blue
4	S	0	Blue
5	F	T	Green
6	F	0	Blue
7	S	0	Green
8	F	T	Blue
9	F	0	Blue
10	S	0	Green.

Entropy Calculation

$$\text{Entropy}(S) = -P(\text{yes}) \log_2 P(\text{yes}) - P(\text{no}) \log_2 P(\text{no})$$

where;
- S is the total sample space
- P(yes) is probability of yes.

if number of yes = number of no i.e $P(S) = 0.5$
$\Rightarrow$ Entropy (S) = 1

if it contains all yes or all no i.e $(P(S) = 1 \text{ or } 0$
$\Rightarrow$ Entropy (S) = 0

$$E(S) = -P(yes)\log_2 P(yes) - P(no)\log_2 P(no)$$

$$= -0.5 \log_2 0.5 - 0.5 \log_2 0.5$$

$$= -0.5(\log_2 0.5 - \log_2 0.5)$$

$$=$$

$$= 1$$

$\longrightarrow$

- Step 1: Entropy of entire dataset

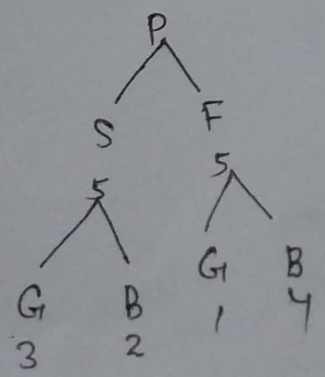
$$O\{4,6\} = -\frac{4}{10}\log_2 \frac{4}{10} - \frac{6}{10}\log_2 \frac{6}{10} = 0.97$$

Step 2: Entropy of an attribute in pitch

$$\{3,2\} = -\frac{3}{5}\log_2 \frac{3}{5} - \frac{2}{5}\log_2 \frac{2}{5} = 0.97$$

Entropy of Spin (S)

IG (P) = entropy (whole)



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progres SQL

Microsoft ... training, free. → Check ...

Entropy of pace (F)

$$\{1,4\} = -\frac{1}{5}\log_2\frac{1}{5} - \frac{4}{5}\log_2\frac{4}{5} = 0.72$$

Information Gain (C, pitch) = Entropy(C) $- \frac{5}{10}$ Ent(S) $- \frac{5}{10}$ Ent(F)

$$= 0.97 - 0.485 - 0.360$$

$$= 0.13$$

* what is gini- Index

Gini index measures the impurity of the data.

higher Gini means more impurity.

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