Data Mining – Supervised

Decision Tree & Random Forest

Machine Learning is ubiquitous

ML is ubiquitous

- Medical Diagnosis: Identify new disorders for observations.
- Loan Applications: Predict Risk of default
- Speech/Object Recognition:
  From examples, generalize to others.
- Prediction: (climate, stocks, etc.)
  Predict future from current and past data.

What is learning?

- More than just memorizing facts.
- Learning the underlying structure of the problem or data.

A fundamental aspect of learning is generalize:

- Give few examples, can you generalize to others?

What are Decision Trees?

A Decision Tree is a tree like structure in which internal node represent test on an attribute, each branch represents outcome of test and each leaf node represents class label (decision taken after computing all attributes).

A path from root to leaf node represents classification rules.

A decision tree consists of 3 types of nodes:

Types of nodes:

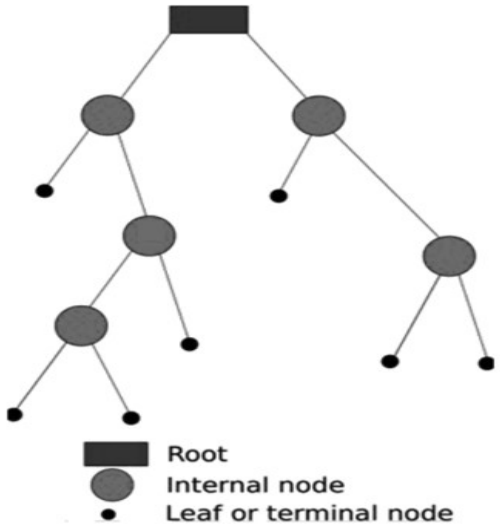
- Root node
- Branch node
- Leaf node

How to build a decision tree?

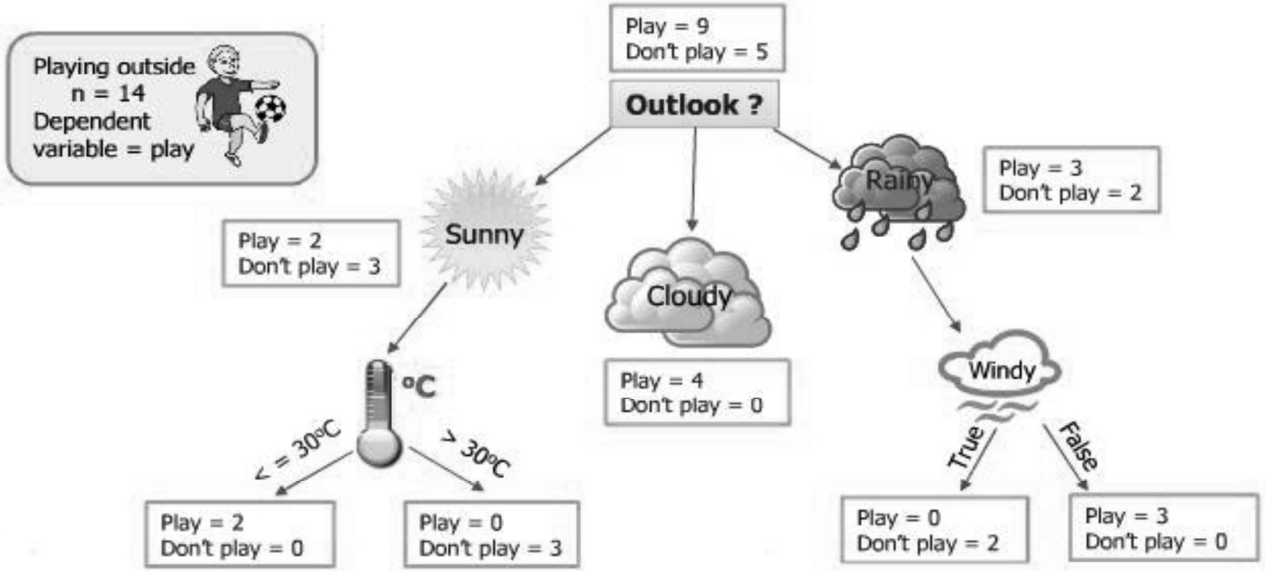
Uses training data to build model.

Tree generator determines:

- Which variable to split at a node and what will be the value of the split.
- Decision to stop (make a terminal note) or split again has to be made.
- Assign terminal nodes to a label.



Decision trees – Example



Algorithm for Decision Tree Induction

Basic algorithm (a greedy algorithm)

- → Tree is constructed in a top-down recursive divide-and-conquer manner
- → At start, all the training examples are at the root
- → Attributes are categorical (if continuous-valued, they are discretized in advance)
- → Input data is partitioned recursively based on selected attributes
- → Test attributes at each node are selected on the basis of a heuristic or statistical measure (e.g., information gain)

Conditions for stopping partitioning

- → All samples for a given node belong to the same class
- → There are no remaining attributes for further partitioning – majority voting is employed for classifying the leaf
- → There are no samples left

Basic Algorithm (a greedy algorithm)

- Tree is constructed in a top-down recursive divide –and – conquer manner.
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- There are no remaining attributes for further partitioning – majority voting is employed for classifying the leaf
- There are no samples left.

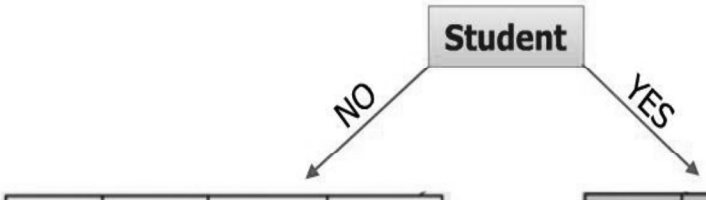
Decision Tree Examples

Training Data

rec	Age	Income	Student	Credit_rating	Buys_computer
r1	<=30	High	No	Fair	No
r2	<=30	High	No	Excellent	No
r3	31...40	High	No	Fair	Yes
r4	>40	Medium	No	Fair	Yes
r5	>40	Low	Yes	Fair	Yes
r6	>40	Low	Yes	Excellent	No
r7	31...40	Low	Yes	Excellent	Yes
r8	<=30	Medium	No	Fair	No
r9	<=30	Low	Yes	Fair	Yes
r10	>40	Medium	Yes	Fair	Yes
r11	<-=30	Medium	Yes	Excellent	Yes
r12	31...40	Medium	No	Excellent	Yes
r13	31...40	High	Yes	Fair	Yes
r14	>40	Medium	No	Excellent	No

Decision Tree 1, Root: Students

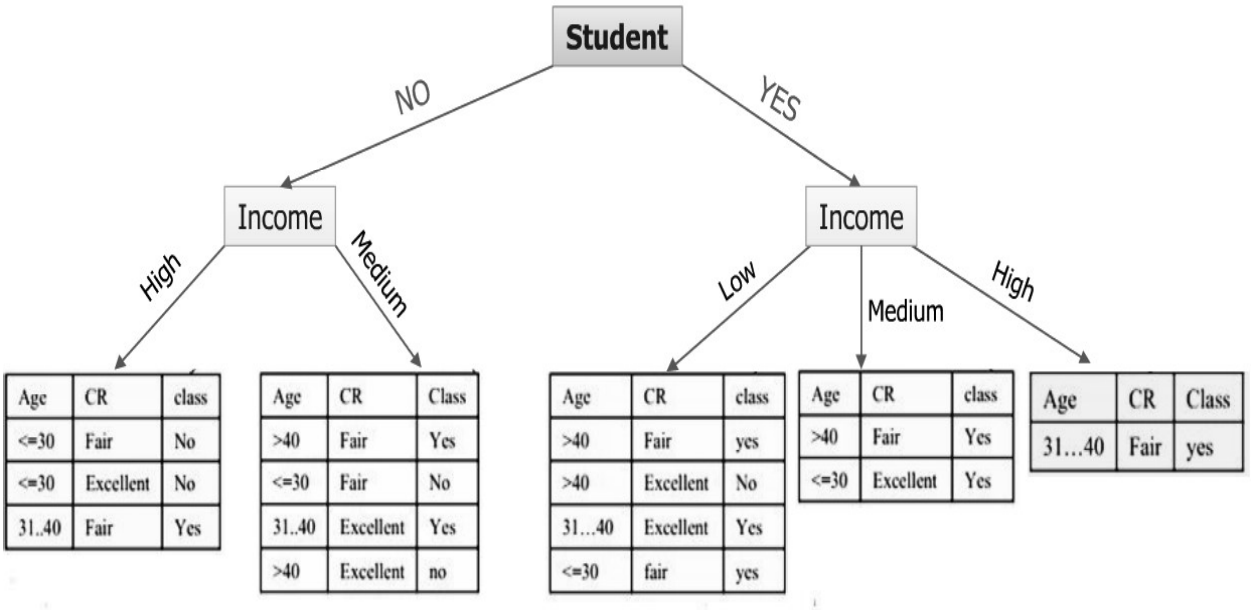
Step-1



Age	income	CR	Class
<=30	High	Fair	No
<=30	High	Excellent	No
30…40	High	Fair	Yes
>40	Medium	Fair	Yes
<=30	Medium	Fair	No
31…40	Medium	Excellent	Yes
>40	Medium	Excellent	no

Age	income	CR	Class
>40	Low	Fair	Yes
>40	Low	excellent	No
31…40	Low	Excellent	Yes
<=30	Low	Fair	Yes
>40	Medium	Fair	Yes
<=30	Medium	Excellent	Yes
31…40	high	fair	yes

Step-2



Age	CR	class
<=30	Fair	No
<=30	Excellent	No
31..40	Fair	Yes

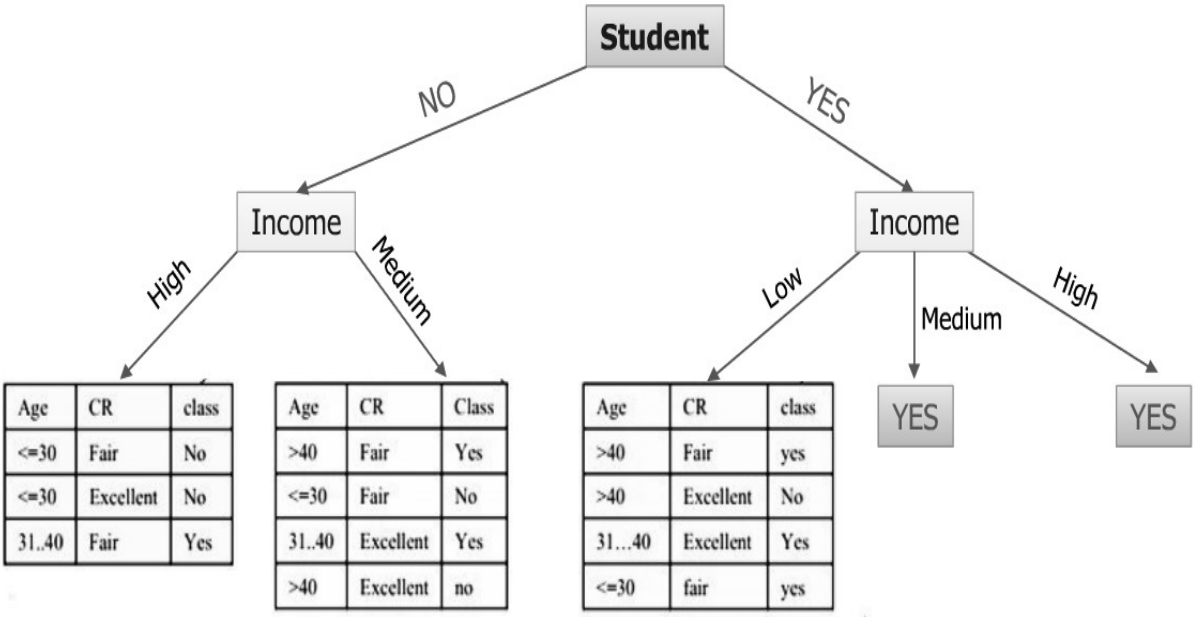
Age	CR	Class
>40	Fair	Yes
<=30	Fair	No
31..40	Excellent	Yes
>40	Excellent	no

Age	CR	class
>40	Fair	yes
>40	Excellent	No
31…40	Excellent	Yes
<=30	fair	yes

Age	CR	class
>40	Fair	Yes
<=30	Excellent	Yes

Age	CR	Class
31…40	Fair	yes

Step-3

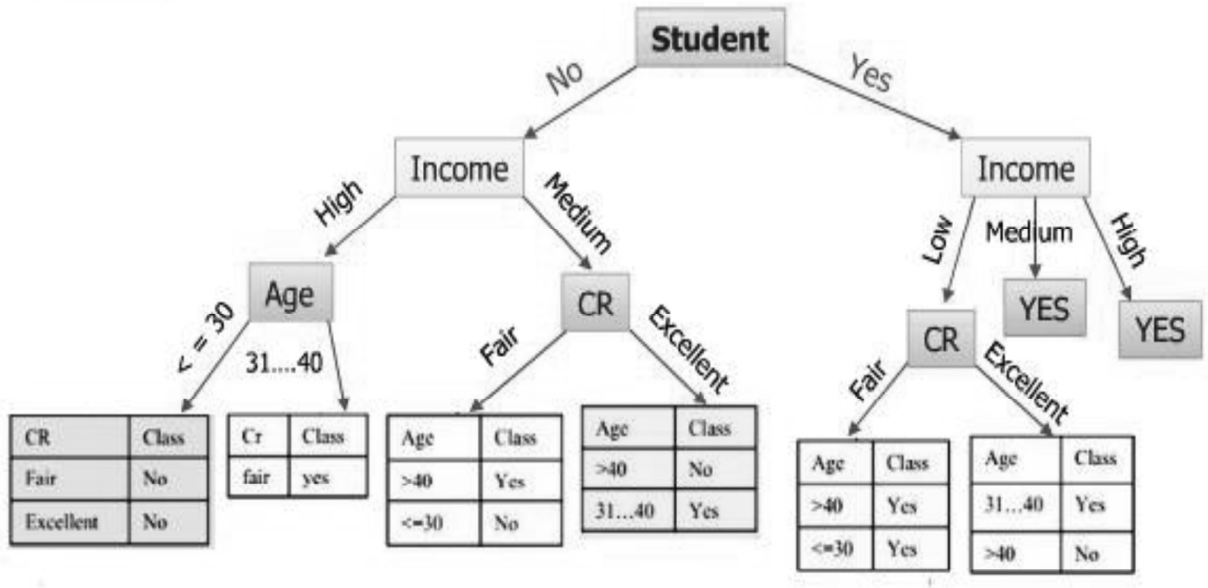


Age	CR	class
<=30	Fair	No
<=30	Excellent	No
31..40	Fair	Yes

Age	CR	Class
>40	Fair	Yes
<=30	Fair	No
31..40	Excellent	Yes
>40	Excellent	no

Age	CR	class
>40	Fair	yes
>40	Excellent	No
31…40	Excellent	Yes
<=30	fair	yes

Step-4



CR	Class
Fair	No
Excellent	No

Cr	Class
fair	yes

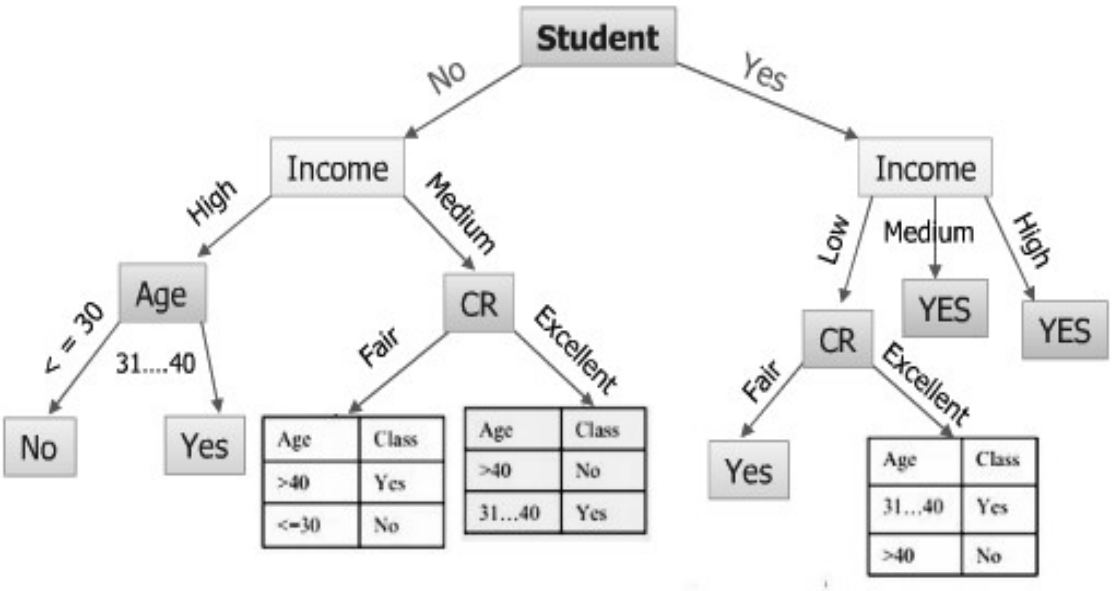
Age	Class
>40	Yes
<=30	No

Age	Class
>40	No
31…40	Yes

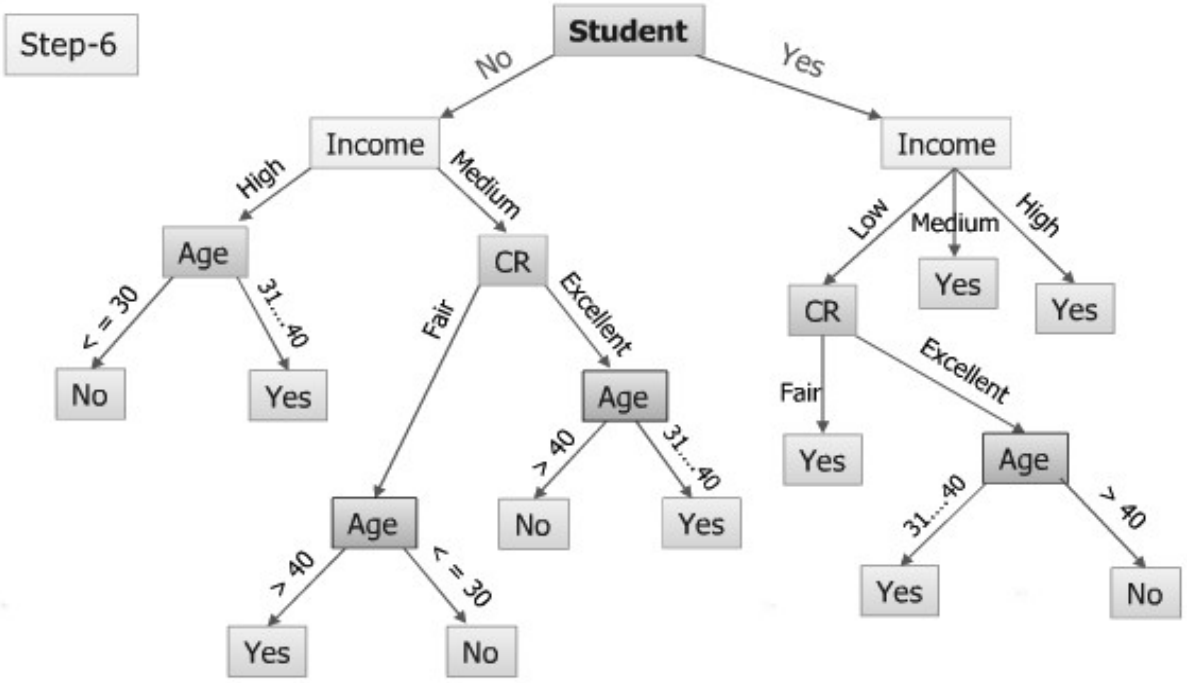
Age	Class
>40	Yes
<=30	Yes

Age	Class
31…40	Yes
>40	No

Step-5


Student
No
Yes
Income
Income
High
Medium
Low
Medium
High
Age
CR
YES
YES
CR
<= 30
31....40
Fair
Excellent
Fair
Excellent
No
Yes
Yes
Age
Class
>40
Yes
<=30
No
Age
Class
>40
No
31...40
Yes
Age
Class
31...40
Yes
>40
No

Step-6


Student
No
Yes
Income
Income
High
Medium
Low
Medium
High
Age
CR
Yes
Yes
CR
<= 30
31....40
Fair
Excellent
Fair
Excellent
No
Yes
Age
Yes
Age
> 40
31....40
31....40
> 40
Age
> 40
<= 30
No
Yes
Yes
No
Yes
No

Decision Tree 1, Root: Income

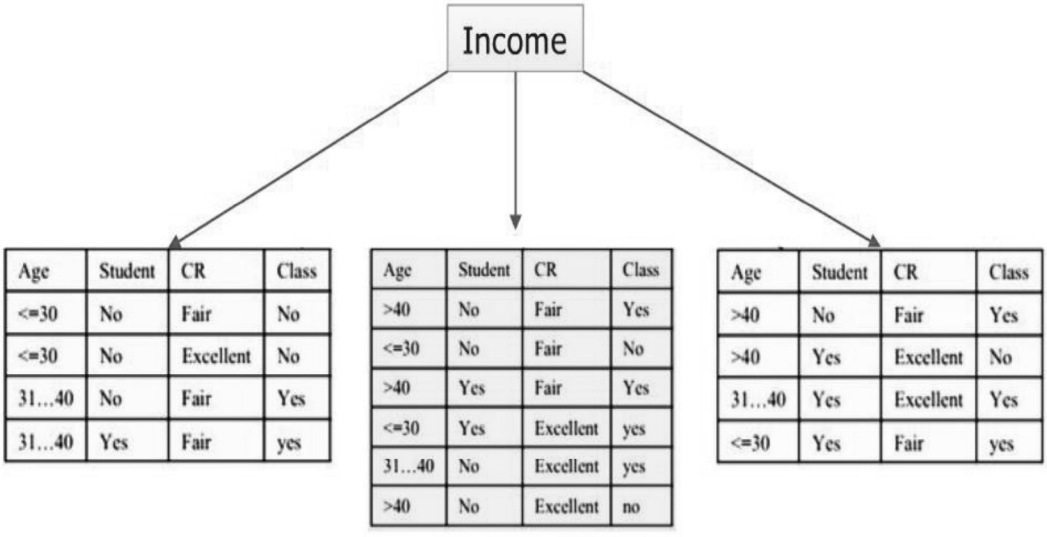
Classification Rules:

→ 1. student(no)^income(high)^age(<=30) => buys_computer(no)
→ 2. student(no)^income(high)^age(31…40) => buys_computer(yes)
→ 3. student(no)^income(medium)^CR(fair)^age(>40) => buys_computer(yes)
→ 4. student(no)^income(medium)^CR(fair)^age(<=30) => buys_computer(no)
→ 5. student(no)^income(medium)^CR(excellent)^age(>40) => buys_computer(no)
→ 6. student(no)^income(medium)^CR(excellent)^age(31..40) =>buys_computer(yes)
→ 7. student(yes)^income(low)^CR(fair) => buys_computer(yes)
→ 8. student(yes)^income(low)^CR(excellent)^age(31..40) => buys_computer(yes)
→ 9. student(yes)^income(low)^CR(excellent)^age(>40) => buys_computer(no)
→ 10. student(yes)^income(medium)=> buys_computer(yes)
→ 11. student(yes)^income(high)=> buys_computer(yes)

Decision Tree 2, Root: Income

Step-1

Now consider another approach to build the decision tree.
Let's take the attribute: Income

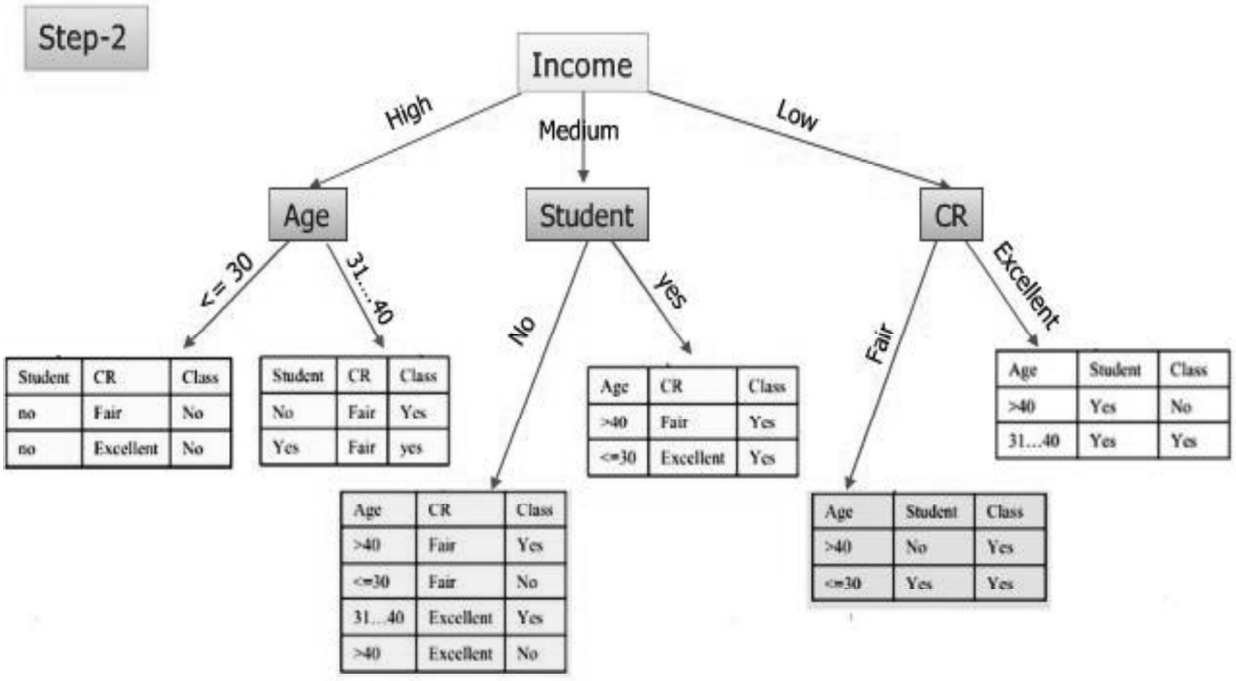


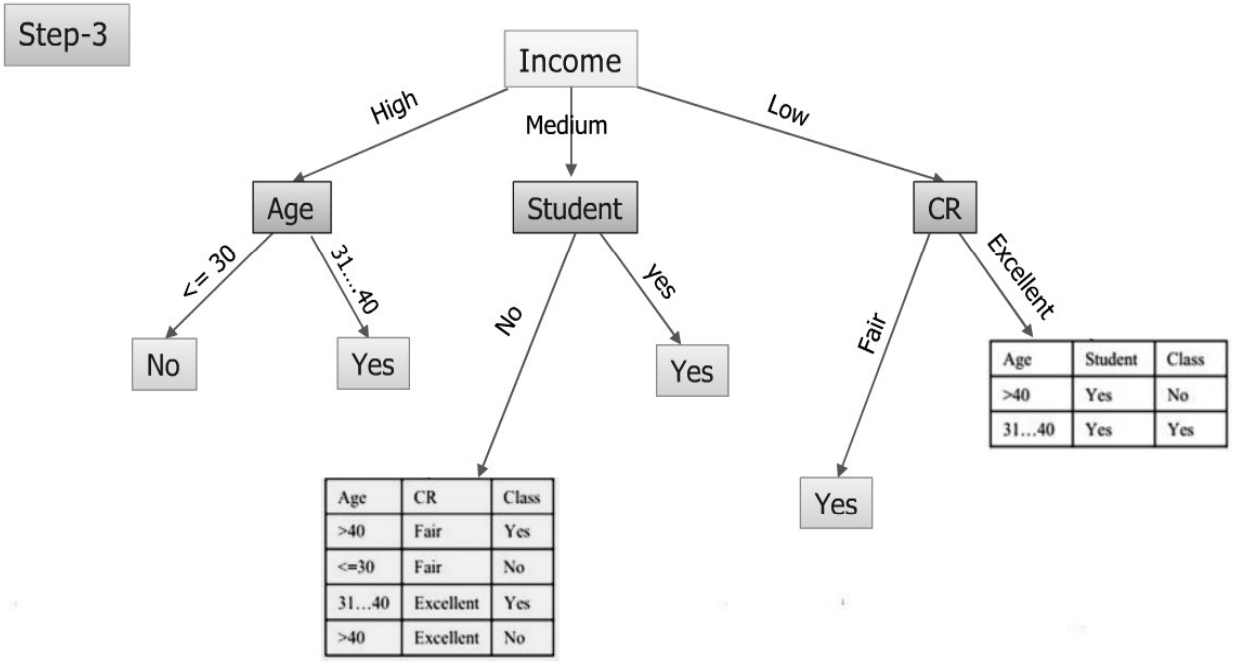
Age	Student	CR	Class
<=30	No	Fair	No
<=30	No	Excellent	No
31…40	No	Fair	Yes
31…40	Yes	Fair	yes

Age	Student	CR	Class
>40	No	Fair	Yes
<=30	No	Fair	No
>40	Yes	Fair	Yes
<=30	Yes	Excellent	yes
31…40	No	Excellent	yes
>40	No	Excellent	no

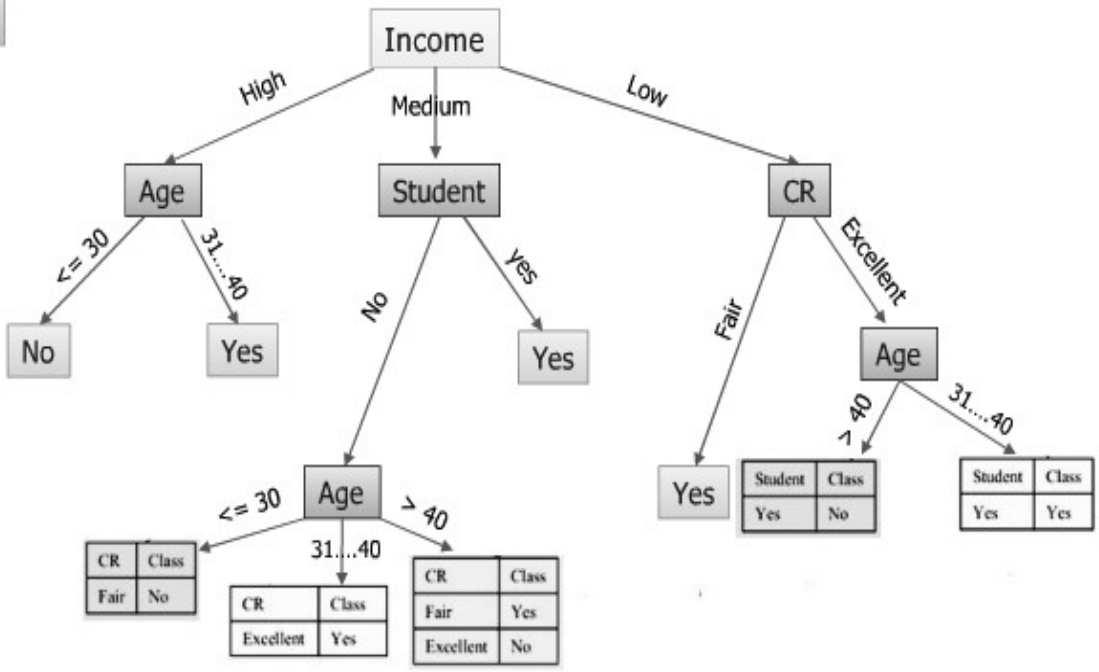
Age	Student	CR	Class
>40	No	Fair	Yes
>40	Yes	Excellent	No
31…40	Yes	Excellent	Yes
<=30	Yes	Fair	yes

Decision Tree, Root: Student

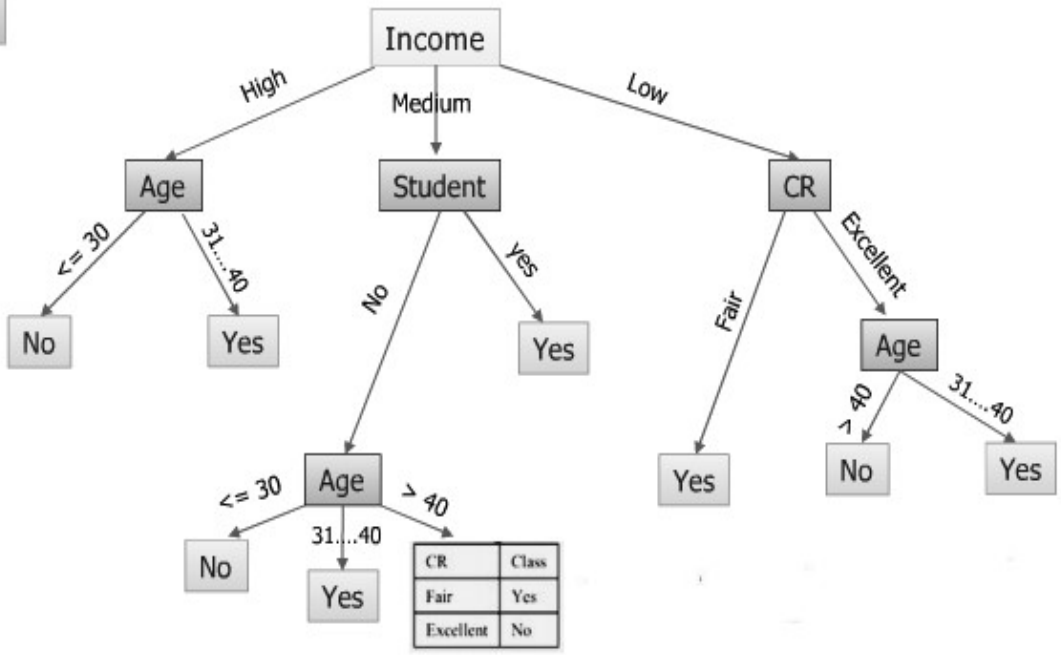


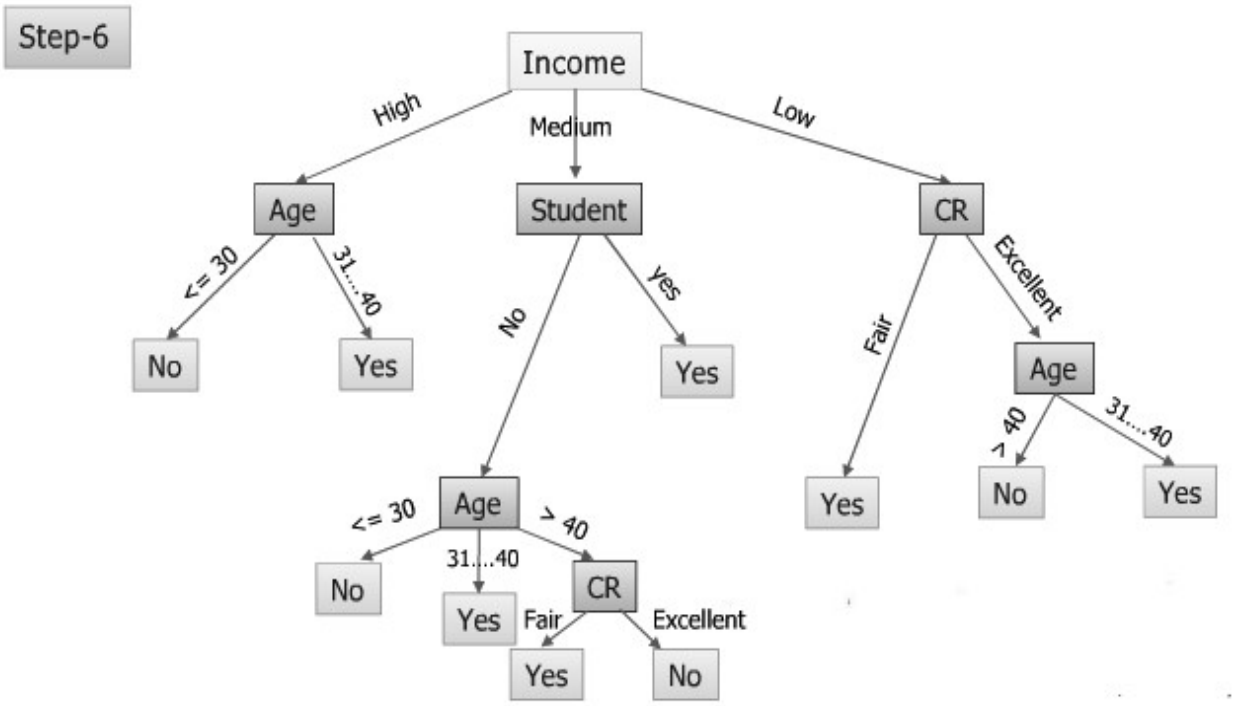


Step-4


Income
High
Medium
Low
Age
Student
CR
<= 30
31....40
No
Yes
No
Yes
Fair
Excellent
Yes
Age
> 40
31....40
Student Class
Yes No
Student Class
Yes Yes
<= 30
Age
> 40
31....40
CR Class
Fair No
CR Class
Excellent Yes
CR Class
Fair Yes
Excellent No

Step-5


Income
High
Medium
Low
Age
Student
CR
<= 30
31....40
No
Yes
No
Yes
Fair
Excellent
Yes
Age
> 40
31....40
No
Yes
No
Yes
<= 30
Age
> 40
31....40
No
Yes
CR Class
Fair Yes
Excellent No



Decision Tree, Root: Income

Classification Rules:

→ 1. income(high)^age(<=30) => buys_computer(no)
→ 2. income(high)^age(31...40) => buys_computer(yes)
→ 3. income(medium)^student(no)^age(<=30) => buys_computer(no)
→ 4. income(medium)^student(no)^age(31...40) => buys_computer(yes)
→ 5. income(medium)^student(no)^age(>40)^CR(fair) => buys_computer(yes)
→ 6. income(medium)^student(no)^age(>40)^CR(excellent) => buys_computer(no)
→ 7. income(medium)^student(yes)=> buys_computer(yes)
→ 8. income(medium)^CR(fair)=> buys_computer(yes)
→ 9. income(medium)^ CR(excellent)^age(>40)=> buys_computer(no)
→ 10. income(medium)^ CR(excellent)^age(31...40)=> buys_computer(yes)

Greedy Approach and Entropy

We want to use the attribute that does the “belt job” splitting up the training data, but can this be measured?

We use entropy and information again?

Entropy:

- Measure of disorder or impurity
- We will find entropy of the output values of a set of training instances.
- If output values split 50%-50% set is impure – 1
- If output is 0, set is pure -0
- If the output values are split 25-27% then entropy -0.811

Information Gain:

The information gain is based on the decrease in entropy after a dataset in split on attribute.

Constructing a decision tree is all about finding attribute that returns the highest information gain (i.e., the most homogenous branches).

Entropy(Information theory)

Measure of uncertainty(unpredictability) of random variable

Measure of information content

Highly unpredictable = High information content = Large entropy

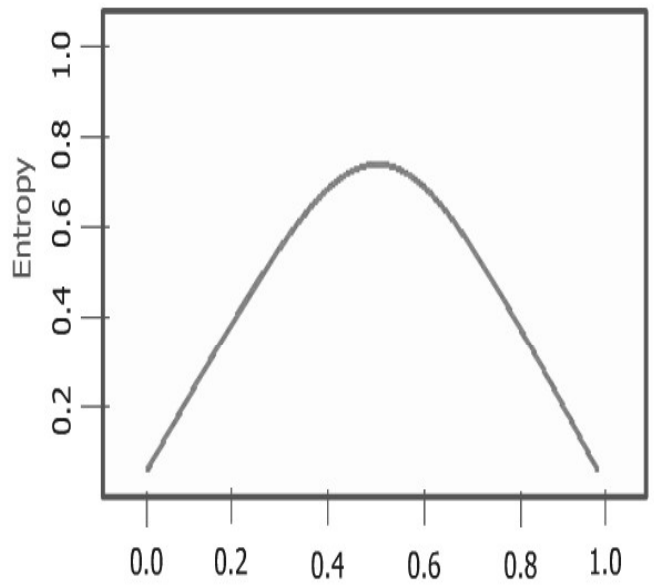
Less unpredictable = Low information content = Small entropy

Discrete random variable X taking m distinct values {x1, x2, ….. , xm}

Mathematical Formula:

$$H(X) = - \sum_{i=1}^{m} p_i \cdot \log_2(p_i),\ p_i = P(X = x_i)$$

Entropy (Information Theory)



Example:

X = Winning party in 2014 elections
x_1 = Congress, x_2=BJP
p_1=0.5, p_2=0.5 -> H(X) = 1
p_1 =0.2, p_2=0.8 -> H(X) = 0.515
p_1 =0.9, p_2=0.1 -> H(X) = 0.468

In previous example

P(Buys=YES) = 9/14, P(Buys=No) = 5/14

Information Gain: Attribute Selection Measure

Heuristic: Select the attribute with the highest information gain i.e., attribute that results in most homogenous branches.

Let pi be the probability that an arbitrary tuple in D belongs to class Ci, estimated by |Ci, D|/|D|

Expected information (entropy) needed to classify a tuple in D:

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

Information needed (After using A to split D into v partitions) to classify D:

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

Information gained by branching on attribute A

$$Gain(A) = Info(D) - Info_A(D)$$

Creating a Perfect Decision Tree:

Attribute Selection Example

Age	Income	Student	Credit Rating	Buys Computer
<=30	High	No	Fair	No
<=30	High	No	Excellent	No
31...40	High	No	Fair	Yes
>40	Low	Yes	Fair	Yes
>40	Low	Yes	Excellent	No
31...40	Low	Yes	Excellent	Yes
<=30	Medium	No	Fair	No
<=30	Low	Yes	Fair	Yes
>40	Medium	Yes	Fair	Yes
<=30	Medium	Yes	Excellent	Yes
31...40	Medium	No	Excellent	Yes
31...40	High	Yes	Fair	Yes
>40	Medium	No	Excellent	No

→ Two classes

» Postive: buys_computer=yes $P(buys = yes) = \frac{9}{14}$

» Negative: buys_computer=no $P(buys = no) = \frac{5}{14}$

→ Entropy in D

$$Info(D) = I(9,5) = -\frac{9}{14}\log_2(\frac{9}{14}) - \frac{5}{14}\log_2(\frac{5}{14}) = 0.940$$

→ What is information gain if we split on "Age"?

age	pos	neg	I(pos,neg)
<=30	2	3	0.971
31…40	4	0	0
>40	3	2	0.971

$Info(Age <= 30) = 0.971$

$Info(31 <= Age <= 40) = 0$

$Info(Age > 40) = 0.971$

$$Info_{age}(D) = \frac{5}{14} Info(Age <= 30) + \frac{4}{14} Info(Age = 31..40) + \frac{5}{14} Info(Age > 40)$$

$$= \frac{5}{14} * 0.971 + \frac{4}{14} * 0 + \frac{5}{14} * 0.971$$

$$= 0.694$$

$$Gain(age) = Info(D) - Info_{age}(D)$$

$$= 0.246$$

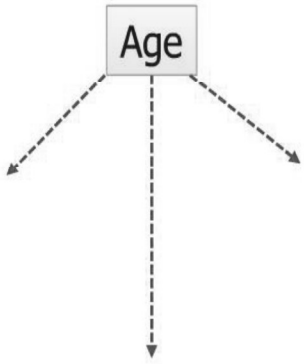
Attribute Selection Example

$Gain(Age) = 0.246$

$Gain(income) = 0.029$

$Gain(student) = 0.151$

$Gain(credit\_rating) = 0.048$

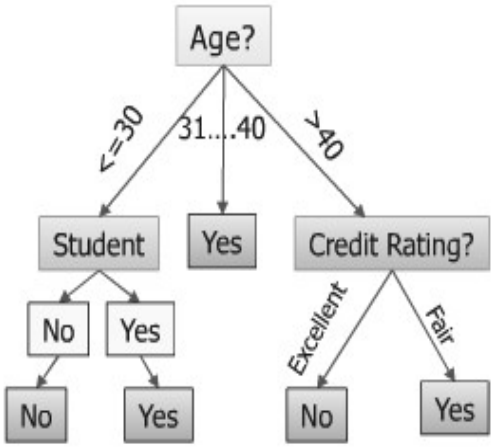


Age	Income	Student	Credit Rating	Buys Computer
<=30	High	No	Fair	No
<=30	High	No	Excellent	No
<=30	Medium	No	Fair	No
<=30	Low	Yes	Fair	Yes
<=30	Medium	Yes	Excellent	Yes

Age	Income	Student	Credit Rating	Buys Computer
>40	Medium	No	Fair	Yes
>40	Low	Yes	Fair	Yes
>40	Low	Yes	Excellent	No
>40	Medium	Yes	Fair	Yes
>40	High	No	Excellent	No

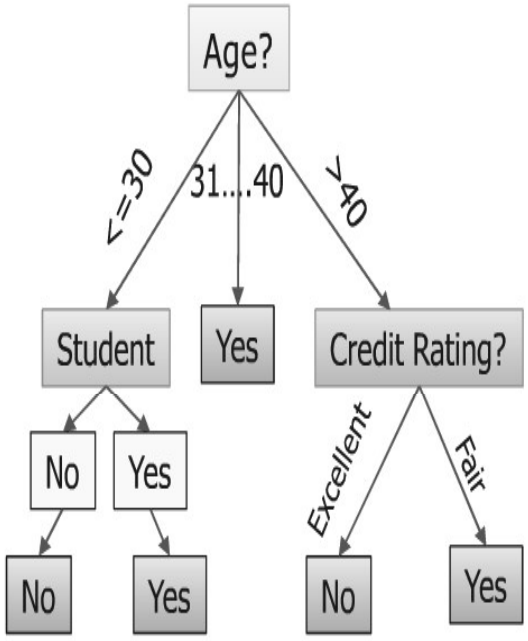
Age	Income	Student	Credit Rating	Buys Computer
31...40	High	No	Fair	Yes
31...40	Low	Yes	Excellent	Yes
31...40	Medium	No	Excellent	Yes
31...40	High	Yes	Fair	Yes

Final Tree



Age	Income	Student	Credit Rating	Buys Computer
<=30	High	No	Fair	No
<=30	High	No	Excellent	No
31...40	High	No	Fair	Yes
>40	Low	Yes	Fair	Yes
>40	Low	Yes	Excellent	No
31...40	Low	Yes	Excellent	Yes
<=30	Medium	No	Fair	No
<=30	Low	Yes	Fair	Yes
>40	Medium	Yes	Fair	Yes
<=30	Medium	Yes	Excellent	Yes
31...40	Medium	No	Excellent	Yes
31...40	High	Yes	Fair	Yes
>40	Medium	No	Excellent	No

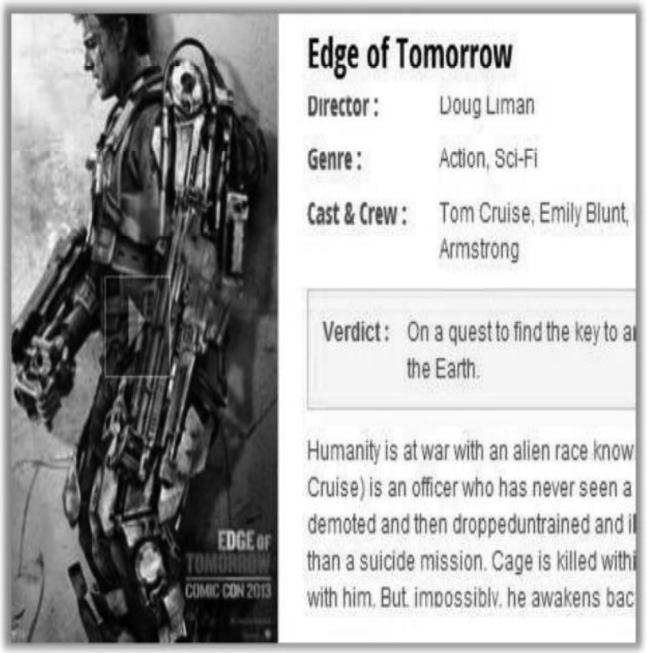
Classification Tree



→ Age(<30) ^ student(no) = NO
→ Age(<30) ^ student(yes) = YES
→ Age(31...40) = YES
→ Age(>40) ^ credit_rating(excellent) = NO
→ Age(>40) ^ credit_rating(fair) = Yes

Random Forest

Random Forest: An example



Suppose you're very indecisive about watching a movie.

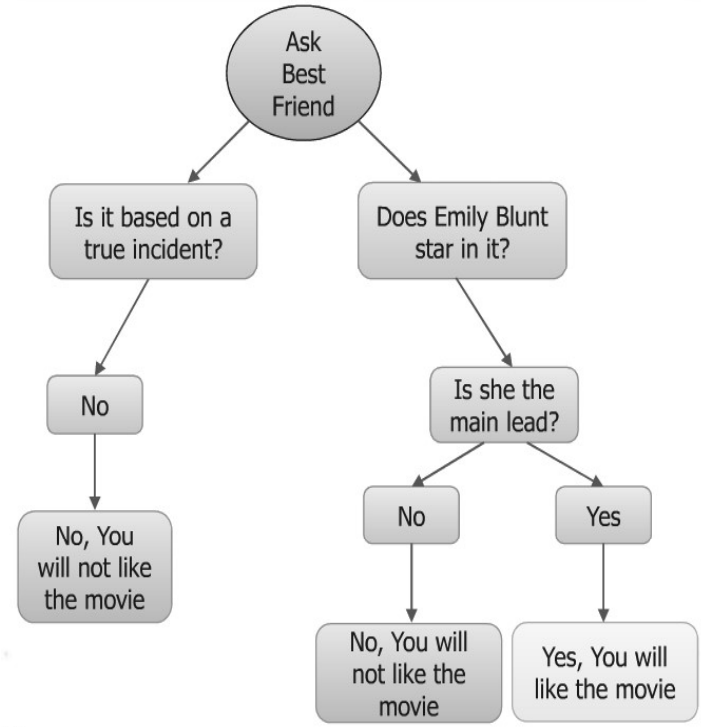
"Edge of Tomorrow"

You can decide to perform either of the two operations about it:

→ Either you ask your best friend, whether you will like the movie.

→ Or You can ask your group of friends.

Random Forest: An example



In order to answer, your best friend first needs to figure out what movies you like, so you give her a bunch of movies and tell her whether you liked each one or not (i.e., you give her a labelled training set).

Example:
You like movies starring Emily Blunt.

Based on such labels, she finds out whether or not you will like "Edge of Tomorrow".

Thus, a decision tree is created of your best friend(attribute).

Random Forest: An example

But your best friend might not always generalize your preferences very well (i.e., she overfits).

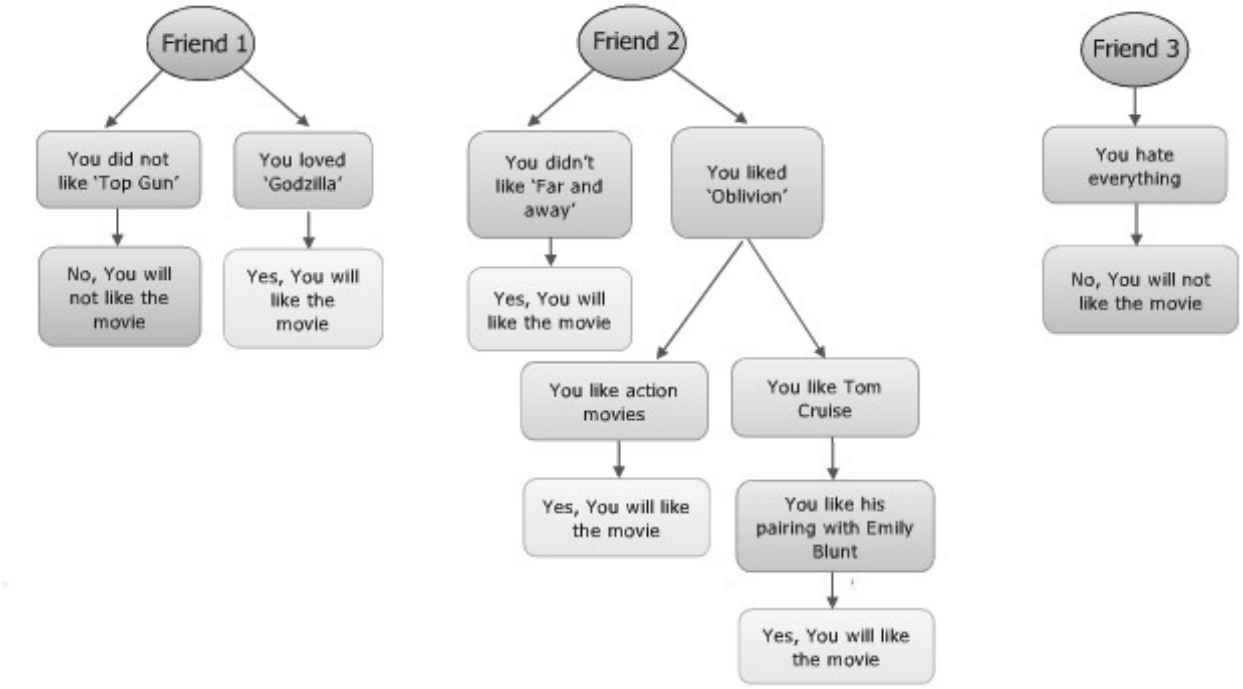
In order to get more accurate recommendations, you'd like to ask a bunch of your friends, whether you will like the movie "Edge of Tomorrow" or not.

You want to ask your other friends as well e.g. Friend#1, Friend #2, and Friend #3 and they vote on whether you will like a movie.

The majority of the votes will decide the final outcome.

Thus, you build an ensemble classifier of the decision tree (Random Forest) of the group of friends.

Random Forest: An example

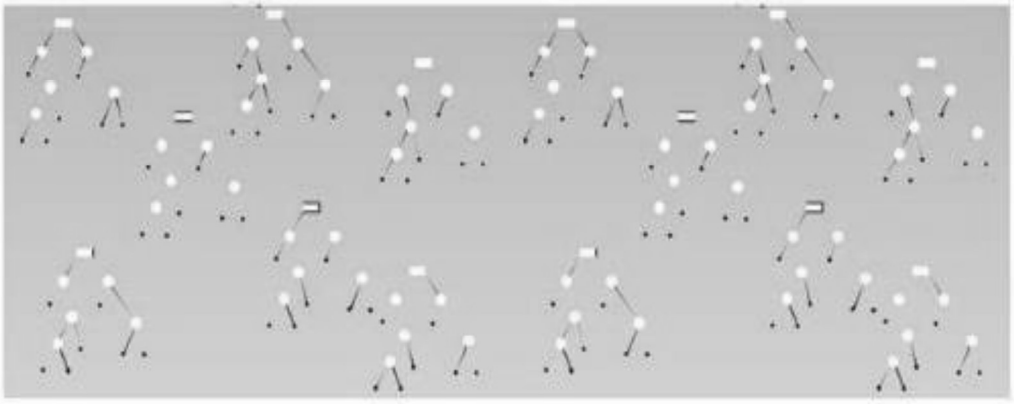


What is Random Forest?

Random Forest is an ensemble classifier made using many decision tree models.

What are ensemble models?

→ Ensemble models combine the results from different models.
→ The result from an ensemble model is usually better than the result from one of the individual models.



How Random Forest works?

Each Tree is grown as follow:

- Let the number of training cases be N, and the number of variables in the classifier be M.
- From M input variables, a number m<<M is specified such that at each node, m variables are selected at random out of the M and the best split on these m is used to split the node. The value of m is held constant during the growth of the forest.
- Each tree is grown to the largest extent possible.
- The number of votes makes decision from all of the trees.
- A different subset of the training data are selected (~2/3), with replacement, to train each tree.
- Remaining training data is used to estimate error and variable importance.

Features of Random Forests:

- It is unexcelled in accuracy among the current algorithms
- It runs efficiently on large databases.
- It can handle thousands of input variables without variable deletion.
- It gives estimates of what variables are important in the classification
- It generates an internal unbiased estimate of the generalization error as the forest building progresses.
- It has an effective method for estimating missing data and maintains accuracy when a large proportion of the data is missing.

- Generated forests can be saved for future use on other data.
- Prototypes are computed, that gives information about the relation between the variables and the classification.

Applications:

A manager has to decide whether he should hire more human resources or not in order to optimize the work load balance.

An individual has to make a decision such as whether or not to undertake a capital project, or must choose between two competing ventures.

A bank wants to classify its future customers into two categories "Risky" and "Good" based on customer's available attributes.

Let's say a customer xyz has the following attributes. How will the bank know to which category this customer belong.

Undergrad	Marital Status	Taxable Income	City Population	Work Experience (Yrs)	Urban	Category
No	Married	98,727	1,01,894	14	NO	????

Possible algorithms:

Such type of problems comes under "classification"

It is the separation or ordering of objects into classes

- There are few techniques in classification method, like :
- Decision Tree
- Naïve Bayes
- K- nearest neighbors
- Support Vector machines etc..