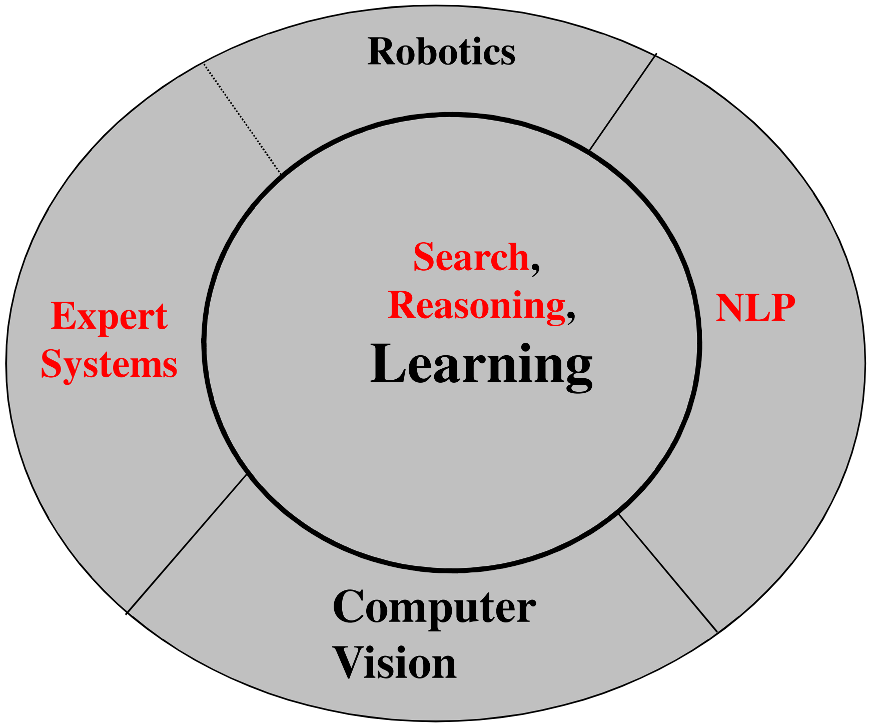
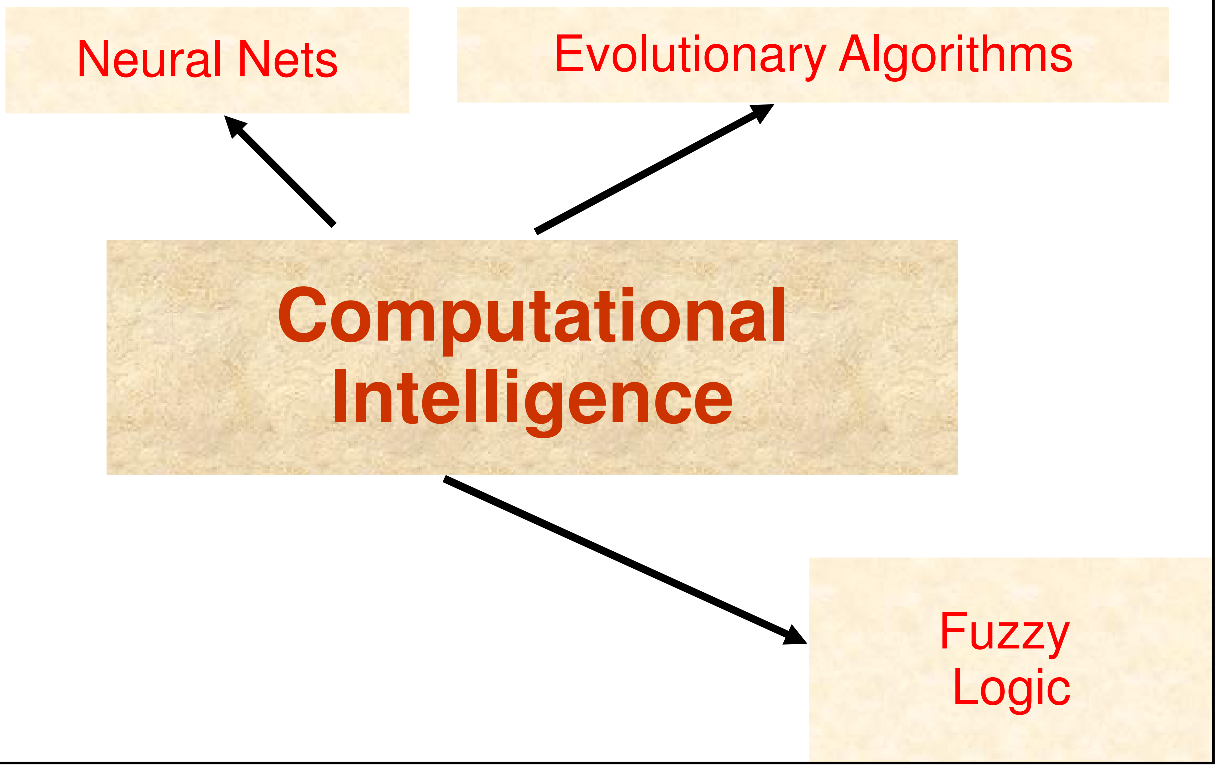
Advanced Topics in Artificial Intelligence 691-B

Lecture Notices will be available on the cu scholar website
http://scholar.cu.edu.eg/?q=areegsaid/classes

Recall


Robotics
Expert Systems
Search,
Reasoning,
Learning
NLP
Computer Vision

“Soft Computing”



Machine Learning (ML)

- ❑ Machine Learning is the study of how to build computer systems that adapt and improve with experience. It is a subfield of Artificial Intelligence and intersects with cognitive science, information theory, and probability theory, …etc
- ❑ Intelligent agents must be able to mange through the course of their interactions with the world, as well as through the experience of their own internal states and processes.
- ❑ Simon's definition (1983) describes learning as allowing the system to "perform better the second time.“ : “Learning is any process by which a system improves performance from experience.”

Task of ML

- Prediction: To predict the desired output for a given input based on previous input/output pairs. E.g., to predict the value of a stock given other inputs like interest rates etc.
- Categorization: To classify an object into one of several categories based on features of the object. E.g., a spam email based on subject
- Clustering: To organize a group of objects into homogeneous segments. E.g., a satellite image analysis system which groups land areas into forest, urban…etc, for better utilization of natural resources.
- Planning: To generate an optimal sequence of actions to solve a particular problem. E.g., an Automated Vehicle which plans its path to avoid obstacles

Classification

Assign object/event to one of a given finite set of categories:

- Medical diagnosis
- Credit card applications or transactions
- Fraud detection in e-commerce
- Worm detection in network packets
- Spam filtering in email
- Recommended articles in a newspaper
- Recommended books, movies, music, or jokes
- Financial investments
- Spoken words
- Handwritten letters

Planning

Performing actions in an environment in order to achieve a goal:

- Playing checkers, chess, or backgammon
- Driving a car or a jeep
- Flying a plane, helicopter, or rocket
- Controlling an elevator
- Controlling a character in a video game
- Controlling a mobile robot

Models of Learning

- ❑ Classical AI deals mainly with deductive reasoning, learning represents inductive reasoning.

→Deductive reasoning arrives at answers to queries relating to a particular situation starting from a set of general axioms,

→ inductive reasoning arrives at general axioms from a set of particular instances.

- ❑ Classical AI often suffers from the knowledge acquisition problem in real life applications where obtaining and updating the knowledge base is costly and prone to errors.
- ❑ Machine learning serves to solve the knowledge acquisition bottleneck by obtaining the result from data by induction.

Why Machine Learning

❑ Machine learning is important in several real life problem because of the following reasons:

→ Some tasks cannot be defined well except by example

→ Working environment may not be known at design time

→ Explicit knowledge encoding may be difficult and not available

→ Environments change over time

❑ learning is widely used in a number of application areas such as:

- Data mining and knowledge discovery
- Speech/image/video (pattern) recognition
- Adaptive control
- Autonomous vehicles/robots
- Decision support systems
- Bioinformatics and WWW

Models of Learning

- Induction, which is learning a generalization from a set of examples, is one of the most fundamental learning tasks.

Different Approaches:

- Symbolic approach
- Neural Nets
- genetic and evolutionary learning.

- Strongest models of learning we have, may be seen in the human and animal systems that have evolved towards equilibration with the world. This approach to learning through adaptation is reflected in genetic algorithms, genetic programming
- In the real world this information is often not immediately available   AI needs to be able to learn from experience

Different kinds of learning

Supervised learning:

- Someone gives us examples and the right answer for those examples
- We have to predict the right answer for unseen examples

Unsupervised learning:

- We see examples but get no feedback
- We need to find patterns in the data

Reinforcement learning:

- We take actions and get rewards
- Have to learn how to get high rewards

Classification

To lend money to people. We have to predict whether they will pay you back or not. People have various (say, binary) features:

do we know their Address? do they have a Criminal record? high Income? Educated? Old? Unemployed?

We see examples: (Y = paid back, N = not)

+a, -c, +i,+e,+o,+u: Y

-a, +c, -i, +e, -o, -u: N

+a, -c, +i, -e, -o, -u: Y

-a, -c, +i, +e, -o, -u: Y

-a, +c, +i, -e, -o, -u: N

-a, -c, +i, -e, -o, +u: Y

+a, -c, -i, -e, +o, -u: N

+a, +c, +i, -e, +o, -u: N

Next person is +a, -c, +i, -e, +o, -u. Will we get paid back?

Classification…

We want some hypothesis h that predicts whether we will be paid back

- +a, -c, +i,+e,+o,+u: Y
- -a, +c, -i, +e, -o, -u: N
- +a, -c, +i, -e, -o, -u: Y
- -a, -c, +i, +e, -o, -u: Y
- -a, +c, +i, -e, -o, -u: N
- -a, -c, +i, -e, -o, +u: Y
- +a, -c, -i, -e, +o, -u: N
- +a, +c, +i, -e, +o, -u: N

Lots of possible hypotheses: will be paid back if…

- Income is high *(wrong on 2 occasions in training data)*
- Income is high and no Criminal record *(always right in training data)*
- (Address is known AND ((NOT Old) OR Unemployed)) OR ((NOT Address is known) AND (NOT Criminal Record)) *(always right in training data)*

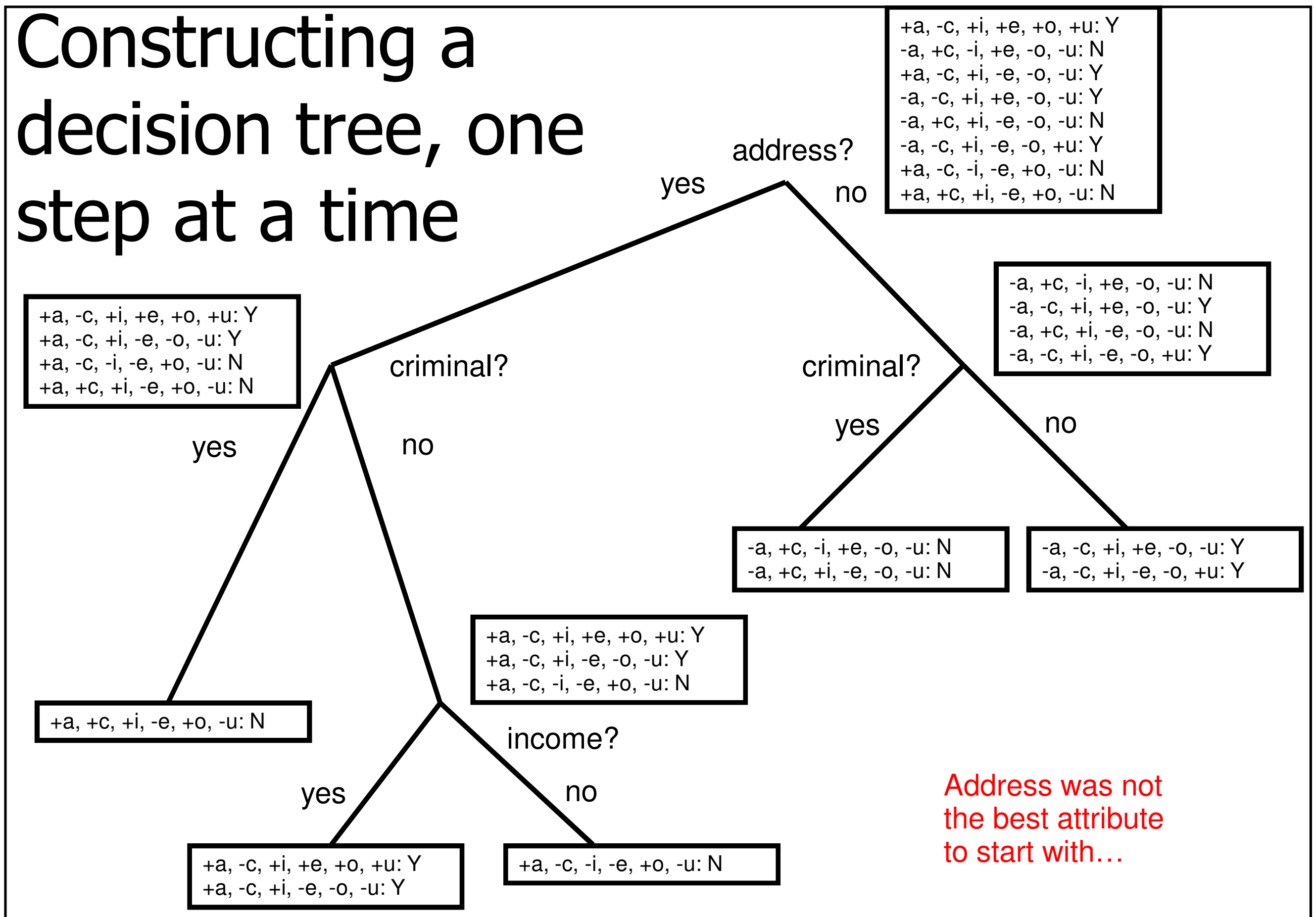
Which one seems best? Anything better?

Occam’s Razor

(William of Occam in 1324)

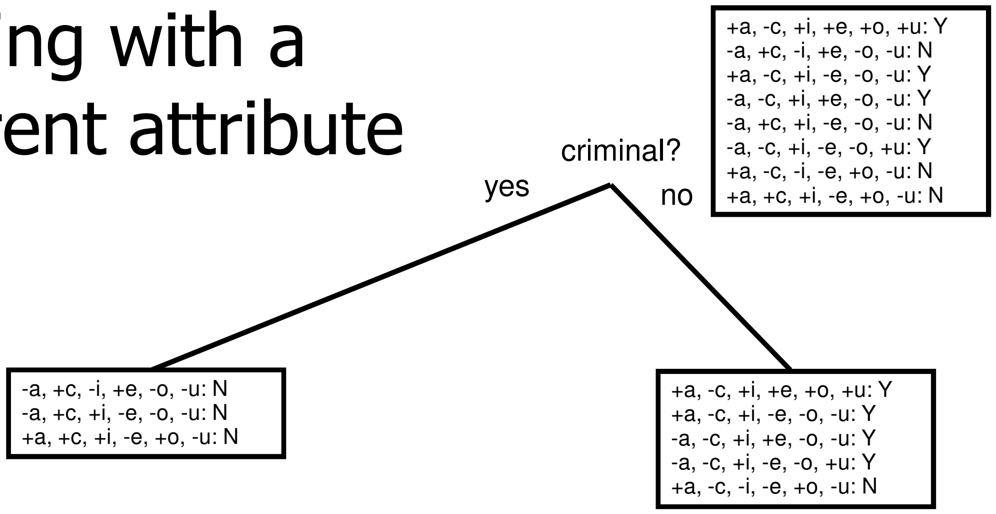
- preferring simplicity and avoiding unnecessary assumptions.
- we should always accept the simplest answer that correctly fits our data.
- ***simpler hypotheses tend to generalize to better data***
- Intuition: given limited training data, it is likely that there is some complicated hypothesis that is not actually good but that happens to perform well on the training data
- it is less likely that there is a simple hypothesis that is not actually good but that happens to perform well on the training data

Constructing a decision tree, one step at a time


+a, -c, +i, +e, +o, +u: Y
-a, +c, -i, +e, -o, -u: N
+a, -c, +i, -e, -o, -u: Y
-a, -c, +i, +e, -o, -u: Y
-a, +c, +i, -e, -o, -u: N
-a, -c, +i, -e, -o, +u: Y
+a, -c, -i, -e, +o, -u: N
+a, +c, +i, -e, +o, -u: N
address?
yes
no
+a, -c, +i, +e, +o, +u: Y
+a, -c, +i, -e, -o, -u: Y
+a, -c, -i, -e, +o, -u: N
+a, +c, +i, -e, +o, -u: N
criminal?
yes
no
-a, +c, -i, +e, -o, -u: N
-a, -c, +i, +e, -o, -u: Y
-a, +c, +i, -e, -o, -u: N
-a, -c, +i, -e, -o, +u: Y
criminal?
yes
no
-a, +c, -i, +e, -o, -u: N
-a, +c, +i, -e, -o, -u: N
-a, -c, +i, +e, -o, -u: Y
-a, -c, +i, -e, -o, +u: Y
+a, +c, +i, -e, +o, -u: N
+a, -c, +i, +e, +o, +u: Y
+a, -c, +i, -e, -o, -u: Y
+a, -c, -i, -e, +o, -u: N
income?
yes
no
+a, -c, +i, +e, +o, +u: Y
+a, -c, +i, -e, -o, -u: Y
+a, -c, -i, -e, +o, -u: N

Address was not the best attribute to start with…

Starting with a different attribute


+a, -c, +i, +e, +o, +u: Y
-a, +c, -i, +e, -o, -u: N
+a, -c, +i, -e, -o, -u: Y
-a, -c, +i, +e, -o, -u: Y
-a, +c, +i, -e, -o, -u: N
-a, -c, +i, -e, -o, +u: Y
+a, -c, -i, -e, +o, -u: N
+a, +c, +i, -e, +o, -u: N
criminal?
yes
no
-a, +c, -i, +e, -o, -u: N
-a, +c, +i, -e, -o, -u: N
+a, +c, +i, -e, +o, -u: N
+a, -c, +i, +e, +o, +u: Y
+a, -c, +i, -e, -o, -u: Y
-a, -c, +i, +e, -o, -u: Y
-a, -c, +i, -e, -o, +u: Y
+a, -c, -i, -e, +o, -u: N

Seems like a much better starting point than address

- Almost completely predicts whether we will be paid back

Decision Tree Learning

- ❑ Decision tree is a class of learning models that are more robust to noise as well as more powerful as compared to concept learning.
- ❑ Decision tree can be seen as rules for performing a categorisation

  E.g., “will we be paid back?”
- ❑ We’re learning from examples

  Not turning thought processes into decision trees

Decision Tree Learning

- A decision-tree learning algorithm approximates a target concept using a tree representation, where each internal node corresponds to an attribute, and every terminal node corresponds to a class.
- Attributes describe examples (background knowledge)

  Each attribute takes only a finite set of values
- They classify instances or examples by starting at the root of the tree and moving through it until a leaf node.

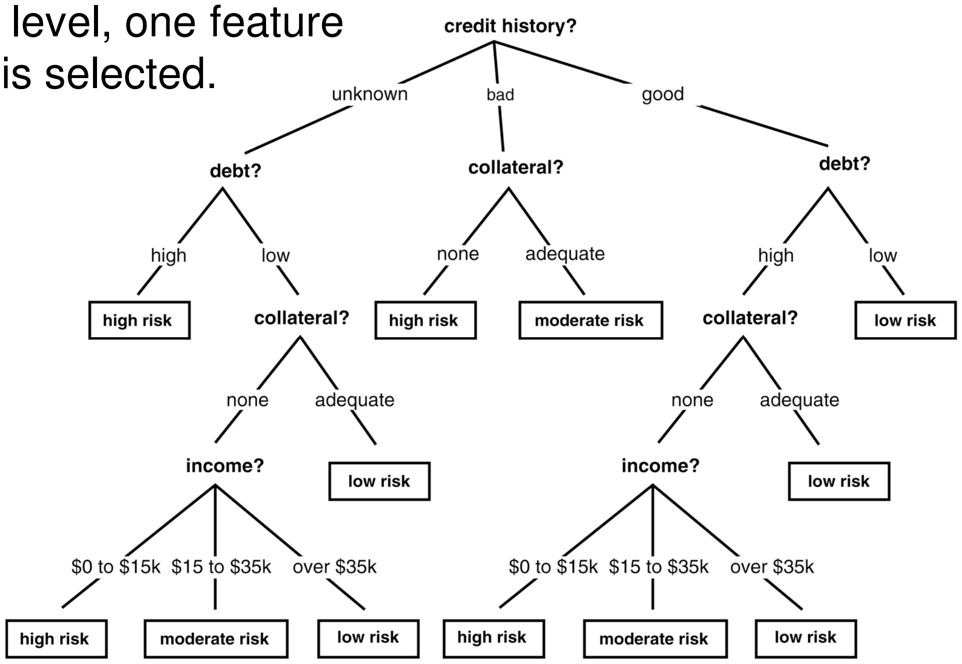
Decision Tree

Example (from the book): The problem of estimating credit risk by considering four features of a potential creditor. Such data can be derived from the history of credit applications.

NO.	RISK	CREDIT HISTORY	DEBT	COLLATERAL	INCOME
1.	high	bad	high	none	$0 to $15k
2.	high	unknown	high	none	$15 to $35k
3.	moderate	unknown	low	none	$15 to $35k
4.	high	unknown	low	none	$0 to $15k
5.	low	unknown	low	none	over $35k
6.	low	unknown	low	adequate	over $35k
7.	high	bad	low	none	$0 to $15k
8.	moderate	bad	low	adequate	over $35k
9.	low	good	low	none	over $35k
10.	low	good	high	adequate	over $35k
11.	high	good	high	none	$0 to $15k
12.	moderate	good	high	none	$15 to $35k
13.	low	good	high	none	over $35k
14.	high	bad	high	none	$15 to $35k

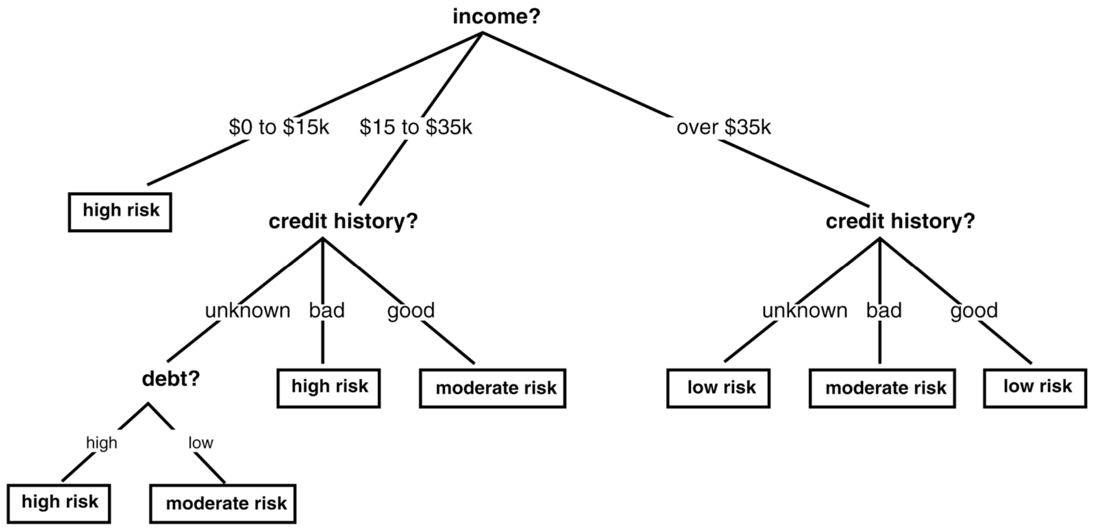
Decision Tree

At every level, one feature value is selected.



Decision Tree

Another possible decision tree:



The ID3 Algorithm

- The major question in decision tree learning Which nodes to put in which positions
- ID3 uses a measure called Information Gain Based on the notion of ***entropy***
- Used to choose which node to put in next
- Node with the highest information gain is chosen
- When there are no choices, a leaf node is put on

information gain

measures how well a given attribute separates the training examples according to their target classification

This measure is used to select among the candidate attributes at each step while growing the tree

Entropy – General Idea

Definition:

"In order to define information gain precisely, we begin by defining a measure commonly used in information theory, called entropy that characterizes the (im)purity of an arbitrary collection of examples"

Given a set of examples, S. And a binary categorisation

Where p_+ is the proportion of positive "examples"

And p_- is the proportion of negatives

$$Entropy(S) = -p_+ \log_2(p_+) - p_- \log_2(p_-)$$

Entropy – General Idea

- Entropy as a measure of Information

Ex. The information content of a message telling the outcome of flipping an honest coin is

$$\begin{aligned} I(\text{Coin Toss}) &= -p(\text{heads}) \log_2 p(\text{heads}) - p(\text{tails}) \log_2 p(\text{tails}) \\ &= -1/2 \log_2(1/2) - 1/2 \log_2(1/2) \\ &= 1 \text{ bit} \end{aligned}$$

If the coin has been rigged to come up heads 75% of the time, the information content will be less or more ?!

Entropy – General Idea

- Entropy as a measure of Information

Ex. The information content of a message telling the outcome of flipping an honest coin is

I(Coin Toss) = $-p(\text{heads}) \log_2 p(\text{heads}) - p(\text{tails}) \log_2 p(\text{tails})$

$= - 1/2 \log_2(1/2) - 1/2 \log_2(1/2)$

$= 1$ bit

If the coin has been rigged to come up heads 75% of the time, the information content will be less or more ?!

I[Coin Toss] $= - 3/4 \log_2(3/4) - 1/4 \log_2(1/4)$

$= 0.811$ bits

Remark: Note for users of old calculators:

May need to use the fact that $\log_2(x) = \ln(x)/\ln(2)$

And also note that, by convention: $0*\log_2(0)$ is taken to be 0

Entropy – General Idea

- In categorisations c_1 to c_n

Where p_n is the proportion of examples in c_n

$$Entropy(S) = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

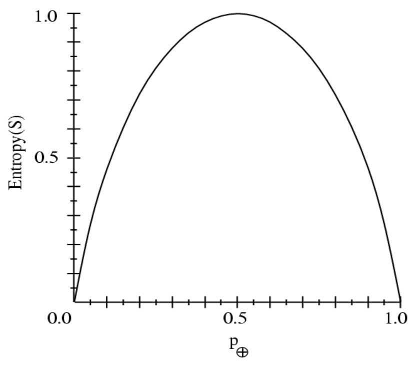
p_i is the probability of class i

Computes the entropy as the proportion of class i in the set.

The higher the entropy the more the information content.

Entropy – General Idea

Entropy



- S is a sample of training examples

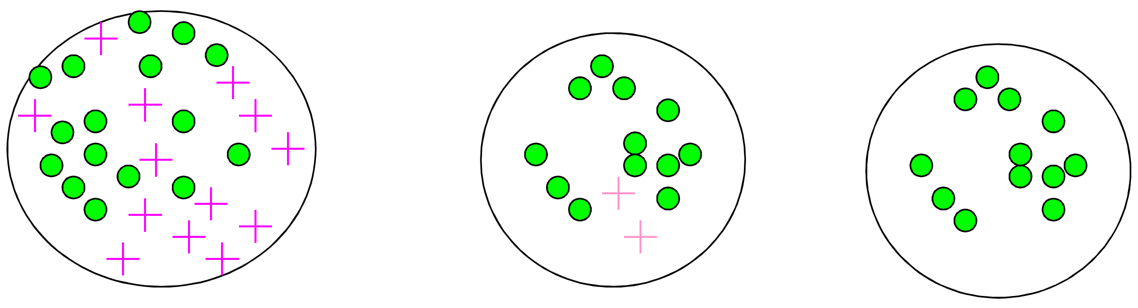
Entropy(S)
positives p+ approaches 0.5 (very impure),
the Entropy of S converges to 1.0

Entropy – General Idea Impurity

Very impure group

Less impure

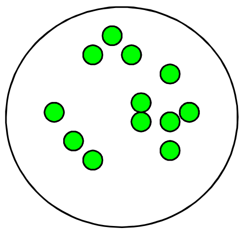
Minimum impurity



Entropy – General Idea Impurity

- What is the entropy of a group in which all examples belong to the same class?
  - entropy = - 1 $\log_2 1$ = 0
  - **not a good training set for learning**

Minimum impurity



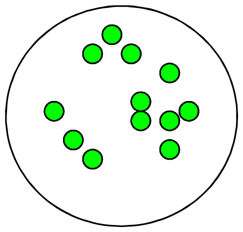
Entropy – General Idea Impurity

- What is the entropy of a group in which all examples belong to the same class?
  - entropy = - 1 $\log_2 1$ = 0
  - **not a good training set for learning**

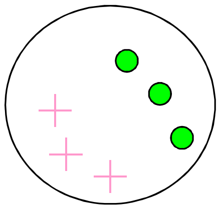
- What is the entropy of a group with 50% in either class?
  - entropy = -0.5 $\log_2 0.5$ – 0.5 $\log_2 0.5$ =1

good training set for learning

Minimum impurity



Maximum impurity



Information Gain

We want to determine which attribute in a given set of training feature vectors is most useful for discriminating between the classes to be learned.

i.e.

Information gain tells us how important a given attribute of the feature vectors is.

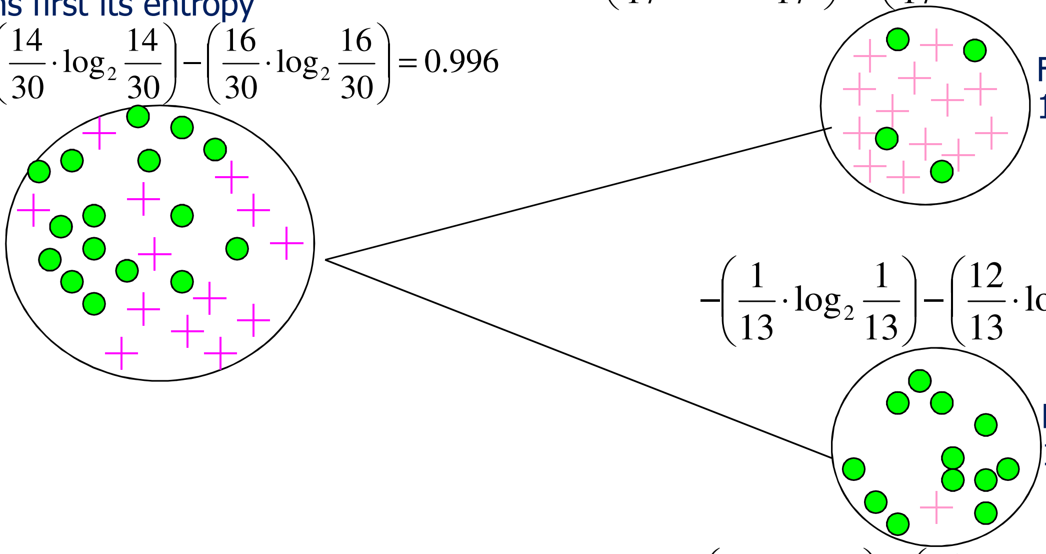
We will use it to decide the order of attributes in the nodes of a decision tree.

Calculating Information Gain

Entire population (30 instances)
Fins first its entropy

$$-\left(\frac{14}{30}\cdot\log_2\frac{14}{30}\right)-\left(\frac{16}{30}\cdot\log_2\frac{16}{30}\right)=0.996$$

$$-\left(\frac{13}{17}\cdot\log_2\frac{13}{17}\right)-\left(\frac{4}{17}\cdot\log_2\frac{4}{17}\right)=0.787$$



Find its entropy
17 instances

$$-\left(\frac{1}{13}\cdot\log_2\frac{1}{13}\right)-\left(\frac{12}{13}\cdot\log_2\frac{12}{13}\right)=0.391$$

Find its entropy
13 instances

(Weighted) Average Entropy of Children = $\left(\frac{17}{30}\cdot 0.787\right)+\left(\frac{13}{30}\cdot 0.391\right)=0.615$

Information Gain= 0.996 - 0.615 = 0.38

Credit Risk Example

Let us consider our credit risk data. There are three feature values in 14 classes.

6 classes have high risk, 3 have moderate risk, 5 have low risk. Assuming ***uniform*** distribution, their probabilities are as follows:

NO.	RISK	CREDIT HISTORY	DEBT	COLLATERAL	INCOME
1.	high	bad	high	none	$0 to $15k
2.	high	unknown	high	none	$15 to $35k
3.	moderate	unknown	low	none	$15 to $35k
4.	high	unknown	low	none	$0 to $15k
5.	low	unknown	low	none	over $35k
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13.	low	good	high	none	over $35k
14.	high	bad	high	none	$15 to $35k

high $\frac{6}{14}$, moderate $\frac{3}{14}$,low $\frac{5}{14}$

Information contained in this partition:

Info(S) $= -(6/14) \log_2 (6/14) - (3/14) \log_2 (3/14) - (5/14)\log_2 (5/14)$

$\approx$ 1.531 bits

Expected Info.

Let property A(Income) be at the root, and let C_1, ..., C_n be the partitions of the examples on this feature.

Information needed to build a tree for partition C_i is $I(C_i)$.

Expected information needed to build the whole tree is a ***weighted average*** of $I(C_i)$.

Let |S| be the cardinality of set S.

Let $\{C_i\}$ be the set of all partitions.

Expected information needed to complete the tree with root A

$$Info_A(S) = \sum_{i=1}^{n} \frac{|C_i|}{|S|} \times I(C_i)$$

Expected Info.

In our data, there are three partitions based on income:

All examples have high risk:

$I(C_1) = -1 \log_2 1 = 0.0$.

$C_1 = \{1, 4, 7, 11\}$, $|C_1| = 4$, $I(C_1) = 0.0$

Two examples have high risk, two have moderate:

$I(C_2) = - 1/2 \log_2 1/2 - 1/2 \log_2 1/2 = 1.0$.

$C_2 = \{2, 3, 12, 14\}$, $|C_2| = 4$, $I(C_2) = 1.0$

$I(C_3) = - 1/6 \log_2 1/6 - 5/6 \log_2 5/6 \approx 0.65$.

$C_3 = \{5, 6, 8, 9, 10, 13\}$, $|C_3| = 6$, $I(C_3) \approx 0.65$

The expected information to complete the tree using income as the root feature is this:

$4/14 * 0.0 + 4/14 * 1.0 + 6/14 * 0.65 \approx 0.564$ bits

i.e. $Info_A(S) = 0.564$

The gain of a property A

Now the information gain from selecting feature P for tree-building, given a set of classes C.

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

For our sample data and for P = income, we get

Gain(A)= 1.531 - 0.564 bits = 0.967 bits.

The gain of a property A

Our analysis will be complete, and our choice clear, after we have similarly considered the remaining three features. The values are as follows:

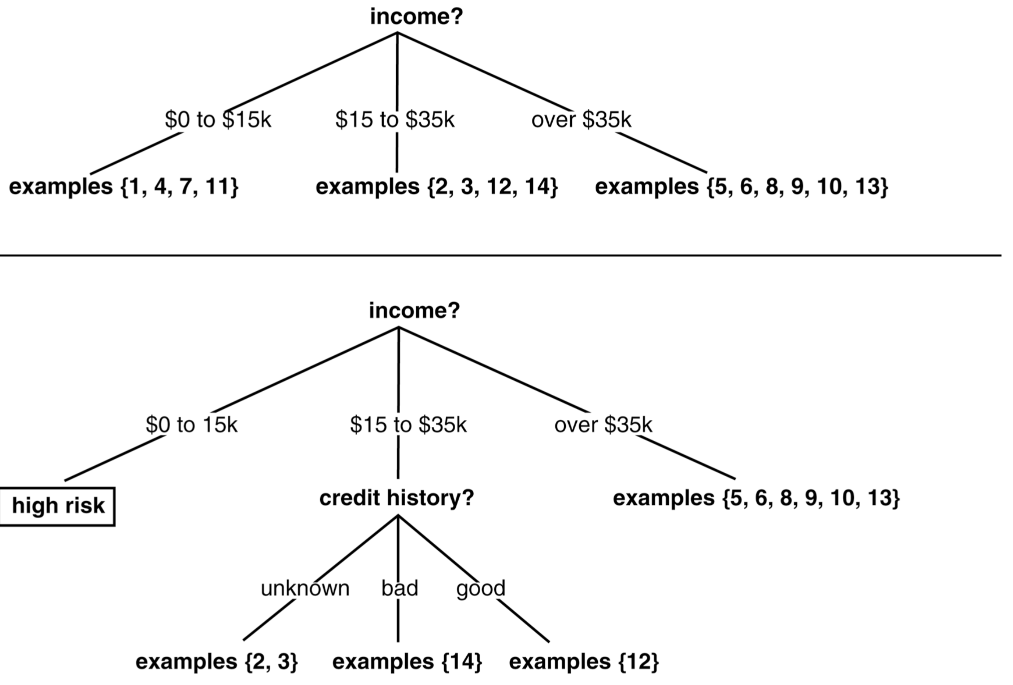
Gain(COLLATERAL) ≈ 0.756 bits,

Gain(DEBT) ≈ 0.581 bits,

Gain(CREDIT HISTORY) ≈ 0.266 bits.

That is, we should choose INCOME as the criterion in the root of the best decision tree that we can construct. And continue recursively…

Recursively Creating the Decision Tree



income?
$0 to $15k
$15 to $35k
over $35k
examples {1, 4, 7, 11}
examples {2, 3, 12, 14}
examples {5, 6, 8, 9, 10, 13}
income?
$0 to 15k
$15 to $35k
over $35k
high risk
credit history?
examples {5, 6, 8, 9, 10, 13}
unknown
bad
good
examples {2, 3}
examples {14}
examples {12}