Information Gain & Decision Trees

Slides adopted from

Data Mining for Business Analytics

Lecture 3: Supervised Classification

Stern School of Business
New York University
Spring 2014

Supervised Classification

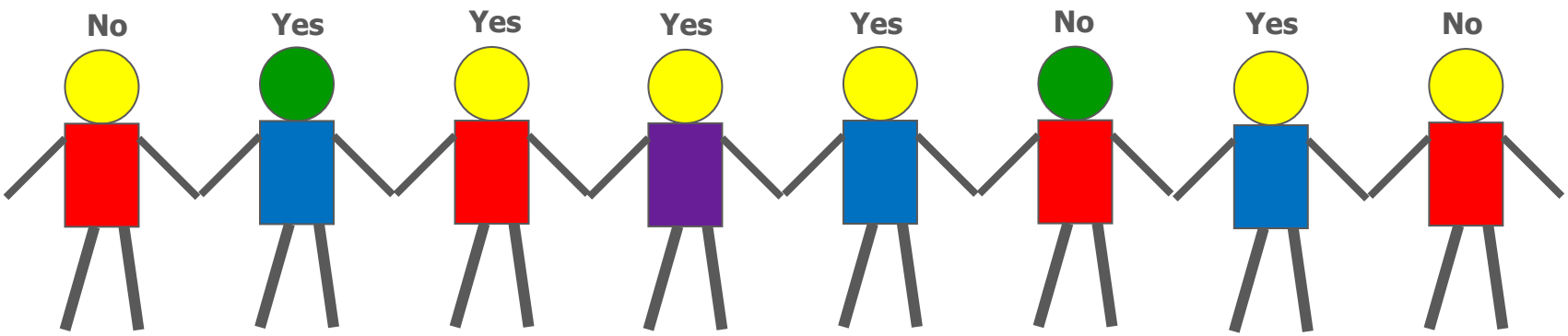
- How can we classify the population into groups that differ from each other with respect to some quantity of interest?
- Informative attributes
  - Find **knowable** attributes that correlate with the target of interest
    - Increase accuracy
    - Alleviate computational problems
    - E.g., *tree induction*

Supervised Classification

- How can we judge whether a variable contains important information about the target variable?
  - How much?

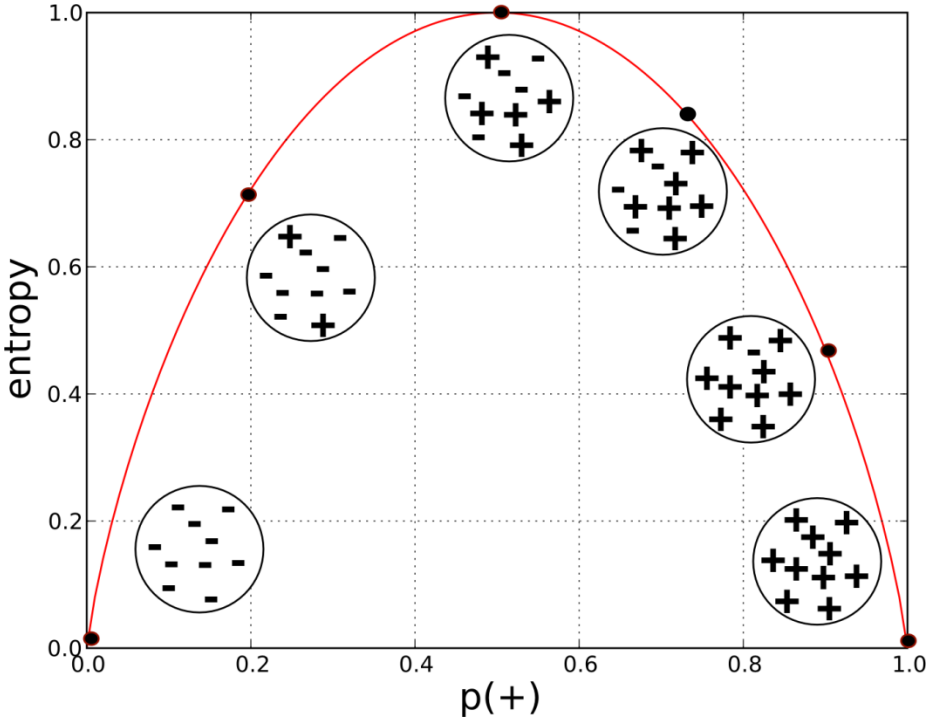
Selecting Informative Attributes

Objective: Based on customer attributes, partition the customers into subgroups that are less impure – with respect to the class (i.e., such that in each group as many instances as possible belong to the same class)



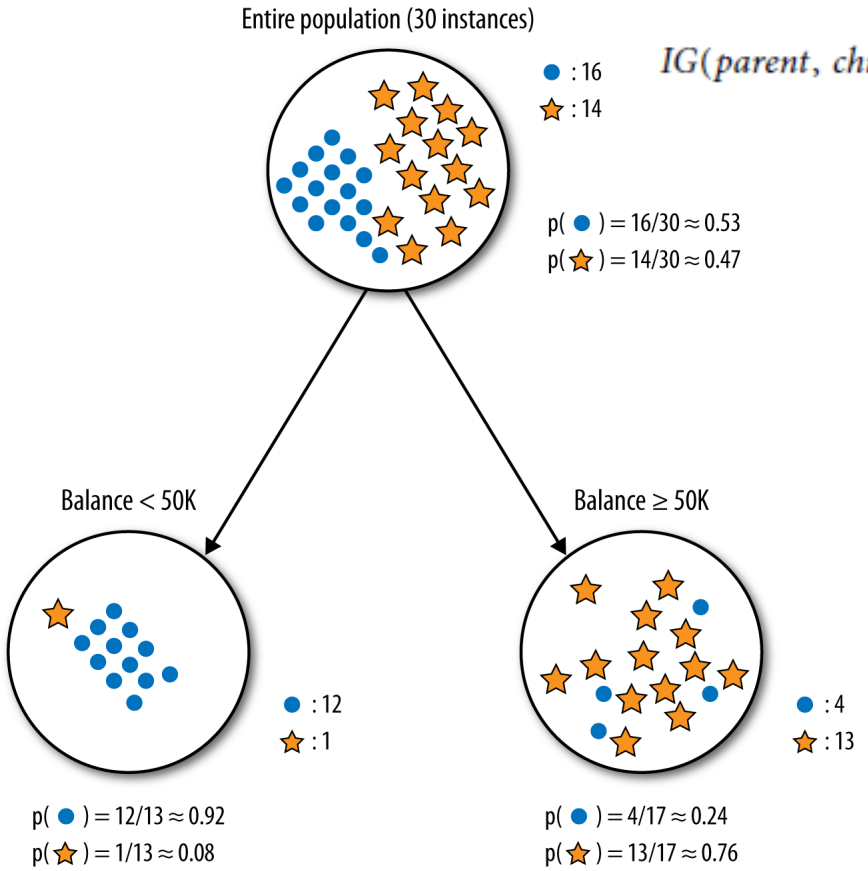
Selecting Informative Attributes

- The most common splitting criterion is called **information gain** (IG)
  - It is based on a **purity measure** called **entropy**
    - $entropy = -\mathrm{p}_1 \log_2(p_1) - p_2 \log_2(p_2) - ..$
    - Measures the general disorder of a set



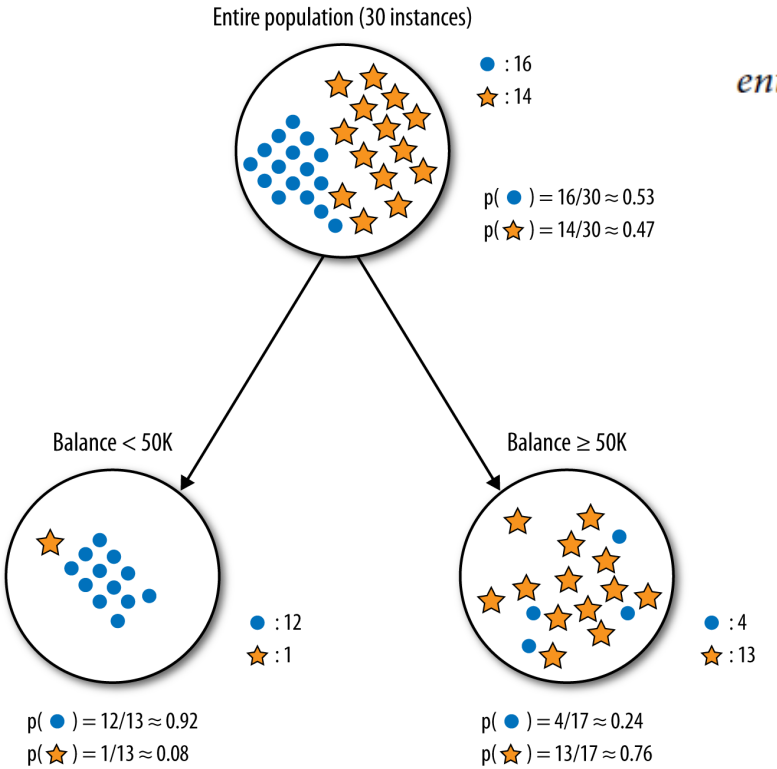
Information Gain

- Information gain measures the *change* in entropy due to any amount of new information being added



$$IG(parent, children) = entropy(parent) - [p(c_1) \times entropy(c_1) + p(c_2) \times entropy(c_2) + \cdots]$$

Information Gain



$$entropy(parent) = -[p(\bullet) \times \log_2 p(\bullet) + p(\star) \times \log_2 p(\star)]$$
$$\approx -[0.53 \times -0.9 + 0.47 \times -1.1]$$
$$\approx 0.99 \quad \text{(very impure)}$$

The entropy of the *left* child is:

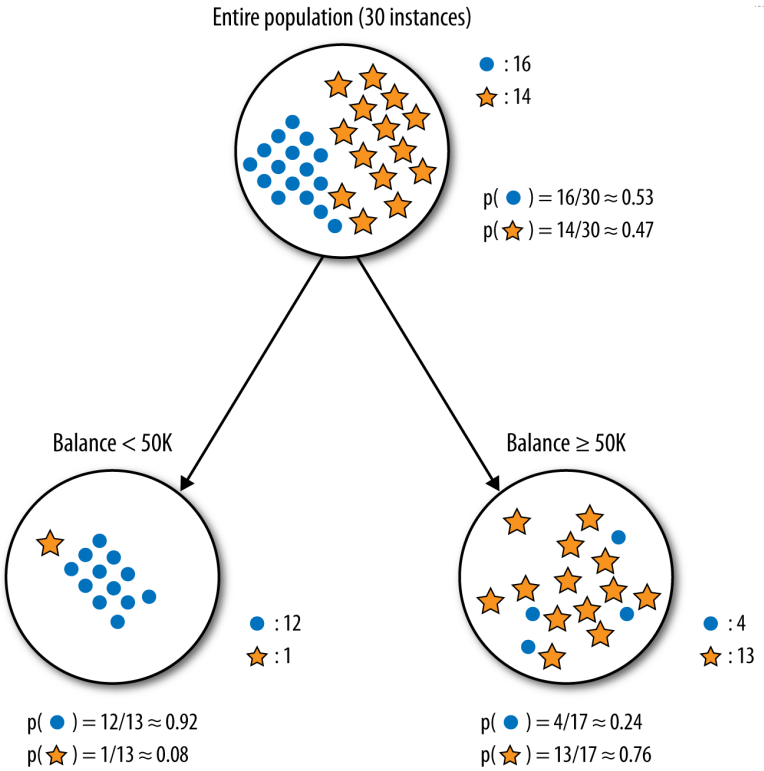
$$entropy(Balance < 50K) = -[p(\bullet) \times \log_2 p(\bullet) + p(\star) \times \log_2 p(\star)]$$
$$\approx -[0.92 \times (-0.12) + 0.08 \times (-3.7)]$$
$$\approx 0.39$$

The entropy of the *right* child is:

$$entropy(Balance \geq 50K) = -[p(\bullet) \times \log_2 p(\bullet) + p(\star) \times \log_2 p(\star)]$$
$$\approx -[0.24 \times (-2.1) + 0.76 \times (-0.39)]$$

=0.79

Information Gain



$$
\begin{aligned}
IG &= entropy(parent) - [p(\text{Balance} < 50\text{K}) \times entropy(\text{Balance} < 50\text{K}) \\
&\quad + p(\text{Balance} \geq 50\text{K}) \times entropy(\text{Balance} \geq 50\text{K})] \\
&\approx 0.99 - [0.43 \times 0.39 + 0.57 \times 0.79] \\
&\approx 0.37
\end{aligned}
$$

Relative IG = IG/entropy(parent)=0.37/0.99=0.37

Attribute Selection

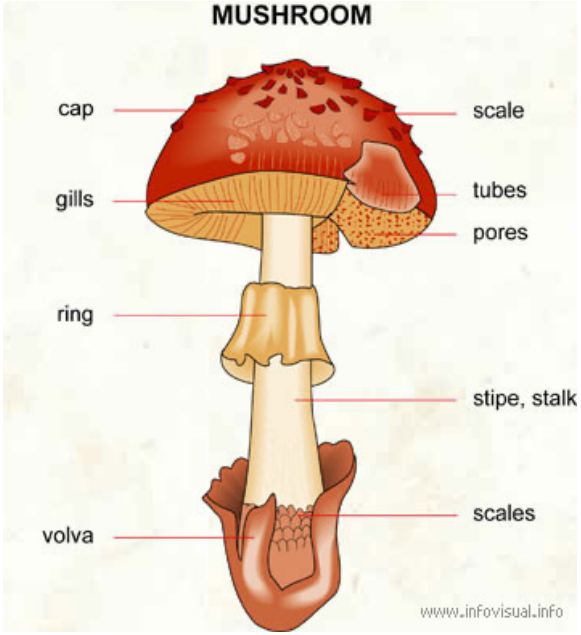
Reasons for selecting only a subset of attributes:

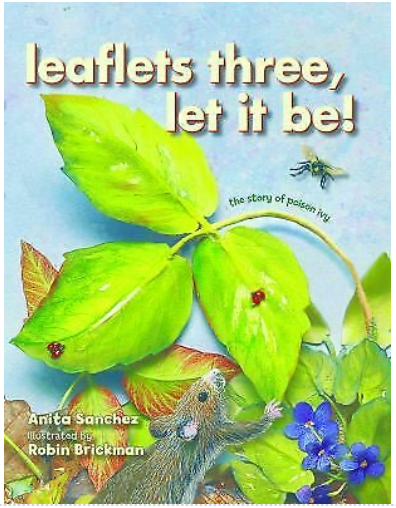
- Better insights and business understanding
- Better explanations and more tractable models
- Reduced cost
- Faster predictions
- Better predictions!
  - Over-fitting (*to be continued*..)

and also determining the most informative attributes.

Example: Attribution Selection with Information Gain

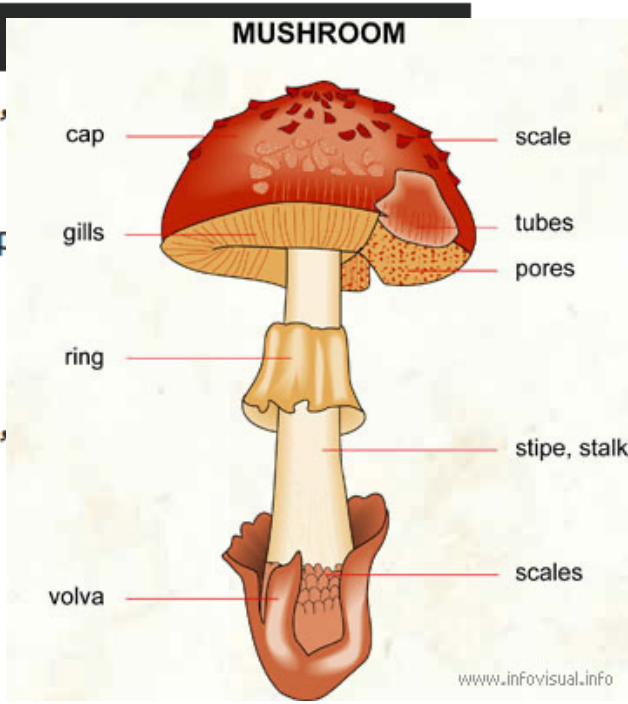
- This dataset includes descriptions of hypothetical samples corresponding to 23 species of gilled mushrooms in the Agaricus and Lepiota Family
- Each species is identified as definitely edible, definitely poisonous, or of unknown edibility and not recommended
  - This latter class was combined with the poisonous one
- The Guide clearly states that there is no simple rule for determining the edibility of a mushroom; no rule like “leaflets three, let it be” for Poisonous Oak and Ivy



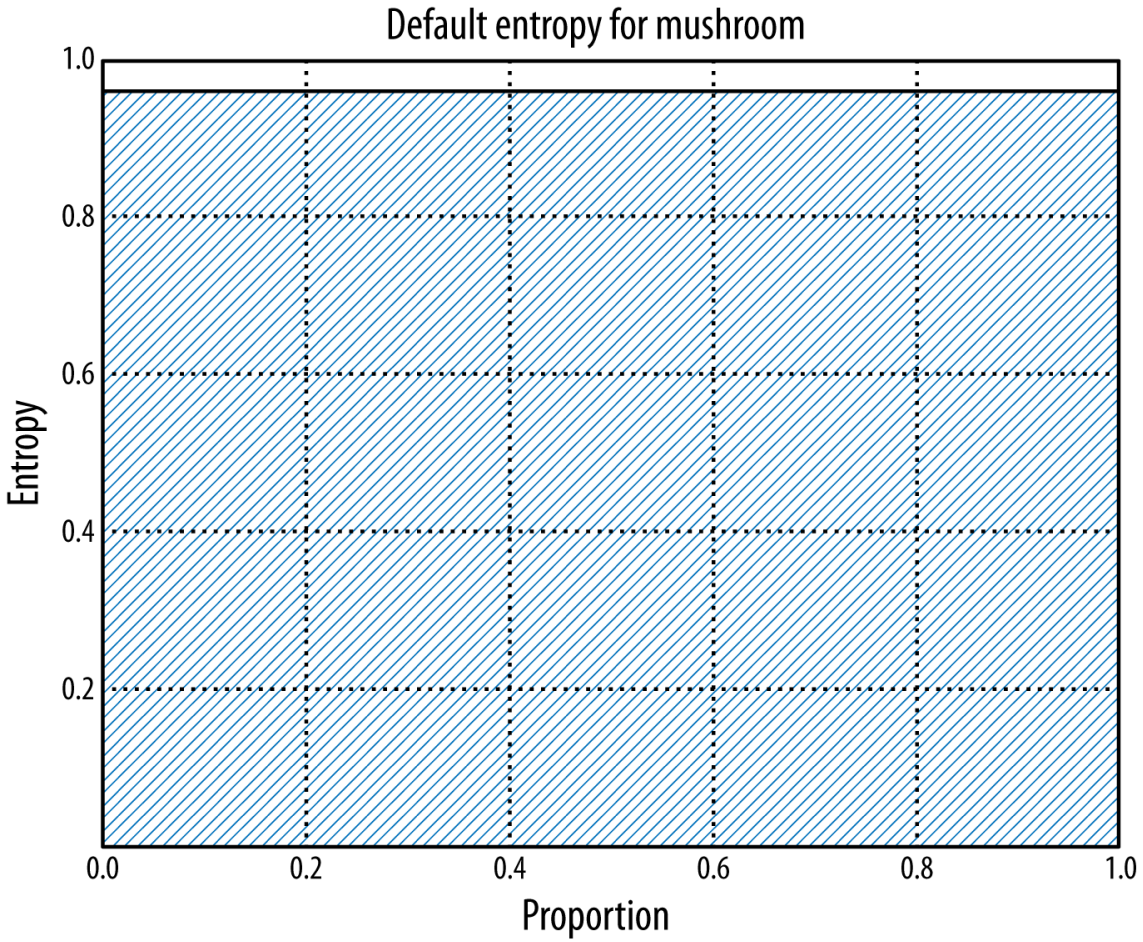


Example: Attribution Selection with Information Gain

Attribute name	Possible values
CAP-SHAPE	bell, conical, convex, flat, knobbed,
CAP-SURFACE	fibrous, grooves, scaly, smooth
CAP-COLOR	brown, buff, cinnamon, gray, green, p white, yellow
BRUISES?	yes, no
ODOR	almond, anise, creosote, fishy, foul, pungent, spicy
GILL-ATTACHMENT	attached, descending, free, notched
GILL-SPACING	close, crowded, distant
GILL-SIZE	broad, narrow
GILL-COLOR	black, brown, buff, chocolate, gray, green, orange, pink, purple, red, white, yellow
STALK-SHAPE	enlarging, tapering
STALK-ROOT	bulbous, club, cup, equal, rhizomorphs, rooted, missing
STALK-SURFACE-ABOVE-RING	fibrous, scaly, silky, smooth
STALK-SURFACE-BELOW-RING	fibrous, scaly, silky, smooth

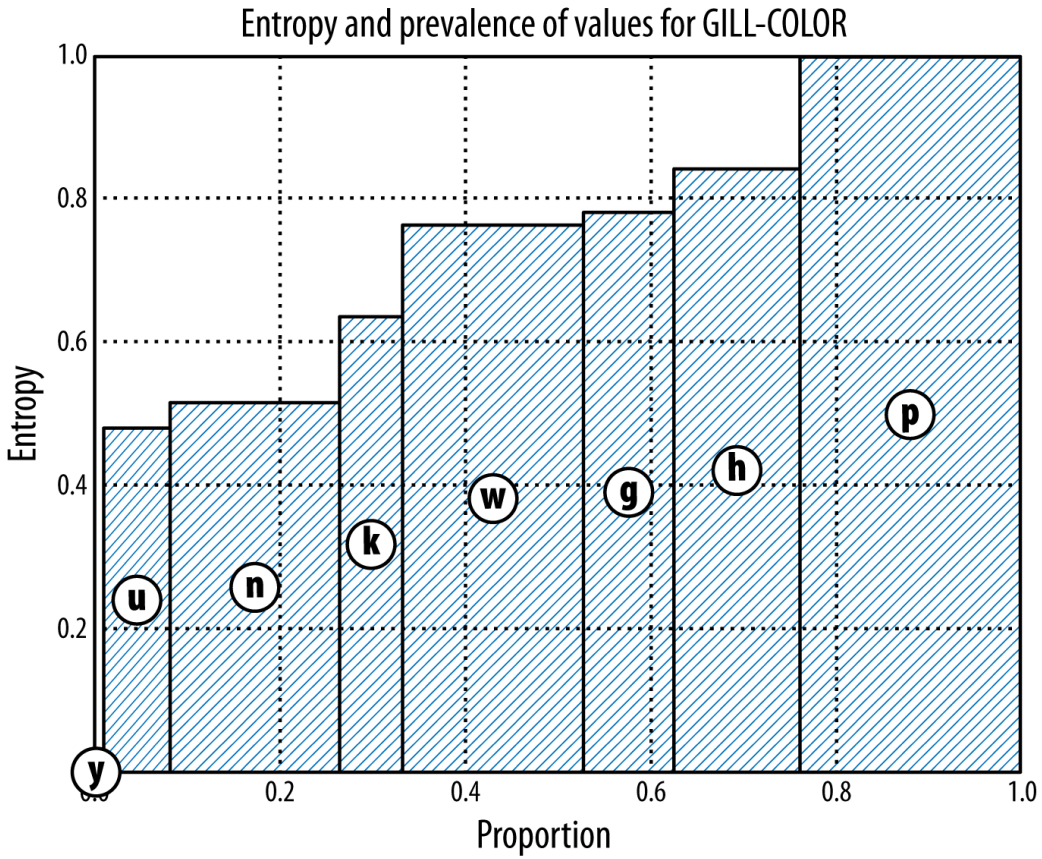


Example: Attribution Selection with Information Gain



We can think of this as our starting entropy—any informative attribute should produce a new graph with less shaded area.

Example: Attribution Selection with Information Gain

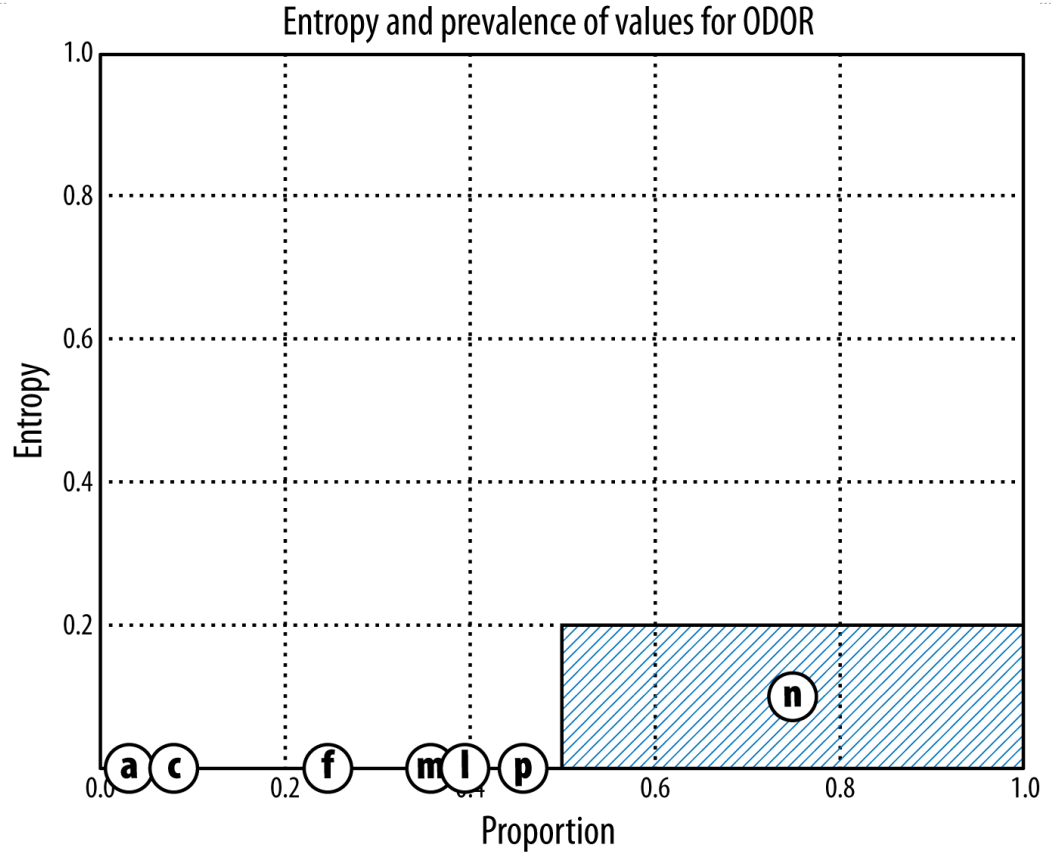


GILL-COLOR black, brown, buff, chocolate, gray, green, orange, pink, purple, red, white, yellow

The width of each attribute represents what proportion of the dataset has that value, and the height is its entropy.

We can see that GILL-COLOR reduces the entropy somewhat; the shaded area is considerably less than the area in the last page

Example: Attribution Selection with Information Gain



ODOR almond, anise, creosote, fishy, foul, musty, none, pungent, spicy

ODOR has the highest information gain of any attribute in the Mushroom dataset. It can reduce the dataset's total entropy to about 0.1, which gives it an information gain of 0.96 – 0.1 = 0.86.

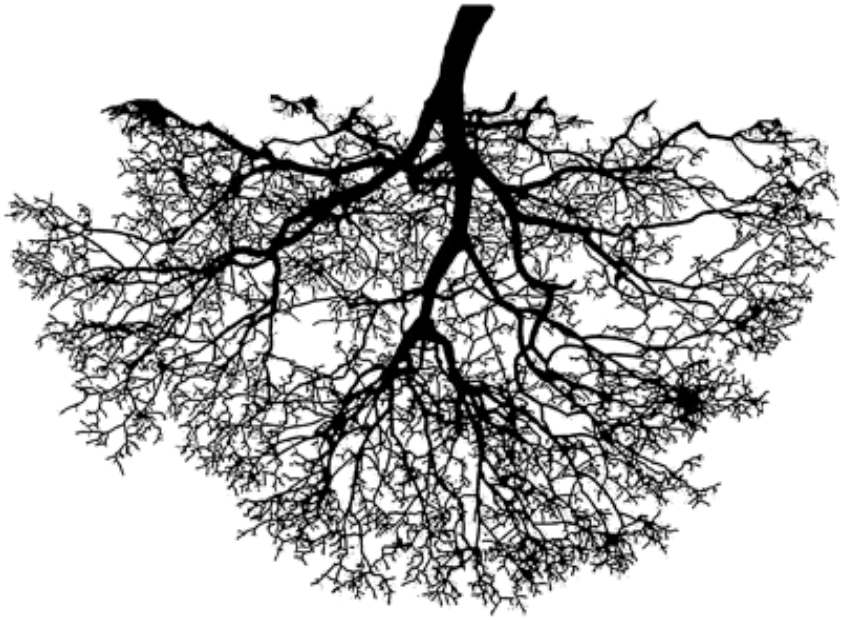
So odor is a very informative attribute to check when considering mushroom edibility.

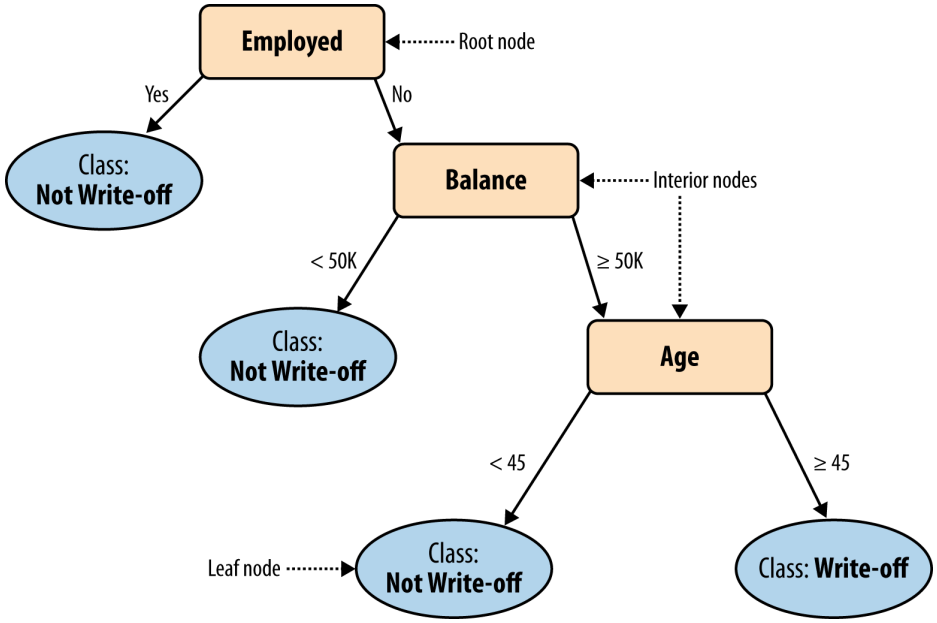
Multivariate Supervised Classification

- If we select the *single* variable that gives the most information gain, we create a very *simple* classification

- If we select multiple attributes each giving some information gain, how do we put them together?

Tree-Structured Models

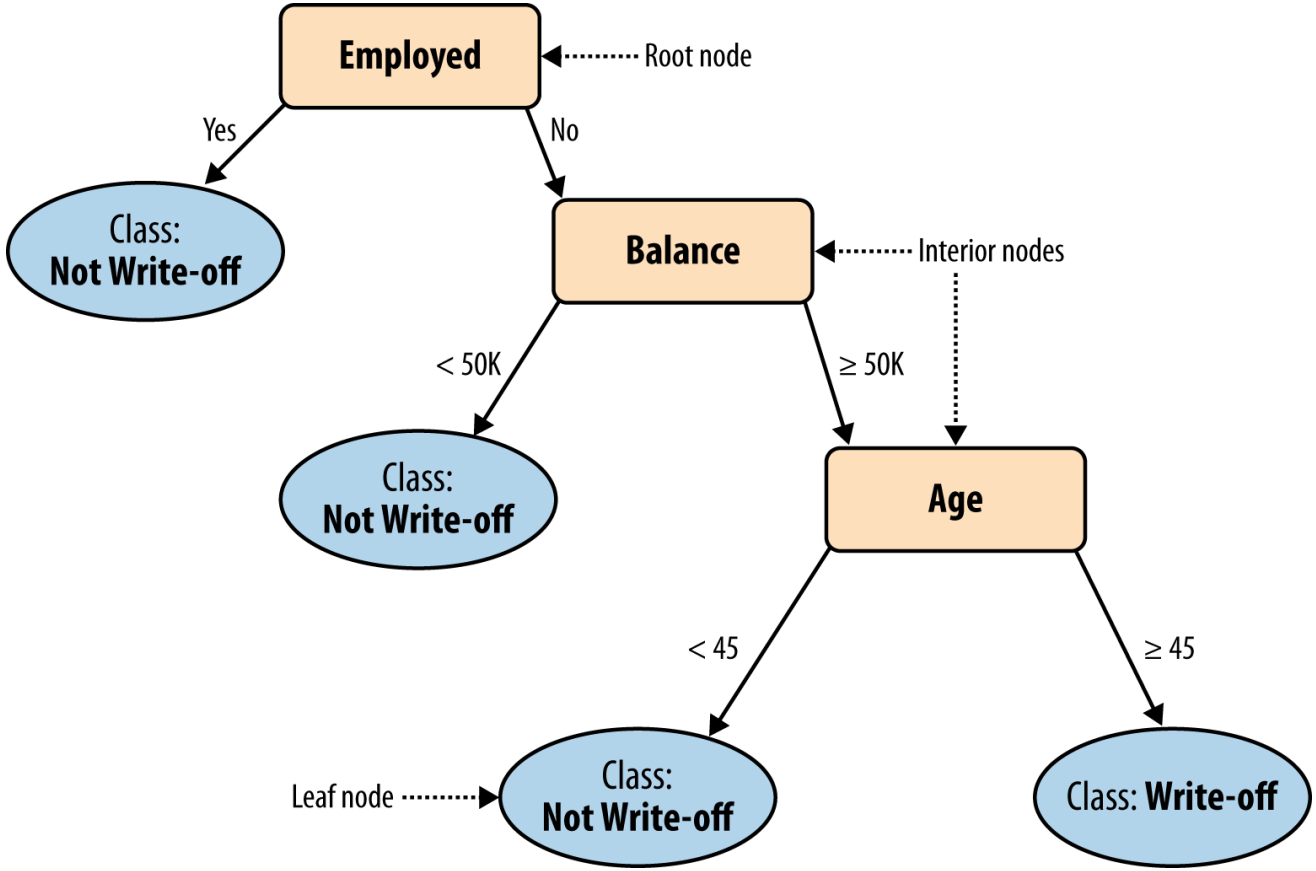




Write-off: not to pay off their account balances. i.e., defaulting on one's phone bill or credit card balance

Tree-Structured Models

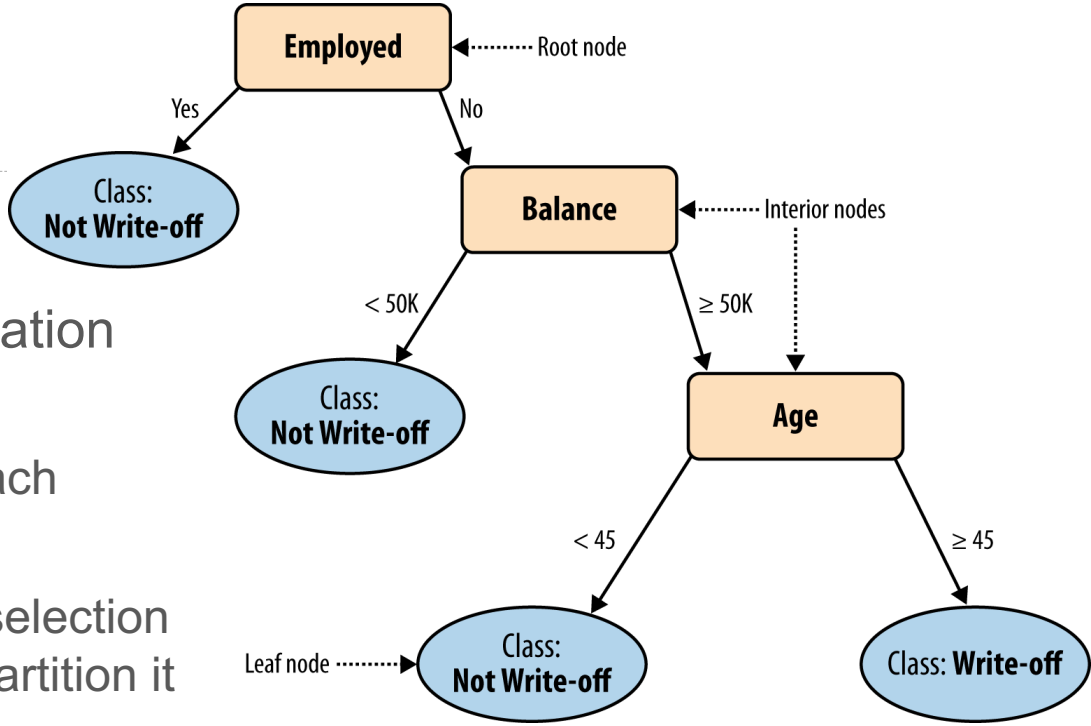
- Classify 'John Doe'
  - Balance=115K, Employed=No, and Age=40



Tree-Structured Models: “Rules”

- No two parents share descendants
- There are no cycles
- The branches always “point downwards”
- Every example always ends up at a leaf node with some specific class determination
  - Probability estimation trees, regression trees (*to be continued*..)

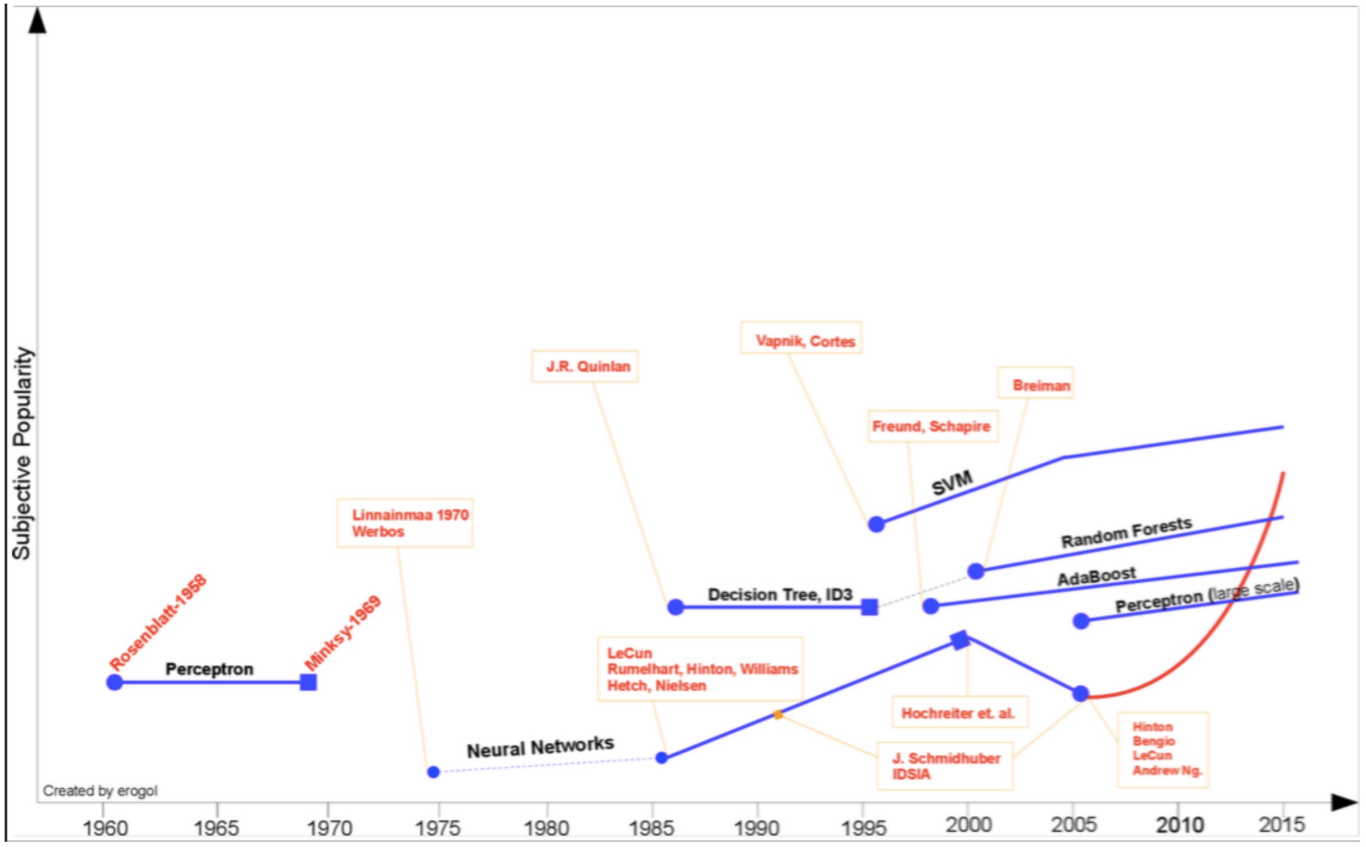
Tree Induction



- How do we create a classification tree from data?
  - **divide-and-conquer** approach
  - take each data subset and ***recursively*** apply attribute selection to find the best attribute to partition it
- When do we stop?
  - The nodes are pure,
  - there are no more variables, or
  - even earlier (over-fitting – *to be continued*..)

Why trees?

- Decision trees (DTs), or classification trees, are one of the most popular data mining tools
  - (along with linear and logistic regression)
- They are:
  - Easy to understand
  - Easy to implement
  - Easy to use
  - Computationally cheap
- Almost all data mining packages include DTs
- They have advantages for model interpretability, which is important for:
  - model evaluation
  - communication to non-Machine-Learning-savvy stakeholders


Subjective Popularity
Rosenblatt-1958
Perceptron
Minksy-1969
Linnainmaa 1970
Werbos
Neural Networks
J.R. Quinlan
Decision Tree, ID3
Vapnik, Cortes
Freund, Schapire
Breiman
SVM
Random Forests
AdaBoost
Perceptron (large scale)
LeCun
Rumelhart, Hinton, Williams
Hetch, Nielsen
Hochreiter et. al.
J. Schmidhuber
IDSIA
Hinton
Bengio
LeCun
Andrew Ng.
Created by erogol
1960
1965
1970
1975
1980
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1995
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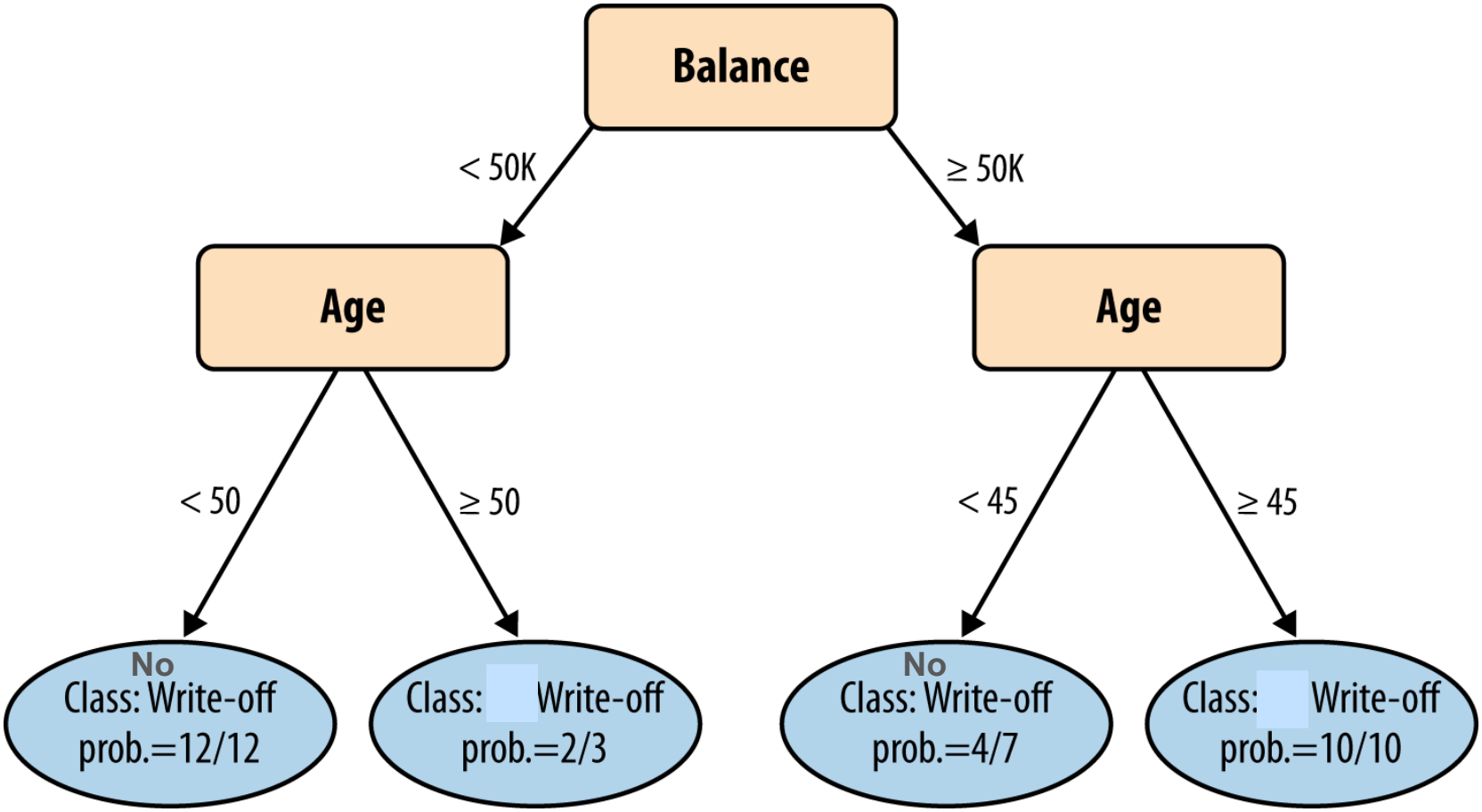
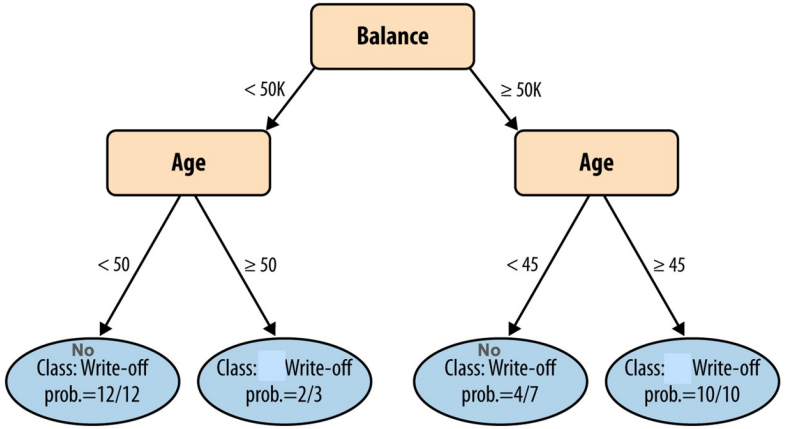
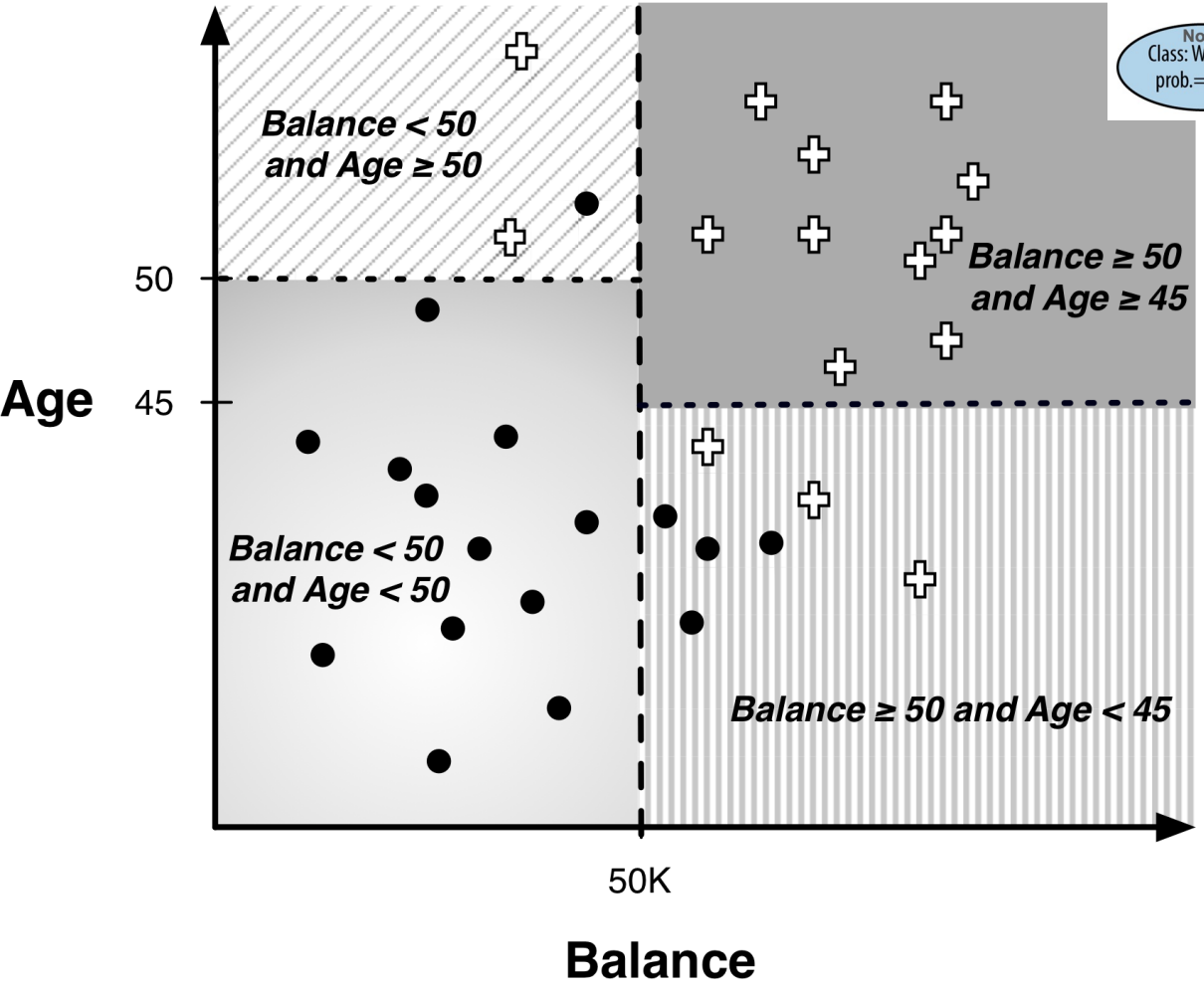
2015

Visualizing Classifications



Visualizing Classifications





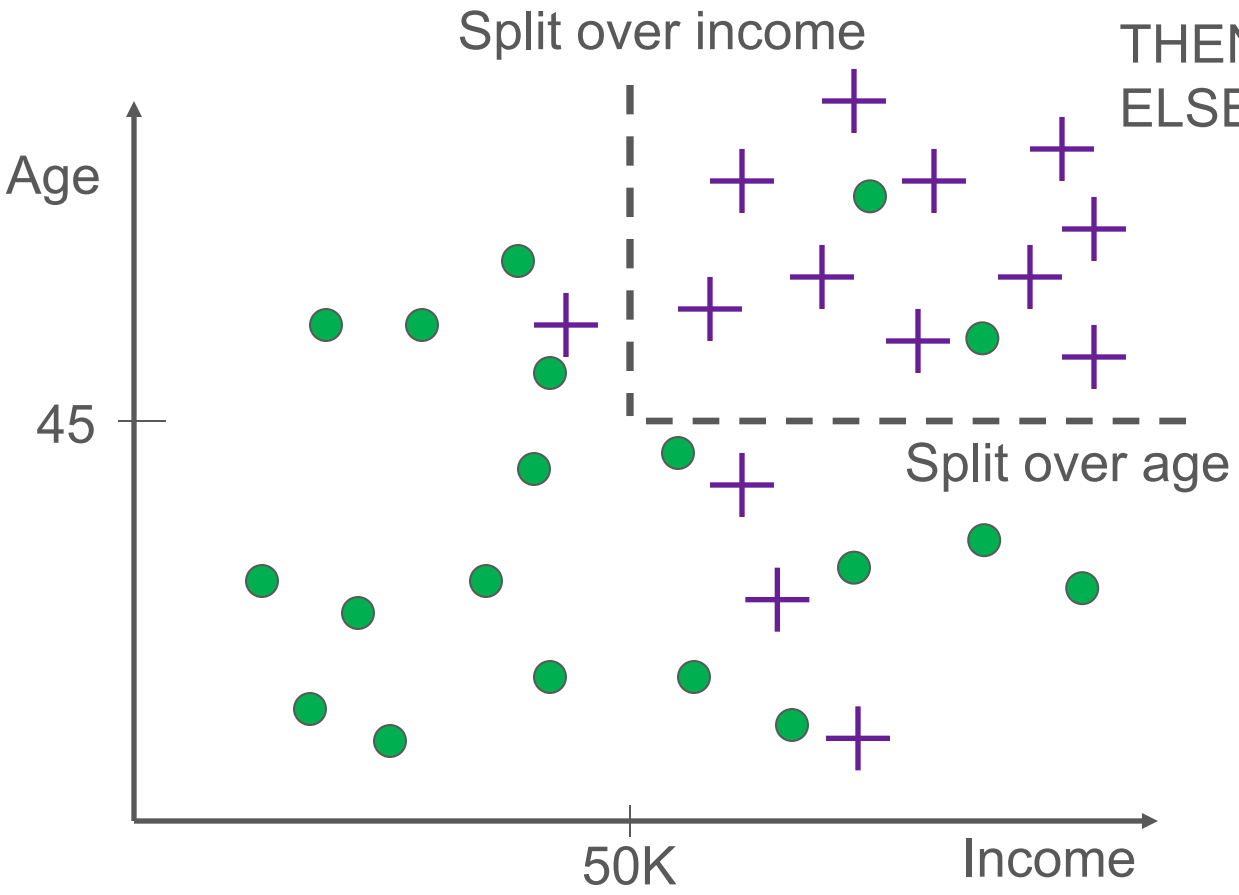
Geometric interpretation of a model

Pattern:

IF Income >= 50K & Age > 45

THEN Buy_Insurance = 'yes'

ELSE Buy_Insurance = 'no'

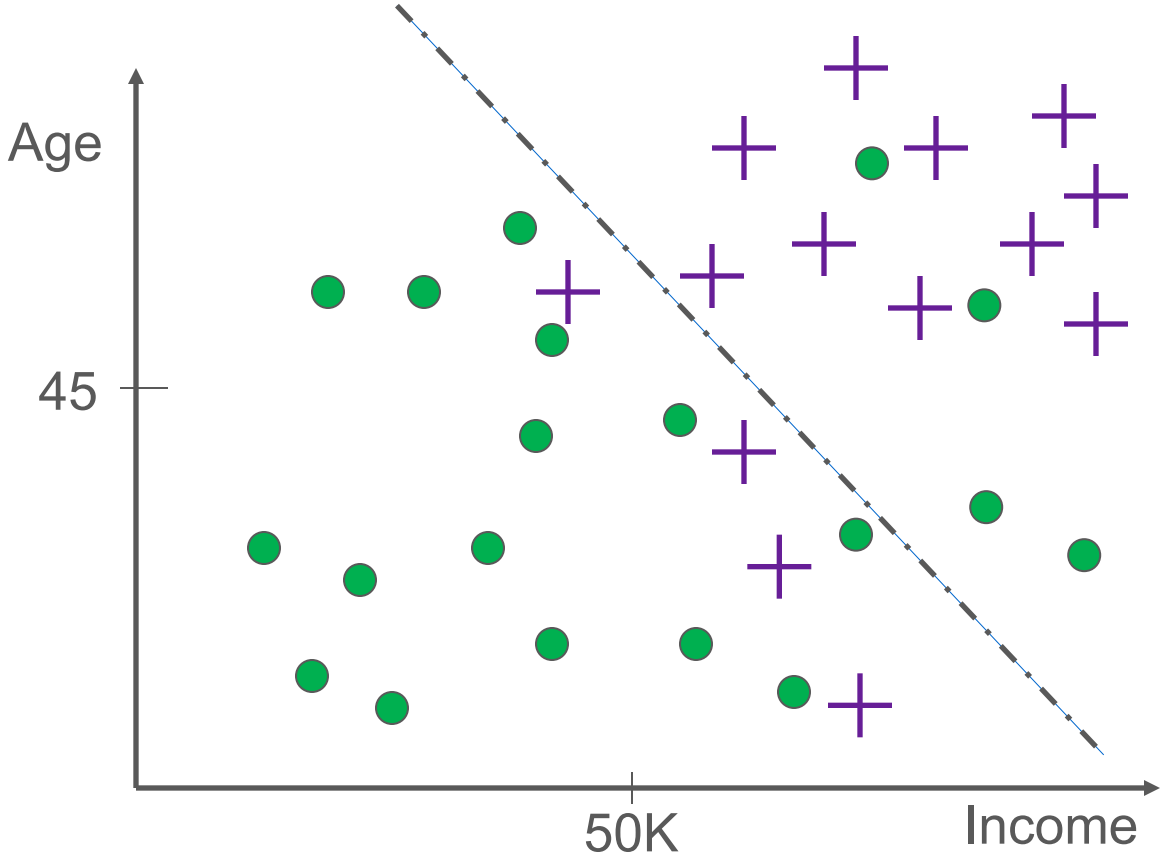


Did not buy life insurance

Bought life insurance

Geometric interpretation of a model

What alternatives are there to partitioning this way?



"True" boundary may not be closely approximated by a linear boundary!

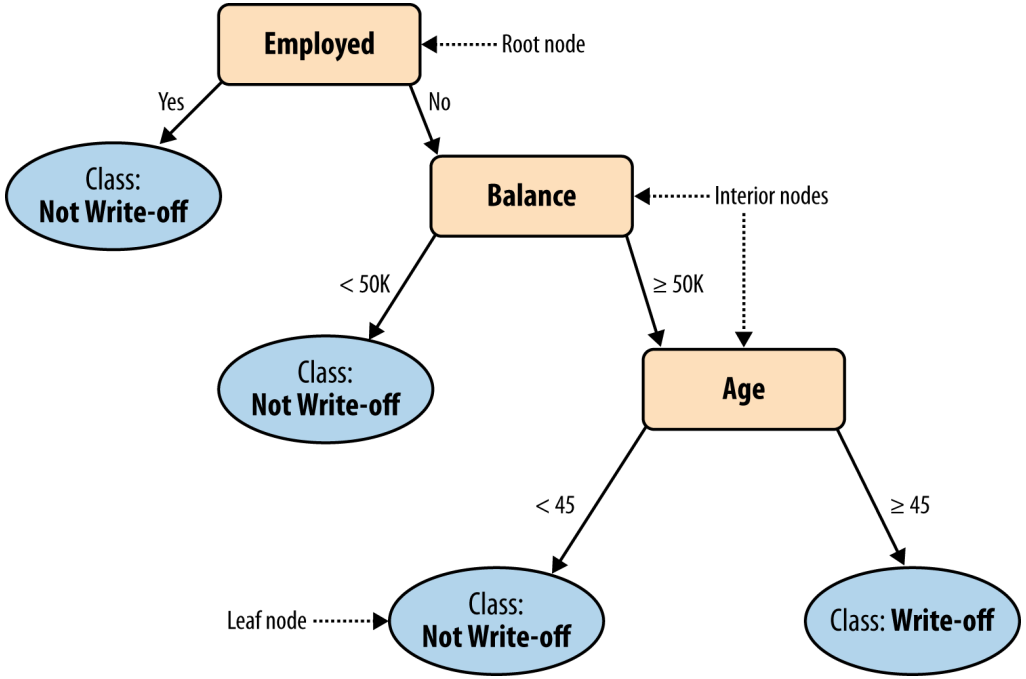
Did not buy life insurance

Bought life insurance

Trees as Sets of Rules

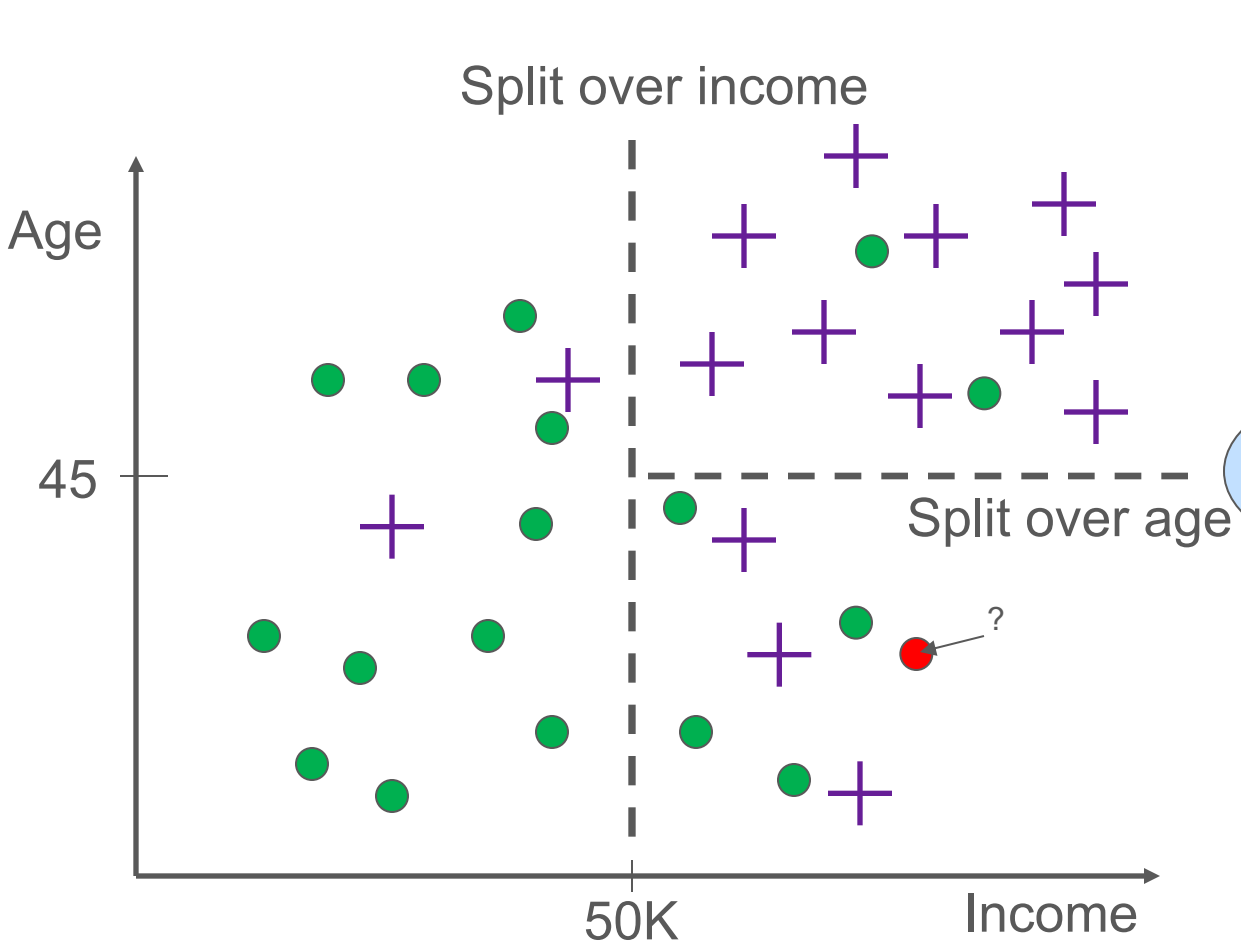
- The classification tree is equivalent to this rule set
- Each rule consists of the attribute tests along the path connected with **AND**

Trees as Sets of Rules: Interpretability

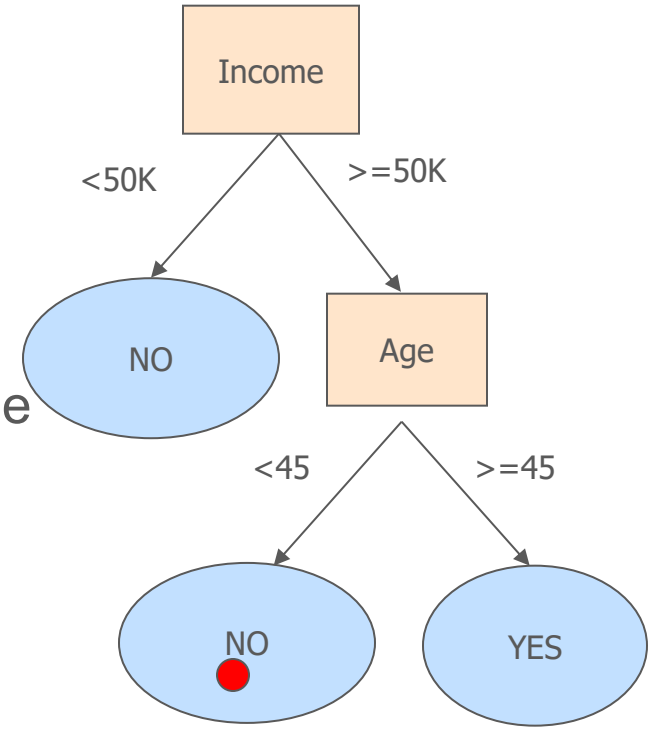


- IF (Employed = Yes) THEN Class=Not Write-off
- IF (Employed = No) AND (Balance < 50k) THEN Class=Not Write-off
- IF (Employed = No) AND (Balance ≥ 50k) AND (Age < 45) THEN Class=Not Write-off
- IF (Employed = No) AND (Balance ≥ 50k) AND (Age ≥ 45) THEN Class=Write-off

What are we predicting?



Classification tree

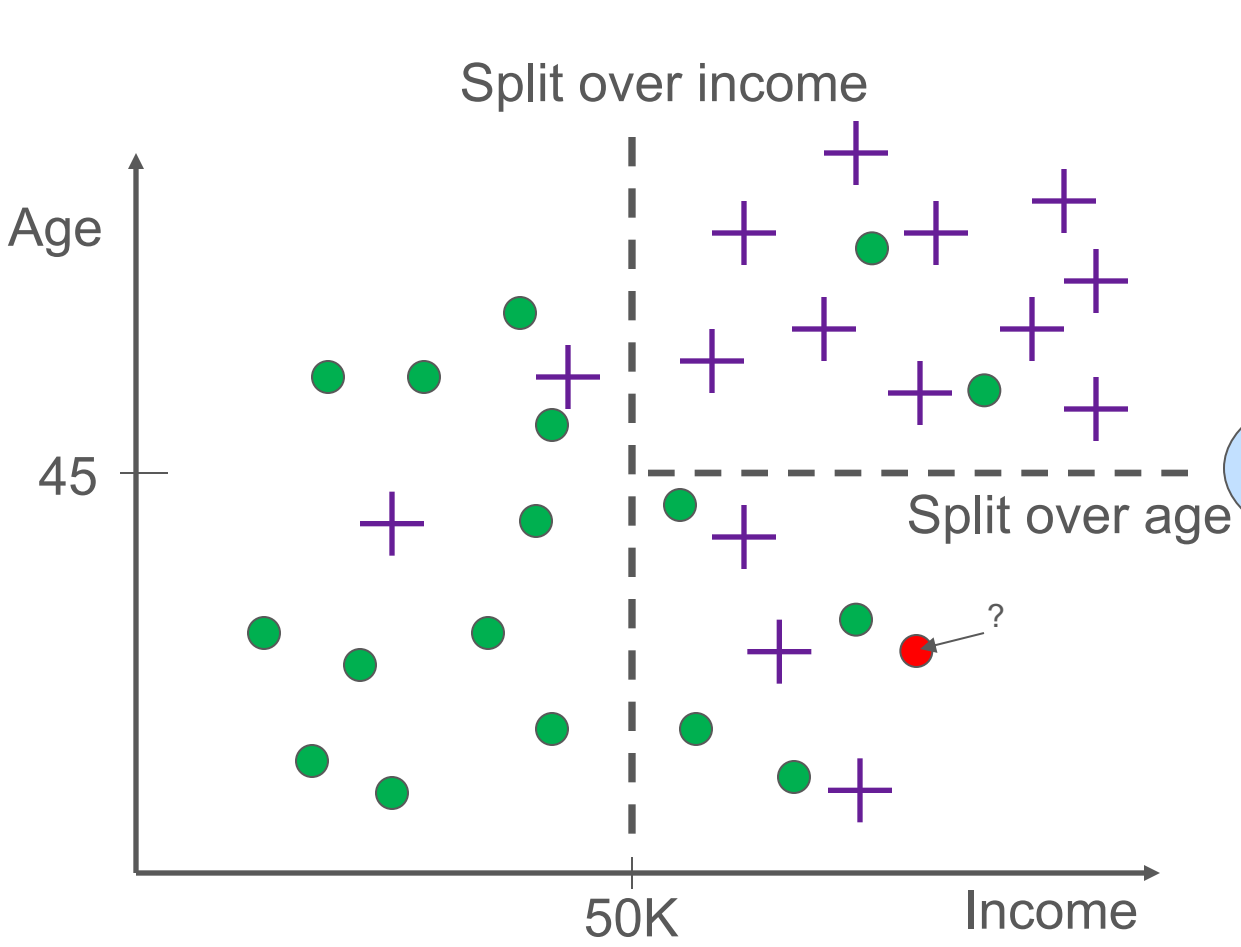


Did not buy life insurance

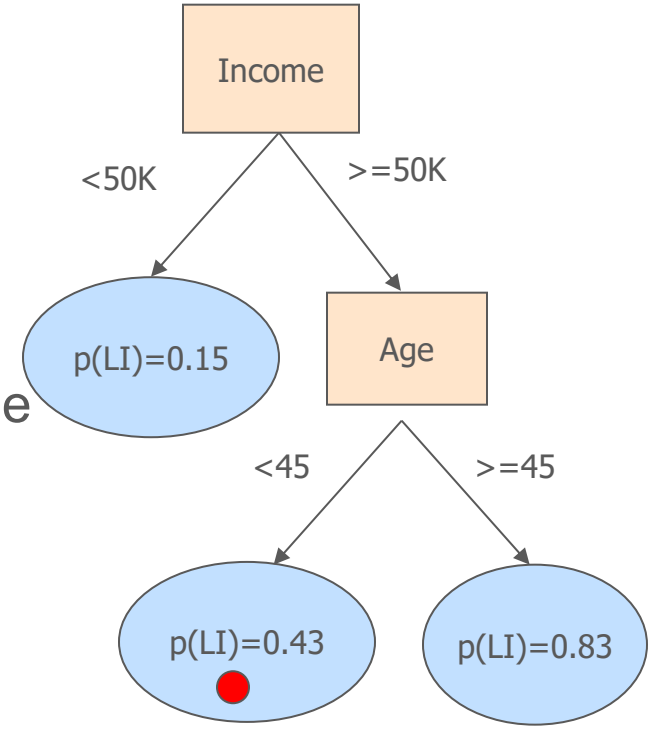
Bought life insurance

Interested in LI? = NO

What are we predicting?



Classification tree



Did not buy life insurance

Bought life insurance

Interested in LI? = 3/7

Questions?