テキストのラベルづけ/レベルづけのための特徴抽出の手法について (Feature Selection in Text Classification/Ranking)

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Background (1/2)

- Measuring text readability

  (小学(1年-6年), 中学(1年-3年), 高校(1年-3年), 大学)

- Judging text level

  (A1, A2, B1, B2, C1, C2 in CEFR)

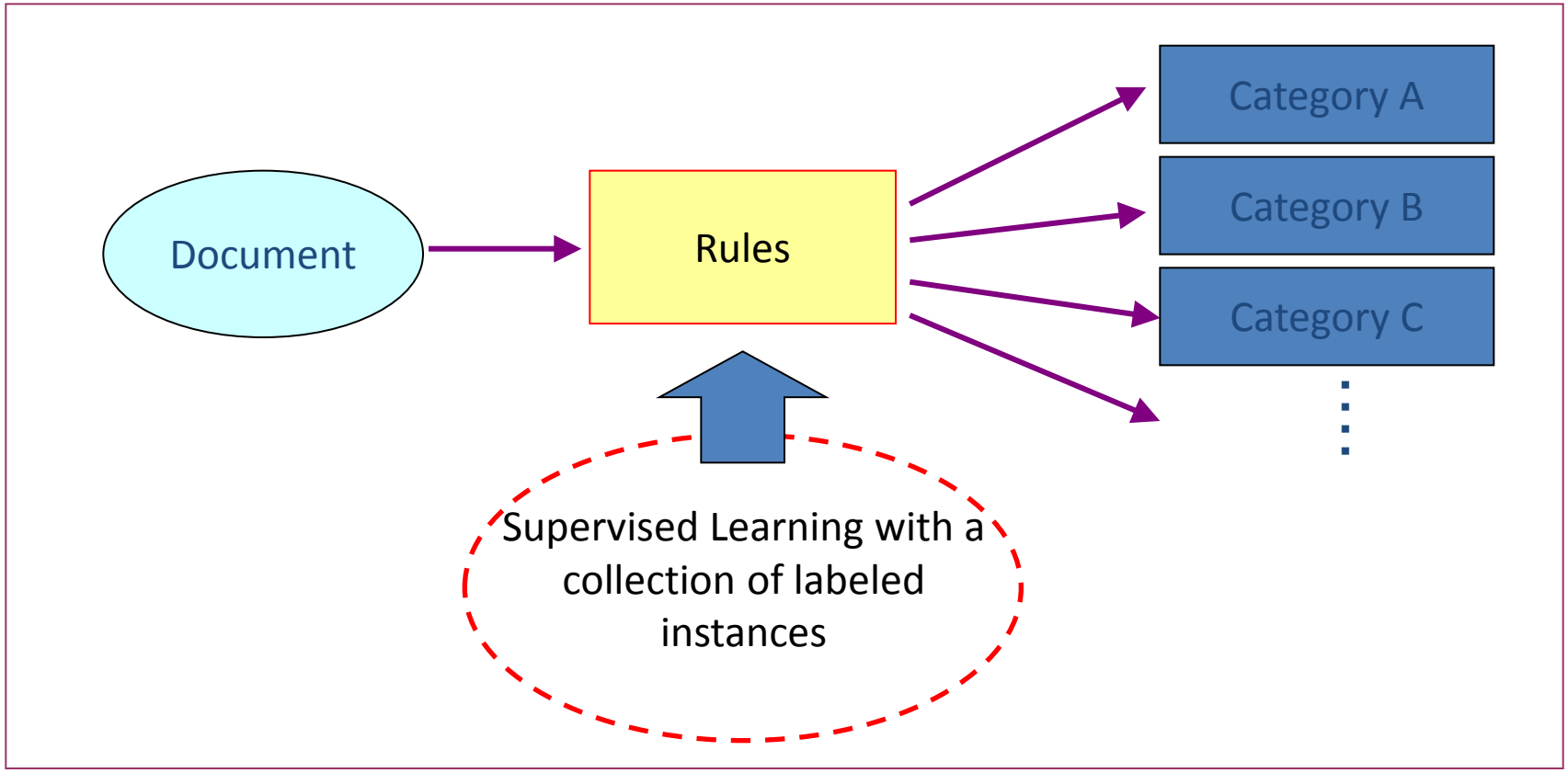
These tasks are considered as text classification/categorization or ranking in NLP (Natural Language Processing).

Background (2/2)

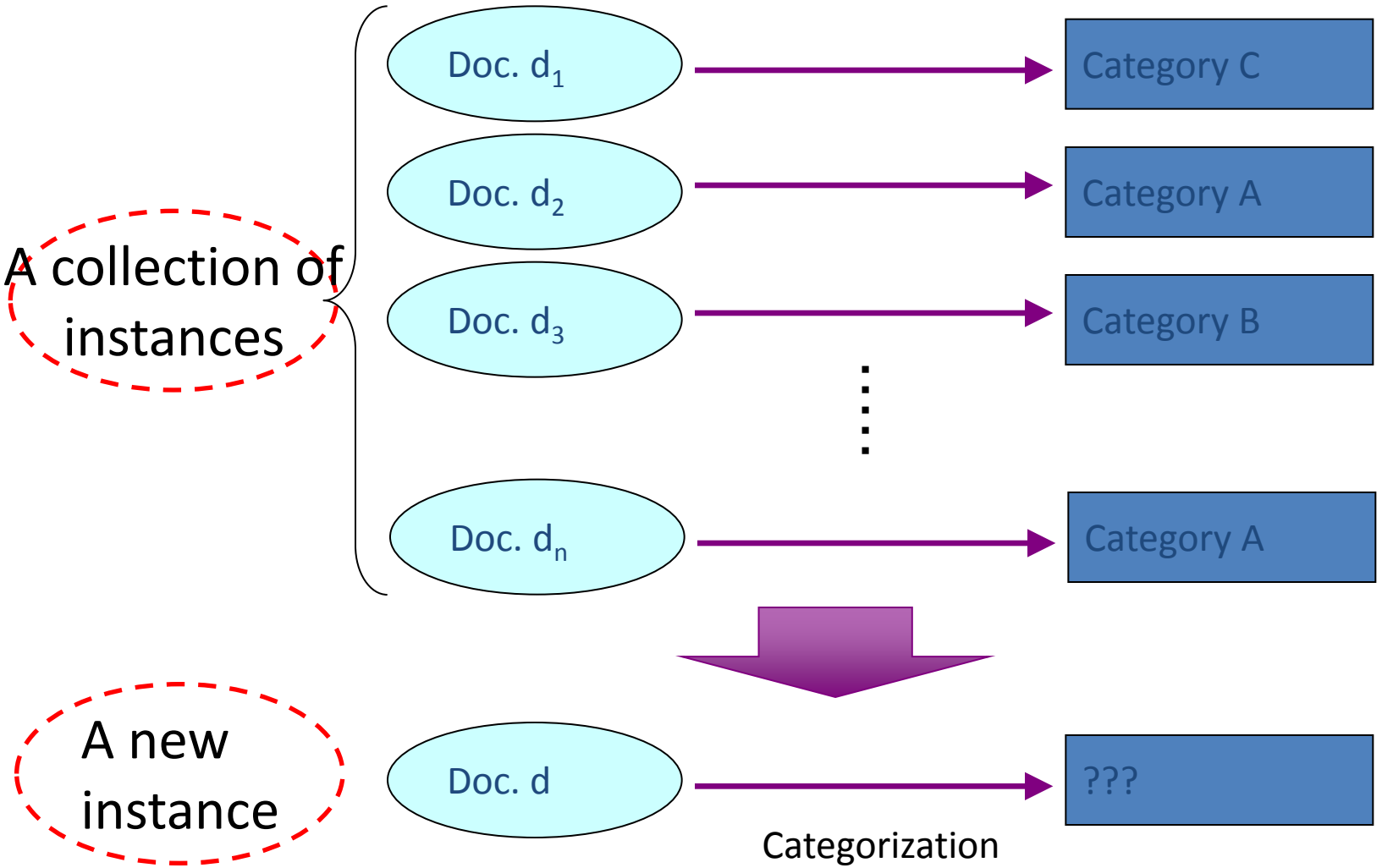
- What are good clues for measuring text readability/judging text level?

  The task is considered as identification of effective features or feature selection in text classification or ranking.

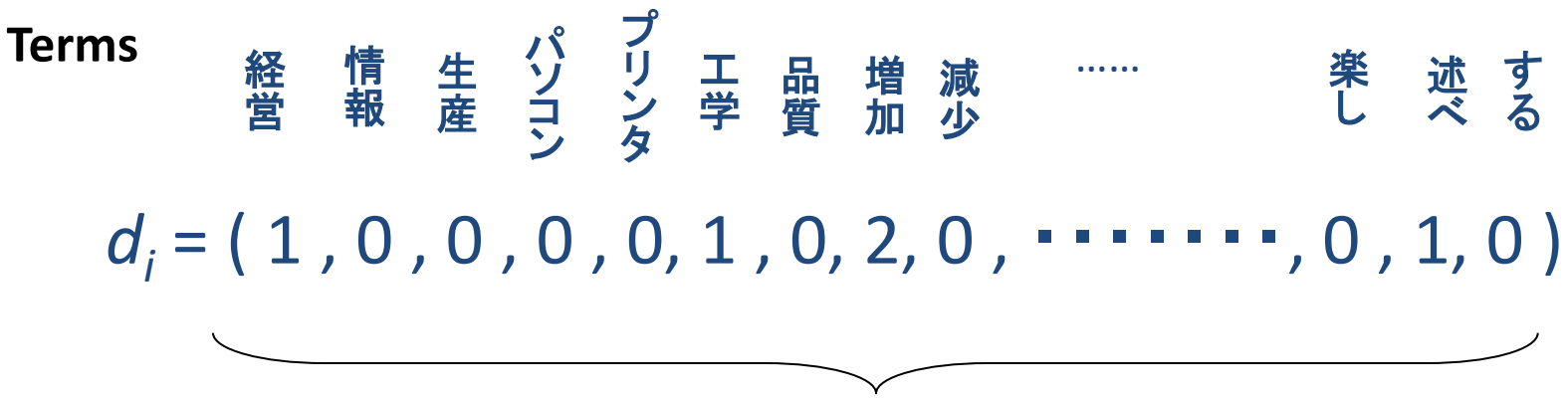
Text Classification (1/2)



Text Classification (2/2)



Representation of documents



Examples of Text Classification

- LABELS=BINARY
  - “spam” / “not spam”
- LABELS=TOPICS
  - “finance” / “sports” / “asia”
- LABELS=OPINION
  - “like” / “hate” / “neutral”
- LABELS=AUTHOR
  - “Shakespeare” / “Marlowe” / “Ben Jonson”
- …

Machine learning and our focus

- Like human learning from past experiences.
- A computer does not have "experiences".
- A computer system learns from data, which represent some "past experiences" of an application domain.
- Our focus: learn a target function that can be used to predict the values of a discrete class attribute, e.g., approve or not-approved, and high-risk or low risk.
- The task is commonly called: Supervised learning, classification.

A portion of the slides are from Prof. Bing Liu's lecture slides.

The data and the goal

- Data: A set of data records (also called examples, instances or cases) described by
  - *k* attributes: A_1, A_2, … A_k.
  - a class: Each example is labelled with a pre-defined class.
- Goal: To learn a classification model from the data that can be used to predict the classes of new (future, or test) cases/instances.

An example: data (loan application)

Approved or not

ID	Age	Has_Job	Own_House	Credit_Rating	Class
1	young	false	false	fair	**No**
2	young	false	false	good	**No**
3	young	true	false	good	**Yes**
4	young	true	true	fair	**Yes**
5	young	false	false	fair	**No**
6	middle	false	false	fair	**No**
7	middle	false	false	good	**No**
8	middle	true	true	good	**Yes**
9	middle	false	true	excellent	**Yes**
10	middle	false	true	excellent	**Yes**
11	old	false	true	excellent	**Yes**
12	old	false	true	good	**Yes**
13	old	true	false	good	**Yes**
14	old	true	false	excellent	**Yes**
15	old	false	false	fair	**No**

An example: the learning task

- Learn a classification model from the data
- Use the model to classify future loan applications into
  - Yes (approved) and
  - No (not approved)
- What is the class for following case/instance?

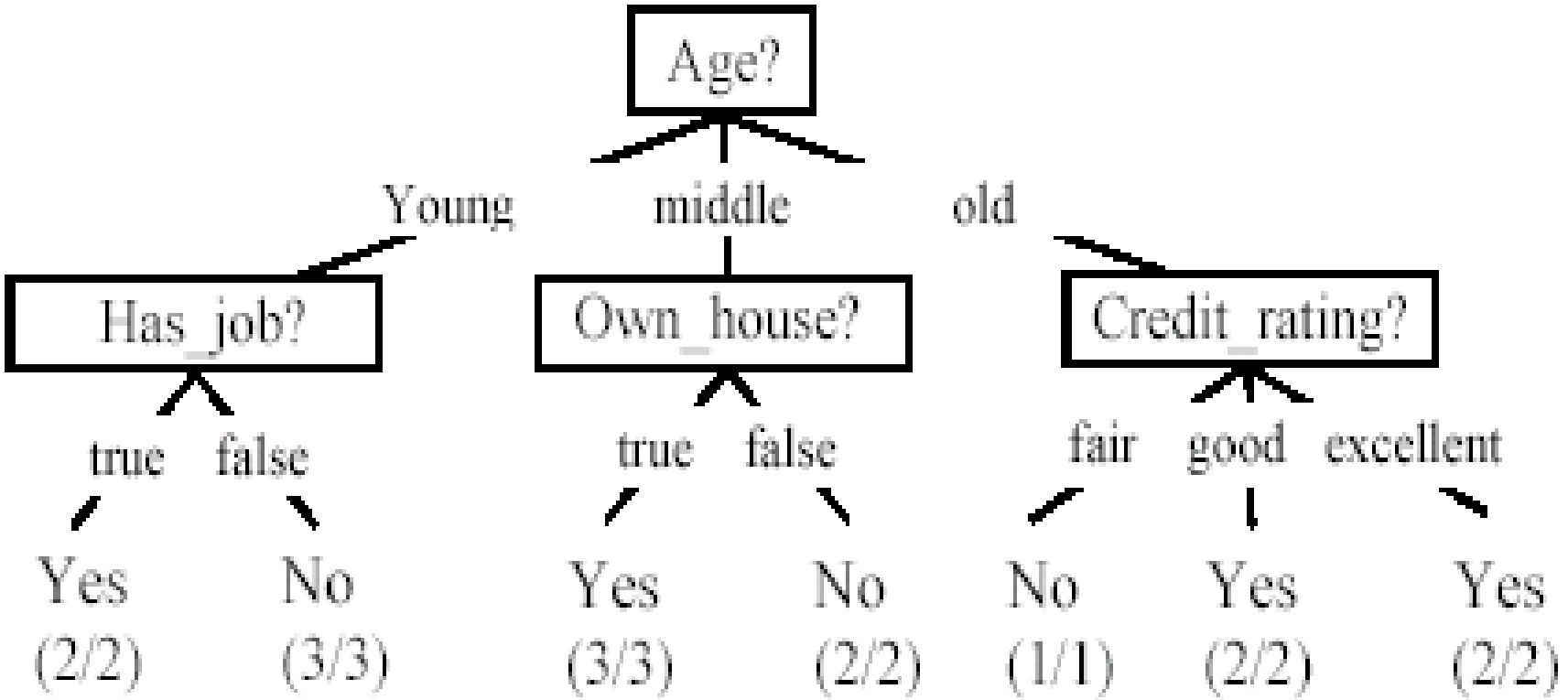
Age	Has_Job	Own_house	Credit-Rating	Class
young	false	false	good	?

Decision Tree Learning

- Decision tree learning is one of the most widely used techniques for classification.
  - Its classification accuracy is competitive with other methods, and
  - it is very efficient.
- The classification model is a tree, called decision tree.
- C4.5 by Ross Quinlan is perhaps the best known system. It can be downloaded from the Web.

A decision tree from the loan data

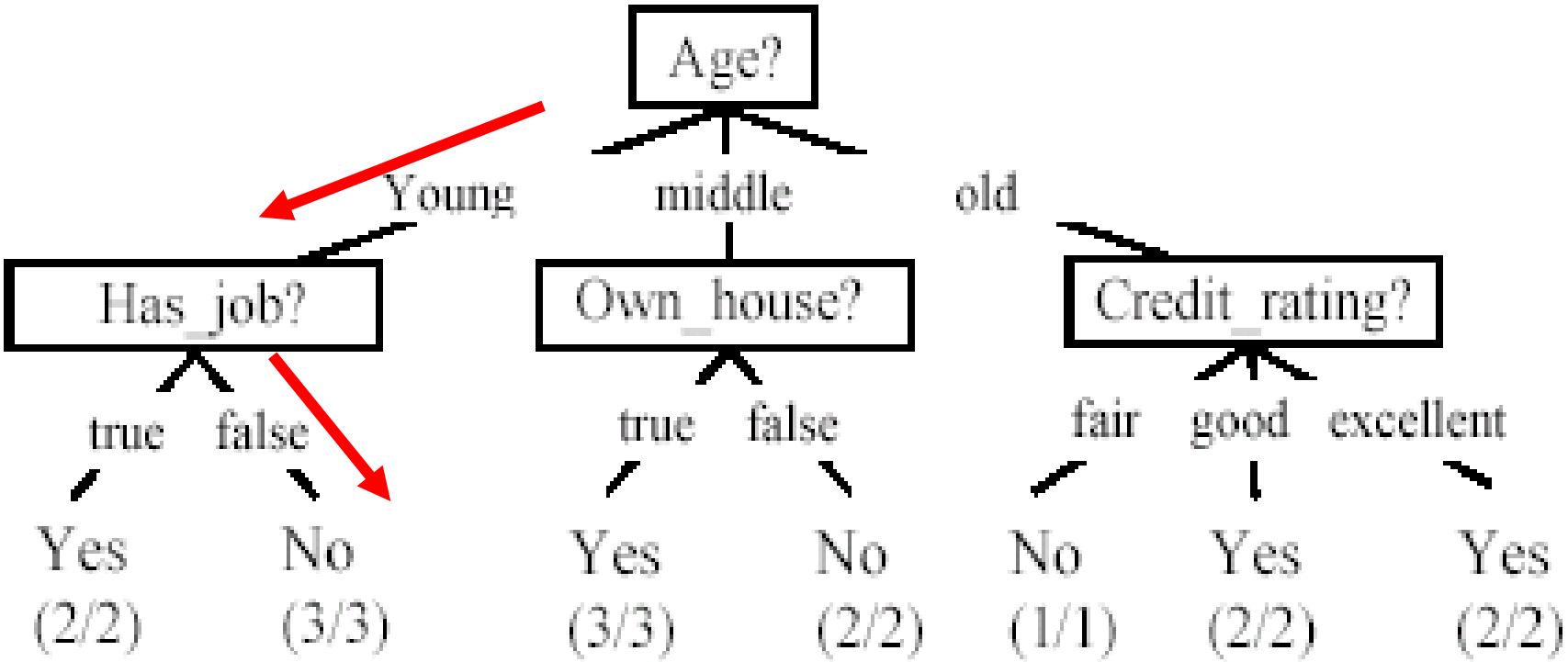
Decision nodes and leaf nodes (classes)



Use the decision tree

Age	Has_Job	Own_house	Credit-Rating	Class
young	false	false	good	?

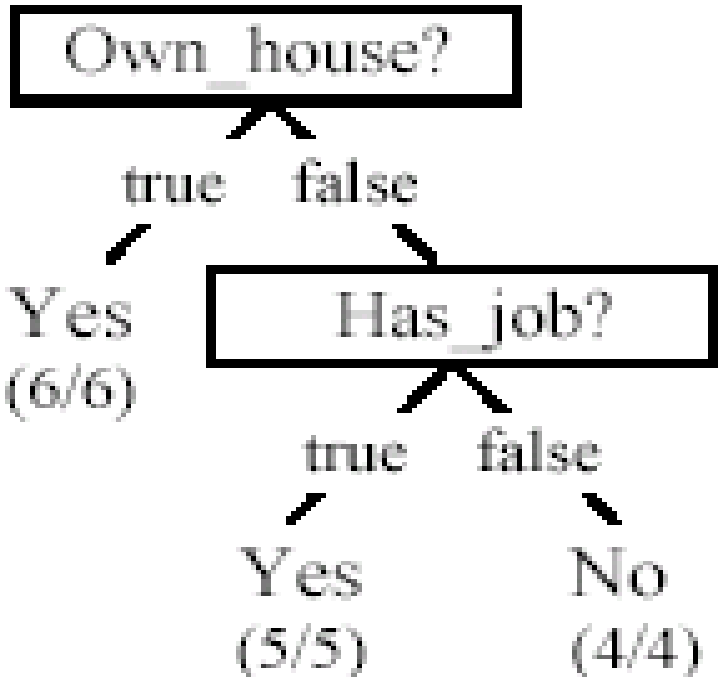
No



From a decision tree to a set of rules

A decision tree can be converted to a set of rules

Each path from the root to a leaf is a rule.



Own_house = true → Class =Yes [sup=6/15, conf=6/6]

Own_house = false, Has_job = true → Class = Yes [sup=5/15, conf=5/5]

Own_house = false, Has_job = false → Class = No [sup=4/15, conf=4/4]

Algorithm for decision tree learning

- Basic algorithm (a greedy **divide-and-conquer** algorithm)
  - Assume attributes are categorical now (continuous attributes can be handled too)
  - Tree is constructed in a top-down recursive manner
  - At start, all the training examples are at the root
  - Examples are partitioned recursively based on selected attributes
  - Attributes are selected on the basis of an impurity function (e.g., information gain)
- Conditions for stopping partitioning
  - All examples for a given node belong to the same class
  - There are no remaining attributes for further partitioning – majority class is the leaf
  - There are no examples left

Choose an attribute to partition data

- The *key* to building a decision tree - which attribute to choose in order to branch.
- The objective is to reduce impurity or uncertainty in data as much as possible.
  - A subset of data is pure if all instances belong to the same class.
- The *heuristic* in C4.5 is to choose the attribute with the maximum Information Gain or Gain Ratio based on information theory.

Two possible roots, which is better?

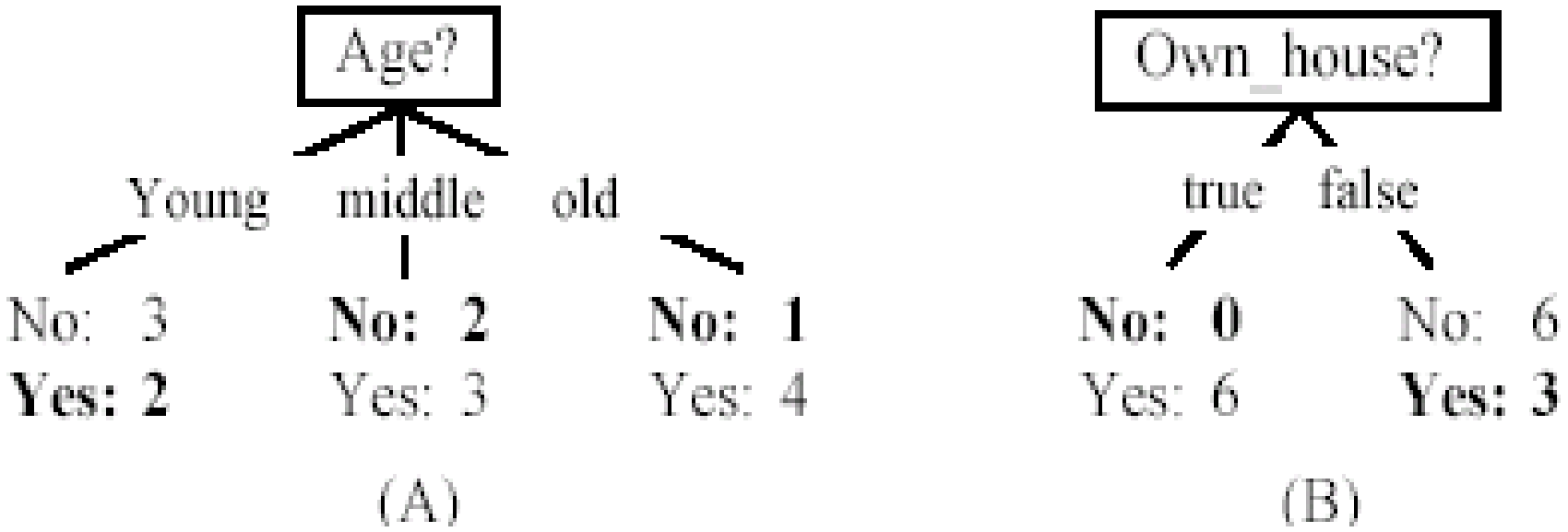


Fig. (B) seems to be better.

Information theory: Entropy measure

- The entropy formula,

$$entropy(D) = -\sum_{j=1}^{|C|} \Pr(c_j) \log_2 \Pr(c_j)$$

$$\sum_{j=1}^{|C|} \Pr(c_j) = 1,$$

- $\Pr(c_j)$ is the probability of class c_j in data set D
- We use entropy as a measure of impurity or disorder of data set D. (Or, a measure of information in a tree)

Information gain

- Given a set of examples *D*, we first compute its entropy:

$$entropy(D) = -\sum_{j=1}^{|C|} \Pr(c_j) \log_2 \Pr(c_j)$$

- If we make attribute A_i, with v values, the root of the current tree, this will partition *D* into v subsets D_1, D_2 …, D_v . The expected entropy if A_i is used as the current root:

$$entropy_{A_i}(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times entropy(D_j)$$

Information gain (cont …)

- Information gained by selecting attribute A_i to branch or to partition the data is

$$gain(D, A_i) = entropy(D) - entropy_{A_i}(D)$$

- We choose the attribute with the highest gain to branch/split the current tree.

An example

$$entropy(D) = -\frac{6}{15} \times \log_2 \frac{6}{15} - \frac{9}{15} \times \log_2 \frac{9}{15} = 0.971$$

ID	Age	Has_Job	Own_House	Credit_Rating	Class
1	young	false	false	fair	No
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12	old	false	true	good	Yes
13	old	true	false	good	Yes
14	old	true	false	excellent	Yes
15	old	false	false	fair	No

$$entropy_{Own\_house}(D) = -\frac{6}{15} \times entropy(D_1) - \frac{9}{15} \times entropy(D_2)$$
$$= \frac{6}{15} \times 0 + \frac{9}{15} \times 0.918$$
$$= 0.551$$

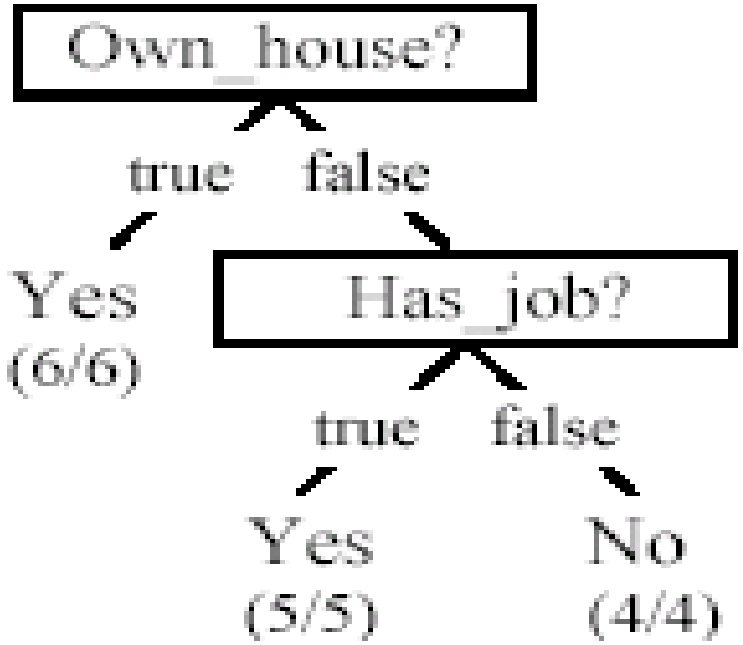
$$entropy_{Age}(D) = -\frac{5}{15} \times entropy(D_1) - \frac{5}{15} \times entropy(D_2) - \frac{5}{15} \times entropy(D_3)$$
$$= \frac{5}{15} \times 0.971 + \frac{5}{15} \times 0.971 + \frac{5}{15} \times 0.722$$
$$= 0.888$$

Age	Yes	No	entropy(Di)
young	2	3	0.971
middle	3	2	0.971
old	4	1	0.722

Own_house is the best choice for the root.

$$gain(D, \text{Age}) = 0.971 - 0.888 = 0.083$$
$$gain(D, \text{Own\_house}) = 0.971 - 0.551 = 0.420$$
$$gain(D, \text{Has\_Job}) = 0.971 - 0.647 = 0.324$$
$$gain(D, \text{Credit\_Rating}) = 0.971 - 0.608 = 0.363$$

We build the final tree



Bayesian classification

- Probabilistic view: Supervised learning can naturally be studied from a probabilistic point of view.
- Let A_1 through A_k be attributes with discrete values. The class is C.
- Given a test example *d* with observed attribute values a_1 through a_k.
- Classification is basically to compute the following posteriori probability. The prediction is the class c_j such that

$$\Pr(C = c_j \mid A_1 = a_1, \ldots, A_{|A|} = a_{|A|})$$

is maximal

Apply Bayes' Rule

$$\Pr(C = c_j \mid A_1 = a_1, \ldots, A_{|A|} = a_{|A|})$$

$$= \frac{\Pr(A_1 = a_1, \ldots, A_{|A|} = a_{|A|} \mid C = c_j)\Pr(C = c_j)}{\Pr(A_1 = a_1, \ldots, A_{|A|} = a_{|A|})}$$

$$= \frac{\Pr(A_1 = a_1, \ldots, A_{|A|} = a_{|A|} \mid C = c_j)\Pr(C = c_j)}{\sum_{r=1}^{|C|} \Pr(A_1 = a_1, \ldots, A_{|A|} = a_{|A|} \mid C = c_r)\Pr(C = c_r)}$$

$\Pr(C=c_j)$ is the class *prior* probability: easy to estimate from the training data.

Computing probabilities

- The denominator $P(A_1=a_1,...,A_k=a_k)$ is irrelevant for decision making since it is the same for every class.
- We only need $P(A_1=a_1,...,A_k=a_k \mid C=c_i)$, which can be written as

  $Pr(A_1=a_1 \mid A_2=a_2,...,A_k=a_k, C=c_j)* Pr(A_2=a_2,...,A_k=a_k \mid C=c_j)$
- Recursively, the second factor above can be written in the same way, and so on.
- Now an assumption is needed.

Conditional independence assumption

- All attributes are conditionally independent given the class $C = c_j$.
- Formally, we assume,

  $\Pr(A_1=a_1 \mid A_2=a_2, \ldots, A_{|A|}=a_{|A|}, C=c_j) = \Pr(A_1=a_1 \mid C=c_j)$

  and so on for A_2 through $A_{|A|}$. I.e.,

$$\Pr(A_1 = a_1, \ldots, A_{|A|} = a_{|A|} \mid C = c_i) = \prod_{i=1}^{|A|} \Pr(A_i = a_i \mid C = c_j)$$

Final naïve Bayesian classifier

$$\Pr(C = c_j \mid A_1 = a_1, \ldots, A_{|A|} = a_{|A|})$$

$$= \frac{\Pr(C = c_j) \prod_{i=1}^{|A|} \Pr(A_i = a_i \mid C = c_j)}{\sum_{r=1}^{|C|} \Pr(C = c_r) \prod_{i=1}^{|A|} \Pr(A_i = a_i \mid C = c_r)}$$

- We are done!
- How do we estimate P($A_i = a_i \mid C = c_j$)? Easy!.

Classify a test instance

- If we only need a decision on the most probable class for the test instance, we only need the numerator as its denominator is the same for every class.
- Thus, given a test example, we compute the following to decide the most probable class for the test instance

$$c = \arg\max_{c_j} \Pr(c_j) \prod_{i=1}^{|A|} \Pr(A_i = a_i \mid C = c_j)$$

An example

Compute all probabilities required for classification

A	B	C
m	b	t
m	s	t
g	q	t
h	s	t
g	q	t
g	q	f
g	s	f
h	b	f
h	q	f
m	b	f

$Pr(C = t) = 1/2$, $Pr(C = f) = 1/2$

$Pr(A=m \mid C=t) = 2/5$
$Pr(A=m \mid C=f) = 1/5$
$Pr(B=b \mid C=t) = 1/5$
$Pr(B=b \mid C=f) = 2/5$

$Pr(A=g \mid C=t) = 2/5$
$Pr(A=g \mid C=f) = 2/5$
$Pr(B=s \mid C=t) = 2/5$
$Pr(B=s \mid C=f) = 1/5$

$Pr(A=h \mid C=t) = 1/5$
$Pr(A=h \mid C=n) = 2/5$
$Pr(B=q \mid C=t) = 2/5$
$Pr(B=q \mid C=f) = 2/5$

Now we have a test example:

$A = m \quad B = q \quad C = ?$

An Example (cont …)

- For C = t, we have

$$\Pr(C=t)\prod_{j=1}^{2}\Pr(A_j=a_j\,|\,C=t)=\frac{1}{2}\times\frac{2}{5}\times\frac{2}{5}=\frac{2}{25}$$

- For class C = f, we have

$$\Pr(C=f)\prod_{j=1}^{2}\Pr(A_j=a_j\,|\,C=f)=\frac{1}{2}\times\frac{1}{5}\times\frac{2}{5}=\frac{1}{25}$$

- C = t is more probable. t is the final class.

Support Vector Machines

- Support vector machines were invented by V. Vapnik and his co-workers in 1970s in Russia and became known to the West in 1992.
- SVMs are linear classifiers that find a hyperplane to separate two class of data, positive and negative.
- Kernel functions are used for nonlinear separation.
- SVM not only has a rigorous theoretical foundation, but also performs classification more accurately than most other methods in applications, especially for high dimensional data.
- It is perhaps the best classifier for text classification.

So far …

- Text classification based on decision tree learning and Bayesian classification
- Effective features are easily identified in decision tree learning and Bayesian classification.

Feature Selection: Why?

- Text collections have a large number of features
  - 10,000 – 1,000,000 unique words … and more
- May make using a particular classifier feasible
  - Some classifiers can't deal with 1,000,000 features
- Reduces training time
  - Training time for some methods is quadratic or worse in the number of features
- Makes runtime models smaller and faster
- Can improve generalization (performance)
  - Eliminates noise features
  - Avoids overfitting

Feature Selection: Frequency

- The simplest feature selection method:
  - Just use the commonest terms
  - No particular foundation
  - But it make sense why this works
    - They're the words that can be well-estimated and are most often available as evidence
  - In practice, this is often 90% as good as better methods

Ranking Problem

- Consider a problem of ranking essays
  - Three ranking categories: good, ok, bad
  - Given a input document, predict its ranking category
- How should we formulate this problem?
- A simple multiple class solution
  - Each ranking category is an independent class
- But, there is something missing here …

- We miss the ordinal relationship between classes !

“Learning to rank” (1/2)

- Classification probably isn’t the right way to think about approaching ranking:
  - Classification problems: Map to a unordered set of classes
  - Regression problems: Map to a real value
  - Ordinal regression problems: Map to an ordered set of classes
    - A fairly obscure sub-branch of statistics, but what we want here
- This formulation gives extra power:
  - Relations between levels are modeled

“Learning to rank” (2/2)

- Assume a number of categories **C** exist
  - These are totally ordered: $c_1 < c_2 < \ldots < c_J$
  - This is the ordinal regression setup
- Assume training data is available consisting of documents represented as feature vectors ψ_i and ranking c_i

- We could do **point-wise learning**, where we try to map items of a certain rank to a subinterval (e.g, Crammer et al. 2002 PRank)
- But most work does **pair-wise learning**, where the input is a pair of results, and the class is the ordering relationship between them

Pairwise learning: The Ranking SVM

[Herbrich et al. 1999, 2000; Joachims et al. 2002]

- Aim is to classify instance pairs as correctly ranked or incorrectly ranked
  - This turns an ordinal regression problem back into a binary classification problem
- We want a ranking function f such that

$$c_i > c_k \text{ iff } f(\psi_i) > f(\psi_k)$$

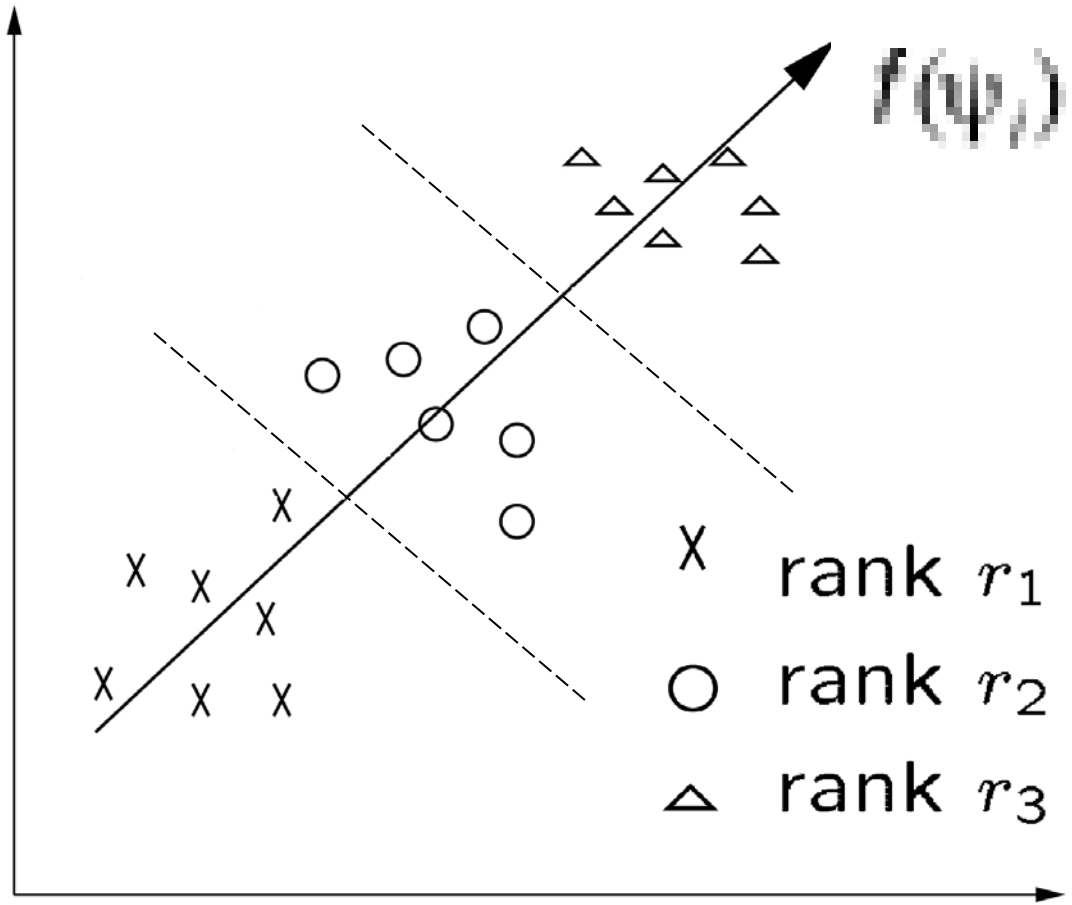
- … or at least one that tries to do this with minimal error
- Suppose that f is a linear function

$$f(\psi_i) = \mathbf{w} \bullet \psi_i$$

The Ranking SVM

[Herbrich et al. 1999, 2000; Joachims et al. 2002]

- Ranking Model: $f(\psi_i)$



Other machine learning methods for learning to rank

- Of course!
- I've only presented the use of SVMs for machine learned ranking, but other machine learning methods have also been used successfully
  - Boosting: RankBoost
  - Ordinal Regression loglinear models
  - Neural Nets: RankNet
  - (Gradient-boosted) Decision Trees

Summary

- Text classification based on decision tree learning and Bayesian classification
- Effective features are easily identified in decision tree learning and Bayesian classification.
- Feature selection based on mutual information and Chi-square
- Methods for learning to rank

Combining Cues via Naive Bayes (1/2)

Authorship ID: Who Wrote a Student's Term Paper?

Word in Text	Frequency as **Student A**	Frequency as **Student B**
optimally	97	1
certainly	84	3
typically	46	4
perspicuous	26	0
actually	13	4
whilst	6	0
the	241	229
awesome	0	63
totally	0	40
wonderful	0	26
incredibly	0	13

these stats come from term papers of *known* authorship

(i.e., supervised training)

$$\frac{P(optimally|StudentA)}{P(optimally|StudentB)} = \frac{97}{1} \qquad \frac{P(the|StudentA)}{P(the|StudentB)} = \frac{1.1}{1}$$

Combining Cues via Naive Bayes (2/2)

$$\frac{P(optimally|StudentA)}{P(optimally|StudentB)} = \frac{97}{1} \qquad \frac{P(the|StudentA)}{P(the|StudentB)} = \frac{1.1}{1}$$

$$\frac{P(awesome|StudentA)}{P(awesome|StudentB)} = \frac{0}{63}$$

$$\frac{P(StudentA)}{P(StudentB)} \times \frac{P(w_1|StudentA)}{P(w_1|StudentB)} \times \frac{P(w_2|StudentA)}{P(w_2|StudentB)} \times \ldots$$

"Naive Bayes" model for classifying text

Would this kind of sentence be more typical of a student A paper or a student B paper?