Data Science
Lecture 3:
Classification

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Thanks to the slides of Prof. P. Domingos from Washington University, Prof. H.-T. Lin and Prof. Lee Hung-Yi Lee from NTU.

Applications

- Automatic Speech Recognition
- Playing Go

Applications

- Automatic Image Caption Generation

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

Source:http://machinelearningmastery.com/inspirational-applications-deep-learnir

From Learning to Machine Learning

- What's learning?
  - knowledge or skill acquired by instruction or study

- What's machine learning?

http://www.csie.ntu.edu.tw/~htlin/mooc/

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A More Concrete Definition

- Skill: improve the performance measurements (e.g., prediction, 3pts shooting percentage)
- Therefore, machine learning is defined to be the improvements on some performance measurements by computing from data.
- For example,
  - Network data -> **ML** -> Better flow control
  - Signal data -> **ML** -> Faster antenna direction detection
  - Sequential web log data -> **ML** -> Higher accuracy of anomaly detection/efficiency of caching algorithm
  - Stock data -> **ML** -> More money

The Machine Learning Route

- ML: an **alternative route** to build complicated systems
- Some Use Scenarios
  - when human cannot program the system manually
    - navigating on Mars
  - when human cannot 'define the solution' easily
    - speech/visual recognition
  - when needing rapid decisions that humans cannot do
    - high-frequency trading
  - when needing to be user-oriented in a massive scale
    - consumer-targeted marketing

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http://www.cartier.hk/content/dam/rcq/car/92/55/67/925567.png.scale.120.high.png

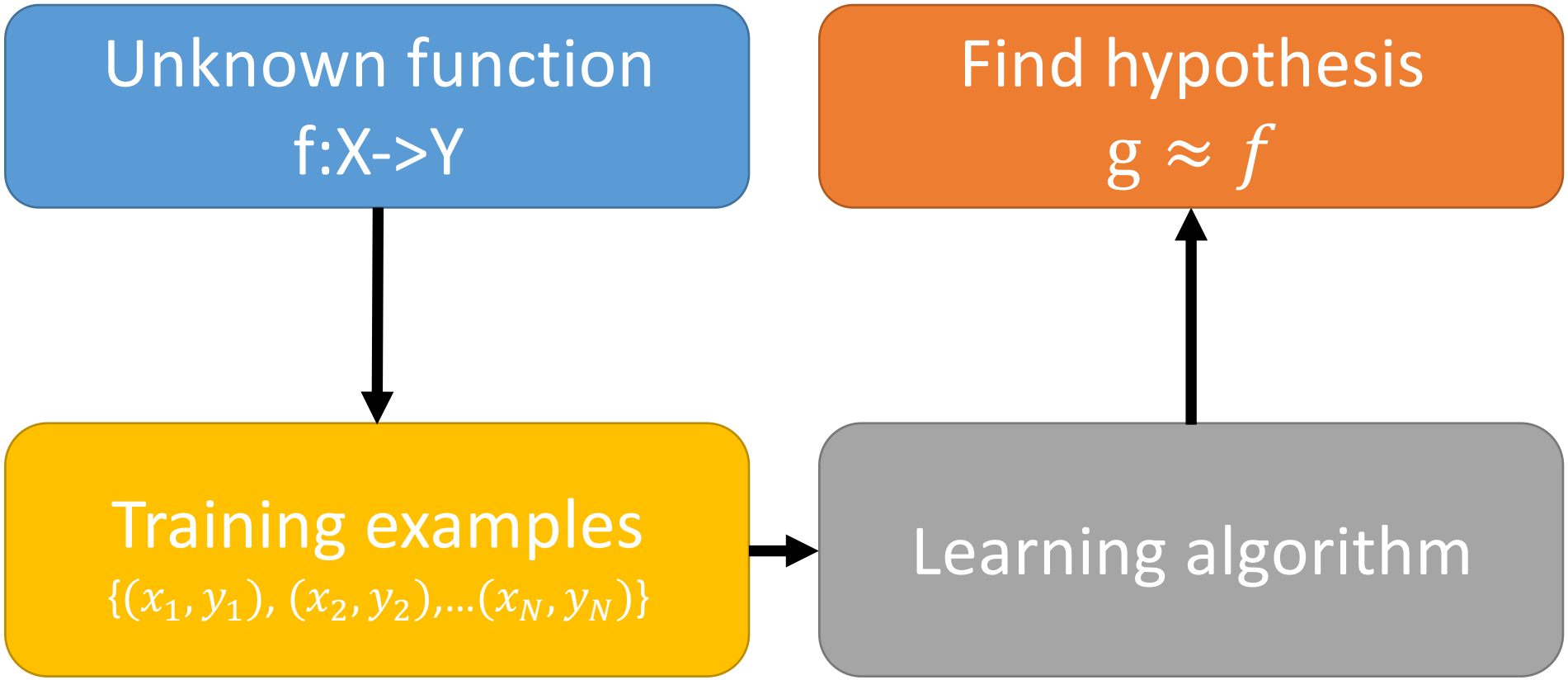
Key Essence of Machine Learning

- Exists some ‘underlying pattern’ to be learned
  - So performance measure can be improved
- But no programmable (easy) definition
  - So machine learning is required
- Somehow there is data about the pattern
  - So machine learning has inputs to learn from

Learning Problem Formulation

- Notation
  - **Input:** $x \in X$(application)
  - **Output:** $y \in Y$(good/bad after approving)
  - **Unknown pattern to be learned can be formulated as a function**
    - f: X->Y (ideal function)
  - **Data:** D=$\{(x_1, y_1), (x_2, y_2), \ldots (x_N, y_N)\}$
  - **Hypothesis:**
    - g:X->Y (hopefully can be as close to f as possible)

Learning Flow



Learning is to find a function

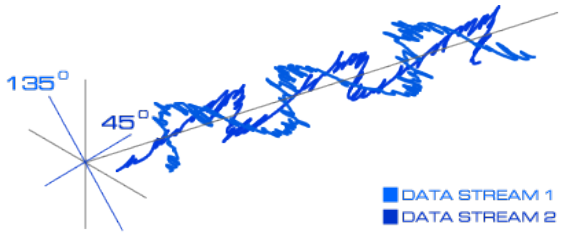
- Speech Recognition

f() = “我不知道你說什麼”

- Image recognition

f() = “Seafood”

- Channel estimation

f(

) = Channel parameters

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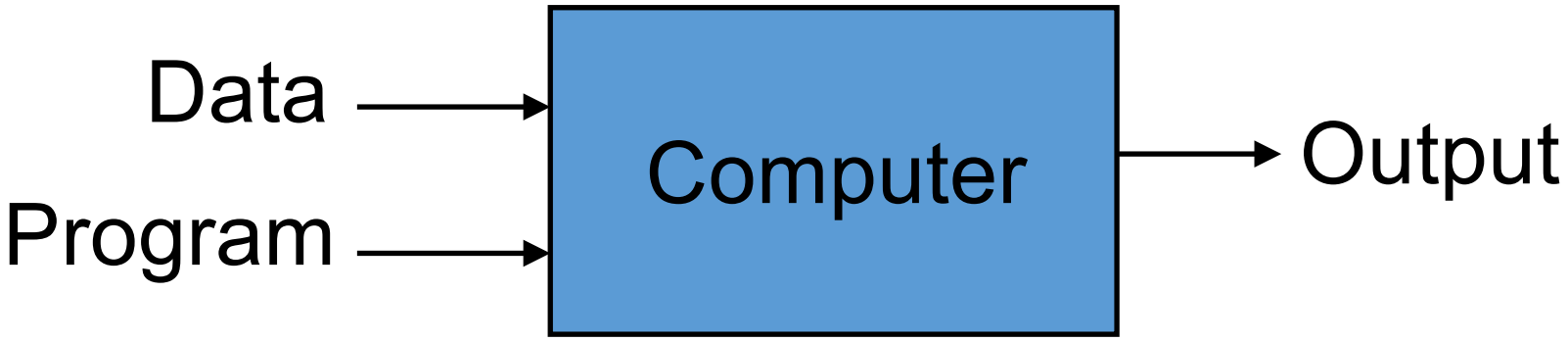
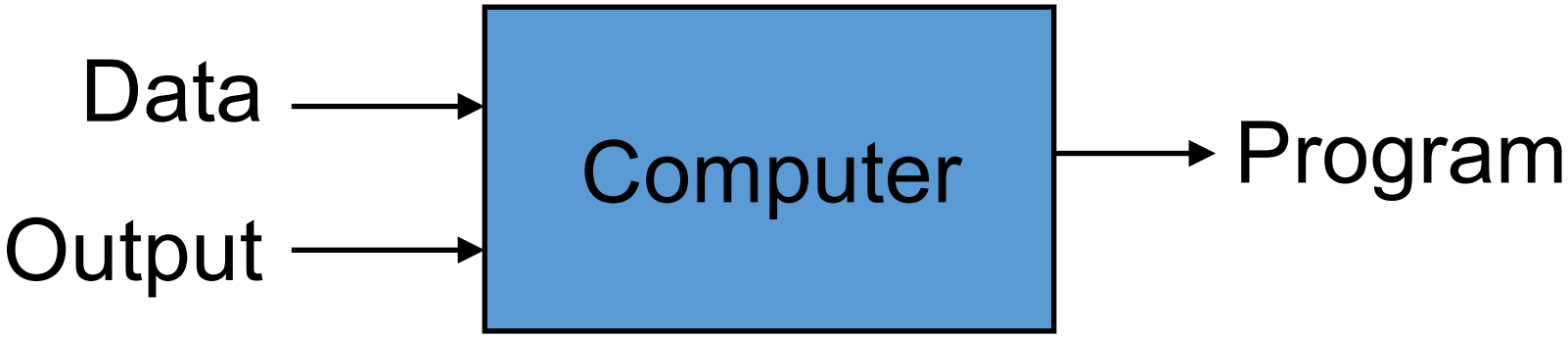
http://www.berkeleywellness.com/sites/default/files/field/image/ThinkstockPhotos-520490716_field_img_hero_988_380.jpg
https://telcoantennas.com.au/site/sites/default/files/images/4G-cross-polarisation-low-signal-areas.png

Traditional Programming



Machine Learning



Magic?

No, more like gardening

- **Seeds** = Algorithms
- **Nutrients** = Data
- **Gardener** = You
- **Plants** = Programs

Classification

Let’s go!

Classification

- Classification – Basic Concepts
- Decision Tree Induction
- Bayes Classification Methods
- Rule-Based Classification
- Techniques to Improve Classification Accuracy: Ensemble Methods
- Lazy Learner
- Support Vector Machine
- Summary

Supervised vs. Unsupervised Learning

- Supervised learning (classification)
  - Supervision: The training data (observations, measurements, etc.) are accompanied by **labels** indicating the class of the observations
  - New data is classified based on the training set
- Unsupervised learning (clustering)
  - The class labels of training data is unknown
  - Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data

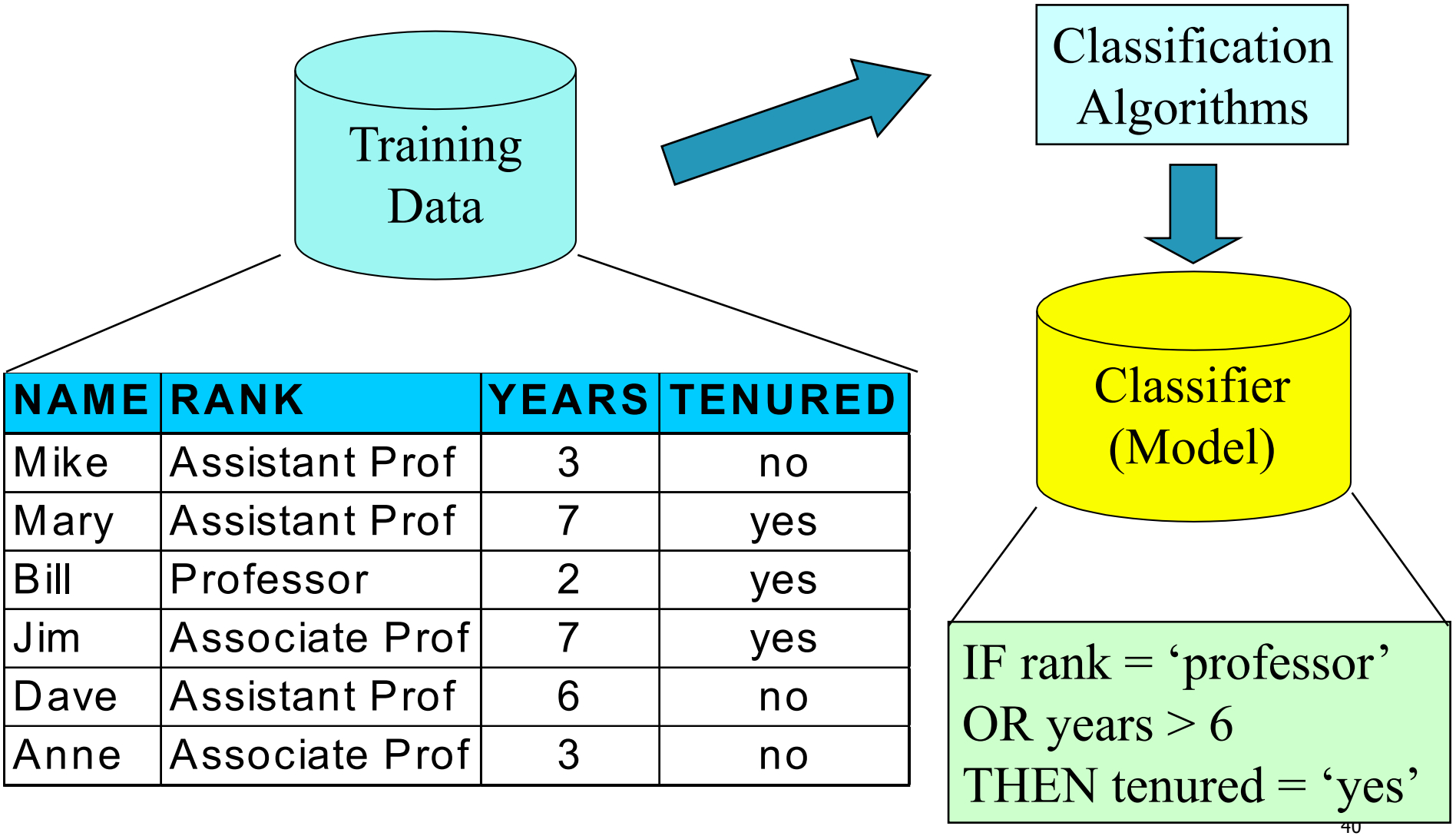
Prediction Problems: Classification vs. Numeric Prediction

- Classification
  - predicts categorical class labels (discrete or nominal)
  - classifies data (constructs a model) based on the training set and the values (class labels) in a classifying attribute and uses it in classifying new data
- Numeric Prediction
  - models continuous-valued functions, i.e., predicts unknown or missing values
- Typical applications
  - Credit/loan approval: if an applicant is qualified
  - Medical diagnosis: if a tumor is cancerous or benign
  - Fraud detection: if a transaction is fraudulent
  - Web page categorization: which category it is

Classification—A Two-Step Process

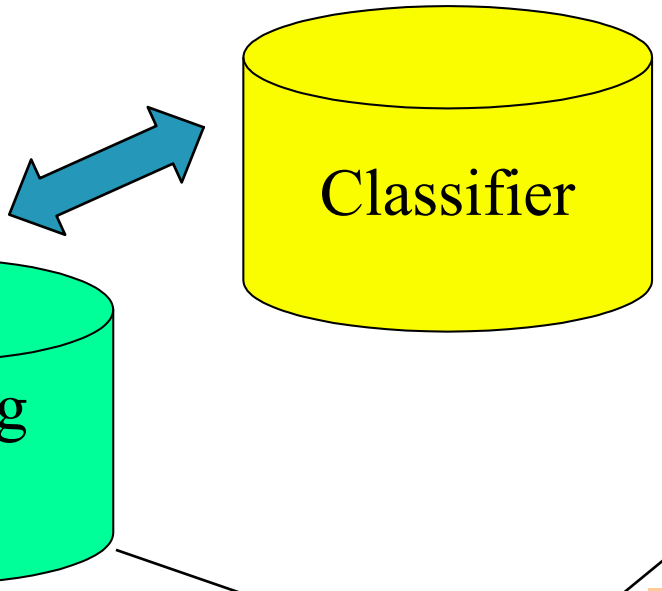
- Model construction: describing a set of predetermined classes
  - Each tuple/sample is assumed to belong to a predefined class, as determined by the class label attribute
  - The set of tuples used for model construction is training set
  - The model is represented as classification rules, decision trees, or mathematical formulae
- Model usage: for classifying future or unknown objects
  - Estimate accuracy of the model
    - The known label of test sample is compared with the classified result from the model
    - Accuracy rate is the percentage of test set samples that are correctly classified by the model
    - Test set is independent of training set (otherwise overfitting)
  - If the accuracy is acceptable, use the model to classify new data
- Note: If *the test set* is used to select models, it is called validation (test) set

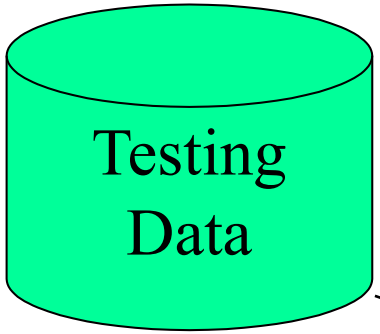
Process (1): Model Construction

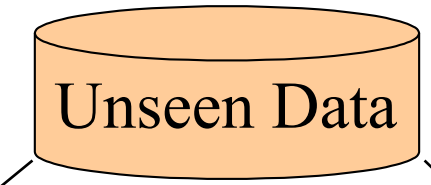


NAME	RANK	YEARS	TENURED
Mike	Assistant Prof	3	no
Mary	Assistant Prof	7	yes
Bill	Professor	2	yes
Jim	Associate Prof	7	yes
Dave	Assistant Prof	6	no
Anne	Associate Prof	3	no

Process (2): Using the Model in Prediction







(Jeff, Professor, 4)

NAME	RANK	YEARS	TENURED
Tom	Assistant Prof	2	no
Merlisa	Associate Prof	7	no
George	Professor	5	yes
Joseph	Assistant Prof	7	yes

Tenured?

Yes

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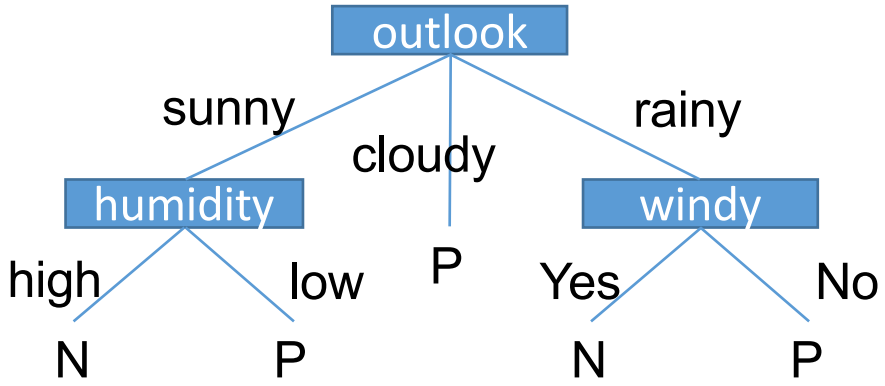
A Decision-Tree Based Classification

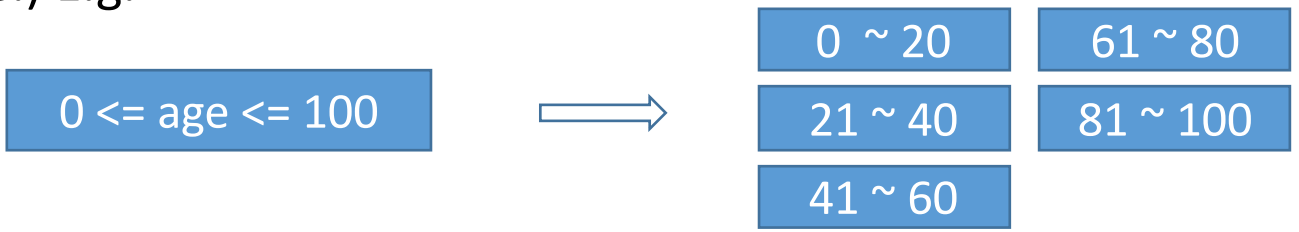
- A decision tree of whether going to play tennis or not:



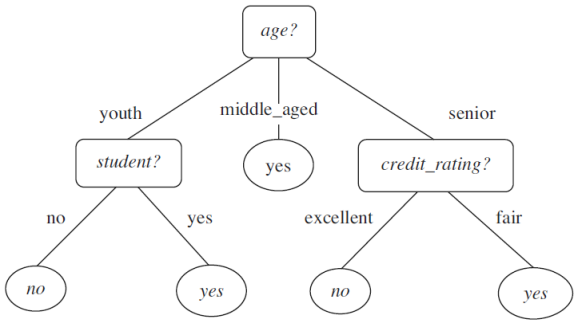
- **ID-3** and its extended version **C4.5** (Quinlan'93):
  A **top-down** decision tree generation algorithm

Algorithm for Decision Tree Induction

- Basic algorithm (a **greedy algorithm**)
  - Tree is constructed in a top-down recursive divide-and-conquer manner.
  - Attributes are categorical.
    (if an attribute is a continuous number, it needs to be discretized in advance.) E.g.

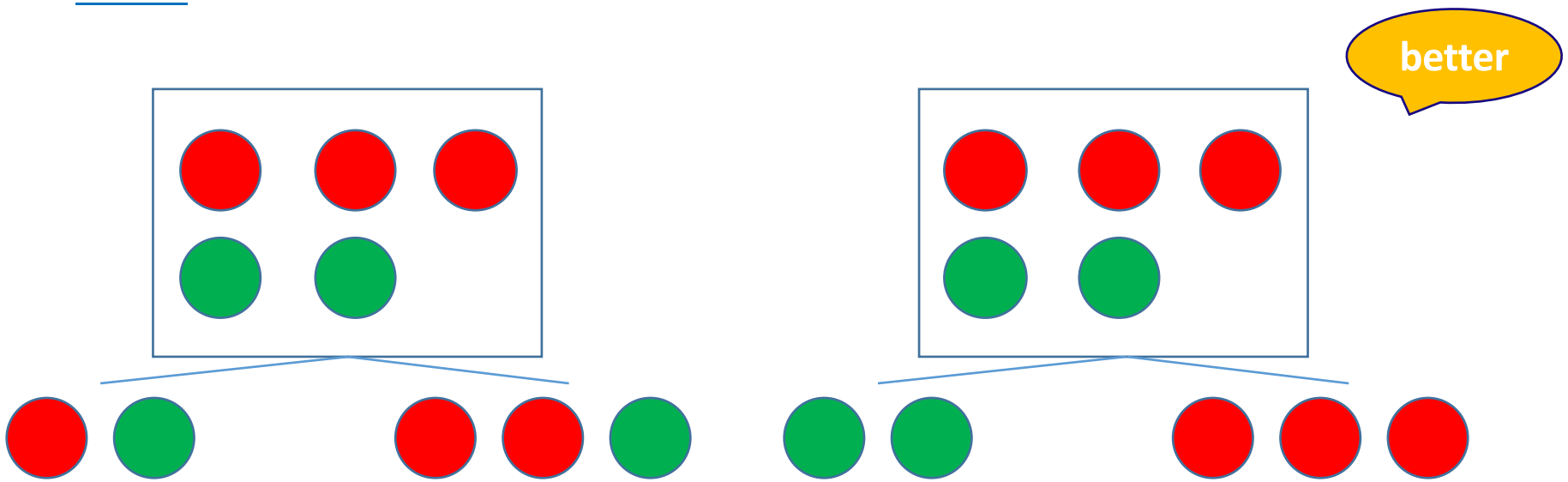


  - At start, all the training examples are at the root.
  - Examples are partitioned recursively based on selected attributes.



Algorithm for Decision Tree Induction

- Basic algorithm (a **greedy algorithm**)
  - Test attributes are selected on the basis of a heuristic or statistical measure (e.g., information gain): maximizing an information gain measure, i.e., **favoring the partitioning which makes the majority of examples belong to a single class**.



Algorithm for Decision Tree Induction

- Basic algorithm (a **greedy algorithm**)
  - Test attributes are selected on the basis of a heuristic or statistical measure (e.g., information gain): maximizing an information gain measure, i.e., **favoring the partitioning which makes the majority of examples belong to a single class**.
  - 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

Primary Issues in Tree Construction (1/2)

- **Split criterion**: *Goodness function*
  - Used to select the attribute to be split at a tree node during the tree generation phase
  - Different algorithms may use different goodness functions:
    - Information gain (used in ID3/C4.5)
    - Gain ratio
    - Gini index (used in CART)

Primary Issues in Tree Construction (2/2)

- **Branching scheme**:
  - Determining the tree branch to which a sample belongs
  - Binary vs. *k-ary* splitting

- When to stop the further splitting of a node? e.g. impurity measure
- Labeling rule: a node is labeled as the class to which most samples at the node belongs.

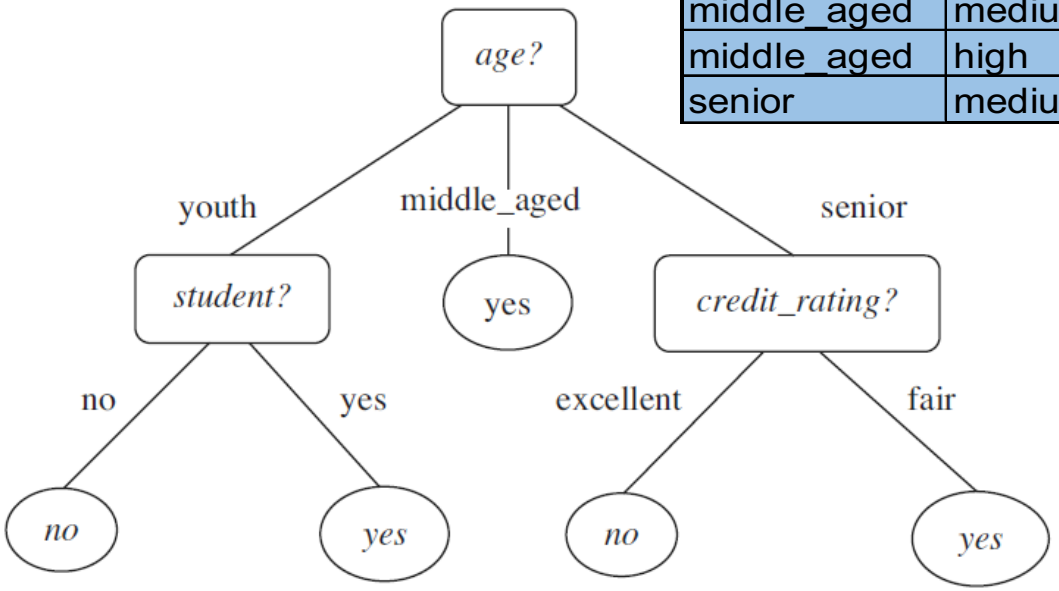
How to Use a Tree?

- Directly
  - Test the attribute value of unknown sample against the tree.
  - A path is traced from root to a leaf which holds the label.
- Indirectly
  - Decision tree is converted to classification rules.
  - One rule is created for each path from the root to a leaf.
  - **IF-THEN** is easier for humans to understand .

Decision Tree Induction: An Example

- Training data set: Buys_computer
- Resulting tree:

age	income	student	credit_rating	buys_computer
youth	high	no	fair	no
youth	high	no	excellent	no
middle_aged	high	no	fair	yes
senior	medium	no	fair	yes
senior	low	yes	fair	yes
senior	low	yes	excellent	no
middle_aged	low	yes	excellent	yes
youth	medium	no	fair	no
youth	low	yes	fair	yes
senior	medium	yes	fair	yes
youth	medium	yes	excellent	yes
middle_aged	medium	no	excellent	yes
middle_aged	high	yes	fair	yes
senior	medium	no	excellent	no

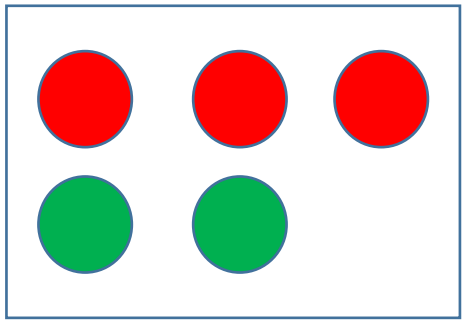


Expected Information (Entropy)

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

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

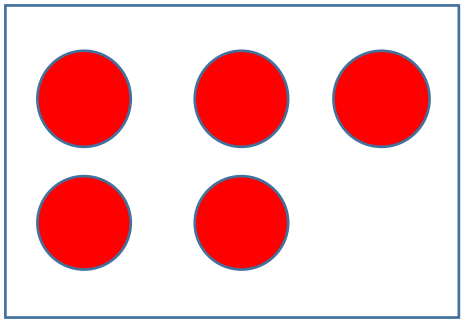
(***p_i***: probability that a tuple in D belongs to class ***C_i***, ***m***: number of classes)



$$Info(D) = I(3,2) = -\frac{3}{5}\log_2(\frac{3}{5}) - \frac{2}{5}\log_2(\frac{2}{5})$$

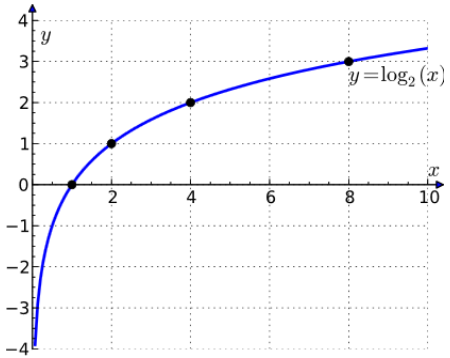
$$\approx -\frac{3}{5}\times(-0.737) - \frac{2}{5}\times(-1.322)$$

$$\approx 0.971$$



$$Info(D) = I(5,0) = -\frac{5}{5}\log_2(\frac{5}{5}) - \frac{0}{5}\log_2(\frac{0}{5})$$

$$= 0 - 0 = 0$$

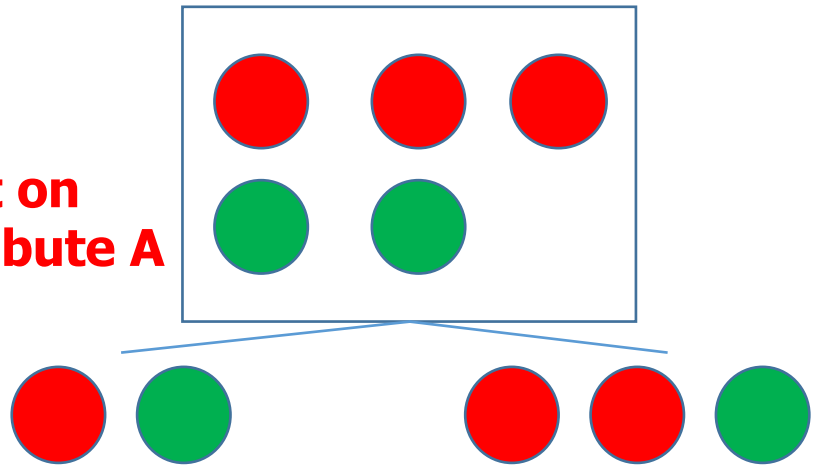


Expected Information (Entropy)

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

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

Split on Attribute A

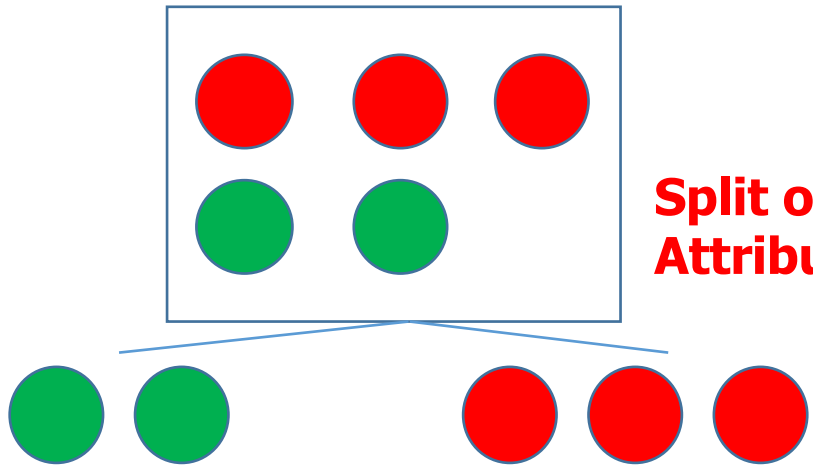


$$Info_A(D) = \frac{2}{5} Info(1,1) + \frac{3}{5} Info(2,1) = 0.918$$

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

$$= 0.971 - 0.918 = 0.053$$

Split on Attribute B



$$Info_B(D) = \frac{2}{5} Info(2,0) + \frac{3}{5} Info(3,0) = 0$$

$$Gain(B) = Info(D) - Info_B(D)$$

$$= 0.971 - 0 = 0.971$$

Attribute Selection Measure: Information Gain (ID3)

- Select the attribute with the highest information gain
  - To minimize # of tests needed to classify a given tuple
- Let p_i be the probability that an arbitrary tuple in D belongs to class C_i, estimated by $|C_{i,D}|/|D|$
- 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

We'd like to maximize ***Gain(A)***, i.e., to minimize ***$Info_A(D)$***, the information still required to finish classifying the tuples

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

Attribute Selection: Information Gain

- Class P: buys_computer = "yes"
- Class N: buys_computer = "no"

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

$$Info_{age}(D) = \frac{5}{14} I(2,3) + \frac{4}{14} I(4,0) + \frac{5}{14} I(3,2) = 0.694$$

age	p_i	n_i	$I(p_i, n_i)$
youth	2	3	0.971
middle_aged	4	0	0
senior	3	2	0.971

$\frac{5}{14} I(2,3)$ means "age = youth" has 5 out of 14 samples, with 2 yes'es and 3 no's. Hence

age	income	student	credit_rating	buys_computer
youth	high	no	fair	no
youth	high	no	excellent	no
middle_aged	high	no	fair	yes
senior	medium	no	fair	yes
senior	low	yes	fair	yes
senior	low	yes	excellent	no
middle_aged	low	yes	excellent	yes
youth	medium	no	fair	no
youth	low	yes	fair	yes
senior	medium	yes	fair	yes
youth	medium	yes	excellent	yes
middle_aged	medium	no	excellent	yes
middle_aged	high	yes	fair	yes
senior	medium	no	excellent	no

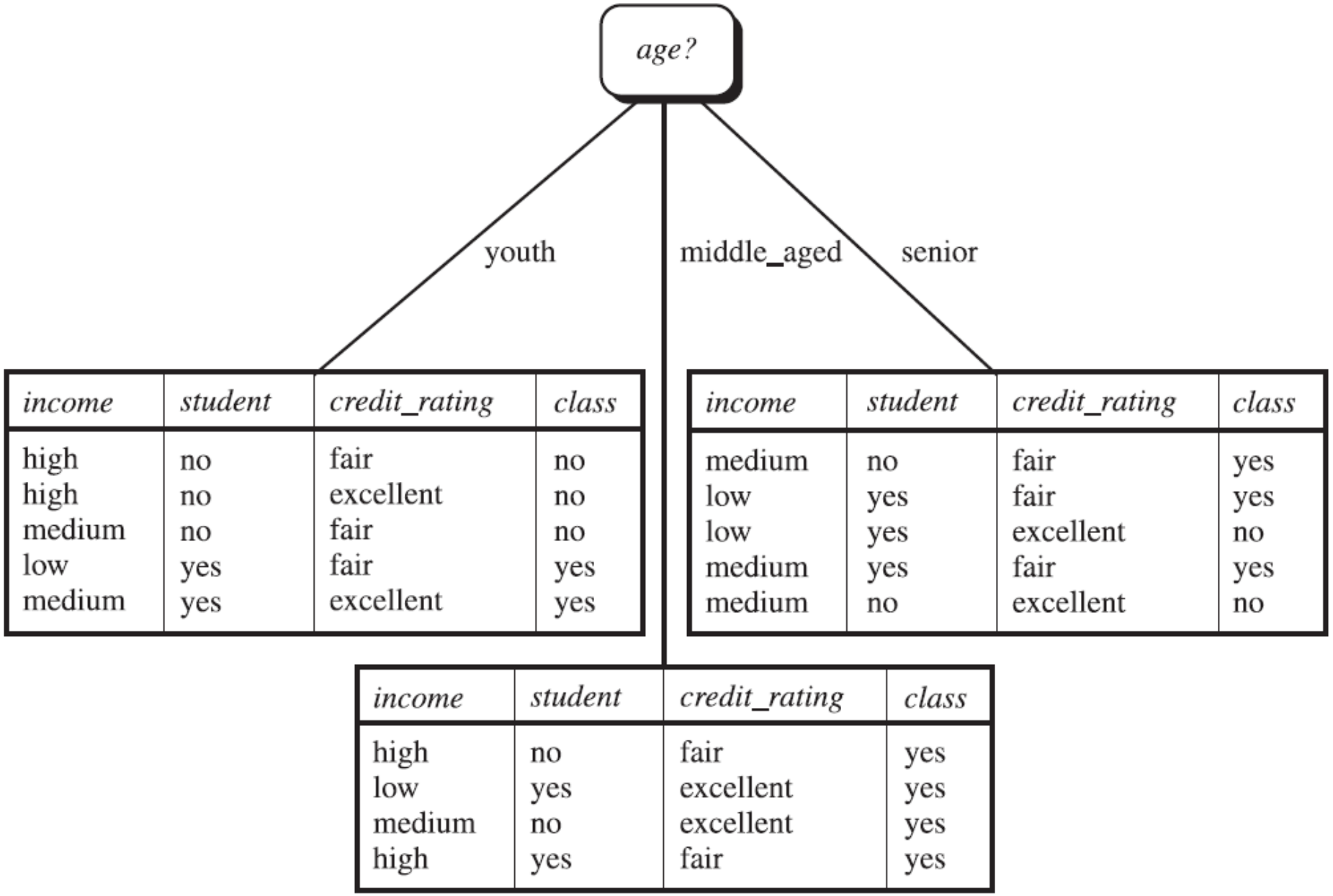
$$Gain(age) = Info(D) - Info_{age}(D) = 0.246$$

Similarly,

$$Gain(income) = 0.029$$

$$Gain(student) = 0.151$$

$$Gain(credit\_rating) = 0.048$$



income	*student*	*credit_rating*	*class*
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

income	*student*	*credit_rating*	*class*
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

income	*student*	*credit_rating*	*class*
high	no	fair	yes
low	yes	excellent	yes
medium	no	excellent	yes
high	yes	fair	yes

Computing Information-Gain for Continuous-Valued Attributes

- Let attribute A be a continuous-valued attribute
- Must determine the *best split point* for A
  - Sort the value A in increasing order
  - Typically, the midpoint between each pair of adjacent values is considered as a possible *split point*
    - $(a_i+a_{i+1})/2$ is the midpoint between the values of a_i and a_{i+1}
  - The point with the *minimum expected information requirement* for A is selected as the split-point for A
- Split:
  - D1 is the set of tuples in D satisfying A ≤ split-point, and D2 is the set of tuples in D satisfying A > split-point

Gain Ratio for Attribute Selection (C4.5)

- Information gain measure is biased towards attributes with a large number of values
  - E.g., unique pID -> split on pID results in large number of partitions, each containing just one tuple => each partition is pure
    => information required to classify this partition would be $\boldsymbol{Info_{pID}(D)=0}$,
    i.e., the information gain is maximal!!
- C4.5 (a successor of ID3) uses gain ratio to overcome the problem (normalization to information gain)

$$SplitInfo_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times \log_2\left(\frac{|D_j|}{|D|}\right)$$

  - GainRatio(A) = Gain(A)/SplitInfo(A)

- E.g., $SplitInfo_{income}(D) = -\frac{4}{14} \times \log_2\left(\frac{4}{14}\right) - \frac{6}{14} \times \log_2\left(\frac{6}{14}\right) - \frac{4}{14} \times \log_2\left(\frac{4}{14}\right) = 1.557$
  - gain_ratio(income) = 0.029/1.557 = 0.019
- The attribute with the maximum gain ratio is selected as the splitting attribute

Gini Index (CART, IBM IntelligentMiner)

- Gini index considers a binary split for each attribute
  - To construct a binary decision tree
- Consider A: discrete-valued attribute
  - with v distinct values $\{a_1, a_2, \dots, a_v\}$
- Examine all possible subsets that can be formed using values of A
  - Each subset S_A is considered as a binary test: "$A \in S_A$"
- E.g., if income has three possible values {low, medium, high}
  - 2^3 possible subsets
  - ~~{low, medium, high}~~, {low, medium}, {low, high}, {medium, high}, {low}, {medium}, {high}, ~~{}~~
  - There are $(2^v - 2)/2$ possible ways to form two partition of the data D, based on a binary split A

Gini Index (CART, IBM IntelligentMiner)

- If a data set *D* contains examples from *m* classes, Gini index, *Gini*(*D*) is defined as

$$Gini(D) = 1 - \sum_{i=1}^{m} p_i^2$$

where p_i is the probability of class C_i in *D,* estimated by $|C_{i,D}|/|D|$

- If a data set *D* is split on A into two subsets D_1 and D_2, the *Gini* index $Gini_A(D)$ given the split on A is:

$$Gini_A(D) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2)$$

- Reduction in Impurity:

$$\Delta Gini(A) = Gini(D) - Gini_A(D)$$

- The attribute provides the largest reduction in impurity, i.e., maximized $\Delta Gini(A)$, is chosen to split the node (*need to enumerate all the possible splitting points for each attribute*)

Computation of Gini Index

- E.g., D has **9** tuples in **buys_computer = "yes"** and **5** in **"no"**

$$Gini(D) = 1 - \left(\frac{9}{14}\right)^2 - \left(\frac{5}{14}\right)^2 = 0.459$$

- Suppose the attribute ***income*** partitions D into **10** in D_1: **{low, medium}** and **4** in D_2

$$Gini_{income \in \{low,medium\}}(D)$$

$$= \left(\frac{10}{14}\right) Gini(D_1) + \left(\frac{4}{14}\right) Gini(D_2)$$

$$= \frac{10}{14}\left(1 - \left(\frac{7}{10}\right)^2 - \left(\frac{3}{10}\right)^2\right) + \frac{4}{14}\left(1 - \left(\frac{2}{4}\right)^2 - \left(\frac{2}{4}\right)^2\right)$$

$$= 0.443$$

$$= Gini_{income \in \{high\}}(D).$$

Gini*$_{\{low,high\}}$** is ***0.458; ***Gini*$_{\{medium,high\}}$** is ***0.450***. Thus, split on the {low,medium} (and {high}) since it has the lowest Gini index

Comparing Attribute Selection Measures

- The three measures, in general, return good results but
  - **Information gain**:
    - biased towards multivalued attributes
  - **Gain ratio**:
    - tends to prefer unbalanced splits in which one partition is much smaller than the others
  - **Gini index**:
    - biased to multivalued attributes
    - has difficulty when # of classes is large (high computation overhead)
    - tends to favor tests that result in equal-sized partitions and purity in both partitions

Other Attribute Selection Measures

- CHAID: a popular decision tree algorithm, measure based on χ^2 test for independence
- C-SEP: performs better than info. gain and gini index in certain cases
- G-statistic: has a close approximation to χ^2 distribution
- MDL (Minimal Description Length) principle (i.e., the simplest solution is preferred):
  - The best tree as the one that requires the fewest # of bits to both (1) encode the tree, and (2) encode the exceptions to the tree
- Multivariate splits (partition based on multiple variable combinations)
  - CART: finds multivariate splits based on a linear comb. of attrs.
- Which attribute selection measure is the best?
  - Most give good results, none is significantly superior than others

Pre - Pruning

- **Based on statistical significance test**
  - Stop growing the tree when there is no statistically significant association between any attribute and the class at a particular node
  - Use all available data for training and apply the statistical test to estimate whether expanding/pruning a node is to produce an improvement beyond the training set
- **Most popular test:** chi-squared test
- $chi^2 = sum((O-E)^2 / E)$

Where, O = observed data, E = expected values based on hypothesis.

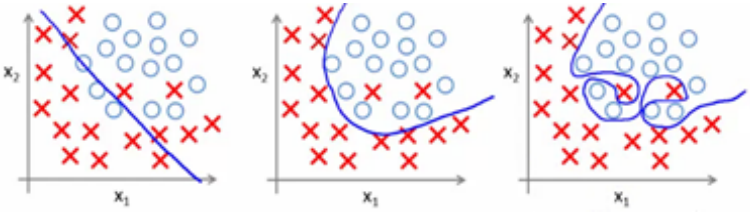
Example

- Example : 5 schools have the same test. Total score is 375, individual results are: 50, 93, 67, 78 and 87. Is this distribution significant, or was it just luck? Average is 75.

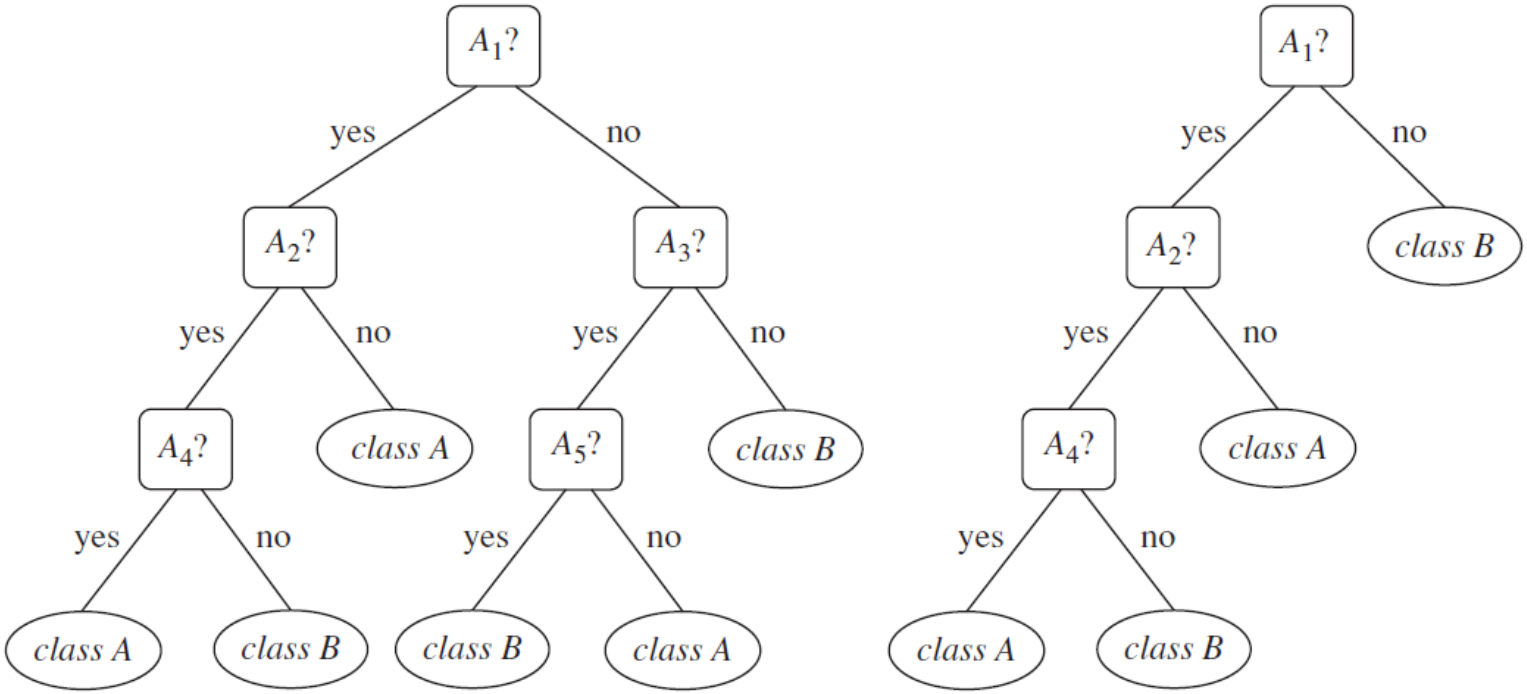
  $(50-75)^2/75 + (93-75)^2/75 + (67-75)^2/75 + (78-75)^2/75 + (87-75)^2/75 = 15.55$

  This distribution is significant !

Overfitting and Tree Pruning



- Overfitting: An induced tree may overfit the training data
  - Too many branches, some may reflect anomalies due to noise or outliers
  - Poor accuracy for unseen samples, i.e., lose the ability of generalization



Overfitting and Tree Pruning

- Two approaches to avoid overfitting
  - Prepruning: *Halt tree construction early*-do not split a node if this would result in the goodness measure falling below a threshold
    - Difficult to choose an appropriate threshold
  - Postpruning: *Remove branches* from a "fully grown" tree—get a sequence of progressively pruned trees
    - Use a set of data different from the training data to decide which is the "best pruned tree"

Enhancements to Basic Decision Tree Induction

- Allow for **continuous-valued attributes**
  - Dynamically define new discrete-valued attributes that partition the continuous attribute value into a discrete set of intervals
- Handle **missing attribute values**
  - Assign the most common value of the attribute
  - Assign probability to each of the possible values
- **Attribute construction**
  - Create new attributes based on existing ones that are sparsely represented
  - This reduces fragmentation, repetition, and replication

Classification

- Classification – Basic Concepts
- Decision Tree Induction
- Bayes Classification Methods
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Bayesian Classification: Why?

- A statistical classifier: performs *probabilistic prediction, i.e.,* predicts class membership probabilities
- Foundation: Based on Bayes' Theorem.
- Performance: A simple Bayesian classifier, *naïve Bayesian classifier*, has comparable performance with decision tree and selected neural network classifiers
- Incremental: Each training example can incrementally increase/decrease the probability that a hypothesis is correct — prior knowledge can be combined with observed data
- Standard: Even when Bayesian methods are computationally intractable, they can provide a standard of optimal decision making against which other methods can be measured

Bayes' Theorem: Basics

- Total probability Theorem: $P(B) = \sum_{i=1}^{M} P(B|A_i)P(A_i)$
- Bayes' Theorem: $P(H|\mathbf{X}) = \frac{P(\mathbf{X}|H)P(H)}{P(\mathbf{X})} = P(\mathbf{X}|H) \times P(H) / P(\mathbf{X})$
  - Let **X** be a data sample ("*evidence*"): class label is unknown
  - Let H be a *hypothesis* that X belongs to class C
  - Classification is to determine P(H|**X**), (i.e., *posteriori probability):* the probability that the hypothesis holds given the observed data sample **X**
  - P(H) (*prior probability*): the initial probability
    - E.g., **X** will buy computer, regardless of age, income, …
  - P(**X**): probability that sample data is observed
  - P(**X**|H) (likelihood): the probability of observing the sample **X**, given that the hypothesis holds
    - E.g., Given that **X** will buy computer, the prob. that X is 31..40, medium income

Prediction Based on Bayes' Theorem

- Given training data **X**, *posteriori probability of a hypothesis* H, P(H|**X**), follows the Bayes' theorem

$$P(H|\mathbf{X}) = \frac{P(\mathbf{X}|H)P(H)}{P(\mathbf{X})} = P(\mathbf{X}|H) \times P(H) / P(\mathbf{X})$$

- Informally, this can be viewed as

  posteriori = likelihood x prior/evidence

- Predicts **X** belongs to C_i iff the probability $P(C_i|\mathbf{X})$ is the highest among all the $P(C_k|X)$ for all the *k* classes

- Practical difficulty: It requires initial knowledge of many probabilities, involving significant computational cost

Classification is to Derive the Maximum Posteriori

- Let D be a training set of tuples and their associated class labels, and each tuple is represented by an n-D attribute vector **X** = (x_1, x_2, …, x_n)
- Suppose there are *m* classes C_1, C_2, …, C_m.
- Classification is to derive the maximum posteriori, i.e., the maximal $P(C_i|\mathbf{X})$
- This can be derived from Bayes' theorem

$$P(C_i|\mathbf{X}) = \frac{P(\mathbf{X}|C_i)P(C_i)}{P(\mathbf{X})}$$

- Since P(**X**) is constant for all classes, only

$$P(C_i|\mathbf{X}) = P(\mathbf{X}|C_i)P(C_i)$$

needs to be maximized

Naïve Bayes Classifier

- A simplified assumption: attributes are conditionally independent (i.e., no dependence relation between attributes):

$$P(\mathbf{X}|C_i) = \prod_{k=1}^{n} P(x_k|C_i) = P(x_1|C_i) \times P(x_2|C_i) \times \ldots \times P(x_n|C_i)$$

- This greatly reduces the computation cost: Only counts the class distribution
- If A_k is categorical, $P(x_k|C_i)$ is the # of tuples in C_i having value x_k for A_k divided by $|C_{i,D}|$ (# of tuples of C_i in D)
- If A_k is continous-valued, $P(x_k|C_i)$ is usually computed based on Gaussian distribution with a mean μ and standard deviation σ

and $P(x_k|C_i)$ is

$$g(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$P(\mathbf{X}|C_i) = g(x_k, \mu_{C_i}, \sigma_{C_i})$$

Naïve Bayes Classifier: Training Dataset

Class:

C1:buys_computer = 'yes'

C2:buys_computer = 'no'

Data to be classified:

X = (age = youth,

income = medium,

student = yes

credit_rating = Fair)

age	income	student	credit_rating	buys_computer
youth	high	no	fair	no
youth	high	no	excellent	no
middle_aged	high	no	fair	yes
senior	medium	no	fair	yes
senior	low	yes	fair	yes
senior	low	yes	excellent	no
middle_aged	low	yes	excellent	yes
youth	medium	no	fair	no
youth	low	yes	fair	yes
senior	medium	yes	fair	yes
youth	medium	yes	excellent	yes
middle_aged	medium	no	excellent	yes
middle_aged	high	yes	fair	yes
senior	medium	no	excellent	no

We need to maximize $P(X|C_i)P(C_i)$, for $i = 1, 2$

Naïve Bayes Classifier: An Example

- The prior probability of each class:
  $P(C_i)$: P(buys_computer = "yes") = 9/14 = 0.643
  P(buys_computer = "no") = 5/14= 0.357
- Compute **$P(X|C_i)$** for each class
  P(age = youth | buys_computer = "yes") = 2/9 = 0.222
  P(age = youth | buys_computer = "no") = 3/5 = 0.6
  P(income = "medium" | buys_computer = "yes") = 4/9 = 0.444
  P(income = "medium" | buys_computer = "no") = 2/5 = 0.4
  P(student = "yes" | buys_computer = "yes) = 6/9 = 0.667
  P(student = "yes" | buys_computer = "no") = 1/5 = 0.2
  P(credit_rating = "fair" | buys_computer = "yes") = 6/9 = 0.667
  P(credit_rating = "fair" | buys_computer = "no") = 2/5 = 0.4
- **X** = (age = youth, income = medium, student = yes, credit_rating = fair)

$P(X|C_i)$: P(X|buys_computer = "yes") = 0.222 x 0.444 x 0.667 x 0.667 = **0.044**
P(X|buys_computer = "no") = 0.6 x 0.4 x 0.2 x 0.4 = **0.019**

$P(X|C_i)*P(C_i)$: P(**X**|buys_computer = "yes") * P(buys_computer = "yes") = 0.028
P(**X**|buys_computer = "no") * P(buys_computer = "no") = 0.007

Therefore, X belongs to class ("buys_computer = yes")

Avoiding the Zero-Probability Problem

- Naïve Bayesian prediction requires each conditional prob. be **non-zero**. Otherwise, the predicted prob. will be zero

$$P(X \mid C_i) = \prod_{k=1}^{n} P(x_k \mid C_i)$$

- E.g., Suppose a dataset with 1000 tuples, income=low (0), income= medium (990), and income = high (10)
- Use **Laplacian correction** (or Laplacian estimator)
  - *Adding **1** to each case*

    Prob(income = low) = 1/1003

    Prob(income = medium) = 991/1003

    Prob(income = high) = 11/1003
  - The "corrected" prob. estimates are close to their "uncorrected" counterparts

Naïve Bayes Classifier: Comments

- Advantages
  - Easy to implement
  - Good results obtained in most of the cases
- Disadvantages
  - Assumption: class conditional independence, therefore loss of accuracy
  - Practically, dependencies exist among variables
    - E.g., hospitals, patients: Profile: age, family history, etc.
      Symptoms: fever, cough etc., Disease: lung cancer, diabetes, etc.
    - Dependencies among these cannot be modeled by Naïve Bayes Classifier

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Using IF-THEN Rules for Classification

- Represent the knowledge in the form of IF-THEN rules

  R: **IF** *age* = youth **AND** *student* = yes **THEN** *buys_computer* = yes

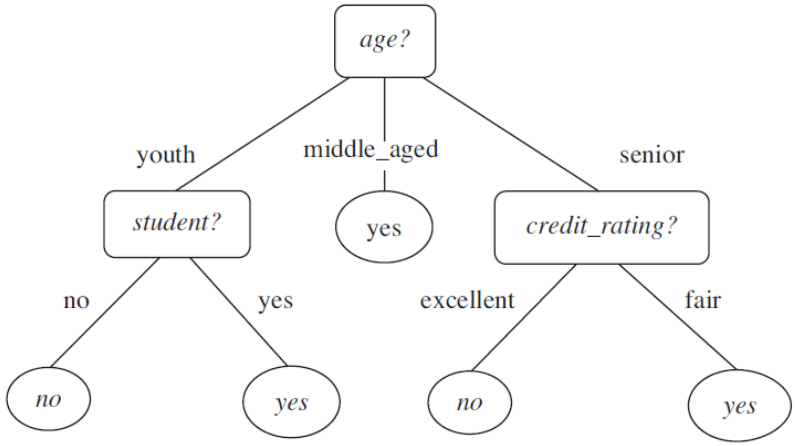
  - Rule antecedent/precondition vs. rule consequent
- Assessment of a rule: *coverage* and *accuracy*
  - n_{covers} = # of tuples covered by R
  - $n_{correct}$ = # of tuples correctly classified by R

  coverage(R) = $\mathbf{n_{covers} / |D|}$ /* D: training data set */

  accuracy(R) = $\mathbf{n_{correct} / n_{covers}}$
- If more than one rule are triggered, need **conflict resolution**
  - Size ordering: assign the highest priority to the triggering rules that has the "toughest" requirement (i.e., with the ***most attribute tests***)
  - Class-based ordering: decreasing order of *prevalence or misclassification cost per class*
  - Rule-based ordering (**decision list**): rules are organized into one long priority list, according to some measure of rule quality or by experts

Rule Extraction from a Decision Tree

- Rules are *easier to understand* than large trees
- One rule is created *for each path* from the root to a leaf
- Each attribute-value pair along a path forms a conjunction: the leaf holds the class prediction
- Rules are mutually exclusive and exhaustive



No rule conflicts

One rule for each attribute-value combination

• Example: Rule extraction from our *buys_computer* decision-tree

IF *age* = young AND *student* = *no* THEN *buys_computer* = *no*
IF *age* = young AND *student* = *yes* THEN *buys_computer* = *yes*
IF *age* = mid-age THEN *buys_computer* = *yes*
IF *age* = old AND *credit_rating* = *excellent* THEN *buys_computer* = *no*
IF *age* = old AND *credit_rating* = *fair* THEN *buys_computer* = *yes*

Rule Induction: Sequential Covering Method

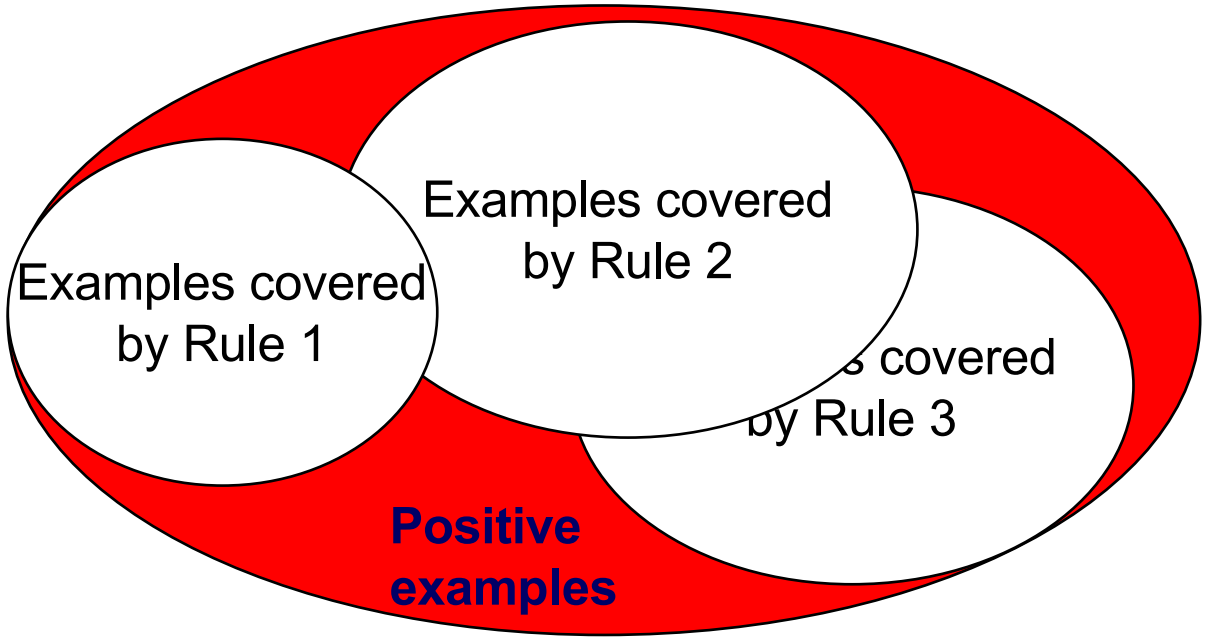
- Sequential covering algorithm =>
  Extracts rules directly from training data
- Typical sequential covering algorithms: FOIL, AQ, CN2, RIPPER
- Rules are learned *sequentially*, each for a given class C_i will cover many tuples of C_i but none (or few) of the tuples of other classes
- Steps:
  - Rules are learned one at a time
    (i.e., procedure *Learn-One-Rule*, detailed later)
  - Each time a rule is learned, the tuples covered by the rules are removed
  - Repeat the process on the remaining tuples until *termination condition*, e.g., when no more training examples or when the quality of a rule returned is below a user-specified threshold
- Comp. w. decision-tree induction:
  Decision-Trees learn a set of rules *simultaneously*

Sequential Covering Algorithm

while (enough target tuples left)

generate a rule

remove positive target tuples satisfying this rule



Rule Generation

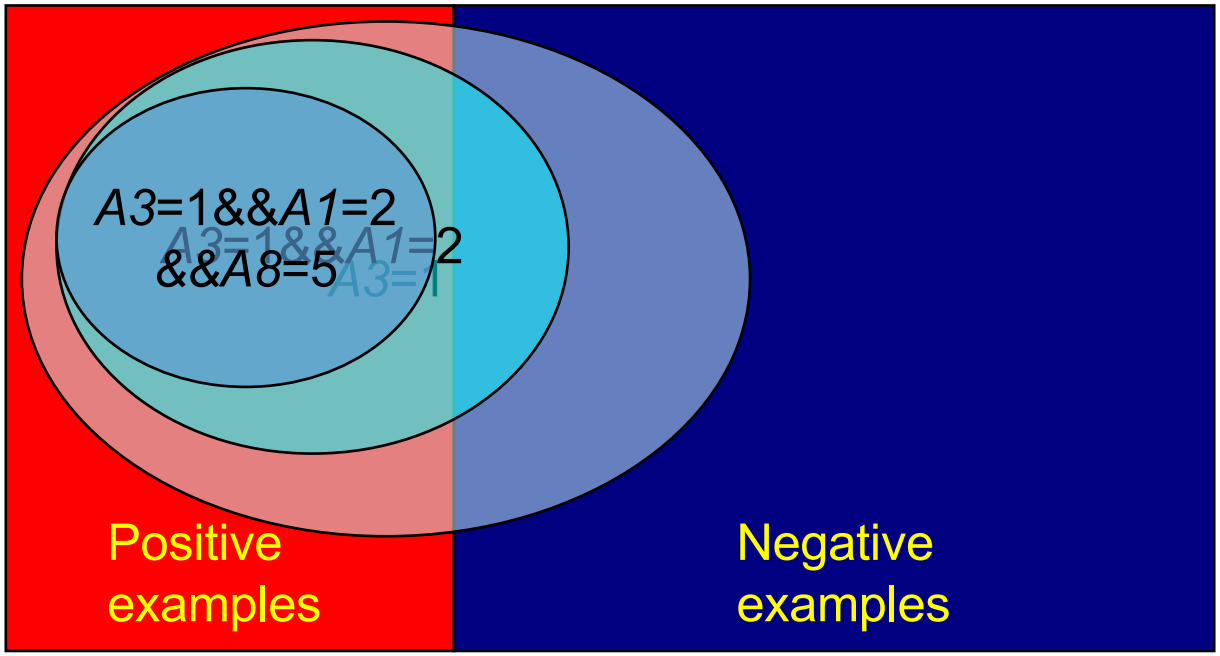
- To generate a rule

  while(true)

    find the best predicate *p*

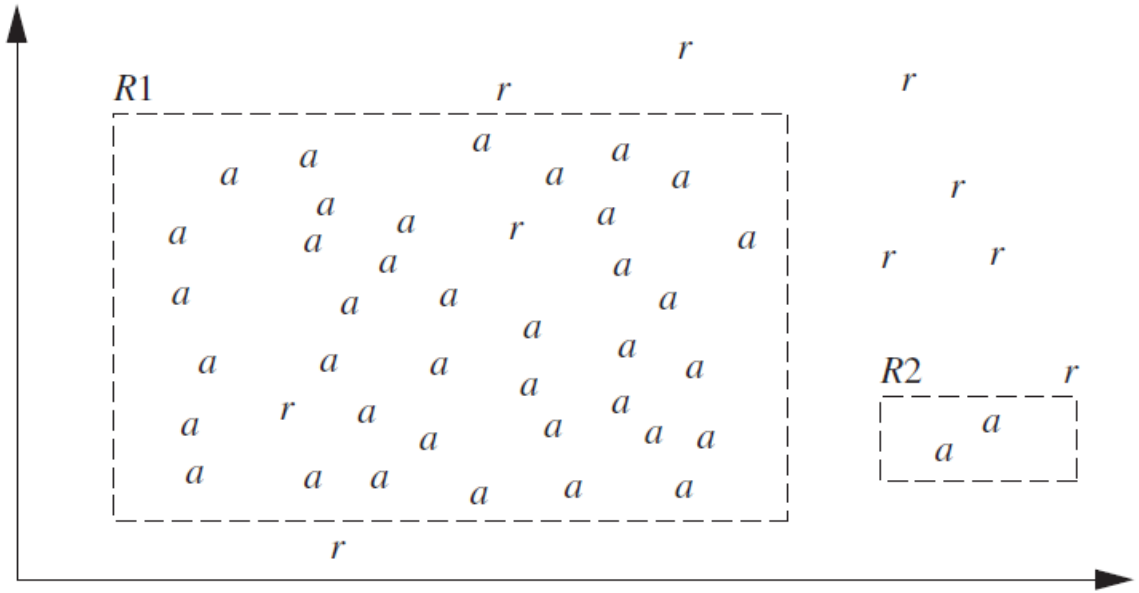
    if foil-gain(*p*) > threshold **then** add *p* to current rule

    else break



How to *Learn-One-Rule*?

- Start with the *most general rule* possible: condition = empty
- *Adding new attributes* by adopting a greedy depth-first strategy
  - Picks the one that most improves the rule quality
- Rule-Quality measures: consider both coverage and accuracy



Rule R1 has accuracy 95%, while R2 has 100% accuracy.
However, R2 is not better because of its poor coverage

How to *Learn-One-Rule*?

- Rule-Quality measures: consider both coverage and accuracy
  - Foil-gain (in FOIL & RIPPER): assesses info_gain by extending condition
    (pos' and neg' are the # of positive, negative tuples covered by our new rule R', respectively)

$$FOIL\_Gain = pos' \times (\log_2 \frac{pos'}{pos'+neg'} - \log_2 \frac{pos}{pos+neg})$$

  - favors rules that have high accuracy and cover many positive tuples

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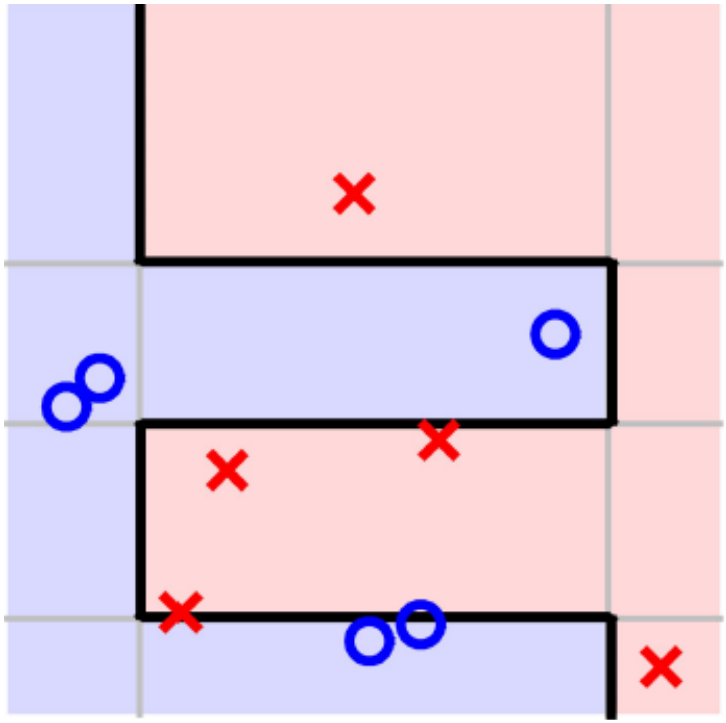
Motivation

- students: simple hypotheses g_t (like vertical/horizontal lines)
- (Class): sophisticated hypothesis G (like black curve)
- Teacher: a tactic learning algorithm that **directs the students to focus on key examples**



Goal of Supervised Learning?

- Minimize the probability of model prediction errors on ***future*** data

- Two Competing Methodologies
  - Build **one** really good model
    - Traditional approach
  - Build **many** models and average the results
    - Ensemble learning (more recent)

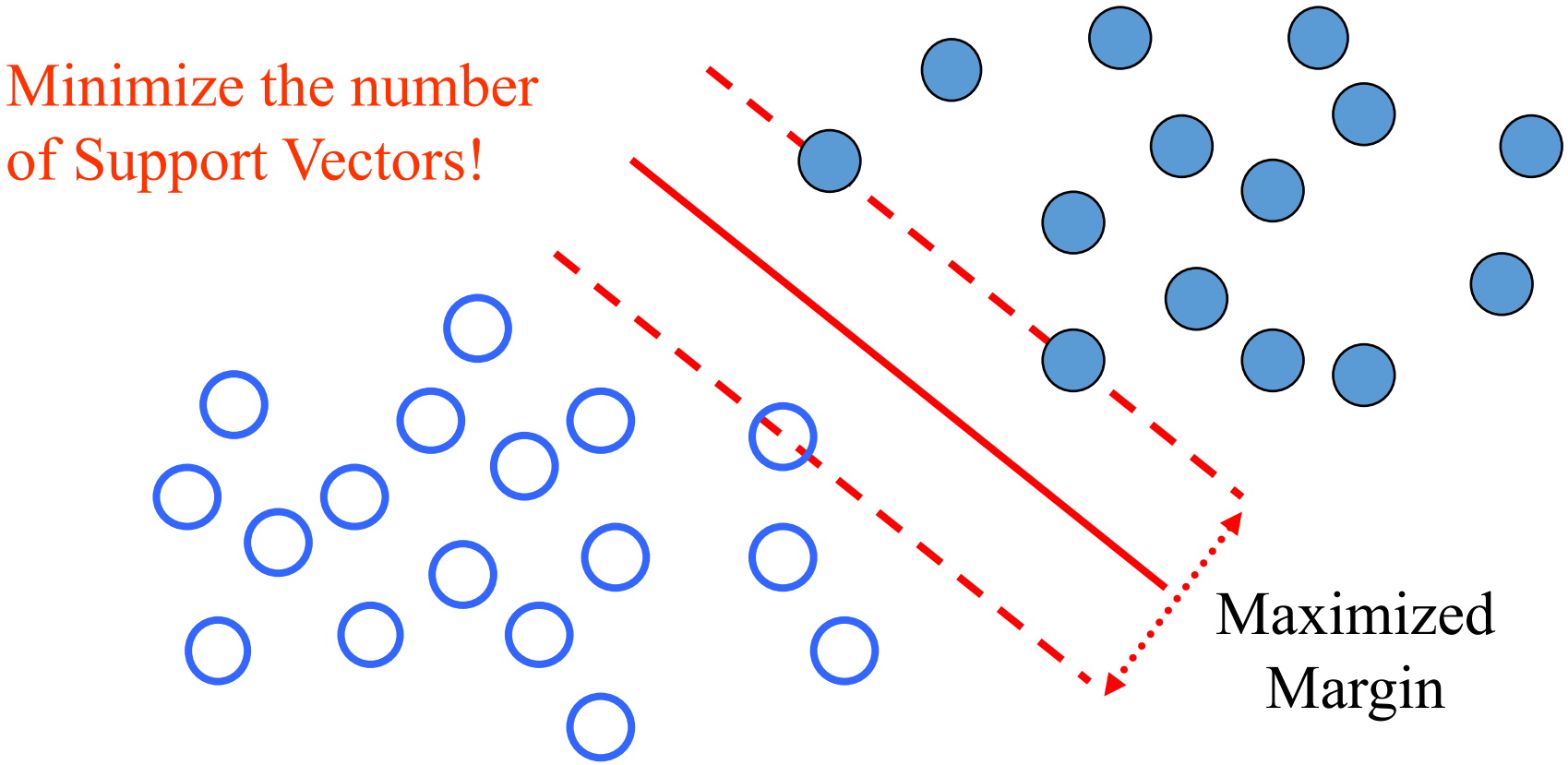
The Single Model Philosophy

- Motivation: Occam's Razor
  - "one should not increase, beyond what is necessary, the number of entities required to explain anything"
- Infinitely many models can explain any given dataset
  - Might as well pick the smallest one…

Exact Occam's Razor Models

- Exact approaches find optimal solutions
- Examples:
  - Support Vector Machines
    - Find a model structure that uses the smallest percentage of training data (to explain the rest of it).
  - Bayesian approaches
    - Minimum description length

How Do Support Vector Machines Define Small?



Approximate Occam's Razor Models

- Approximate solutions use a greedy search approach which is not optimal
- Examples
  - Kernel Projection Pursuit algorithms
    - Find a minimal set of kernel projections
  - Relevance Vector Machines
    - Approximate Bayesian approach
  - Sparse Minimax Probability Machine Classification
    - Find a minimum set of kernels and features

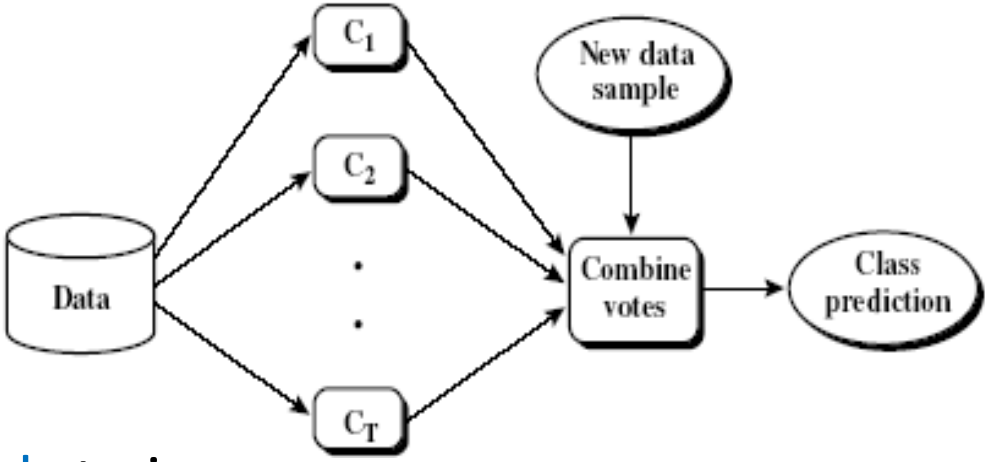
Other Single Models: Not Necessarily Motivated by Occam's Razor

- Minimax Probability Machine (MPM)
- Trees
  - Greedy approach to sparseness
- Neural Networks
- Nearest Neighbor
- Basis Function Models
  - e.g. Kernel Ridge Regression

Ensemble Philosophy

- Build many models and combine them
- Only through averaging do we get at the truth!
- It's too difficult (*impossible*?) to build a single model that works best
- Two types of approaches:
  - Models that don't use randomness
  - Models that incorporate randomness

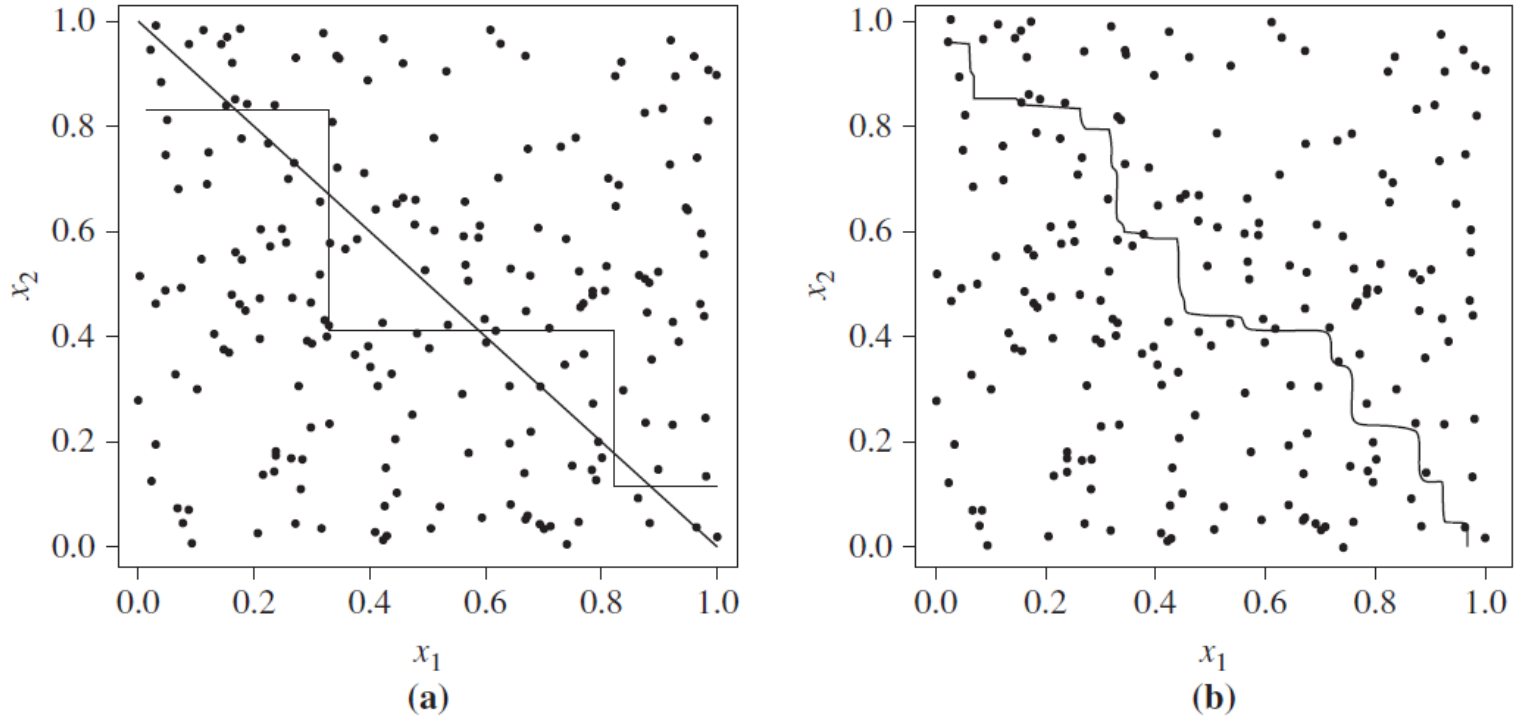
Ensemble Methods: Increasing the Accuracy



- Ensemble methods
  - Use a combination of models to increase accuracy
  - Combine a series of k learned models, M_1, M_2, …, M_k, with the aim of creating an improved model M*
  - Ideally, significant diversity (little correlation) among the models
- Popular ensemble methods
  - **Bagging:** averaging the prediction over a collection of classifiers
  - **Boosting:** weighted vote with a collection of classifiers
  - **Ensemble:** combining a set of heterogeneous classifiers

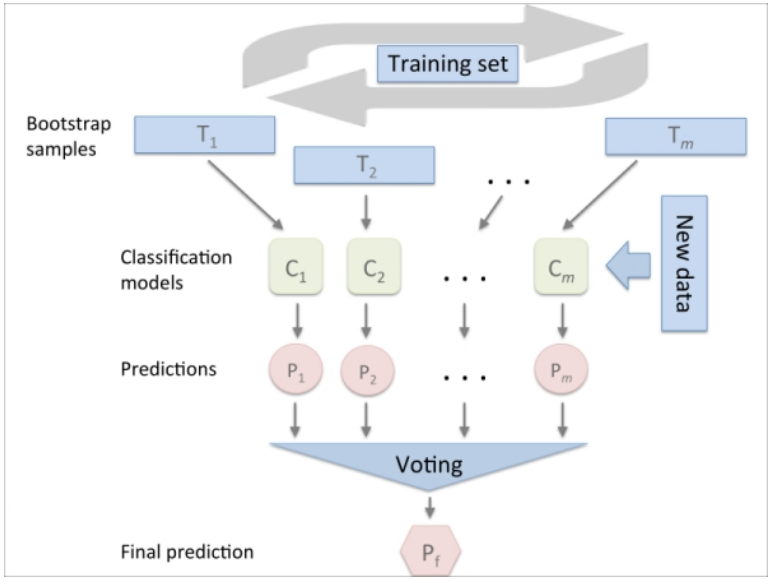
Ensemble methods

- For a two-class problem with attributes x_1, x_2



Decision boundary by (a) a single decision tree and (b) an ensemble of decision trees for a linearly separable problem (i.e., where the actual decision boundary is a straight line). The decision tree struggles with approximating a linear boundary. The decision boundary of the ensemble is closer to the true boundary. *Source:* From Seni and Elder [SE10]. © 2010 Morgan & Claypool Publishers; used with permission.

Bagging: Boostrap Aggregation



- Analogy: Diagnosis based on multiple doctors' **majority vote**
- Training
  - Given a set D of *d* tuples, at each iteration *i*, a training set D_i of *d* tuples is sampled with replacement from D (i.e., **bootstrap**)
  - A classifier model M_i is learned for each training set D_i
- Classification: classify an unknown sample **X**
  - Each classifier M_i returns its class prediction
  - The bagged classifier M* counts the votes and assigns the class with the most votes to **X**
- Prediction: can be applied to the prediction of continuous values by taking the average value of each prediction for a given test tuple
- Accuracy
  - Often significantly better than a single classifier derived from D
  - For noise data: not considerably worse, more robust
  - Proved improved accuracy in prediction

Boosting

- Analogy: Consult several doctors, based on a combination of weighted diagnoses—weight assigned based on the previous diagnosis accuracy
- How boosting works?
  - **Weights** are assigned to each training tuple
  - A series of k classifiers is iteratively learned
  - After a classifier M_i is learned, the weights are updated to allow the subsequent classifier, M_{i+1}, to **pay more attention to the training tuples that were misclassified** by M_i
  - The final **M* combines the votes** of each individual classifier, where the weight of each classifier's vote is a function of its accuracy
- Boosting algorithm can be extended for numeric prediction
- Comparing with bagging: Boosting tends to have greater accuracy, but it also risks overfitting the model to misclassified data

Adaboost (Freund and Schapire, 1997)

- Given *d* class-labeled tuples (y_i is class label): ($\mathbf{X_1}$, y_1), …, ($\mathbf{X_d}$, y_d)
- Initially, all the weights of tuples are set the same (1/d)
- Generate k classifiers in k rounds. At round i,
  - Tuples from D are sampled (with replacement) to form a training set D_i of the same size
  - Each tuple's chance of being selected is based on its weight
  - A classification model M_i is derived from D_i
  - Its error rate is calculated using D_i as a test set
  - If a tuple is misclassified, its weight is increased, o.w. it is decreased
- Error rate: err($\mathbf{X_j}$) is the misclassification error of tuple $\mathbf{X_j}$. Classifier M_i error rate is the sum of the weights of the misclassified tuples:

$$error(M_i) = \sum_{j}^{d} w_j \times err(\mathbf{X_j})$$

Adaboost (Freund and Schapire, 1997)

Weight update

- If tuple in round *i* was correctly classified, its weight is multiplied by

$$\frac{error(M_i)}{1 - error(M_i)}$$

where M_i is the classification model derived from round *i.*

- The weights of all tuples will be normalized, which can be viewed as increasing the weights of misclassifies tuples

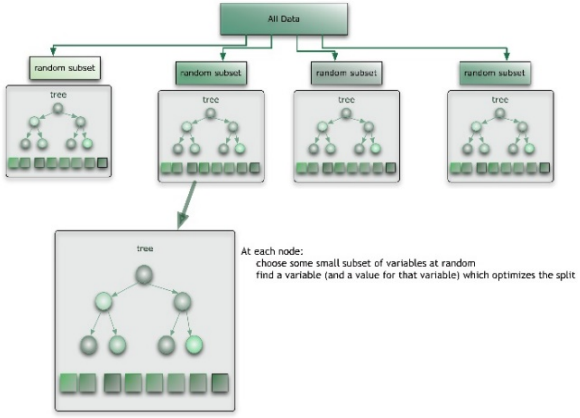
Prediction

- Adaboost assigns a weight to each classifier's M_i's vote
- The weight of classifier M_i's vote is:

$$\log \frac{1 - error(M_i)}{error(M_i)}$$

- The class with highest sum is returned as the prediction

Random Forest



- Random Forest:
  - Each classifier in the ensemble is a ***decision tree*** classifier and is generated using a random selection of attributes at each node to determine the split
  - During classification, each tree votes and the most popular class is returned
- Two Methods to construct Random Forest:
  - Forest-RI (*random input selection*): Randomly select, at each node, F attributes as candidates for the split at the node. The CART methodology is used to grow the trees to maximum size
  - Forest-RC (*random linear combinations*): Creates new attributes (or features) that are a linear combination of the existing attributes (reduces the correlation between individual classifiers)
- Comparable in accuracy to Adaboost, but more robust to errors and outliers
- Insensitive to the number of attributes selected for consideration at each split, and faster than bagging or boosting

Beyond the Buzz

- Quotes from http://www.kdnuggets.com/2017/08/deep-learning-not-ai-future.html
- "*Too many startups and products are named "deep-something", just as buzzword: **very few** are using DL really*"
- "***Decision Trees** like XGBoost are not making headlines, but silently beat DL at many Kaggle tabular data competitions.*"
- "***Legal nightmare** of DL decisions, that even if correct, can't be **explained** when legally questioned*"
- "***For many tasks, Deep Learning AI is or will become **illegal**, not compliant***"
  - *"**GDPR**, about automated decision-making, requires the right to an explanation, and to prevent discriminatory effects based on race, opinions, health, etc."*
  - *"Fines for noncompliance are **4% of global revenue**."*

Classification of Class-Imbalanced Data Sets

- Class-imbalance problem: Rare positive example but numerous negative ones, e.g., medical diagnosis, fraud, oil-spill, fault, etc.
- Traditional methods assume a balanced distribution of classes and equal error costs: not suitable for class-imbalanced data
- Typical methods for imbalance data in 2-class classification:
  - **Oversampling**: re-sampling of data from positive class
  - **Under-sampling**: randomly eliminate tuples from negative class
  - **Threshold-moving**: moves the decision threshold, t, so that the rare class tuples are easier to classify, and hence, less chance of costly false negative errors
  - **Ensemble techniques:** Ensemble multiple classifiers introduced above
- Still difficult for class imbalance problem on multiclass tasks

Multiclass Classification

- Classification involving more than two classes (i.e., > 2 Classes)
- Method 1. **One-vs.-all** (OVA): Learn a classifier one at a time
  - Given m classes, train m classifiers: one for each class
  - Classifier j: treat tuples in class j as *positive* & all others as *negative*
  - To classify a tuple **X**, the set of classifiers vote as an ensemble
- Method 2. **All-vs.-all** (AVA): Learn a classifier for each pair of classes
  - Given m classes, construct m(m-1)/2 binary classifiers
  - A classifier is trained using tuples of the two classes
  - To classify a tuple **X**, each classifier votes. X is assigned to the class with maximal vote
- Comparison
  - All-vs.-all tends to be superior to one-vs.-all
  - Problem: Binary classifier is sensitive to errors, and errors affect vote count

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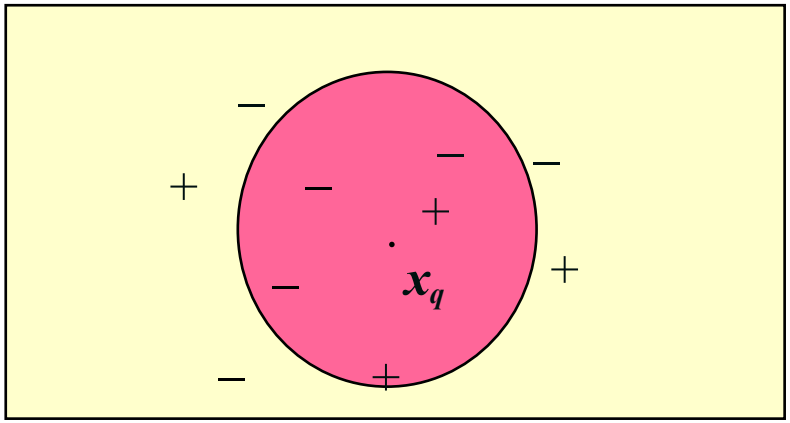
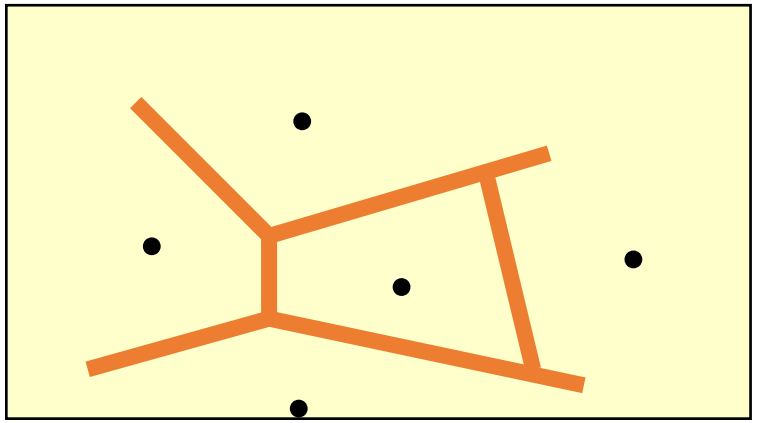
Lazy vs. Eager Learning

- Lazy vs. eager learning
  - **Lazy learning** (e.g., instance-based learning): Simply stores training data (or only minor processing) and waits until it is given a test tuple
  - **Eager learning** (the above discussed methods): Given a set of training tuples, constructs a classification model before receiving new (e.g., test) data to classify
- Lazy: less time in training but more time in predicting
- Accuracy
  - Lazy method effectively uses a richer hypothesis space since it uses many local linear functions to form an implicit global approximation to the target function
  - Eager: must commit to a single hypothesis that covers the entire instance space

The *k*-Nearest Neighbor Algorithm

- All instances correspond to points in the n-D space
- The nearest neighbor are defined in terms of Euclidean distance, dist($\mathbf{X_1}$, $\mathbf{X_2}$)
- Target function could be discrete- or real- valued
- For discrete-valued, *k*-NN returns the most common value among the *k* training examples nearest to x_q
- Vonoroi diagram: the decision surface induced by 1-NN for a typical set of training examples





Discussion on the *k*-NN Algorithm

- *k*-NN for real-valued prediction for a given unknown tuple
  - Returns the mean values of the *k* nearest neighbors
- Distance-weighted nearest neighbor algorithm
  - Weight the contribution of each of the *k* neighbors according to their distance to the query x_q
    - Give greater weight to closer neighbors

$$w \equiv \frac{1}{d(x_q, x_i)^2}$$

- Robust to noisy data by averaging *k*-nearest neighbors
- Curse of dimensionality: distance between neighbors could be dominated by irrelevant attributes
  - To overcome it, axes stretch or elimination of the least relevant attributes

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Support Vector Machines

- Please refer to another set of slides

Model Evaluation and Selection

- Evaluation metrics: How can we measure accuracy? Other metrics to consider?
- Use **validation test set** of class-labeled tuples instead of training set when assessing accuracy
- Methods for estimating a classifier's accuracy:
  - Holdout method, random subsampling
  - Cross-validation
  - Bootstrap
- Comparing classifiers:
  - Cost-benefit analysis and ROC Curves

Classifier Evaluation Metrics: Confusion Matrix

Confusion Matrix:

Actual class\Predicted class	C_1	¬ C_1
C_1	**True Positives (TP)**	**False Negatives (FN)**
¬ C_1	**False Positives (FP)**	**True Negatives (TN)**

Example of Confusion Matrix:

Actual class\Predicted class	buy_computer = yes	buy_computer = no	Total
buy_computer = yes	**6954**	**46**	7000
buy_computer = no	**412**	**2588**	3000
Total	7366	2634	10000

- Given *m* classes, an entry, $\boldsymbol{CM_{i,j}}$ in a **confusion matrix** indicates # of tuples in class *i* that were labeled by the classifier as class *j*
- May have extra rows/columns to provide totals

Classifier Evaluation Metrics: Accuracy, Error Rate, Sensitivity and Specificity

A\P	C	¬C	
C	**TP**	**FN**	**P**
¬C	**FP**	**TN**	**N**
	P'	**N'**	**All**

- **Classifier Accuracy,** or recognition rate: percentage of test set tuples that are correctly classified

  Accuracy = (TP + TN)/All

- **Error rate:** *1 – accuracy*, or

  Error rate = (FP + FN)/All

- **Class Imbalance Problem**:
  - One class may be *rare*, e.g. fraud, or HIV-positive
  - Significant *majority of the negative class* and minority of the positive class
  - **Sensitivity**: True Positive recognition rate
    - **Sensitivity = TP/P**
  - **Specificity**: True Negative recognition rate
    - **Specificity = TN/N**

Classifier Evaluation Metrics: Precision and Recall, and F-measures

- **Precision**: exactness – what % of tuples that the classifier labeled as positive are actually positive

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

  - Does not care how many positive instances are mislabeled as negative, i.e., FN

- **Recall:** completeness – what % of positive tuples did the classifier label as positive?

$$recall = \frac{TP}{TP + FN} = \frac{TP}{P}$$

  - But did not tell how many negative instances are mislabeled as positive, i.e., FP

- Perfect score is 1.0
- Inverse relationship between precision & recall
- ***F* measure (*F_1* or *F*-score)**: harmonic mean of precision and recall,

$$F = \frac{2 \times precision \times recall}{precision + recall}$$

- ***F_β*:** weighted measure of precision and recall
  - assigns ß times as much weight to recall as to precision

$$F_\beta = \frac{(1 + \beta^2) \times precision \times recall}{\beta^2 \times precision + recall}$$

Classifier Evaluation Metrics: Example

Actual Class\Predicted class	cancer = yes	cancer = no	Total	Recognition(%)
cancer = yes	**90**	**210**	300	30.00 (*sensitivity*
cancer = no	**140**	**9560**	9700	98.56 (*specificity)*
Total	230	9770	10000	96.40 (*accuracy*)

- *Precision* = 90/230 = 39.13% *Recall* = 90/300 = 30.00%

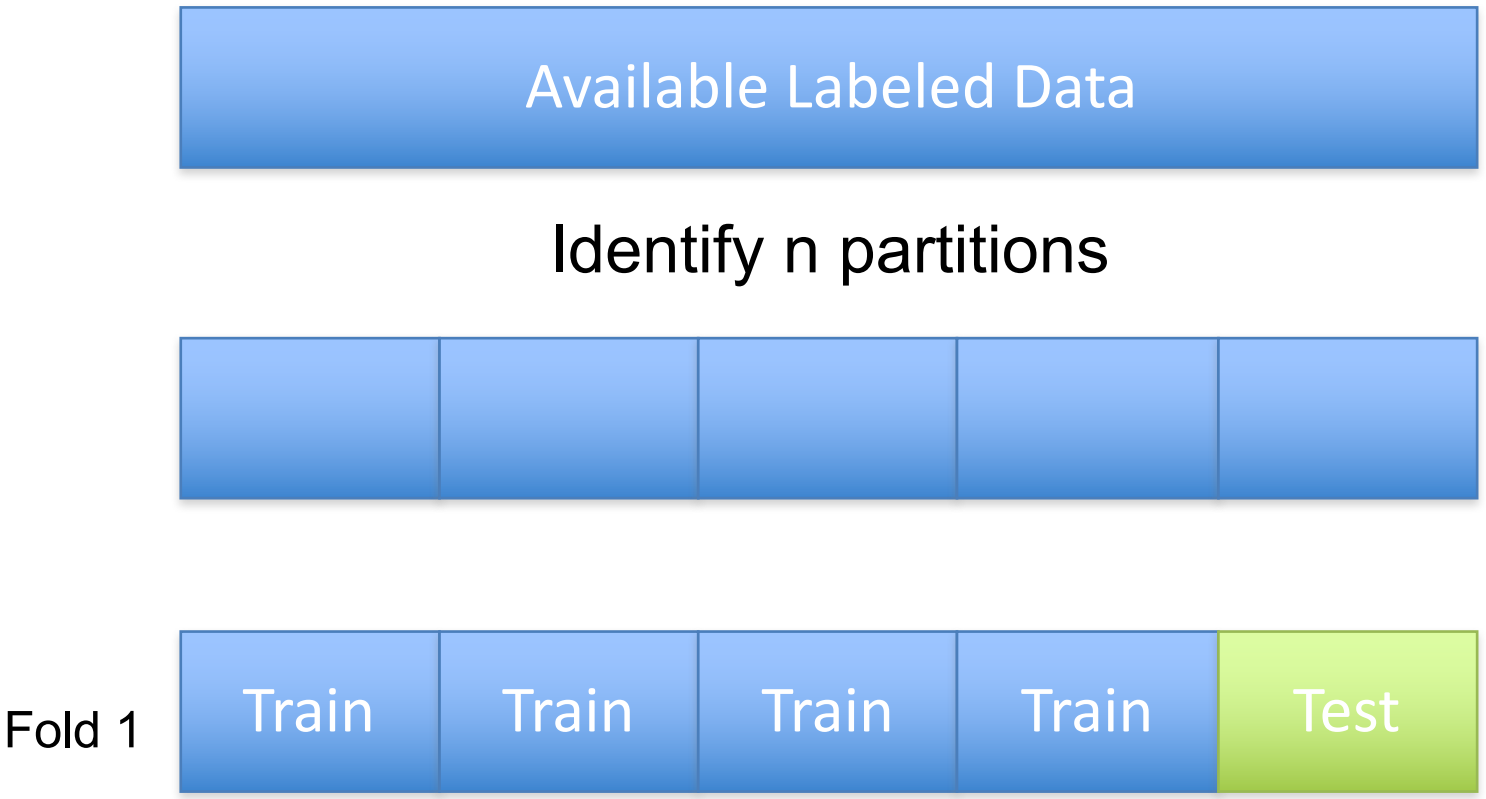
Measure	Formula
accuracy, recognition rate	$\frac{TP+TN}{P+N}$
error rate, misclassification rate	$\frac{FP+FN}{P+N}$
sensitivity, true positive rate, recall	$\frac{TP}{P}$
specificity, true negative rate	$\frac{TN}{N}$
precision	$\frac{TP}{TP+FP}$
F, F_1, F-score, harmonic mean of precision and recall	$\frac{2 \times precision \times recall}{precision + recall}$
F_β, where β is a non-negative real number	$\frac{(1+\beta^2) \times precision \times recall}{\beta^2 \times precision + recall}$

Evaluating Classifier Accuracy: Holdout & Cross-Validation Methods

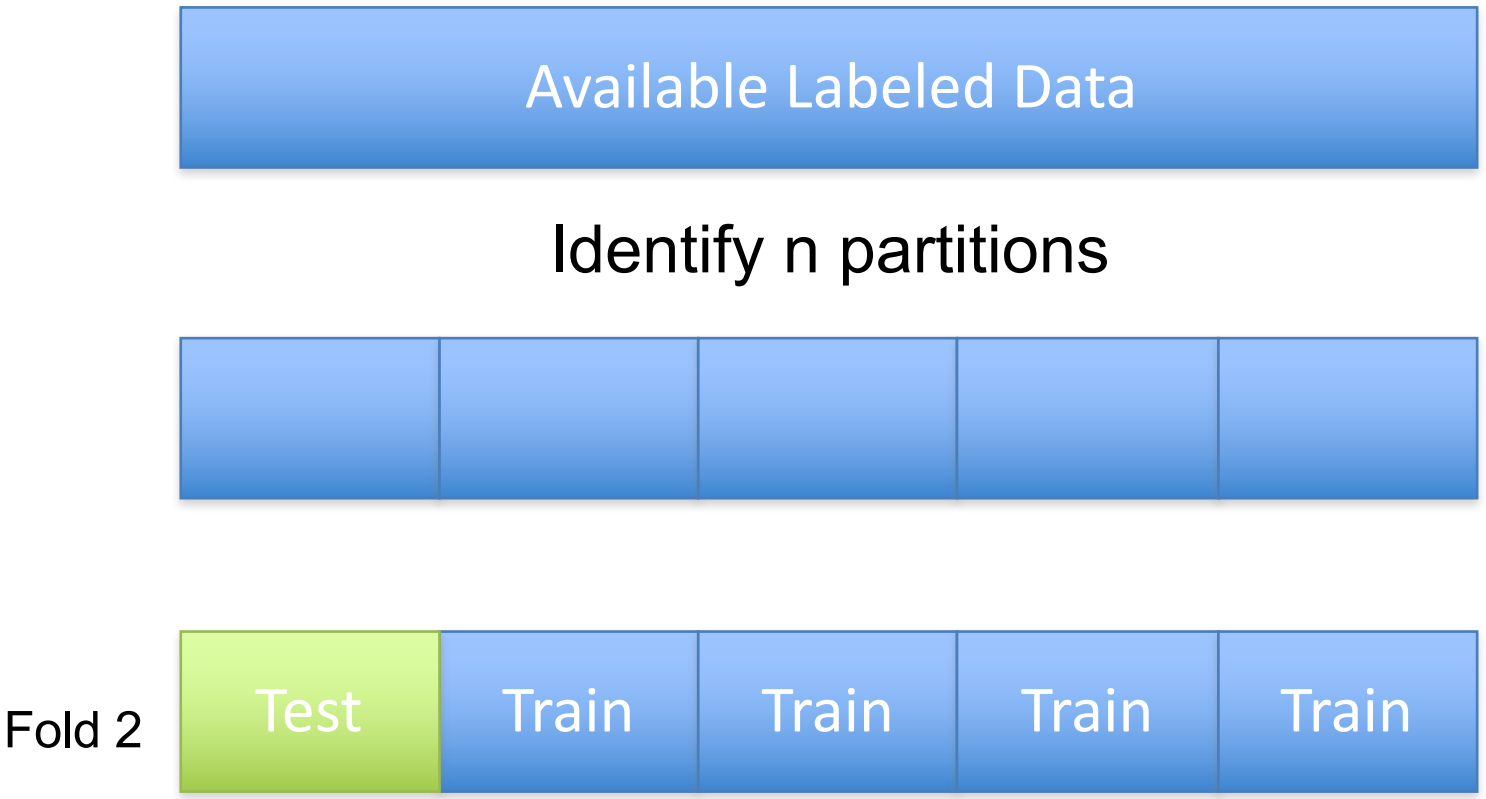
- **Holdout method**
  - Given data is randomly partitioned into two independent sets
    - Training set (e.g., 2/3) for model construction
    - Test set (e.g., 1/3) for accuracy estimation
  - Random sampling: a variation of holdout
    - Repeat holdout k times, accuracy = avg. of the accuracies obtained

- **Cross-validation** (*k*-fold, where k = 10 is most popular)
  - Randomly partition the data into *k mutually exclusive* subsets, each approximately equal size
  - At *i*-th iteration, use D_i as test set and others as training set
  - Leave-one-out: *k* folds where *k* = # of tuples, for small sized data
  - ***Stratified cross-validation***: folds are stratified so that class dist. in each fold is approx. the same as that in the initial data

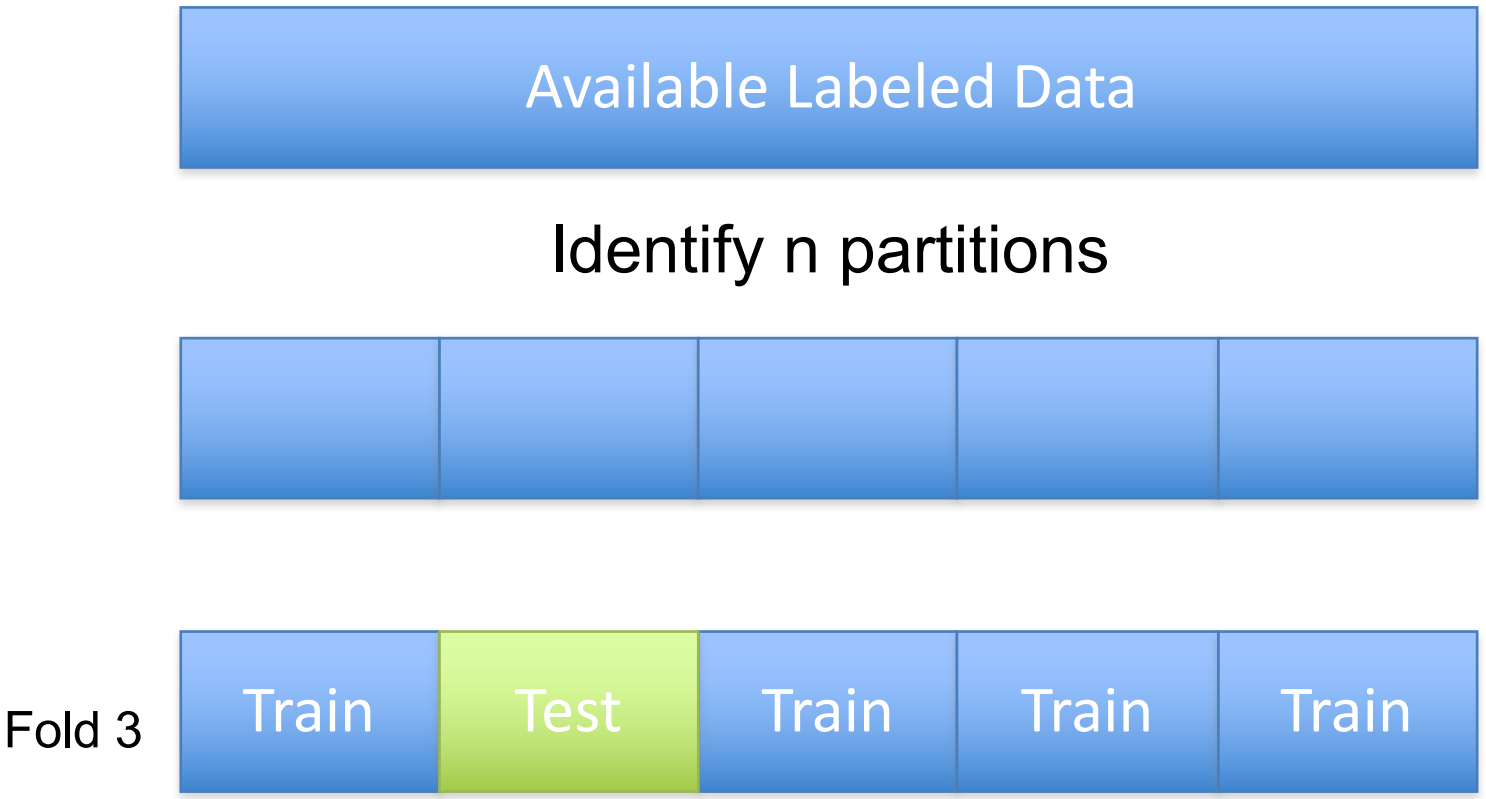
Cross-validation visualized



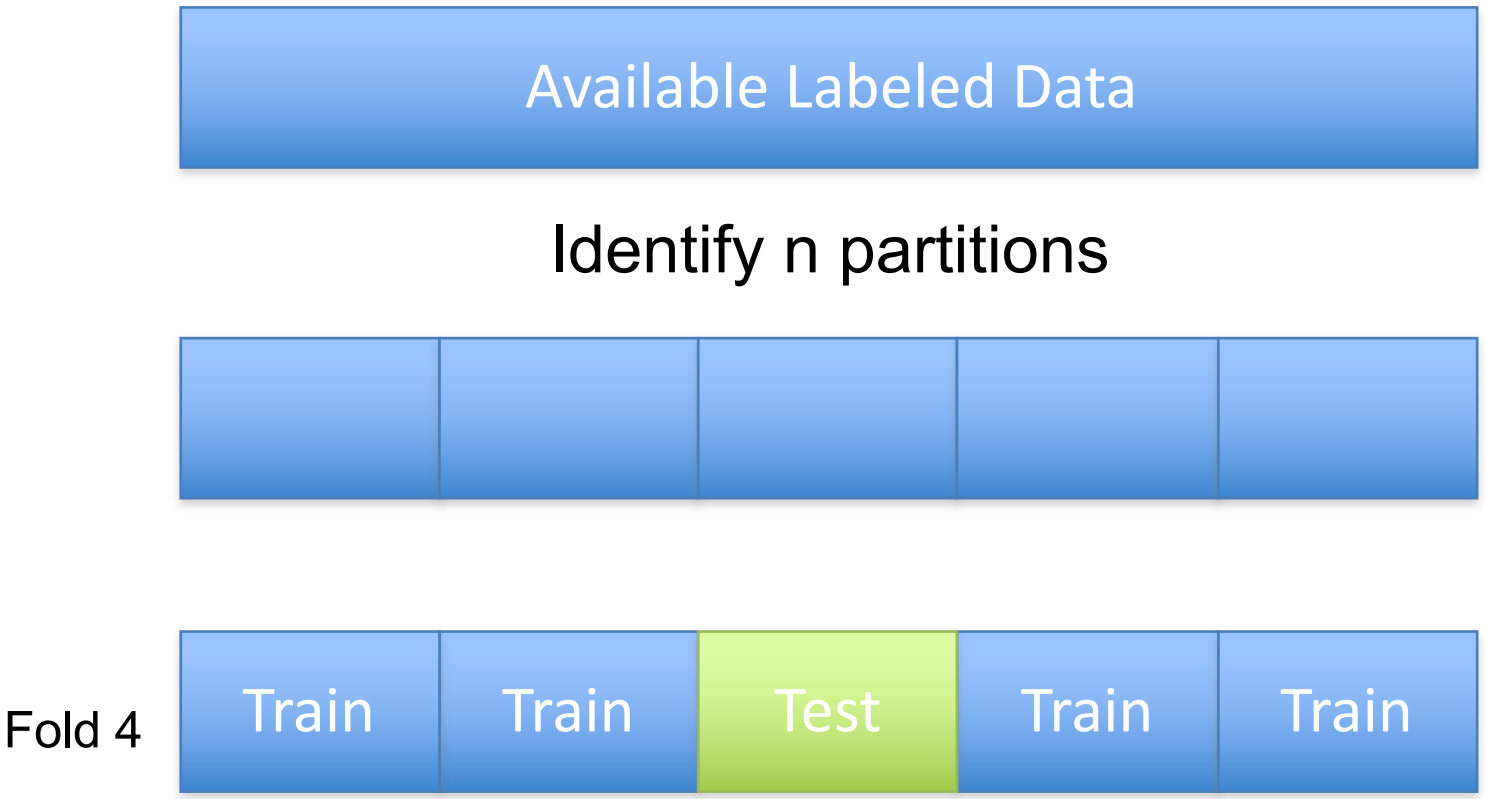
Cross-validation visualized



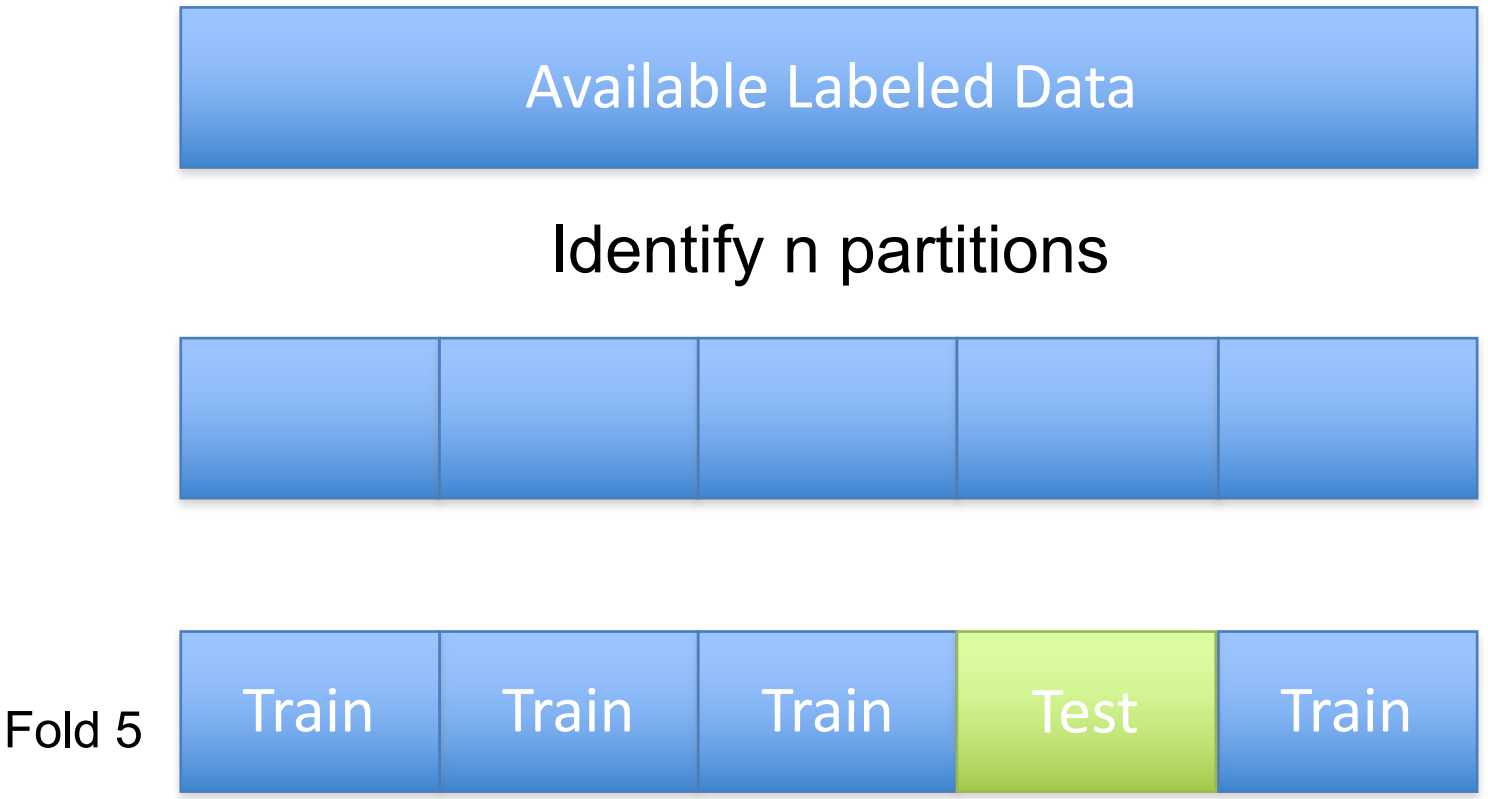
Cross-validation visualized



Cross-validation visualized

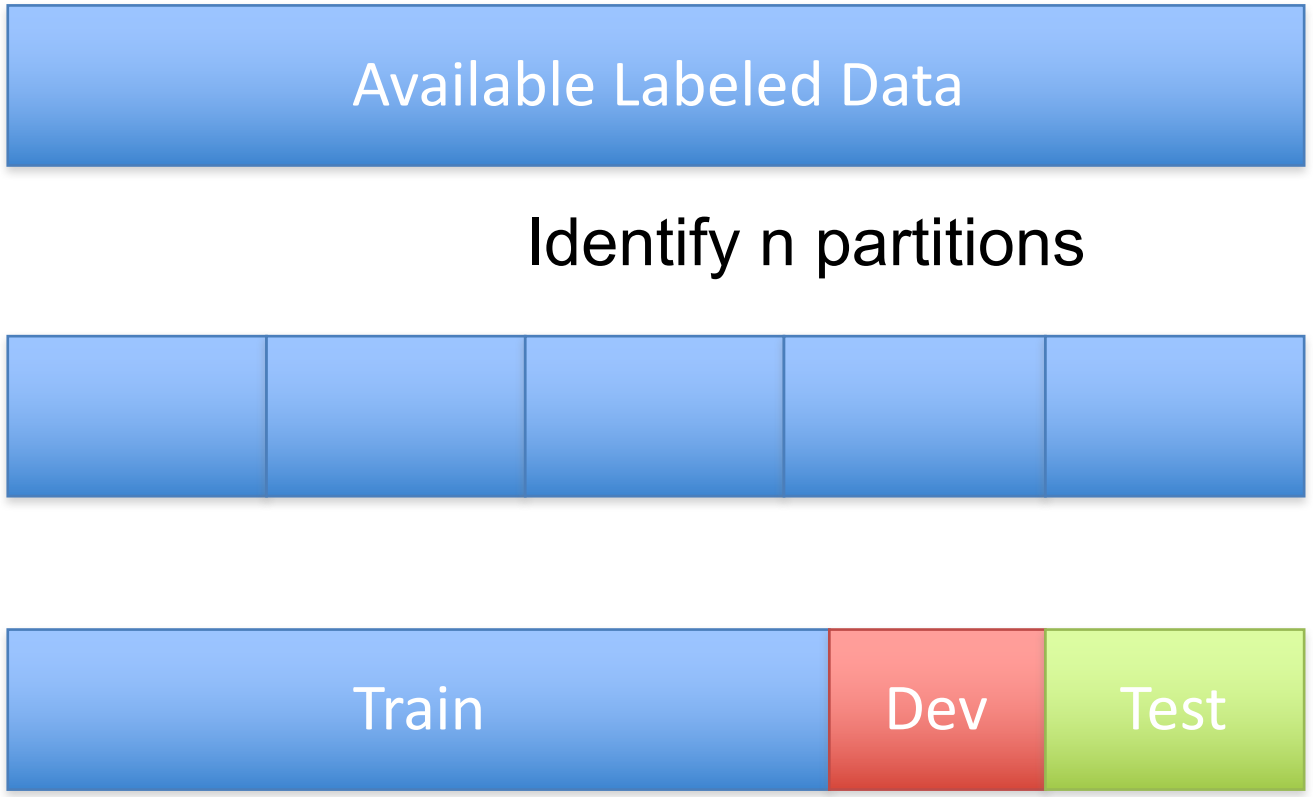


Cross-validation visualized



Calculate Average Performance

Cross-validation visualized



Develop/Tuning set for adjusting hyper parameters

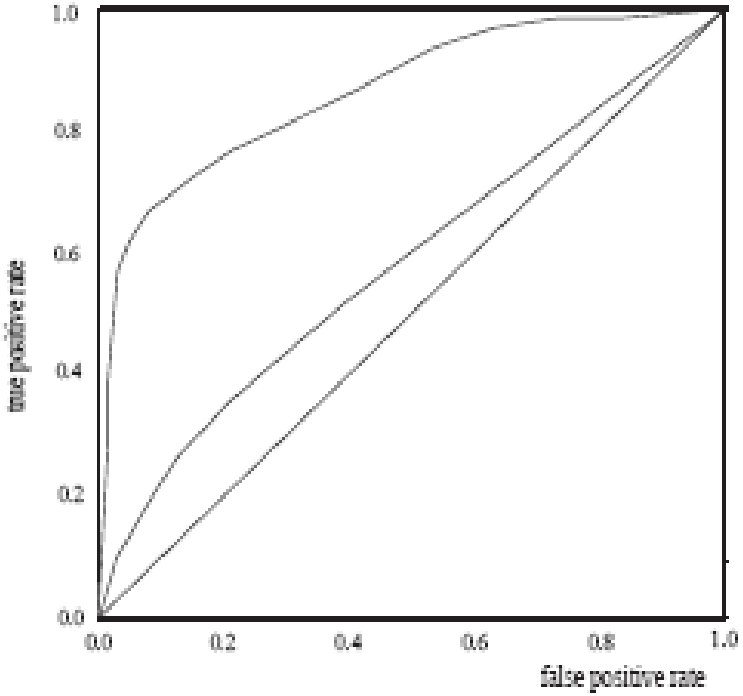
Evaluating Classifier Accuracy: Bootstrap

- **Bootstrap**
  - Works well with small data sets
  - Samples the given training tuples uniformly *with replacement*
    - i.e., each time a tuple is selected, it is equally likely to be selected again and re-added to the training set
- Several bootstrap methods, and a common one is **.632 boostrap**
  - A data set with *d* tuples is sampled *d* times, with replacement, resulting in a training set of *d* samples. The data tuples that did not make it into the training set end up forming the test set. About 63.2% of the original data end up in the bootstrap, and the remaining 36.8% form the test set (since $(1 – 1/d)^d \approx e^{-1} = 0.368$)
  - Repeat the sampling procedure *k* times, overall accuracy of the model:

$$Acc(M) = \frac{1}{k}\sum_{i=1}^{k}(0.632 \times Acc(M_i)_{test\_set} + 0.368 \times Acc(M_i)_{train\_set})$$

Model Selection: ROC Curves

- **ROC** (Receiver Operating Characteristics) curves: for visual comparison of classification models
- Shows the trade-off between the true positive rate and the false positive rate
- The area under the ROC curve is a measure of the accuracy of the model
- Rank the test tuples in decreasing order: the one that is most likely to belong to the positive class appears at the top of the list
- The closer to the diagonal line (i.e., the closer the area is to 0.5), the less accurate is the model



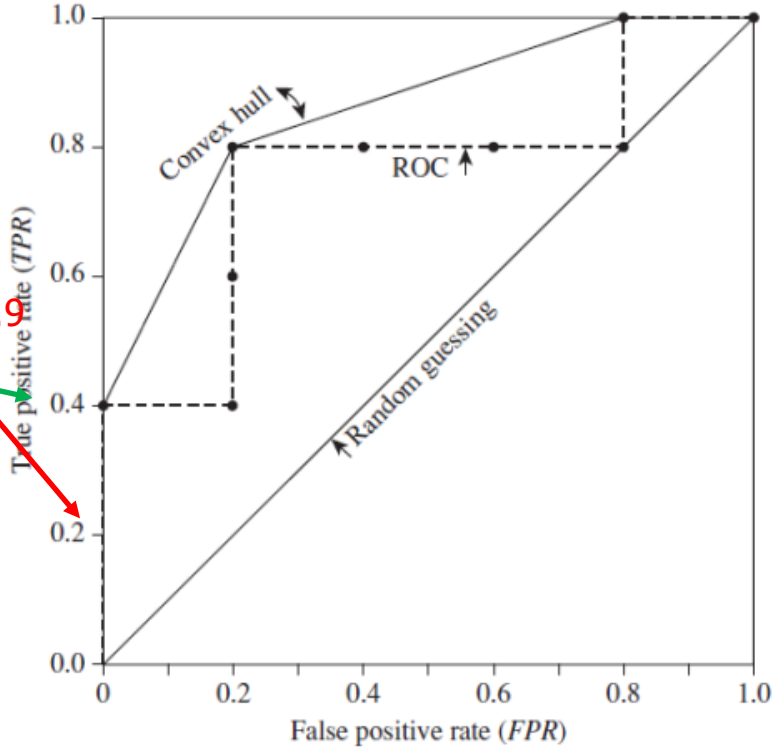
- Vertical axis represents the true positive rate
- Horizontal axis rep. the false positive rate
- The plot also shows a diagonal line
- A model with perfect accuracy will have an area of 1.0

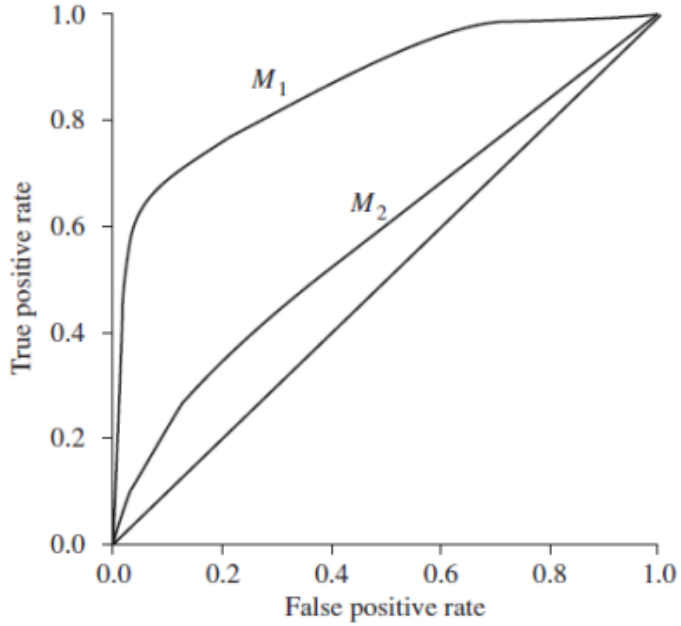
ROC curves

Tuple #	Class	Prob.	TP	FP	TN	FN	TPR	FPR
1	P	0.90	1	0	5	4	0.2	0
2	P	0.80	2	0	5	3	0.4	0
3	N	0.70	2	1	4	3	0.4	0.2
4	P	0.60	3	1	4	2	0.6	0.2
5	P	0.55	4	1	4	1	0.8	0.2
6	N	0.54	4	2	3	1	0.8	0.4
7	N	0.53	4	3	2	1	0.8	0.6
8	N	0.51	4	4	1	1	0.8	0.8
9	P	0.50	5	4	1	0	1.0	0.8
10	N	0.40	5	5	0	0	1.0	1.0

t=0.9

t=0.8





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Issues Affecting Model Selection

- **Accuracy**
  - classifier accuracy: predicting class label
- **Speed**
  - time to construct the model (training time)
  - time to use the model (classification/prediction time)
- **Robustness**: handling noise and missing values
- **Scalability**: efficiency in disk-resident databases
- **Interpretability**
  - understanding and insight provided by the model
- Other measures, e.g., goodness of rules, such as decision tree size or compactness of classification rules

Summary (I)

- Classification is a form of data analysis that extracts models describing important data classes.
- Effective and scalable methods have been developed for decision tree induction, Naive Bayesian classification, rule-based classification, and many other classification methods.
- Evaluation metrics include: accuracy, sensitivity, specificity, precision, recall, *F* measure, and F_{β} measure.
- Stratified k-fold cross-validation is recommended for accuracy estimation. Bagging and boosting can be used to increase overall accuracy by learning and combining a series of individual models.

Summary (II)

- Significance tests and ROC curves are useful for model selection.
- There have been numerous comparisons of the different classification methods; the matter remains a research topic
- No single method has been found to be superior over all others for all data sets
- Issues such as accuracy, training time, robustness, scalability, and interpretability must be considered and can involve trade-offs, further complicating the quest for an overall superior method

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Low-Density Cut based Tree Decomposition for Large-Scale SVM Problems

L. He, H.-H. Shuai, X. Kong, P. S. Yu, Z. Hao, and X. Yang

ICDM, 2014

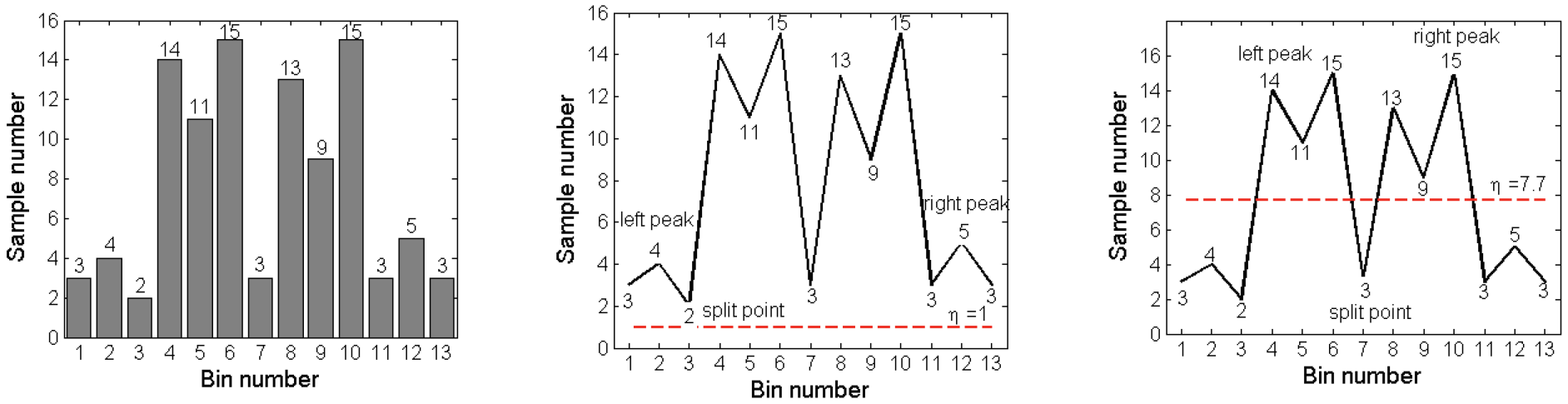

Fig. 1. An illustrative example of splitting point selection with different density threshold η. (a) One-dimensional histogram, (b) η is too small, and (c) ηequals to the average density.

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