



CS 412 Intro. to Data Mining

Chapter 8. Classification: Basic Concepts

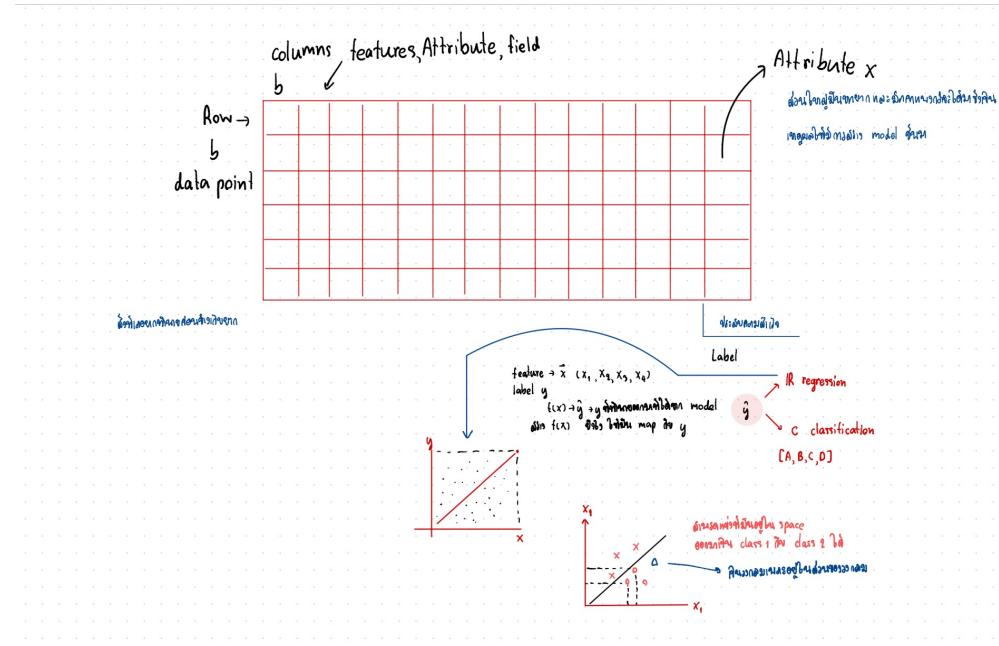
Jiawei Han, Computer Science, Univ. Illinois at Urbana-Champaign, 2017





Chapter 8. Classification: Basic Concepts

- Classification: Basic Concepts
- Decision Tree Induction
- Bayes Classification Methods
- Linear Classifier
- Model Evaluation and Selection
- Techniques to Improve Classification Accuracy: Ensemble Methods
- Additional Concepts on Classification
- Summary

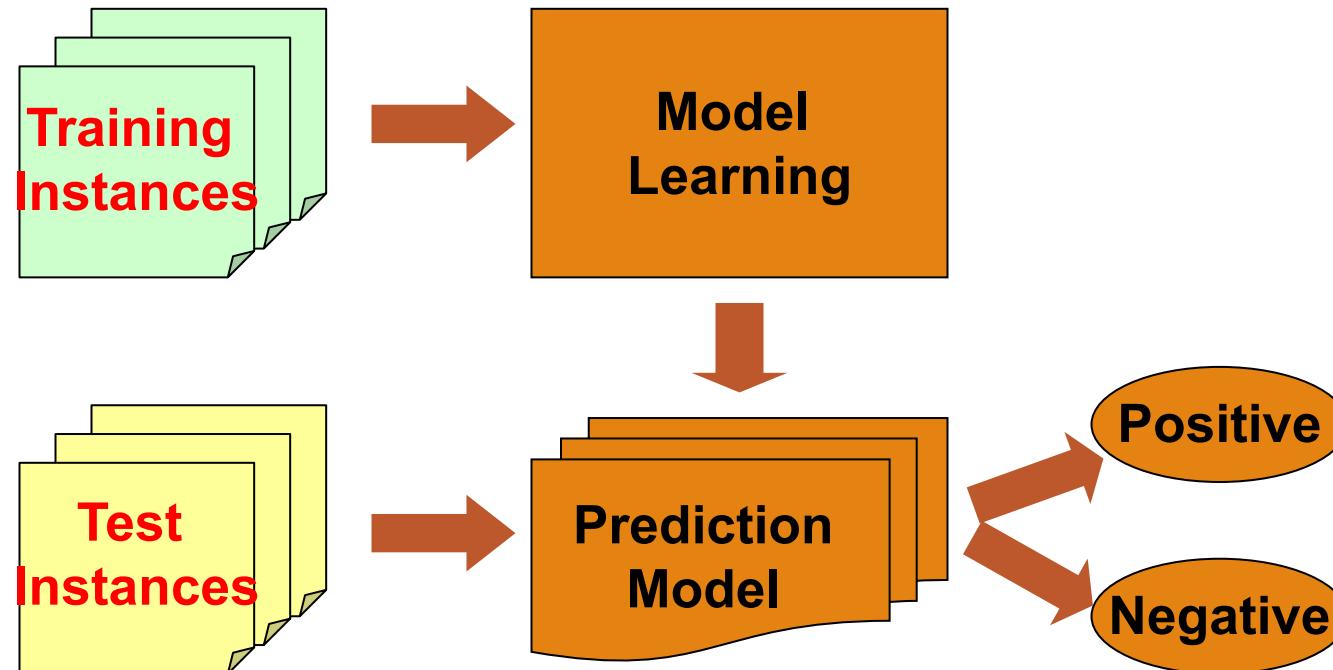


Supervised vs. Unsupervised Learning (1)

- Supervised learning (classification)
 - Supervision: The training data such as observations or measurements are accompanied by **labels** indicating the classes which they belong to
 - New data is classified based on the models built from the training set

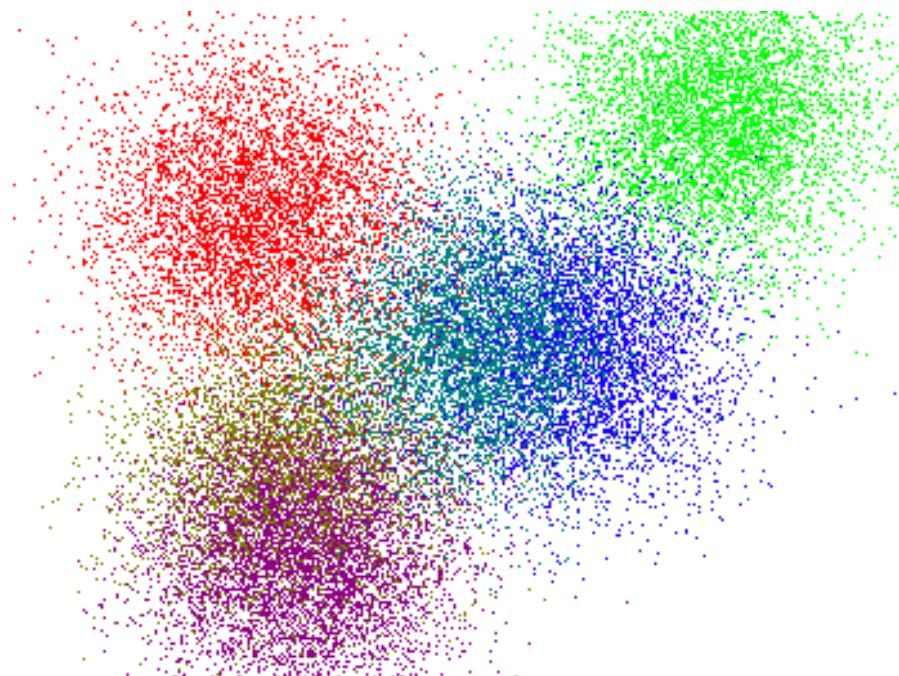
Training Data with class label:

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31...40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no



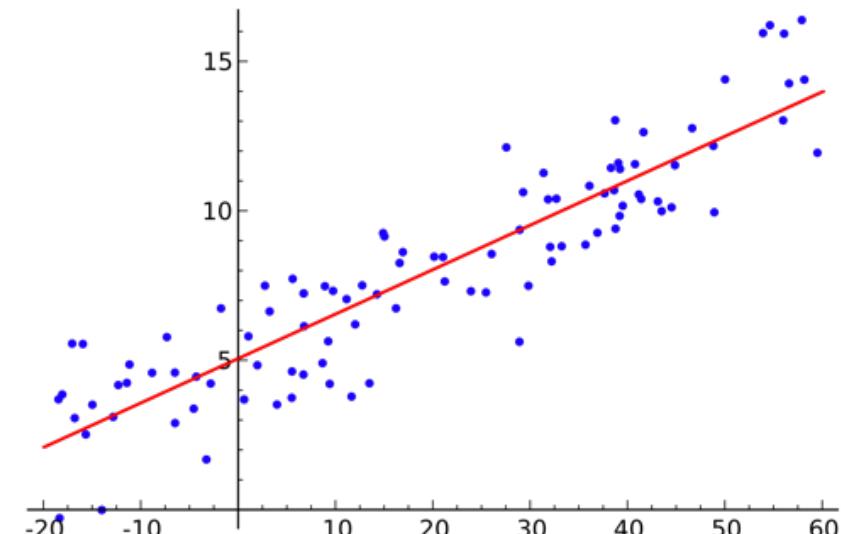
Supervised vs. Unsupervised Learning (2)

- ❑ Unsupervised learning (clustering)
 - ❑ The class labels of training data are unknown
 - ❑ Given a set of observations or measurements, establish the possible existence of classes or clusters in the data



Prediction Problems: Classification vs. Numeric Prediction

- Classification
 - Predict categorical class labels (discrete or nominal)
 - Construct a model based on the training set and the **class labels** (the values in a classifying attribute) and use it in classifying new data
- Numeric prediction
 - Model continuous-valued functions (i.e., predict unknown or missing values)
- Typical applications of classification
 - Credit/loan approval
 - Medical diagnosis: if a tumor is cancerous or benign
 - Fraud detection: if a transaction is fraudulent
 - Web page categorization: which category it is



Classification—Model Construction, Validation and Testing

- **Model construction**
 - Each sample is assumed to belong to a predefined class (shown by the **class label**)
 - The set of samples used for model construction is **training set**
 - Model: Represented as decision trees, rules, mathematical formulas, or other forms
- **Model Validation and Testing:**
 - **Test:** Estimate accuracy of the model
 - The known label of test sample is compared with the classified result from the model
 - **Accuracy:** % of test set samples that are correctly classified by the model
 - Test set is independent of training set
 - **Validation:** If *the test set* is used to select or refine models, it is called **validation (or development) (test) set**
- **Model Deployment:** If the accuracy is acceptable, use the model to classify new data

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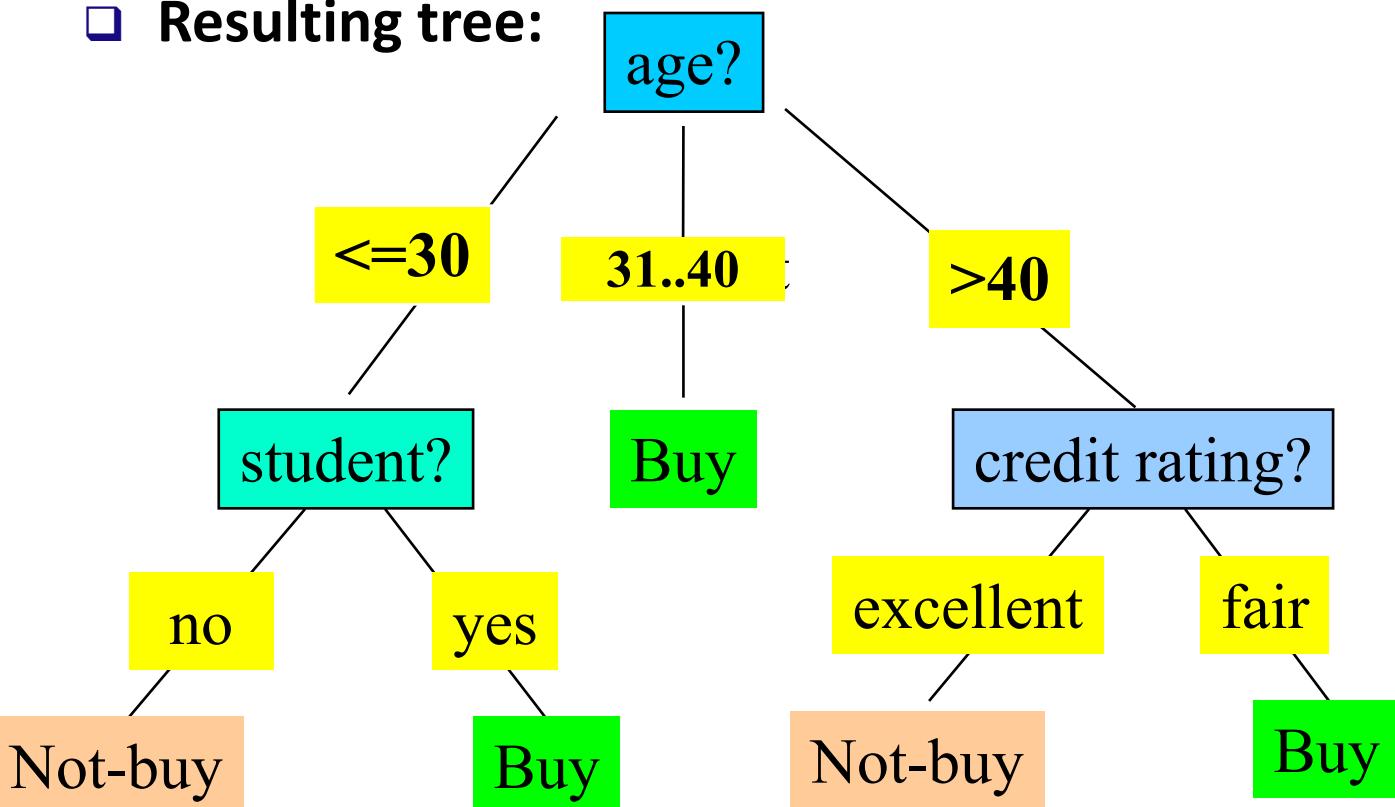


Decision Tree Induction: An Example

- Decision tree construction:

- A top-down, recursive, divide-and-conquer process

- Resulting tree:



Training data set: Who buys computer?

age	income	student	credit_rating	buys_computer
≤ 30	high	no	fair	no
≤ 30	high	no	excellent	no
31..40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31..40	low	yes	excellent	yes
≤ 30	medium	no	fair	no
≤ 30	low	yes	fair	yes
>40	medium	yes	fair	yes
≤ 30	medium	yes	excellent	yes
31..40	medium	no	excellent	yes
31..40	high	yes	fair	yes
>40	medium	no	excellent	no

Note: The data set is adapted from "Playing Tennis" example of R. Quinlan

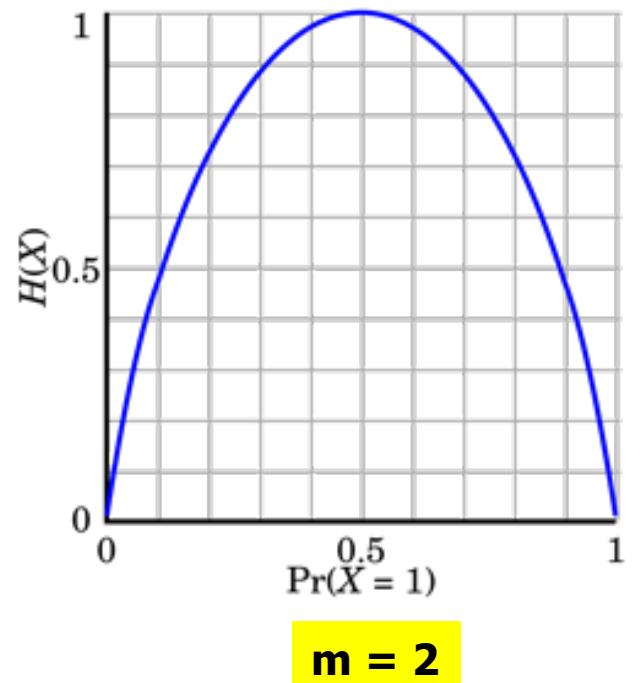
From Entropy to Info Gain: A Brief Review of Entropy

- Entropy (Information Theory)
 - A measure of uncertainty associated with a random number
 - Calculation: For a discrete random variable Y taking m distinct values $\{y_1, y_2, \dots, y_m\}$

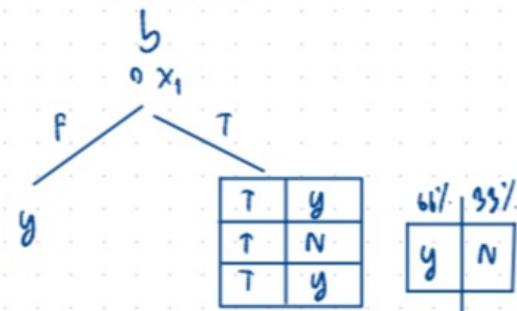
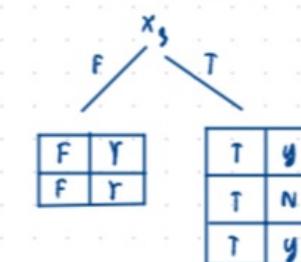
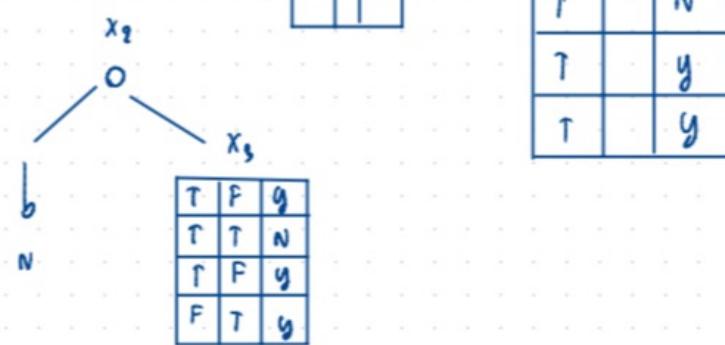
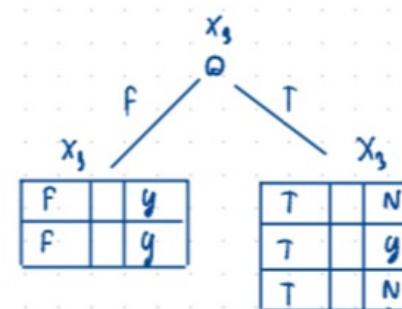
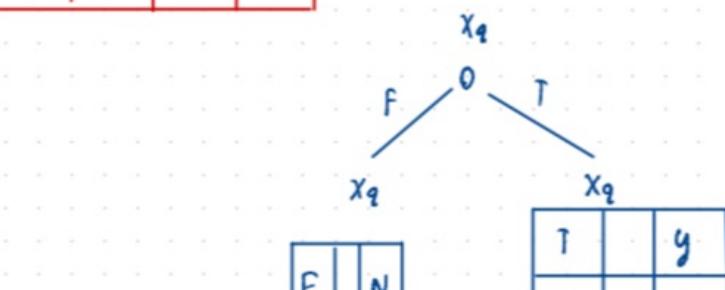
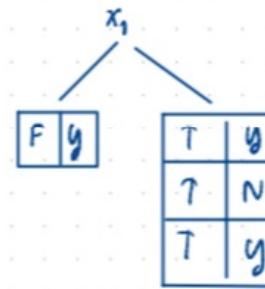
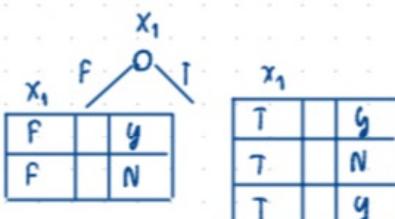
$$H(Y) = - \sum_{i=1}^m p_i \log(p_i) \text{ where } p_i = P(Y = y_i)$$

- Interpretation
 - Higher entropy \rightarrow higher uncertainty
 - Lower entropy \rightarrow lower uncertainty
- Conditional entropy

$$H(Y|X) = \sum_x p(x) H(Y|X = x)$$



x_1	x_2	x_3	y
T	T	F	y
T	T	T	N
T	T	F	y
F	T	T	y
F	F	T	N



greedy ត្រូវការងារចំណាំរាយរបស់ខ្លួន

ទម្រង់ការងារ disision tree នឹង greedy រាយរបស់ខ្លួន

Information Gain: An Attribute Selection Measure

- Select the attribute with the highest information gain (used in typical decision tree induction algorithm: ID3/C4.5)
- 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:

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

Class partition summation rule
subsets

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

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

- Information gained by branching on attribute A

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

Example: Attribute Selection with Information Gain

- Class P: buys_computer = “yes”
- Class N: buys_computer = “no”

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

age	p_i	n_i	$I(p_i, n_i)$
≤ 30	2	3	0.971
31...40	4	0	0
>40	3	2	0.971

age	income	student	credit_rating	buys_computer
≤ 30	high	no	fair	no
≤ 30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
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31...40	high	yes	fair	yes
>40	medium	no	excellent	no

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

$\frac{5}{14} I(2,3)$ means “age ≤ 30 ” has 5 out of 14 samples, with 2 yes’es and 3 no’s.

Hence

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

Similarly, we can get

$$Gain(income) = 0.029$$

$$Gain(student) = 0.151$$

$$Gain(credit_rating) = 0.048$$

Decision Tree Induction: Algorithm

- Basic algorithm
 - Tree is constructed in a **top-down, recursive, divide-and-conquer manner**
 - At start, all the training examples are at the root
 - Examples are partitioned recursively based on selected attributes
 - On each node, attributes are selected based on the training examples on that node, and a heuristic or statistical measure (e.g., **information gain**)
- Conditions for stopping partitioning
 - All samples for a given node belong to the same class
 - There are no remaining attributes for further partitioning
 - There are no samples left
- Prediction
 - **Majority voting** is employed for classifying the leaf

How to Handle Continuous-Valued Attributes?

- Method 1: Discretize continuous values and treat them as categorical values
 - E.g., age: < 20, 20..30, 30..40, 40..50, > 50
- Method 2: Determine the ***best split point*** for continuous-valued attribute A
 - Sort the value A in increasing order:, e.g. 15, 18, 21, 22, 24, 25, 29, 31, ...
 - *Possible split point:* the midpoint between *each pair of adjacent values*
 - $(a_i + a_{i+1})/2$ is the midpoint between the values of a_i and a_{i+1}
 - e.g., $(15+18)/2 = 16.5, 19.5, 21.5, 23, 24.5, 27, 30, \dots$
 - The point with the *maximum information gain* for A is selected as the **split-point** for A
- Split: Based on split point P
 - The set of tuples in D satisfying $A \leq P$ vs. those with $A > P$

Gain Ratio: A Refined Measure for Attribute Selection

- Information gain measure is biased towards attributes with a large number of values
- Gain ratio: Overcomes the problem (as a normalization to information gain)

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

- $\text{GainRatio}(A) = \text{Gain}(A)/\text{SplitInfo}(A)$
- The attribute with the maximum gain ratio is selected as the splitting attribute
- Gain ratio is used in a popular algorithm C4.5 (a successor of ID3) by R. Quinlan
- Example
 - $\text{SplitInfo}_{\text{income}}(D) = - \frac{4}{14} \log_2 \frac{4}{14} - \frac{6}{14} \log_2 \frac{6}{14} - \frac{4}{14} \log_2 \frac{4}{14} = 1.557$
 - $\text{GainRatio}(\text{income}) = 0.029/1.557 = 0.019$

Another Measure: Gini Index

- Gini index: Used in CART, and also in IBM IntelligentMiner
- If a data set D contains examples from n classes, gini index, $gini(D)$ is defined as
 - $$gini(D) = 1 - \sum_{j=1}^n p_j^2$$
 - p_j is the relative frequency of class j in D
- If a data set D is split on A into two subsets D_1 and D_2 , the gini index $gini(D)$ is defined as
 - $$gini_A(D) = \frac{|D_1|}{|D|} gini(D_1) + \frac{|D_2|}{|D|} gini(D_2)$$
- Reduction in Impurity:
 - $\Delta gini(A) = gini(D) - gini_A(D)$
- The attribute provides the smallest $gini_{split}(D)$ (or the largest reduction in impurity) is chosen to split the node (*need to enumerate all the possible splitting points for each attribute*)

Computation of Gini Index

- Example: 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

- $gini_{income \in \{low, medium\}}(D) = \frac{10}{14} gini(D_1) + \frac{4}{14} gini(D_2)$
 $= \frac{10}{14} \left(1 - \left(\frac{7}{10}\right)^2 - \left(\frac{3}{10}\right)^2\right) + \frac{4}{14} \left(1 - \left(\frac{2}{4}\right)^2 - \left(\frac{2}{4}\right)^2\right) = 0.443$
 $= Gini_{income \in \{high\}}(D)$

- 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
- All attributes are assumed continuous-valued
- May need other tools, e.g., clustering, to get the possible split values
- Can be modified for categorical attributes

Comparing Three Attribute Selection Measures

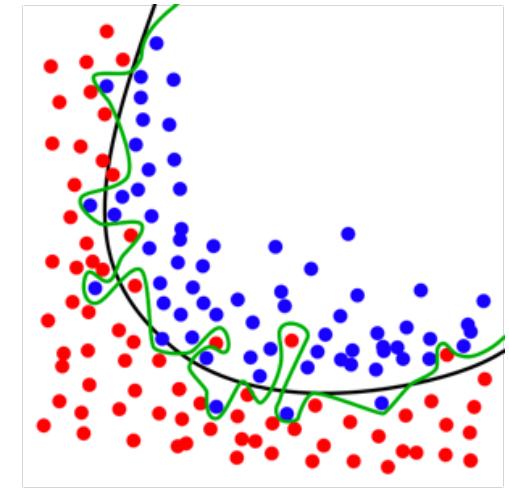
- The three measures, in general, return good results but
 - **Information gain:**
 - biased towards multivalued attributes
 - **Gain ratio:**
 - tends to prefer unbalanced splits in which one partition is much smaller than the others
 - **Gini index:**
 - biased to multivalued attributes
 - has difficulty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

Other Attribute Selection Measures

- Minimal Description Length (MDL) principle
 - Philosophy: 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
- CHAID: a popular decision tree algorithm, measure based on χ^2 test for independence
- Multivariate splits (partition based on multiple variable combinations)
 - CART: finds multivariate splits based on a linear combination of attributes
- There are many other measures proposed in research and applications
 - E.g., G-statistics, C-SEP
- Which attribute selection measure is the best?
 - Most give good results, none is significantly superior than others

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
- 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”



Classification in Large Databases

- Classification—a classical problem extensively studied by statisticians and machine learning researchers
- Scalability: Classifying data sets with millions of examples and hundreds of attributes with reasonable speed
- Why is decision tree induction popular?
 - Relatively fast learning speed
 - Convertible to simple and easy to understand classification rules
 - Easy to be adapted to database system implementations (e.g., using SQL)
 - Comparable classification accuracy with other methods
- **RainForest** (VLDB'98 — Gehrke, Ramakrishnan & Ganti)
 - Builds an AVC-list (attribute, value, class label)

RainForest: A Scalable Classification Framework

- ❑ The criteria that determine the quality of the tree can be computed separately
 - ❑ Builds an AVC-list: **AVC (Attribute, Value, Class_label)**
- ❑ **AVC-set** (of an attribute X)
 - ❑ Projection of training dataset onto the attribute X and class label where counts of individual class label are aggregated
- ❑ **AVC-group** (of a node n)
 - ❑ Set of AVC-sets of all predictor attributes at the node n

age	income	student	credit_rating	comp
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31...40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no

The Training Data

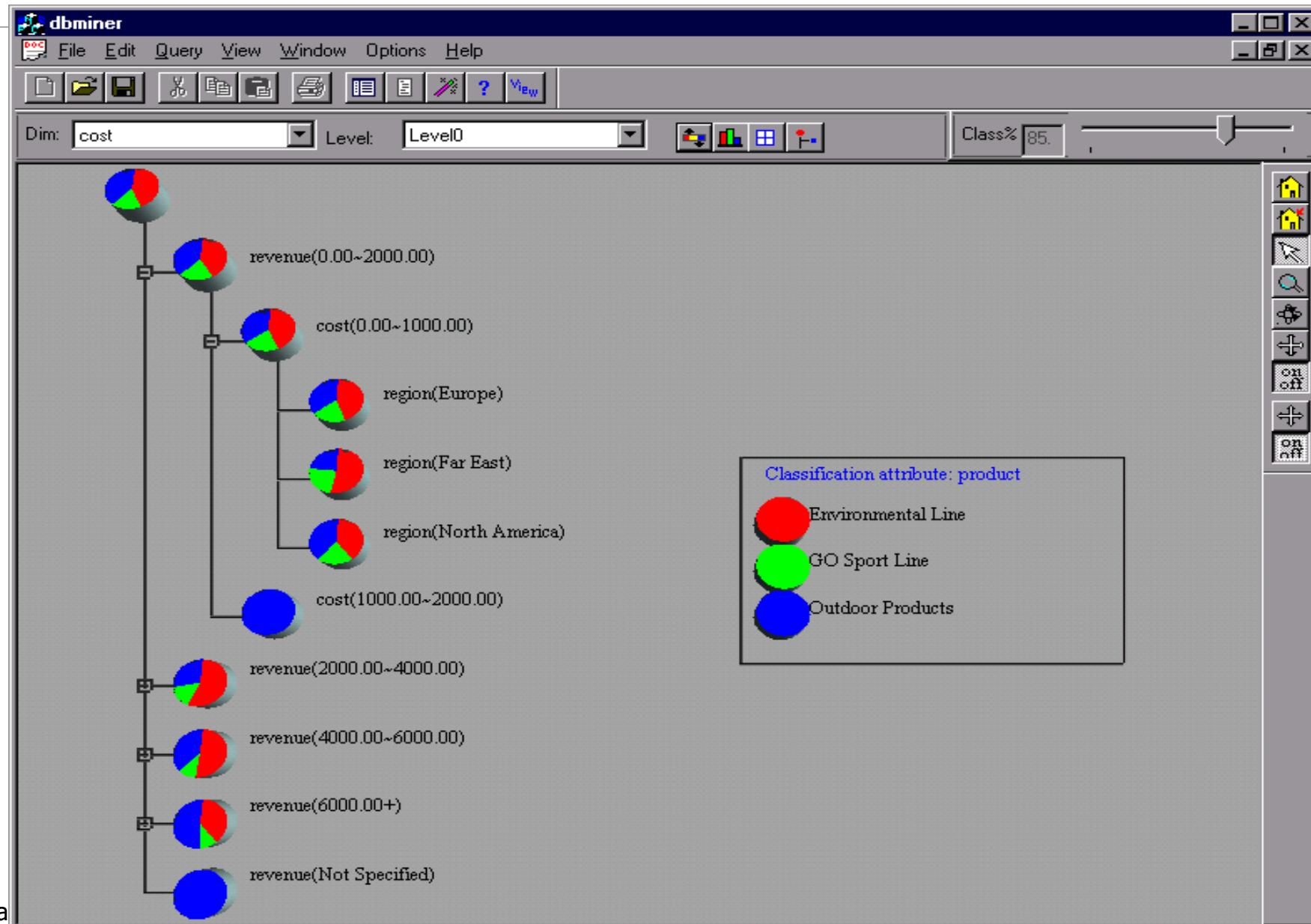
AVC-set on Age	
Age	Buy_Computer
yes	no
<=30	2
31..40	4
>40	3
	2

AVC-set on Income	
income	Buy_Computer
yes	no
high	2
medium	2
low	1

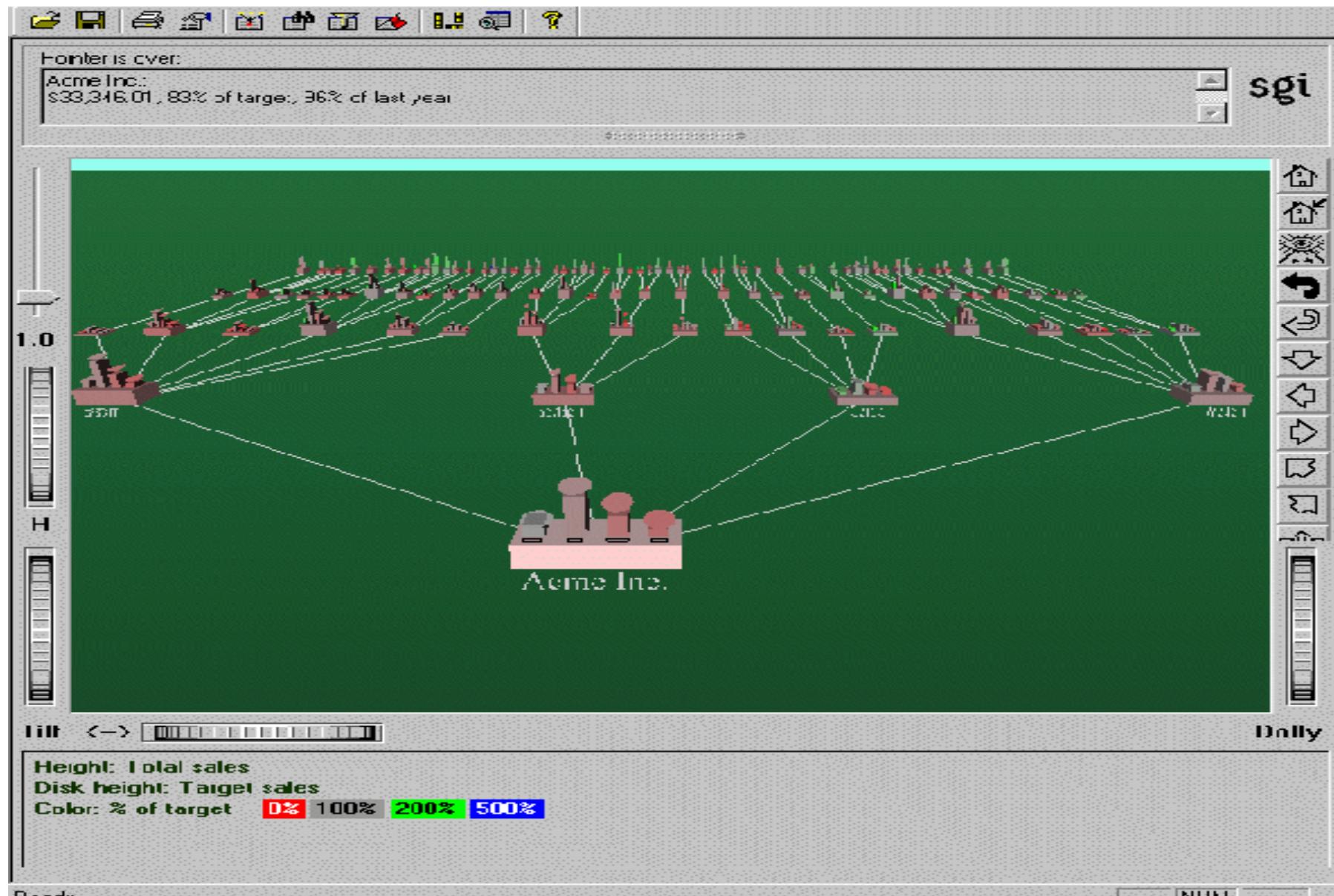
AVC-set on Student		AVC-set on Credit_Rating	
student	Buy_Computer	Credit rating	Buy_Computer
	yes		no
yes	6	fair	2
	1		6
no	3	excellent	3
	4		3

Its AVC Sets

Presentation of Classification Results

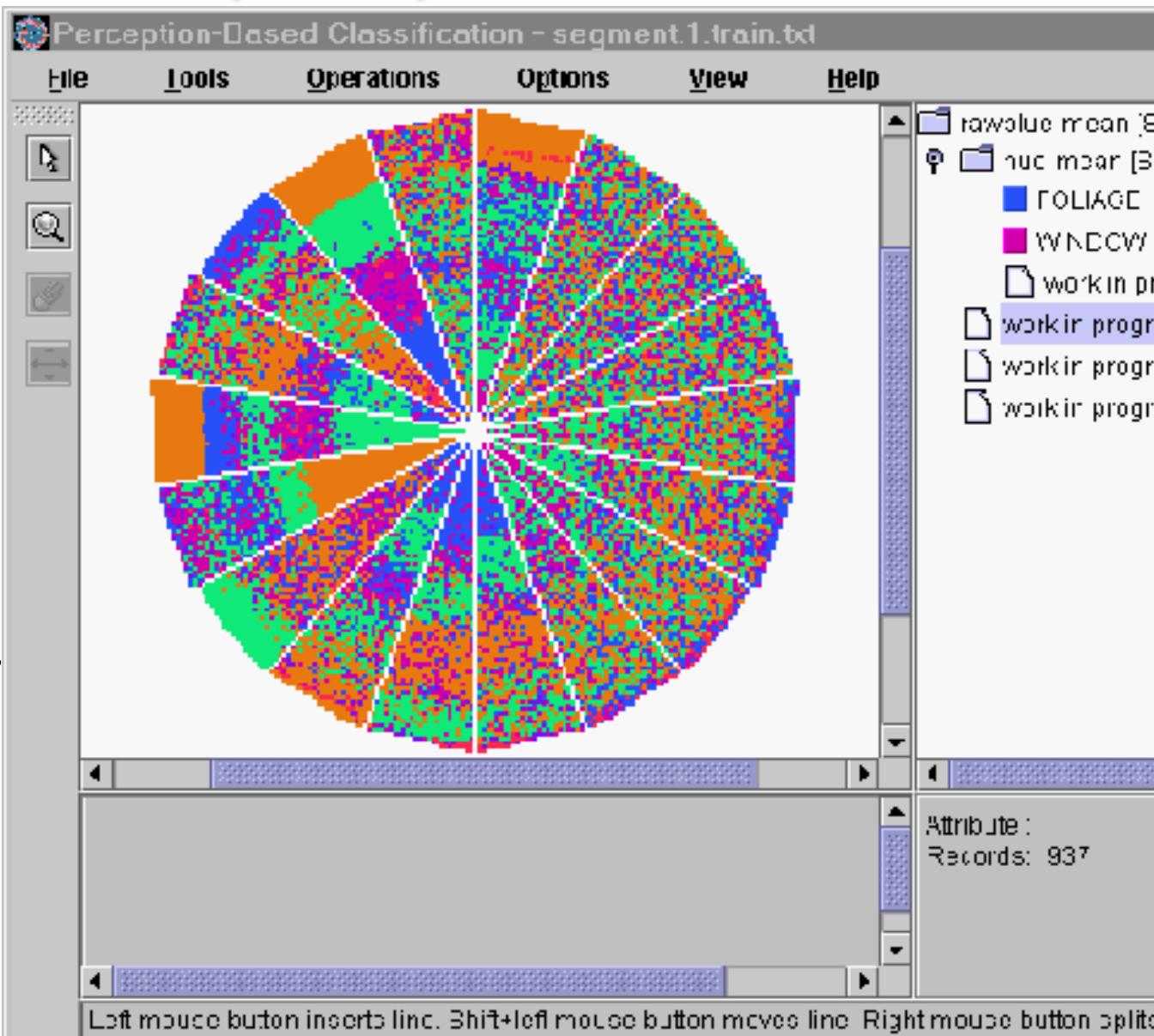


Visualization of a Decision Tree (in SGI/MineSet 3.0)

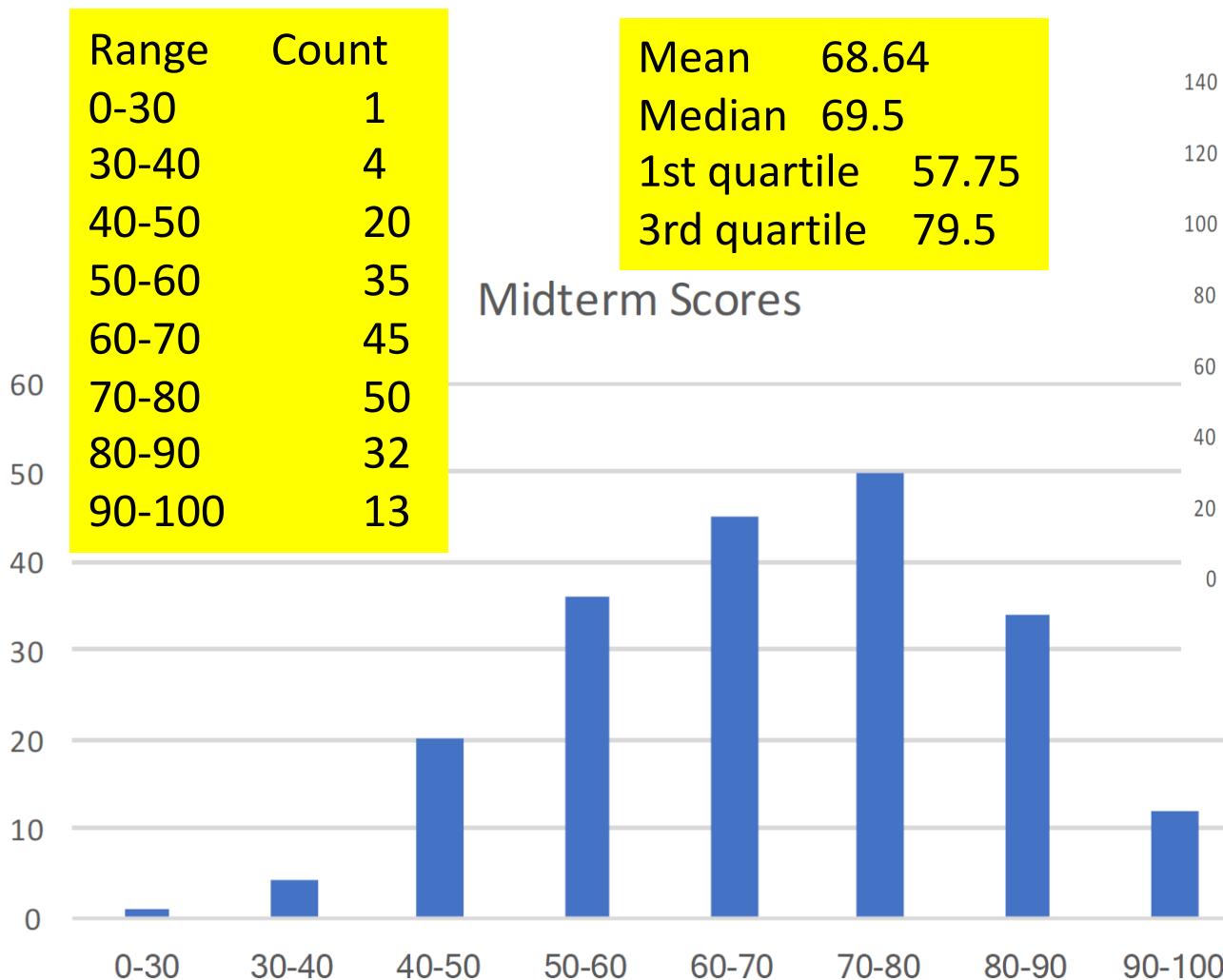


Interactive Visual Mining by Perception-Based Classification (PBC)

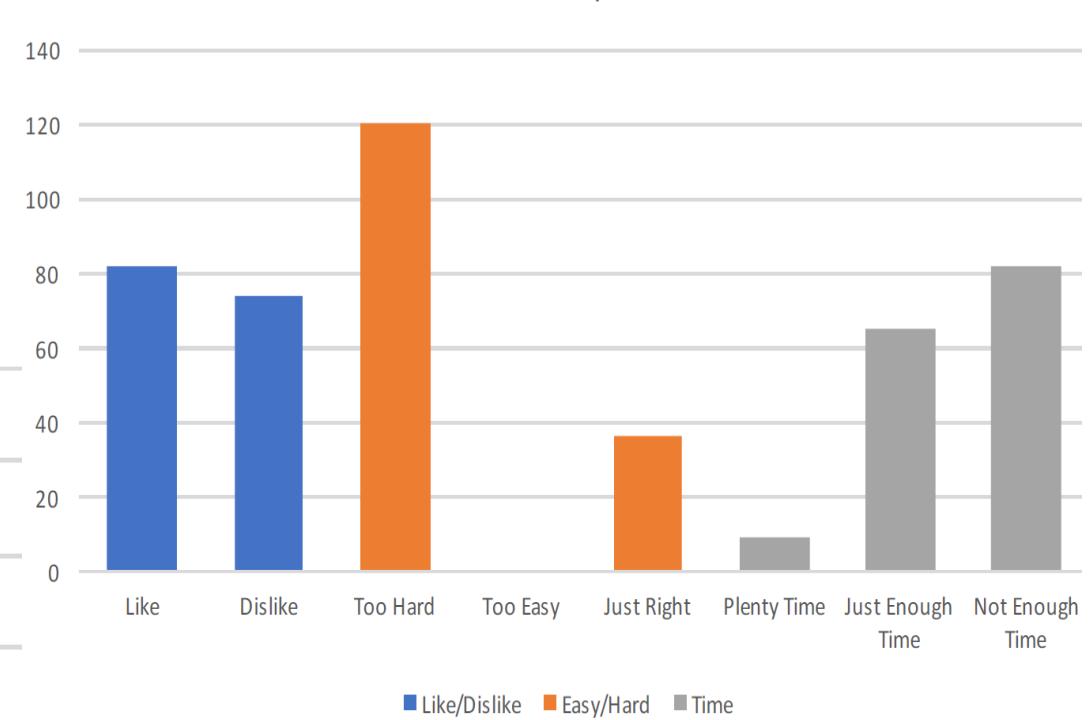
- ❑ Perception-based classifier (PCB): developed at Univ. of Munich (1999)
- ❑ One color represents one class label
- ❑ One pie represents one attribute (or variable)
- ❑ The pie with random spread implies weak classification power
- ❑ The pie with clearly partitioned color strips implies good classification power
- ❑ One can select a good attribute and regenerate new pie charts for classification at the subsequent levels



CS412-Fall 2017: Midterm Statistics



Midterm Options



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- ❑ Summary



What Is Bayesian Classification?

- A statistical classifier
 - Perform *probabilistic prediction* (*i.e.*, predict 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
- Theoretical 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:

$$p(B) = \sum_i p(B|A_i)p(A_i)$$

- Bayes' Theorem:

$$p(H|X) = \frac{p(X|H)p(H)}{p(X)} \propto p(X|H) p(H)$$

posteriori probability

What we should choose

likelihood

What we just see

prior probability

What we knew previously

- X : a data sample ("evidence")

Prediction can be done based on Bayes' Theorem:

- H : X belongs to class C

Classification is to derive the maximum posteriori

Naïve Bayes Classifier: Making a Naïve Assumption

- Practical difficulty of Naïve Bayes inference: It requires initial knowledge of many probabilities, which may not be available or involving significant computational cost
- A Naïve Special Case
 - Make an additional assumption to simplify the model, but achieve comparable performance.

attributes are conditionally independent
(i.e., no dependence relation between attributes)

$$p(X|C_i) = \prod_k p(x_k|C_i) = p(x_1|C_i) \cdot p(x_2|C_i) \cdots p(x_n|C_i)$$

- Only need to count the class distribution w.r.t. features

Naïve Bayes Classifier: Categorical vs. Continuous Valued Features

- If feature x_k is categorical, $p(x_k = v_k | C_i)$ is the # of tuples in C_i with $x_k = v_k$, divided by $|C_{i,D}|$ (# of tuples of C_i in D)

$$p(X|C_i) = \prod_k p(x_k|C_i) = p(x_1|C_i) \cdot p(x_2|C_i) \cdots p(x_n|C_i)$$

- If feature x_k is continuous-valued, $p(x_k = v_k | C_i)$ is usually computed based on Gaussian distribution with a mean μ and standard deviation σ

$$p(x_k = v_k | C_i) = N(x_k | \mu_{C_i}, \sigma_{C_i}) = \frac{1}{\sqrt{2\pi}\sigma_{C_i}} e^{-\frac{(x-v_{C_i})^2}{2\sigma^2}}$$

Naïve Bayes Classifier: Training Dataset

Class:

C1:`buys_computer = 'yes'`

C2:`buys_computer = 'no'`

Data to be classified:

X = (age ≤ 30 , Income = medium,

Student = yes, Credit_rating = Fair)

age	income	student	credit_rating	buys_computer
≤ 30	high	no	fair	no
≤ 30	high	no	excellent	no
31...40	high	no	fair	yes
> 40	medium	no	fair	yes
> 40	low	yes	fair	yes
> 40	low	yes	excellent	no
31...40	low	yes	excellent	yes
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≤ 30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
> 40	medium	no	excellent	no

Naïve Bayes Classifier: An Example

- $P(C_i)$: $P(\text{buys_computer} = \text{"yes"}) = 9/14 = 0.643$
 $P(\text{buys_computer} = \text{"no"}) = 5/14 = 0.357$
- Compute $P(X|C_i)$ for each class
 - $P(\text{age} = \text{"<=30"} | \text{buys_computer} = \text{"yes"}) = 2/9 = 0.222$
 - $P(\text{age} = \text{"<= 30"} | \text{buys_computer} = \text{"no"}) = 3/5 = 0.6$
 - $P(\text{income} = \text{"medium"} | \text{buys_computer} = \text{"yes"}) = 4/9 = 0.444$
 - $P(\text{income} = \text{"medium"} | \text{buys_computer} = \text{"no"}) = 2/5 = 0.4$
 - $P(\text{student} = \text{"yes"} | \text{buys_computer} = \text{"yes"}) = 6/9 = 0.667$
 - $P(\text{student} = \text{"yes"} | \text{buys_computer} = \text{"no"}) = 1/5 = 0.2$
 - $P(\text{credit_rating} = \text{"fair"} | \text{buys_computer} = \text{"yes"}) = 6/9 = 0.667$
 - $P(\text{credit_rating} = \text{"fair"} | \text{buys_computer} = \text{"no"}) = 2/5 = 0.4$

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
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<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no

- $X = (\text{age} \leq 30, \text{income} = \text{medium}, \text{student} = \text{yes}, \text{credit_rating} = \text{fair})$

$$P(X|C_i) : P(X|\text{buys_computer} = \text{"yes"}) = 0.222 \times 0.444 \times 0.667 \times 0.667 = 0.044$$

$$P(X|\text{buys_computer} = \text{"no"}) = 0.6 \times 0.4 \times 0.2 \times 0.4 = 0.019$$

$$P(X|C_i) * P(C_i) : P(X|\text{buys_computer} = \text{"yes"}) * P(\text{buys_computer} = \text{"yes"}) = 0.028$$

$$P(X|\text{buys_computer} = \text{"no"}) * P(\text{buys_computer} = \text{"no"}) = 0.007$$

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

Avoiding the Zero-Probability Problem

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

$$p(X|C_i) = \prod_k p(x_k|C_i) = p(x_1|C_i) \cdot p(x_2|C_i) \cdots p(x_n|C_i)$$

- Example. 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*

$$\text{Prob}(\text{income} = \text{low}) = 1/(1000 + 3)$$

$$\text{Prob}(\text{income} = \text{medium}) = (990 + 1)/(1000 + 3)$$

$$\text{Prob}(\text{income} = \text{high}) = (10 + 1)/(1000 + 3)$$

- The “corrected” probability estimates are close to their “uncorrected” counterparts

Naïve Bayes Classifier: Strength vs. Weakness

- ❑ Strength
 - ❑ Easy to implement
 - ❑ Good results obtained in most of the cases
- ❑ Weakness
 - ❑ Assumption: attributes conditional independence, therefore loss of accuracy
 - ❑ Practically, dependencies exist among variables
 - ❑ E.g., 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
- ❑ How to deal with these dependencies?
 - ❑ Use Bayesian Belief Networks (to be covered in the next chapter)

Chapter 8. Classification: Basic Concepts

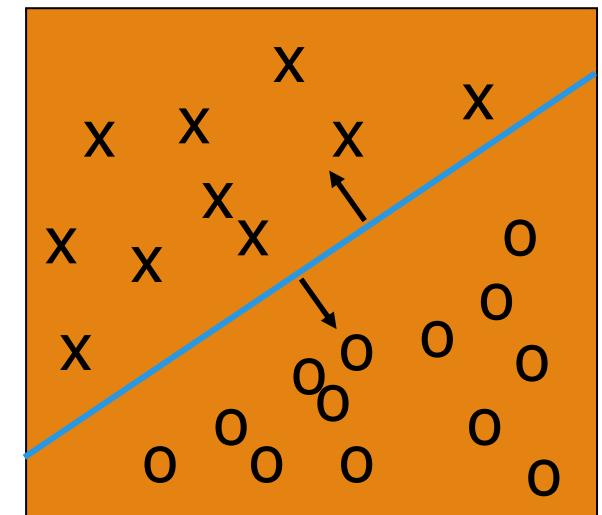
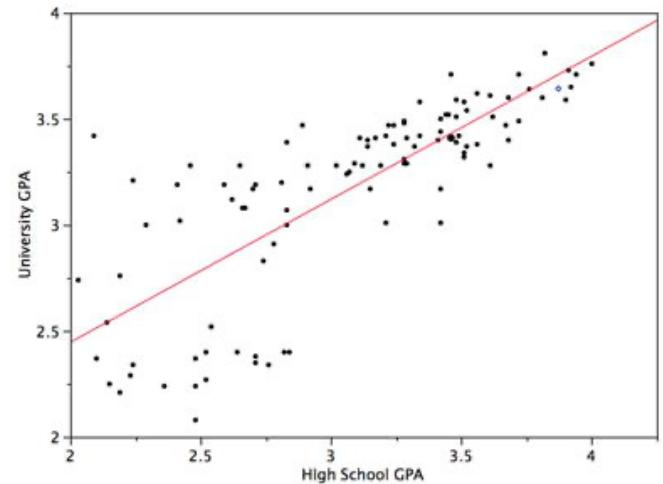
- ❑ Classification: Basic Concepts
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Linear Regression vs. Linear Classifier

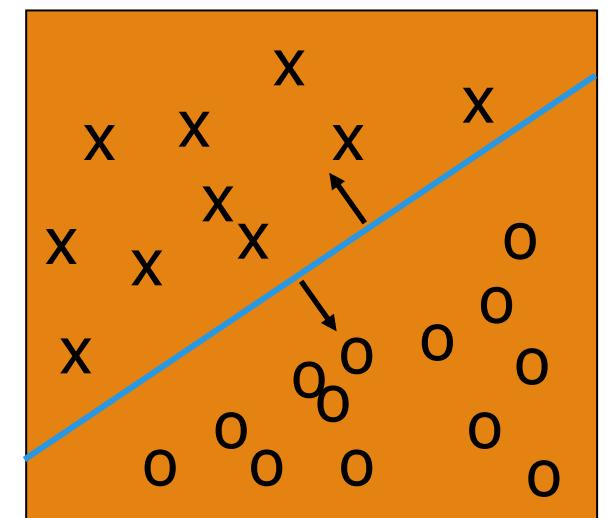
- ❑ Linear regression
 - ❑ Data modeled to fit a straight line
 - ❑ *Linear equation: $Y = w X + b$*
 - ❑ Often uses the least-square method to fit the line
 - ❑ Used to predict continuous values

- ❑ Linear Classifier
 - ❑ Built a classification model using a straight line
 - ❑ Used for (categorical data) binary classification



Linear Classifier: General Ideas

- Binary Classification
- $f(x)$ is a linear function based on the example's attribute values
 - The prediction is based on the value of $f(x)$
 - Data above the blue line belongs to class 'x' (i.e., $f(x) > 0$)
 - Data below blue line belongs to class 'o' (i.e., $f(x) < 0$)
- Classical Linear Classifiers
 - Linear Discriminant Analysis (LDA) (not covered)
 - Logistic Regression
 - Perceptron (later)
 - SVM (later)

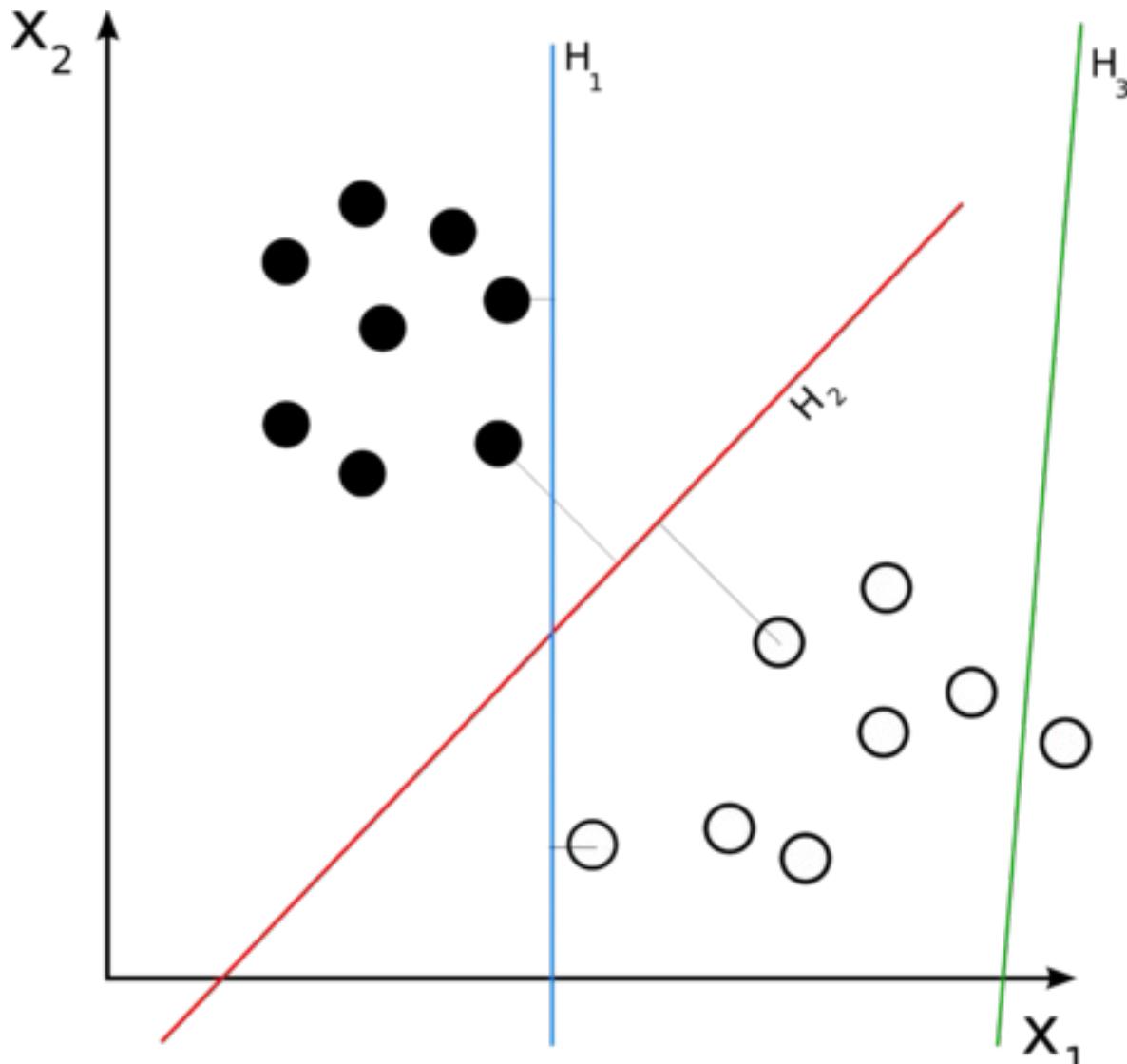


Linear Classifier: An Example

- A toy rule to determine whether a faculty member has tenure
 - Year ≥ 6 or Title = “Professor” \Leftrightarrow Tenure
- How to express the rule as a linear classifier?
- Features
 - $x_1 (x_1 \geq 0)$ is an integer denoting the year
 - x_2 is a Boolean denoting whether the title is “Professor”
- A feasible linear classifier: $f(x) = (x_1 - 5) + 6 \cdot x_2$
 - When x_2 is True, because $x_1 \geq 0$, $f(x)$ is always greater than 0
 - When x_2 is False, because $f(x) > 0 \Leftrightarrow x_1 \geq 6$
- There are many more feasible classifiers
 - $f(x) = (x_1 - 5.5) + 6 \cdot x_2$
 - $f(x) = 2 \cdot (x_1 - 5) + 11 \cdot x_2$
 -

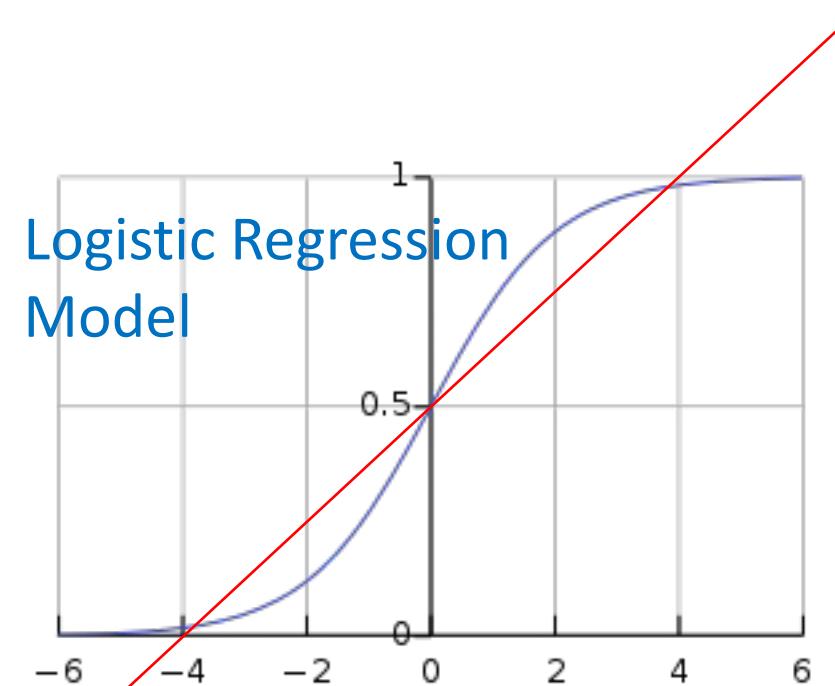
Key Question: Which Line Is Better?

- ❑ There might be many feasible linear functions
 - ❑ Both H_1 and H_2 will work
- ❑ Which one is better?
 - ❑ H_2 looks “better” in the sense that it is also furthest from both groups
- ❑ We will introduce more in the SVM section



Logistic Regression: General Ideas

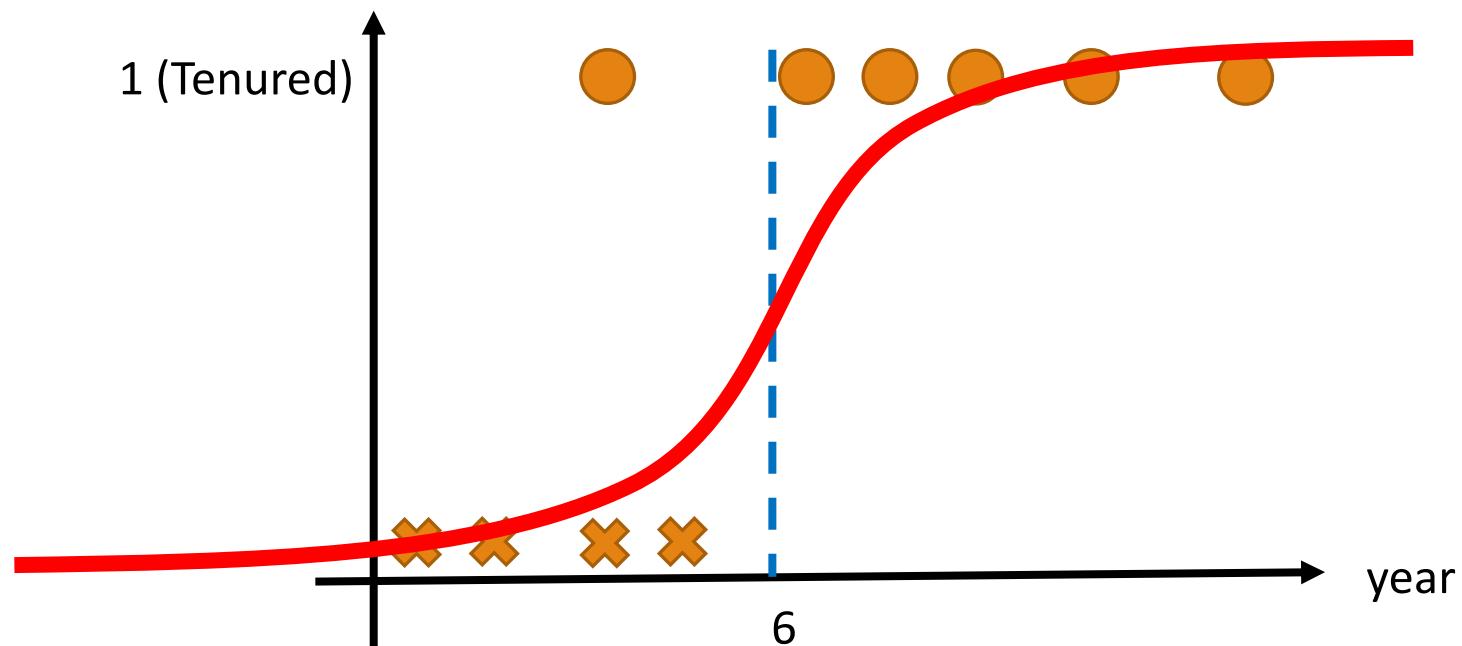
- Key Idea: Turns linear predictions into probabilities
- Sigmoid function:
 - $S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1}$
 - Projects $(-\infty, +\infty)$ to $[0, 1]$
- Compare to linear probability model
- More smooth



Linear Probability
Model

Logistic Regression: An Example

- Suppose we only consider the year as feature



Logistic Regression: Maximum Likelihood

- The prediction function to learn

- $p(Y = 1 | X = x; \mathbf{w}) = S(w_0 + \sum_{i=1}^n w_i \cdot x_i)$
 - $\mathbf{w} = (w_0, w_1, w_2, \dots, w_n)$ are the parameters

- Maximum Likelihood

- Log likelihood:

$$l(\mathbf{w}) = \sum_{i=1}^N y_i \log p(Y = 1 | X = x_i; \mathbf{w}) + (1 - y_i) \log(1 - p(Y = 1 | X = x_i; \mathbf{w}))$$

- There's no close form solution

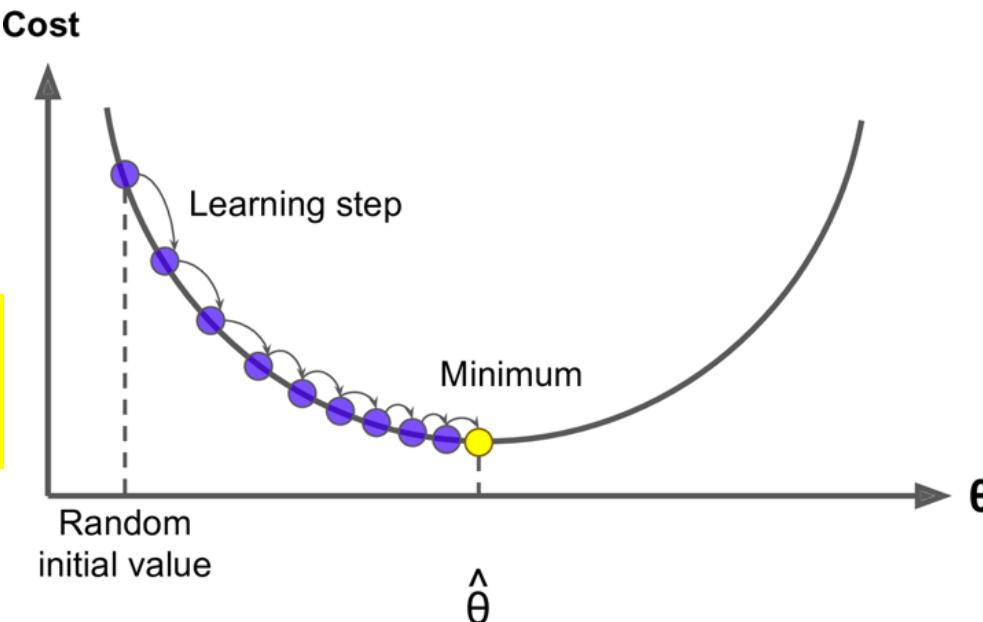
- Gradient Descent
 - Update \mathbf{w} based on training data
 - Chain-rule for the gradient

Gradient Descent

- Gradient Descent is an iterative optimization algorithm for finding the minimum of a function (e.g., the negative log likelihood)
- For a function $F(x)$ at a point a , $F(x)$ decreases fastest if we go in the direction of the negative gradient of a

$$\mathbf{a}_{n+1} = \mathbf{a}_n - \gamma \nabla F(\mathbf{a}_n)$$

When the gradient is zero, we arrive at the local minimum



Generative vs. Discriminative Classifiers

- X: observed variables (features)
- Y: target variables (class labels)
- A generative classifier models $p(Y, X)$
 - It models how the data was "generated"? "what is the likelihood this or that class generated this instance?" and pick the one with higher probability
- Naïve Bayes
- Bayesian Networks
- A discriminative classifier models $p(Y|X)$
 - It uses the data to create a decision boundary
- Logistic Regression
- Support Vector Machines

Further Comments on Discriminative Classifiers

- Strength
 - Prediction accuracy is generally high
 - As compared to generative models
 - Robust, works when training examples contain errors
 - Fast evaluation of the learned target function
 - Comparing to [\(covered in future\)](#) Bayesian networks (which are normally slow)
- Criticism
 - Long training time
 - Difficult to understand the learned function (weights)
 - Bayesian networks can be used easily for pattern discovery
 - Not easy to incorporate domain knowledge
 - Easy in the form of priors on the data or distributions

Chapter 8. Classification: Basic Concepts

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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
 - Cross-validation
 - Bootstrap
- Comparing classifiers:
 - ROC Curves

Classifier Evaluation Metrics: Confusion Matrix

- Confusion Matrix:

Actual class\Predicted class	C_1	$\neg C_1$
C_1	True Positives (TP)	False Negatives (FN)
$\neg C_1$	False Positives (FP)	True Negatives (TN)

- In a confusion matrix w. m classes, $CM_{i,j}$ indicates # of tuples in class i that were labeled by the classifier as class j
 - May have extra rows/columns to provide totals
- 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

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
 - Measures handle the class imbalance problem
- **Sensitivity** (recall): True positive recognition rate
 - **Sensitivity = TP/P**
- **Specificity**: True negative recognition rate
 - **Specificity = TN/N**

Defaut	Recall ↑	F1 ↑
$\geq 90\% \rightarrow P$	$\geq 15\% \rightarrow P$	$\geq 80\% \rightarrow P$
	$R = 100\%$	$R = \frac{2}{3}$
	$P = \frac{3}{5}$	$P = 60\%$
M_1	M_2	M_3
๕๖๘๙๔๗๕๓๑๖	P, R	

Precision រួចកិន្តា $\rightarrow M_3$ ត្រូវ នៅលើ M_3 : $P = 100\%$.

Recall រួចកិន្តា $\rightarrow M_3$ ត្រូវ នៅលើ M_3 : $R = 100\%$.

នៃ F1-score នូវ P នូវ R

$$F_1 = \frac{2 \times P \times R}{P + R}$$

M_2

$$\cdot P = \frac{3}{5} = 0.6$$

$$\cdot R = 100\% = 1.0$$

$$F_1_{M_2} = \frac{2 \times 0.6 \times 1.0}{0.6 + 1.0} = 2 \times \frac{0.6}{1.6} = 2 \times 0.375 = 0.75$$

M_2

$$\cdot P = 100\% = 1.0$$

$$\cdot R = \frac{2}{3} \approx 0.667$$

$$F_1_{M_3} = \frac{2 \times 1.0 \times 0.667}{1.0 + 0.667} = 0.8$$

∴ នៃ F1-score នៅ M_3 រួចកិន្តា M_2 នូវលក្ខណៈ M_3 ។

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

- ❑ **Precision:** Exactness: what % of tuples that the classifier labeled as positive are actually positive?

$$P = \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

- ❑ **Recall:** Completeness: what % of positive tuples did the classifier label as positive?

$$R = \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- ❑ Range: $[0, 1]$
- ❑ The “inverse” relationship between precision & recall
- ❑ **F measure (or F-score):** harmonic mean of precision and recall
- ❑ In general, it is the weighted measure of precision & recall

$$F_{\beta} = \frac{1}{\alpha \cdot \frac{1}{P} + (1 - \alpha) \cdot \frac{1}{R}} = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

Assigning β times as much weight to recall as to precision)

- ❑ **F1-measure (balanced F-measure)**

- ❑ That is, when $\beta = 1$,

$$F_1 = \frac{2PR}{P + R}$$

Classifier Evaluation Metrics: Example

- Use the same confusion matrix, calculate the measure just introduced

Actual Class\Predicted class	cancer = yes	cancer = no	Total	Recognition(%)
cancer = yes	90	210	300	30.00 (<i>sensitivity</i>)
cancer = no	140	9560	9700	98.56 (<i>specificity</i>)
Total	230	9770	10000	96.50 (<i>accuracy</i>)

- Sensitivity = $TP/P = 90/300 = 30\%$
- Specificity = $TN/N = 9560/9700 = 98.56\%$
- Accuracy = $(TP + TN)/All = (90+9560)/10000 = 96.50\%$
- Error rate = $(FP + FN)/All = (140 + 210)/10000 = 3.50\%$
- Precision = $TP/(TP + FP) = 90/(90 + 140) = 90/230 = 39.13\%$
- Recall = $TP/ (TP + FN) = 90/(90 + 210) = 90/300 = 30.00\%$
- $F1 = 2 P \times R / (P + R) = 2 \times 39.13\% \times 30.00\% / (39.13\% + 30\%) = 33.96\%$

Classifier Evaluation: Holdout & Cross-Validation

- **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
 - Repeated random sub-sampling validation: 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 distribution, in each fold is approximately the same as that in the initial data

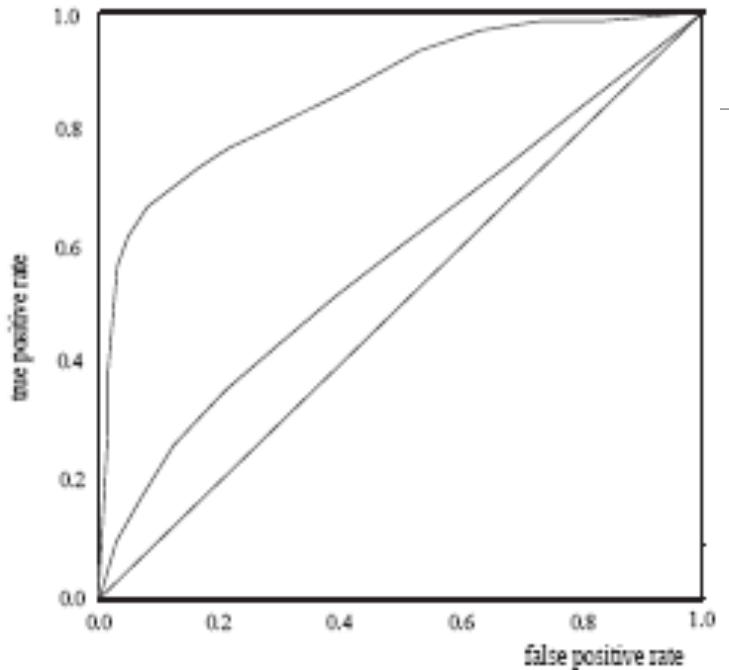
Classifier Evaluation: Bootstrap

- **Bootstrap**
 - Works well with small data sets
 - Samples the given training tuples uniformly *with replacement*
 - 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 bootstrap**
 - 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
- ❑ Originated from signal detection theory
- ❑ Shows the trade-off between the true positive rate and the false positive rate
- ❑ The area under the ROC curve (**AUC**: Area Under 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

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

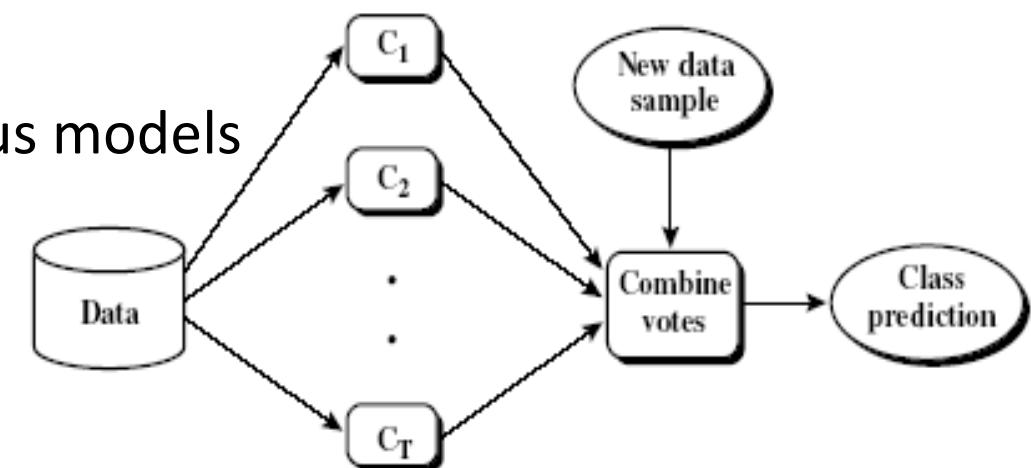
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Ensemble Methods: Increasing the Accuracy

- ❑ Ensemble methods
 - ❑ Use a combination of models to increase accuracy
 - ❑ Combine a series of k learned models, M_1, M_2, \dots, M_k , with the aim of creating an improved model M^*
- ❑ Popular ensemble methods
 - ❑ Bagging: Trains each model using a subset of the training set, and models learned in parallel
 - ❑ Boosting: Trains each new model instance to emphasize the training instances that previous models mis-classified, and models learned in order



Bagging: Bootstrap 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: It can be applied to the prediction of continuous values by taking the average value of each prediction for a given test tuple
- Accuracy: Improved accuracy in prediction
 - Often significantly better than a single classifier derived from D
 - For noise data: Not considerably worse, more robust

Random Forest: Basic Concepts

- Random Forest (first proposed by L. Breiman in 2001)
 - A variation of bagging for *decision trees*
 - *Data bagging*
 - Use a subset of training data by sampling with replacement for each tree
 - *Feature bagging*
 - At each node use a random selection of attributes as candidates and split by the best attribute among them
 - Compared to original bagging, increases the diversity among generated trees
 - During classification, each tree votes and the most popular class is returned

Random Forest

- 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 typical bagging or boosting

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

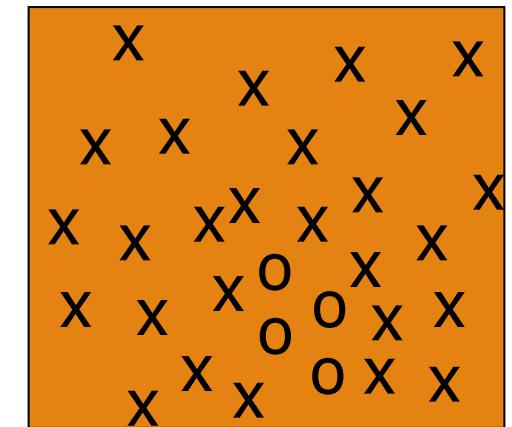
Adaboost (Freund and Schapire, 1997)

- Given a set of d class-labeled tuples, $(\mathbf{X}_1, y_1), \dots, (\mathbf{X}_d, y_d)$
- 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; otherwise, it is decreased
- Error rate: $\text{err}(\mathbf{X}_j)$ is the misclassification error of tuple \mathbf{X}_j . Classifier M_i error rate is the sum of the weights of the misclassified tuples:
- The weight of classifier M_i 's vote is
$$\log \frac{1 - \text{error}(M_i)}{\text{error}(M_i)}$$

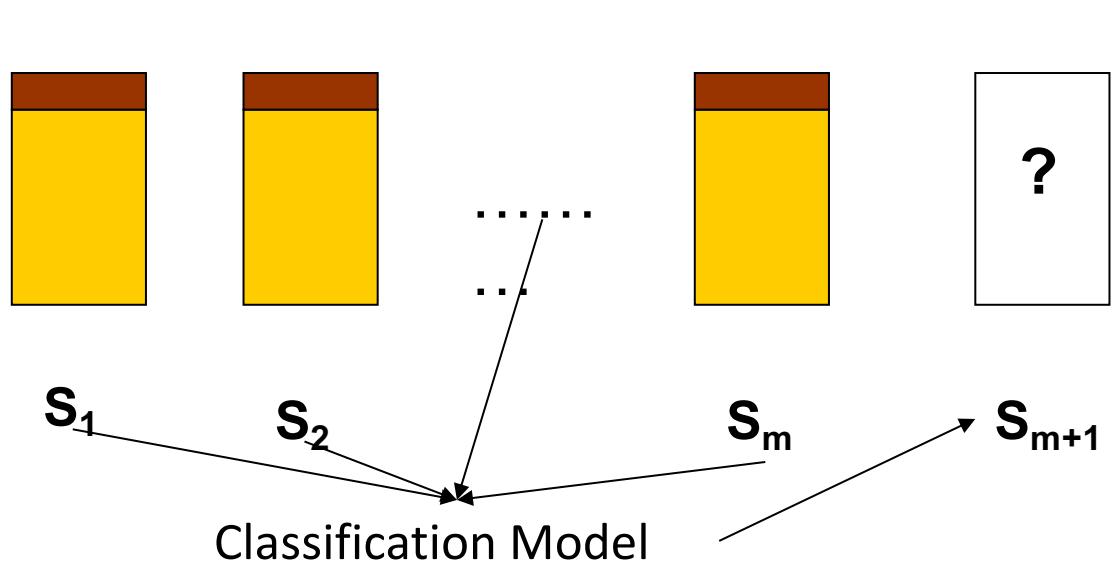
$$\text{error}(M_i) = \sum_j^d w_j \times \text{err}(\mathbf{X}_j)$$

Classification of Class-Imbalanced Data Sets

- Class-imbalance problem: Rare positive examples but numerous negative ones
 - E.g., medical diagnosis, fraud transaction, accident (oil-spill), and product fault
- Traditional methods assume a balanced distribution of classes and equal error costs: not suitable for class-imbalanced data
- Typical methods on imbalanced data in two-class classification
 - **Oversampling:** Re-sampling of data from positive class
 - **Under-sampling:** Randomly eliminate tuples from negative class
 - **Threshold-moving:** Move 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



Classifying Data Streams with Skewed Distribution



S_m as training data? Two few positive examples!

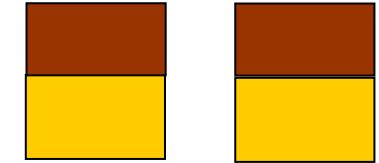
J. Gao, et al., "A General Framework for Mining Concept-Drifting Data Streams with Skewed Distributions", SDM'07

Biased Sampling



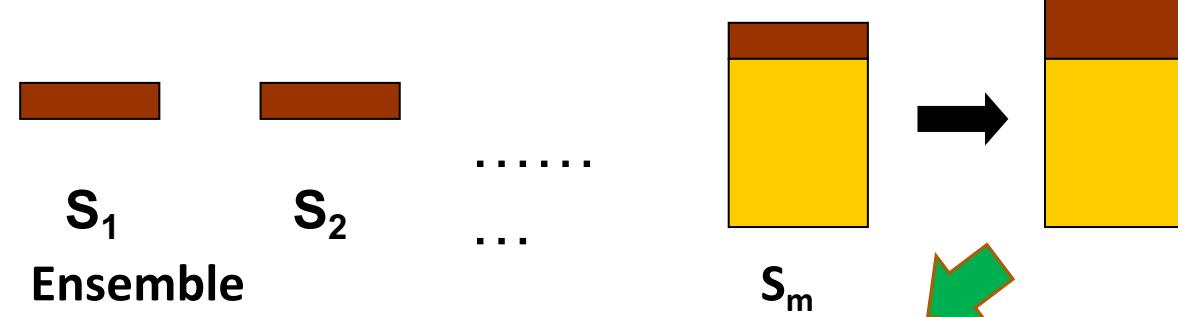
S_1, S_2, \dots, S_m

Ensemble



C_1, C_2, \dots, C_k

$$f^E(x) = \frac{1}{k} \sum_{i=1}^k f^i(x)$$



- Classify data stream with skewed distribution (i.e., rare events)
- **Biased sampling:** Save only the positive examples in the streams
- **Ensemble:** Partition negative examples of S_m into k portions to build k classifiers
- Effectively reduce classification errors on the minority class

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- ❑ Summary

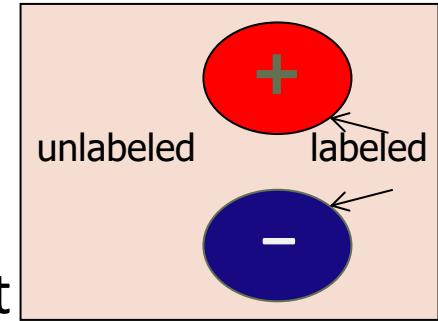


Multiclass Classification

- Classification involving more than two classes (i.e., > 2 Classes)
- Methodology: Reducing the multi-class problem into multiple binary problems
- Method 1. **One-vs.-rest** (or **one-vs.-all**)
 - Given m classes, train m classifiers: one for each class
 - Classifier j: treat tuples in class j as *positive* & **all the rest** as *negative*
 - To classify a tuple X , the set of classifiers vote as an ensemble
- Method 2. **one-vs.-one** (or **all-vs.-all**): 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: One-vs.-one tends to perform better than one-vs.-rest
- Many new algorithms have been developed to go beyond binary classifier method

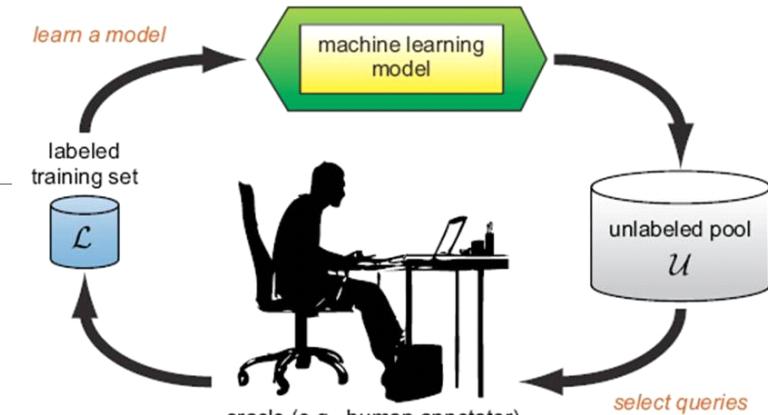
Semi-Supervised Classification

- ❑ Semi-supervised: Uses labeled and unlabeled data to build a classifier
- ❑ Self-training
 - ❑ Build a classifier using the labeled data
 - ❑ Use it to label the unlabeled data, and those with the most confident label prediction are added to the set of labeled data
 - ❑ Repeat the above process
 - ❑ Adv.: easy to understand; Disadv.: may reinforce errors
- ❑ Co-training: Use two or more classifiers to teach each other
 - ❑ Each learner uses a mutually independent set of features of each tuple to train a good classifier, say f_1 and f_2
 - ❑ Then f_1 and f_2 are used to predict the class label for unlabeled data X
 - ❑ Teach each other: The tuple having the most confident prediction from f_1 is added to the set of labeled data for f_2 & vice versa
- ❑ Other methods include joint probability distribution of features and labels



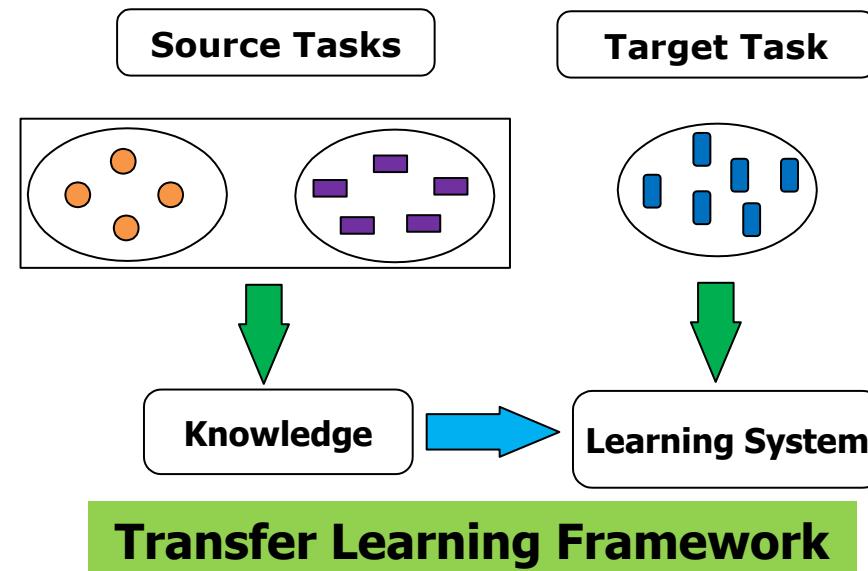
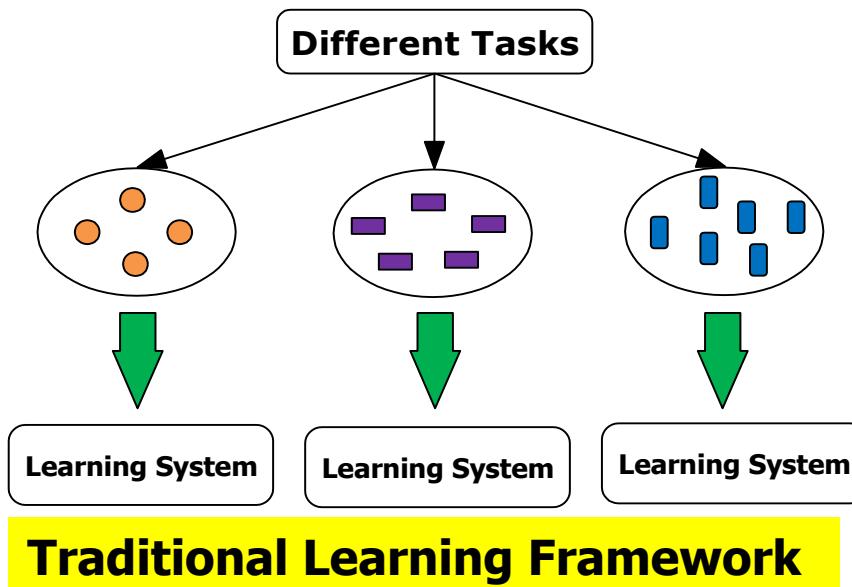
Active Learning

- A special case of semi-supervised learning
 - Unlabeled data: Abundant
 - Class labels are expensive to obtain
- Active learner: Interactively query teachers (oracle) for labels
- Pool-based approach: Uses a pool of unlabeled data
 - L: a small subset of D is labeled, U: a pool of unlabeled data in D
 - Use a query function to carefully select one or more tuples from U and request labels from an oracle (a human annotator)
 - The newly labeled samples are added to L, and learn a model
 - Goal: **Achieve high accuracy using as few labeled data as possible**
- Evaluated using *learning curves*: Accuracy as a function of the number of instances queried (# of tuples to be queried should be small)
- A lot of algorithms have been developed for active learning



Transfer Learning: Conceptual Framework

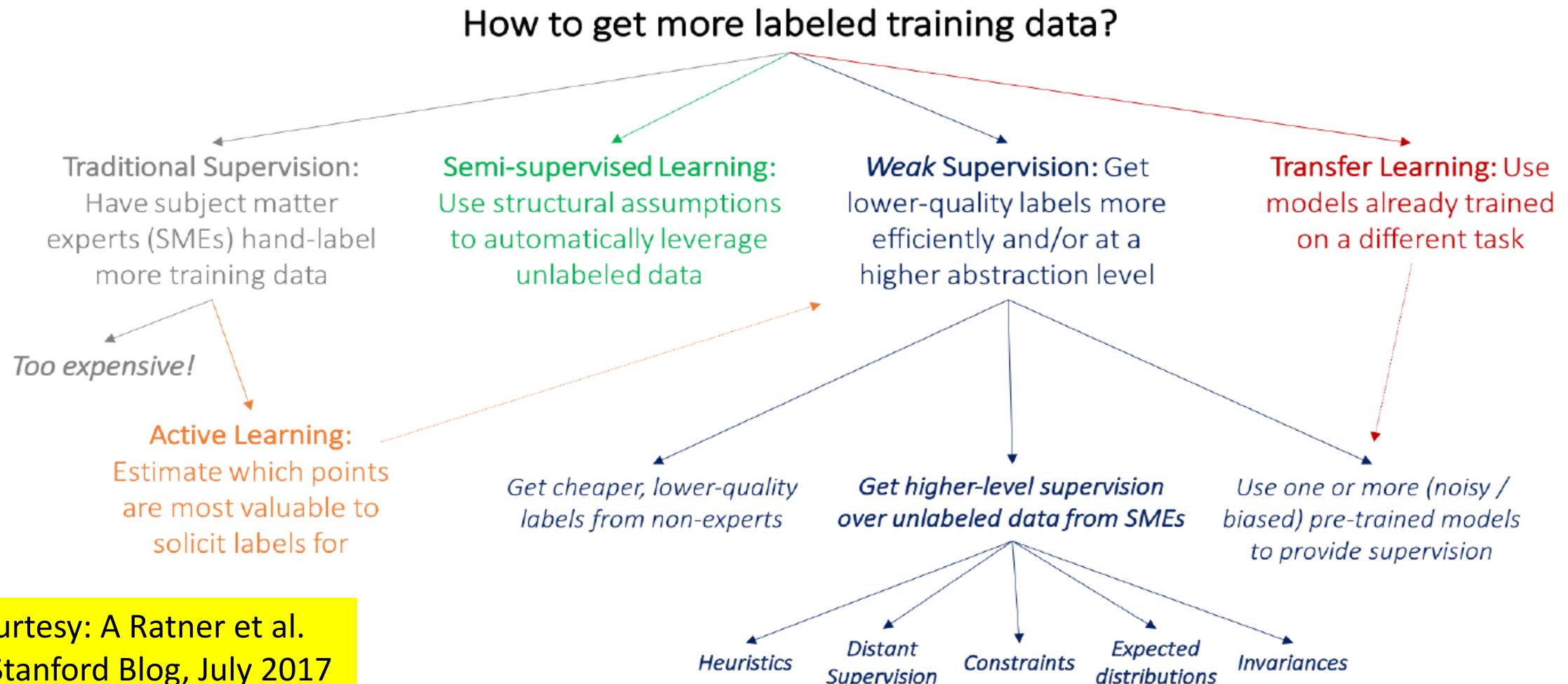
- Transfer learning: Extract knowledge from one or more source tasks (e.g., recognizing cars) and apply the knowledge to a target task (e.g., recognizing trucks)
- Traditional learning: Build a new classifier for each new task
- Transfer learning: Build new classifier by applying existing knowledge learned from source tasks
- Many algorithms are developed, applied to text classification, spam filtering, etc.



Weak Supervision: A New Programming Paradigm for Machine Learning

- ❑ Overcome the training data bottleneck
 - ❑ Leverage higher-level and/or noisier input from experts
- ❑ Exploring weak label distributions provided more cheaply and efficiently by
 - ❑ Higher-level, less precise supervision (e.g., heuristic rules, expected label distributions)
 - ❑ Cheaper, lower-quality supervision (e.g. crowdsourcing)
 - ❑ Existing resources (e.g. knowledge bases, pre-trained models)
- ❑ These weak label distributions could take many forms
 - ❑ Weak Labels from crowd workers, output of heuristic rules, or the result of distant supervision (from KBs), or the output of other classifiers, etc.
 - ❑ Constraints and invariances (e.g., from physics, logic, or other experts)
 - ❑ Probability distributions (e.g., from weak or biased classifiers or user-provided label or feature expectations or measurements)

Relationships Among Different Kinds of Supervisions



Courtesy: A Ratner et al.
@Stanford Blog, July 2017

Many areas of machine learning are motivated by the bottleneck of labeled training data, but are divided at a high-level by what information they leverage instead.

Chapter 8. Classification: Basic Concepts

- ❑ Classification: Basic Concepts
- ❑ Decision Tree Induction
- ❑ Bayes Classification Methods
- ❑ Linear Classifier
- ❑ Model Evaluation and Selection
- ❑ Techniques to Improve Classification Accuracy: Ensemble Methods
- ❑ Additional Concepts on Classification
- ❑ Summary



Summary

- Classification: Model construction from a set of training data
- Effective and scalable methods
 - Decision tree induction, Bayes classification methods, linear classifier, ...
 - No single method has been found to be superior over all others for all data sets
- Evaluation metrics: Accuracy, sensitivity, specificity, precision, recall, F measure
- Model evaluation: Holdout, cross-validation, bootstrapping, ROC curves (AUC)
- Improve Classification Accuracy: Bagging, boosting
- Additional concepts on classification: Multiclass classification, semi-supervised classification, active learning, transfer learning, weak supervision

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

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 $\mathbf{X} = (x_1, x_2, \dots, x_n)$
- Suppose there are m classes C_1, C_2, \dots, 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

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

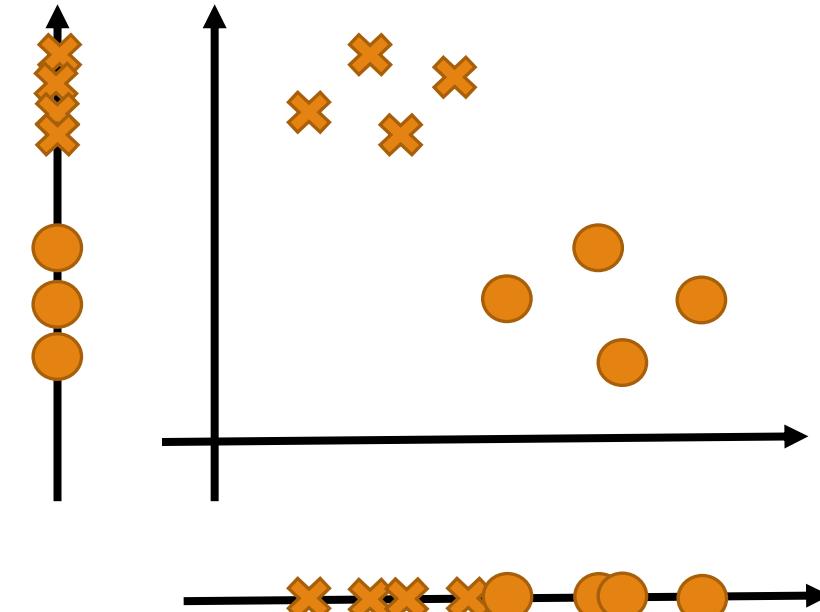
- Since $P(X)$ is constant for all classes, only

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

needs to be maximized

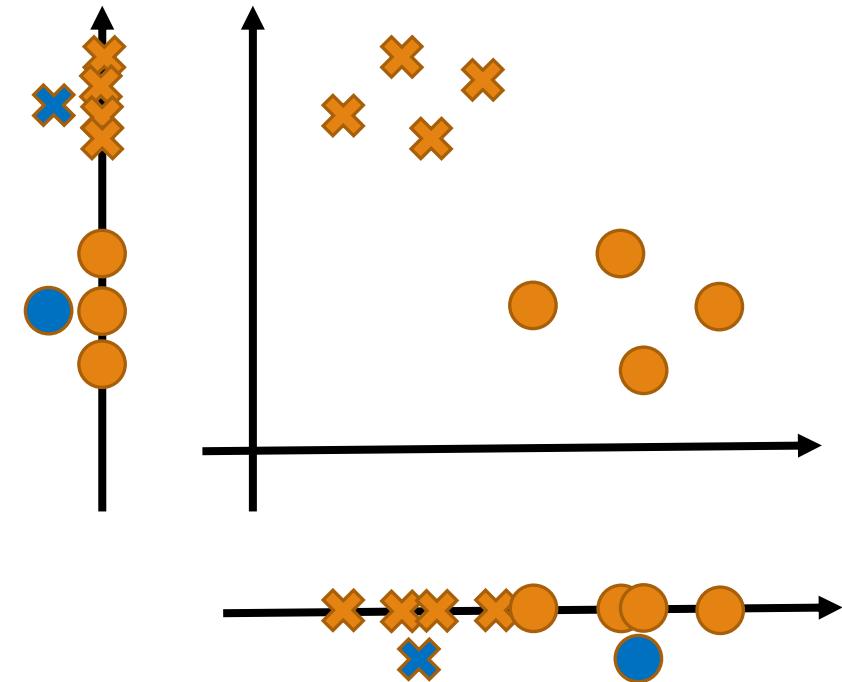
Linear Discriminant Analysis (LDA)

- ❑ Linear Discriminant Analysis (LDA) works when the attributes are all continuous
 - ❑ For the categorical attributes, discriminant correspondence analysis is the equivalent technique
- ❑ Basic Ideas: Project all samples on a line such that different classes are well separated
- ❑ Example: Suppose we have 2 classes and 2-dimensional samples x_1, \dots, x_n
 - ❑ n_1 samples come from class 1
 - ❑ n_2 samples come from class 2
- ❑ Let the line direction be given by unit vector \boldsymbol{v}
- ❑ There are two candidates of projections
 - ❑ Vertical: $\boldsymbol{v} = (0,1)$
 - ❑ Horizontal: $\boldsymbol{v} = (1,0)$
- ❑ Which one looks better?
- ❑ How to mathematically measure it?



Fisher's LDA (Linear Discriminant Analysis)

- ❑ $v^T x_i$ is the distance of projection of x_i from the origin
- ❑ Let μ_1 and μ_2 be the means of class 1 and class 2 in the original space
 - ❑ $\mu_1 = \frac{1}{n_1} \sum_{i \in \text{class 1}} x_i$
 - ❑ $\mu_2 = \frac{1}{n_2} \sum_{i \in \text{class 2}} x_i$
- ❑ The distance between the means of the projected points
 - ❑ $|v^T \mu_1 - v^T \mu_2|$
 - ❑ Good? No. Horizontal one may have larger distance



Fisher's LDA (con't)

- ❑ Normalization needed
- ❑ Scatter: Sample variance multiplied by n

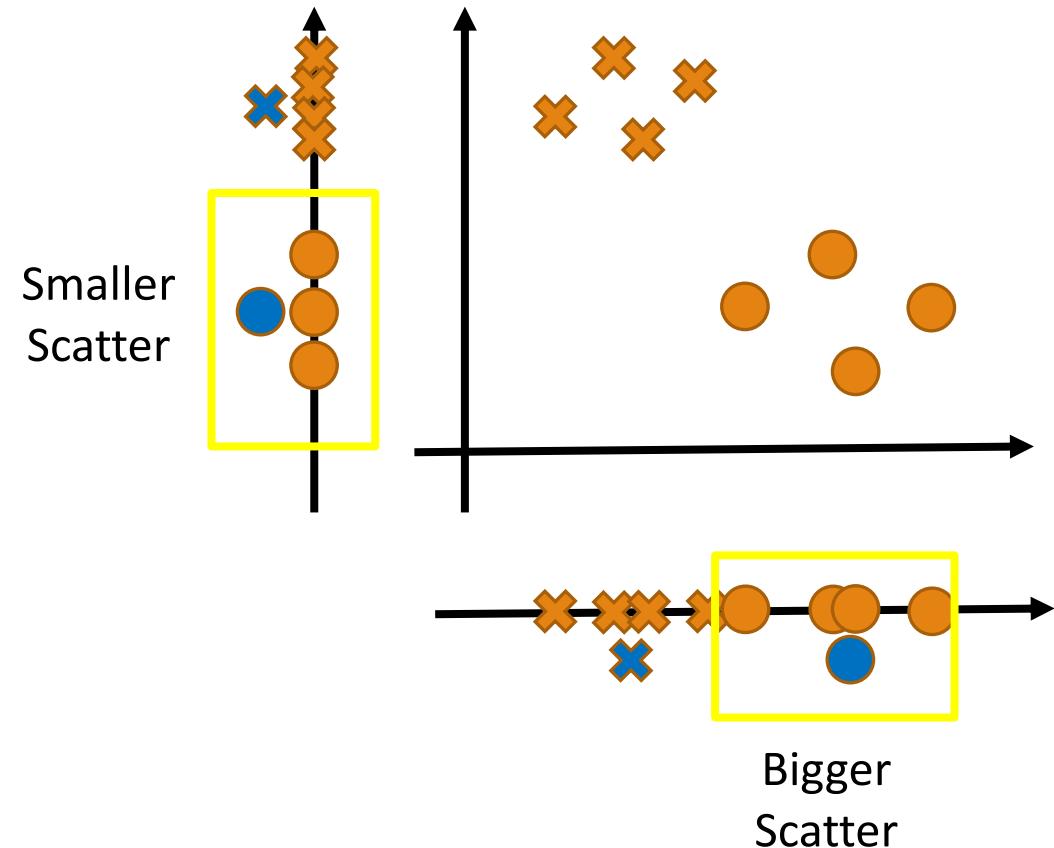
- ❑ $s_1 = \sum_{i \in \text{class 1}} (\mathbf{v}^T \mathbf{x}_i - \mathbf{v}^T \boldsymbol{\mu}_1)^2$

- ❑ $s_2 = \sum_{i \in \text{class 2}} (\mathbf{v}^T \mathbf{x}_i - \mathbf{v}^T \boldsymbol{\mu}_2)^2$

- ❑ Fisher's LDA

- ❑ Maximize $J(\mathbf{v}) = \frac{(\mathbf{v}^T \boldsymbol{\mu}_1 - \mathbf{v}^T \boldsymbol{\mu}_2)^2}{s_1 + s_2}$

- ❑ Closed-form optimal solution



Fisher's LDA: Summary

- Advantages
 - Useful for dimension reduction
 - Easy to extend to multi-classes

- Fisher's LDA will fail
 - When $\mu_1 = \mu_2, J(\nu)$ is always 0.
 - When classes have large overlap when projected to any line