Business Intelligence

Week 7

Data Mining Techniques

- Frequent Pattern Mining
- Association Rule mining
- Classification
- Model Evaluation and Selection

Tilahun Melak(PhD)

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Objectives

At the end of this lecture students will be able to :

- Understand the principles of frequent pattern mining and association rule mining
- Explain supervised and unsupervised learning techniques
- Explain classification and prediction methods
- Discuss Decision Tree and Naïve Bayes classifiers
- Evaluate and compare the performance of different classifiers

Frequent Pattern and Association Mining

- We look into the following questions:
  - How can we find frequent itemsets from large amounts of data, where the data are either transactional or relational?
  - How can we mine association rules in multilevel and multidimensional space?
  - Which association rules are the most interesting?
  - How can we help or guide the mining procedure to discover interesting associations or correlations?
  - How can we take advantage of user preferences or constraints to speed up the mining process?

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Frequent Pattern and Association Mining

- Frequent itemset mining leads to the discovery of associations and correlations among items in large transactional or relational data sets.
- With massive amounts of data continuously being collected and stored, many industries are becoming interested in mining frequent itemset patterns from their databases.
- The discovery of interesting correlation relationships among huge amounts of business transaction records can help in many business decision-making processes such as:
  - market basket analysis, catalog design, cross-marketing, loss-leader analysis and customer shopping behavior analysis.

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Frequent Pattern and Association Mining

- Rule form: "Body (X) -> Head (Y) [support, confidence]".
- Which is read as if body (X) then head (Y) will occur together in the transaction with the stated support and confidence
- Rule support and confidence are two measures of rule **interestingness**. They respectively reflect the **usefulness** and **certainty** of discovered rules.
- Typically, association rules are considered interesting if they satisfy both a minimum support threshold and a minimum confidence threshold.
- Such thresholds can be set by users or domain experts.

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Frequent Pattern and Association Mining

- *The rule A ➔ B holds in the transaction set D* with **support** *s, where s is the percentage of transactions in D that contain A∪B (i.e., the union of itemsets A and B, or say, both A and B).*

- *This is taken to be the probability, P(A ∪ B) =*

$$\frac{\text{\# of transaction with itemset A} \cup \text{B}}{\text{\#of total transaction}}$$

- Support shows the probability that all the predicates in A and B fulfill together.
  - Count of tuples that has both A and B divided by total number of tuples in the working data set

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Frequent Pattern and Association Mining

- The rule *A* ➔ *B has* ***confidence*** *c in the transaction set D, where c is the percentage of* transactions in *D containing A that also contain B.*
- *This is taken to be the conditional* probability, *P(B|A)=*

$$\frac{\#\text{ of transaction with itemset } A \cup B}{\#\text{of transactionwith itemset } A}$$

- Confidence measure how often predicates B fulfilled if predicate A get fulfilled.
  - Count of tuples that has both A and B together divided by total number of tuples that has A
- *That is*

$$support(A \rightarrow B) = P(A \cup B)$$
$$confidence(A \rightarrow B) = P(B|A)$$

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Frequent Pattern and Association Mining

- In order to mine association rule using frequent itemset from a database, we should perform the following basic steps

1. Find the *frequent itemsets*:
   - the sets of items that have minimum support
   - A subset of a frequent itemset must also be a frequent itemset i.e., if {*AB*} is a frequent itemset, both {*A*} and {*B*} should be a frequent itemset
   - A number of algorithms are suggested to find the set of frequent items
2. Use the frequent itemsets to generate association rules.

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Algorithm to find Frequent Itemsets

1. **The apriori algorithm:**
   - Iteratively find frequent itemsets with cardinality from 1 to k (k-itemset)
   - Finds frequent itemset using candidate generation
2. **Frequent patter growth method**
   - Find frequent item set using divide and conquer method of Frequent pattern tree
3. **Vertical data format method**
   - Usually working data set is represented as a set of record where each record is identified by transaction id (TID) and associated itemsets.
   - This format is called **horizontal data format**
   - **Vertical data format** represent a record which is uniquely identified by an item name and having associated transaction ids for that item.

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The Apriori Algorithm

- Input:
  - *D, a database of transactions;*
  - *Min_sup, the minimum support count threshold.*
- Output:
  - *L, frequent itemsets in D.*

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The Apriori Algorithm

- Method:
  1. L_1 = *find frequent 1-itemsets(D);* ***//initialize***
  2. for ($k = 2; L_{k-1} \neq \emptyset; k++$) {
  3. C_k = *apriori_gen*(L_{k-1}); ***//join and prune***
  4. for each transaction $t \in D$ {*// scan D for counts*
  5. C_t = *subset*(C_k, *t*); *// get the subsets of t that are candidates*
  6. for each candidate $c \in C_t$
  7. c.count++;
  8. }
  9. $L_k = \{ c \in C_k \mid c.count \geq min\_sup \}$ ***//generate***
  10. *return* $L = \cup_k L_k$;

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The Apriori Algorithm

procedure apriori_gen(L_{k-1}:*frequent (k-1)-itemsets)*

1. for each itemset $l_1 \in L_{k-1}$
2. for each itemset $l_2 \in L_{k-1}$
3. if ($l_1[1] = l_2[1]$)^($l_1[2] = l_2[2]$)^ . . . ^($l_1[k-2] = l_2[k-2]$)^ ($l_1[k-1] < l_2[k-1]$) *then {*
4. $c = l_1 \bowtie l_2$; *// join step: generate candidates*
5. if has_infrequent_subset(c, L_{k-1}) *then*
6. delete *c; // prune step: remove unfruitful candidate*
7. else add *c to* C_k;
8. }
9. return C_k;

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The Apriori Algorithm

procedure has_infrequent_subset(*c: candidate k-itemset;* L_{k-1}*: frequent (k-1)-itemsets); // use prior knowledge*

1. for each *(k-1)-subset s of c*
2. if $s \notin L_{k-1}$ *then*
3. return TRUE;
4. return FALSE;

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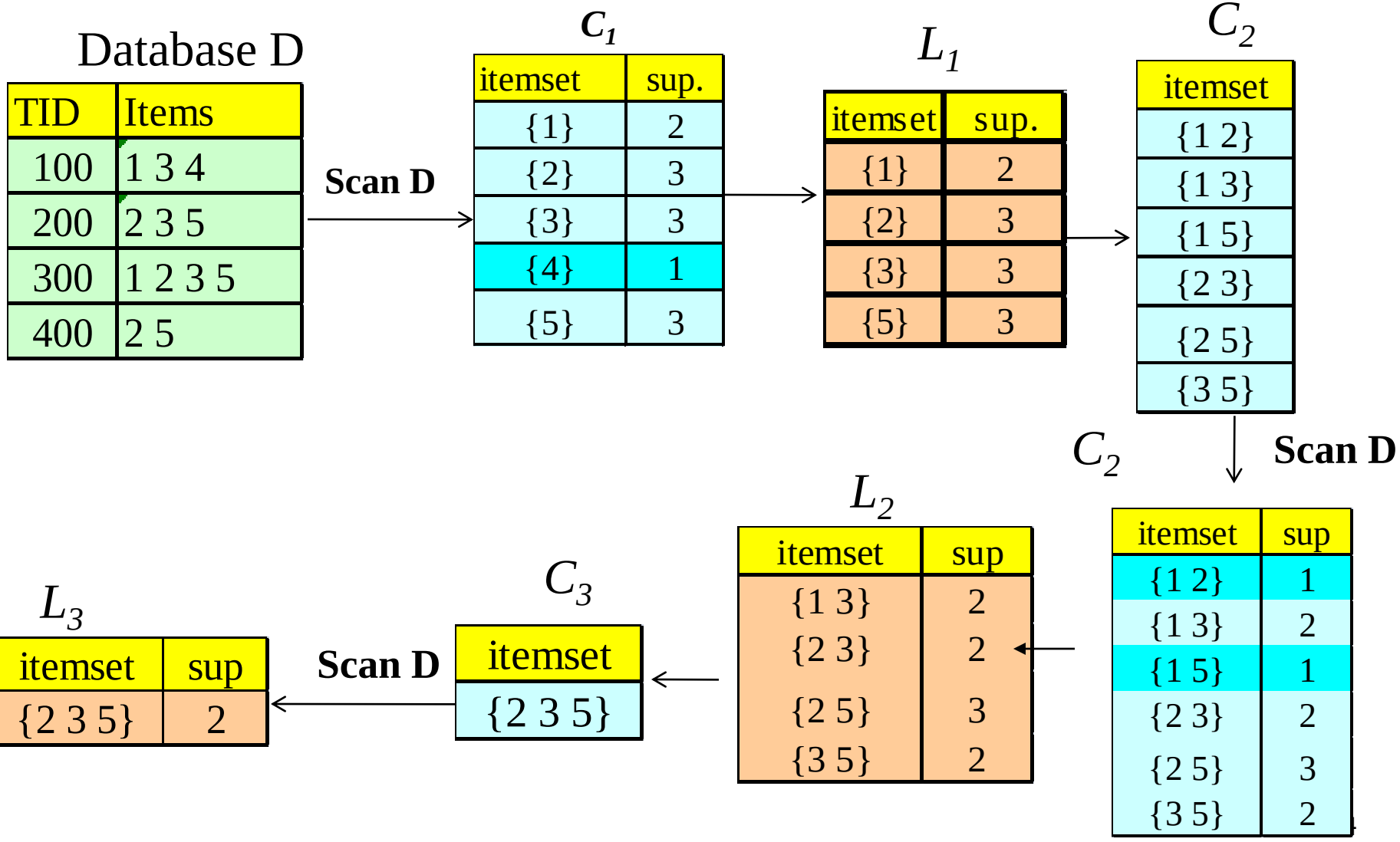
The Apriori Algorithm — Example



Frequent Pattern Growth approach to mine frequent pattern

- Frequent Pattern Growth (FP Growth) approach adopt the divide and conquer strategy to mine frequent pattern
- The approach runs in three phases and avoid candidate generation (sub-database test only)
- **Phase I:**
  - Compress the database representing frequent item into a compact, Frequent-Pattern tree (FP-tree) structure
  - FP-tree is highly condensed, but complete for frequent pattern mining
  - It avoid costly database scans

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Frequent Pattern Growth approach to mine frequent pattern

- **Phase II:**
  - Divide the compressed database into a set of conditional databases, each associated with one frequent item or pattern fragment
- **Phase III**
  - Mine each such database separately

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Generating Association Rules from Frequent Itemsets

- Once the frequent itemsets from transactions in a database D have been found, it is straightforward to generate strong association rules from them (where strong association rules satisfy both minimum support and minimum confidence).
- This can be done as follows
  - For each frequent itemset s, generate all nonempty subsets of s.
  - For every nonempty subset α and β where $\alpha \cup \beta = s$, output the rule "$\alpha \rightarrow \beta$ " if $support\_count(\alpha \cup \beta) * min\_conf \geq support\_count(\alpha)$, where min_conf is the minimum confidence threshold.

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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

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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:
  - Medical diagnosis: if a tumor is cancerous or benign
  - Fraud detection: if a transaction is fraudulent
  - Web page categorization: which category it is

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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

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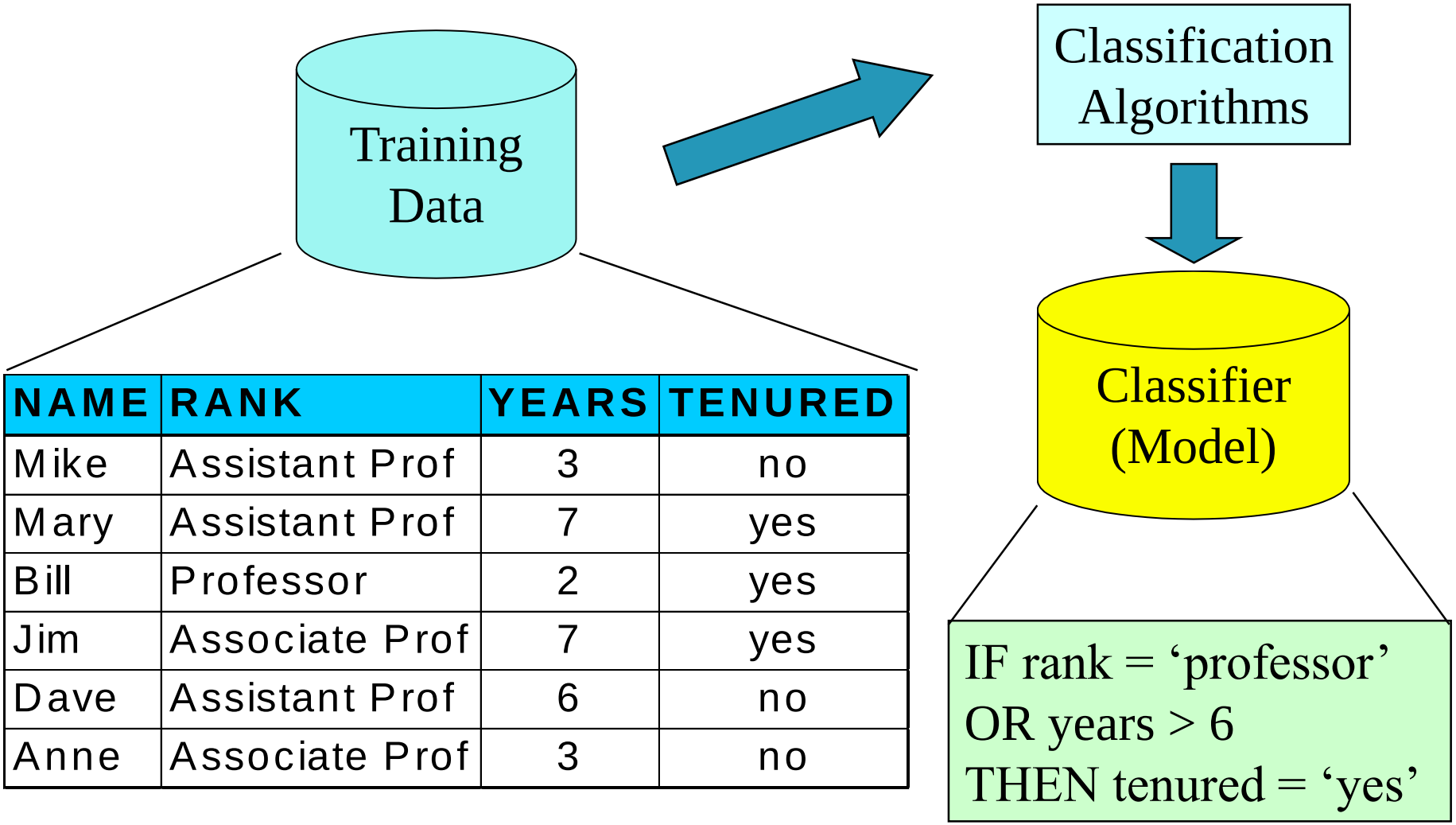
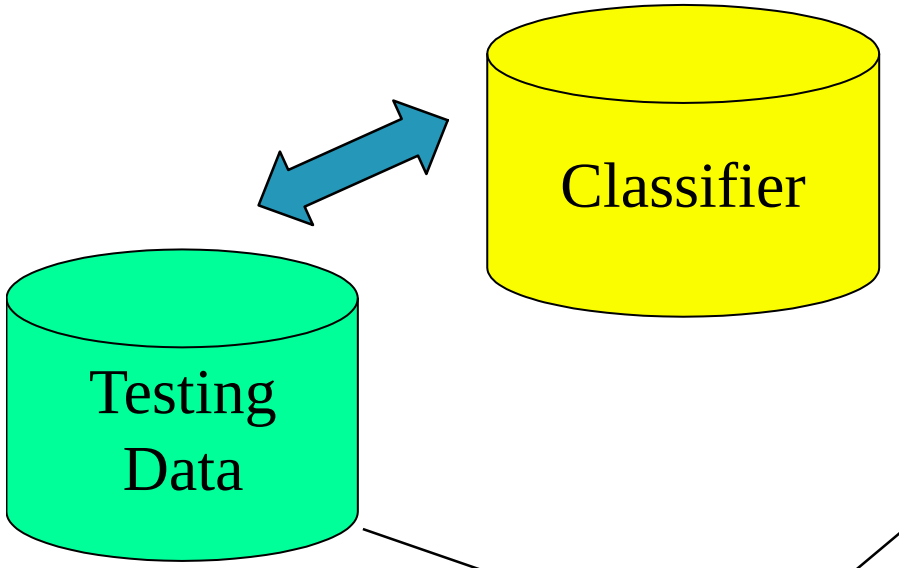
Process (1): Model Construction



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



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

(Jeff, Professor, 4)

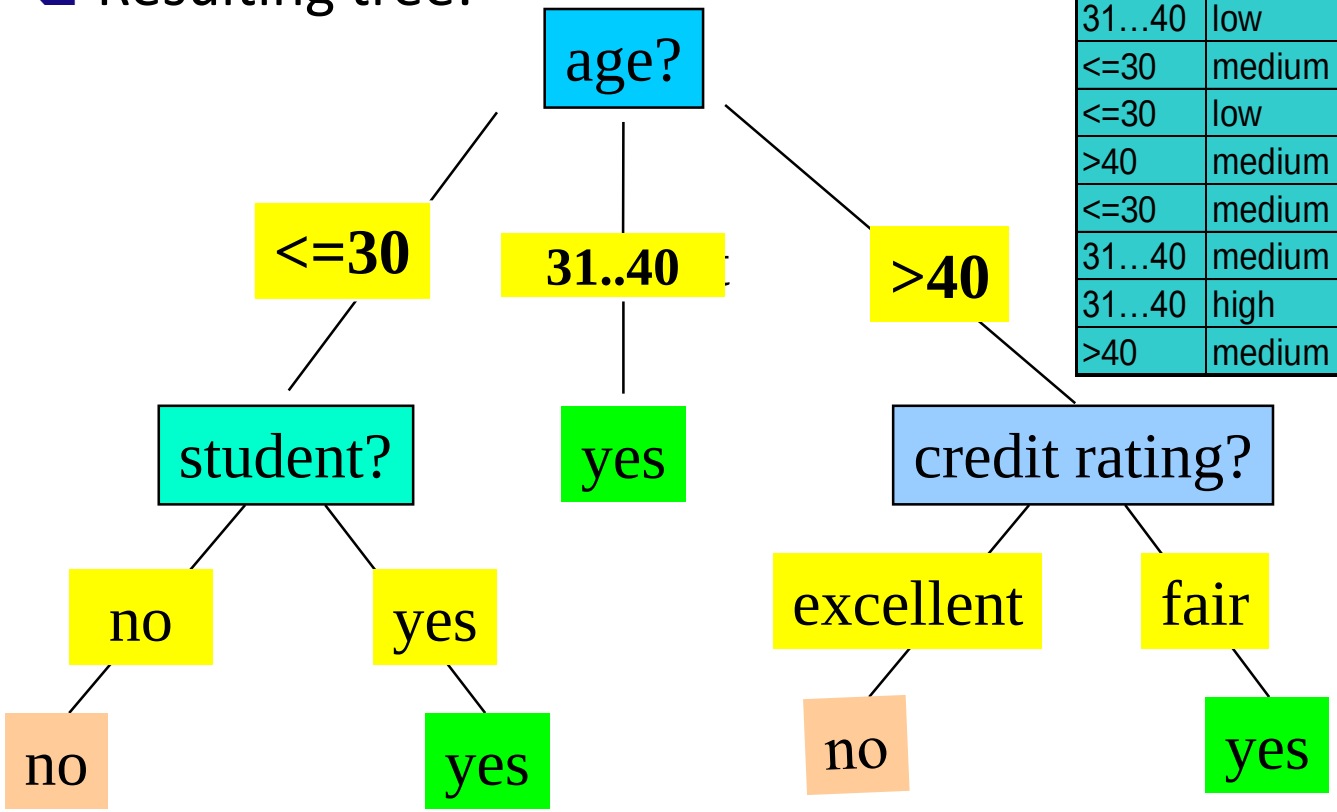
Tenured?

Yes

Decision Tree Induction: An Example

- Training data set: Buys_computer
- The data set follows an example of Quinlan's ID3 (Playing Tennis)
- Resulting tree:

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



Algorithm for Decision Tree Induction

- Basic algorithm (a greedy algorithm)
  - Tree is constructed in a top-down recursive divide-and-conquer manner
  - At start, all the training examples are at the root
  - Attributes are categorical (if continuous-valued, they are discretized in advance)
  - Examples are partitioned recursively based on selected attributes
  - Test attributes are selected on the basis of 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 – majority voting is employed for classifying the leaf
  - There are no samples left

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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
    - tends to favor tests that result in equal-sized partitions and purity in both partitions

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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"

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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

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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 **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

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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

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

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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

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

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

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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	com
<=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
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Naïve Bayes Classifier: An Example

age	income	student	credit_rating	com
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<=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

- $P(C_i)$: 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 = "<=30" | buys_computer = "yes") = 2/9 = 0.222
  P(age = "<= 30" | 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 <= 30 , 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")

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) = n_{covers} /|D| /* D: training data set */

  accuracy(R) = $n_{correct}$ / 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

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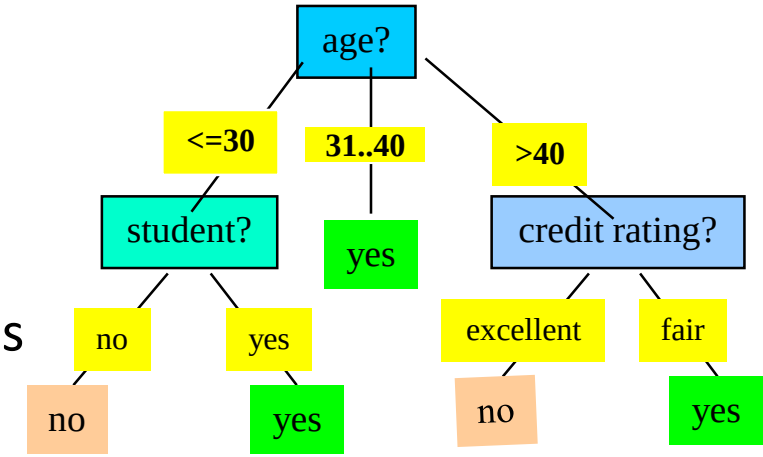
Rule Extraction from a Decision Tree

- 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



- 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*

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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, random subsampling
  - Cross-validation
  - Bootstrap
- Comparing classifiers:
  - Confidence intervals
  - Cost-benefit analysis and ROC Curves

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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, CMi,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**

Han, J., Kamber, M., & Pei, J. (2012). Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann.

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

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

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

- **Recall:** completeness – what % of positive tuples did the classifier label as positive?
- Perfect score is 1.0
- Inverse relationship between precision & recall

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

- ***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

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

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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%

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

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Summary

- In todays lecture we have discussed about;
  - Frequent pattern mining
  - Association rule mining
  - Supervised and unsupervised learning approaches
  - Classification techniques such as decision tree and Naïve Bayes
  - Evaluation of classifier performance

Reference

- Han, J., Kamber, M., & Pei, J. (2012). Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann.