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Carnegie Mellon Univ.
Dept. of Computer Science
15-415/615 – DB Applications

Data Warehousing / Data Mining

(R&G, ch 25 and 26)

C. Faloutsos and A. Pavlo

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Data mining - detailed outline

- Problem
- Getting the data: Data Warehouses, DataCubes, OLAP
- Supervised learning: decision trees
- Unsupervised learning
  - association rules

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Problem

Given: multiple data sources

Find: patterns (classifiers, rules, clusters, outliers...)

PGH

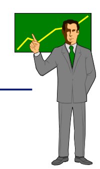
NY

sales(p-id, c-id, date, $price)

???

customers(c-id, age, income, ...)

SF



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Data Ware-housing

First step: collect the data, in a single place (= Data Warehouse)

How?

How often?

How about discrepancies / non-homegeneities?

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Data Ware-housing

First step: collect the data, in a single place (= Data Warehouse)

How? A: Triggers/Materialized views

How often? A: [Art!]

How about discrepancies / non-homegeneities? A: Wrappers/Mediators

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Data Ware-housing

Step 2: collect counts. (DataCubes/OLAP) Eg.:

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OLAP

Problem: "is it true that shirts in large sizes sell better in dark colors?"

sales

ci-d	p-id	Size	Color	$
C10	Shirt	L	Blue	30
~~C10~~	~~Pants~~	~~XL~~	~~Red~~	~~50~~
C20	Shirt	XL	White	20
...				

C / S	S	M	L	TOT
Red	20	3	5	28
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TOT	23	6	18	47

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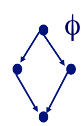
DataCubes

'color', 'size' : DIMENSIONS

'count' : MEASURE



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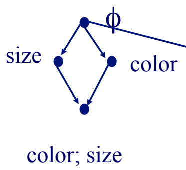

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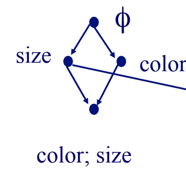

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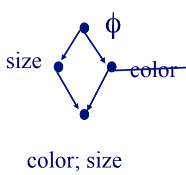

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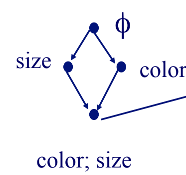

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DataCubes

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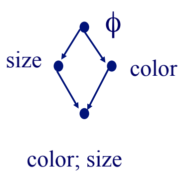

C / S	S	M	L	TOT
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DataCube

DataCubes

SQL query to generate DataCube:

- Naively (and painfully:)

```
select size, color, count(*)
from sales where p-id = 'shirt'
group by size, color

select size, count(*)
from sales where p-id = 'shirt'
group by size
...
```


DataCubes

SQL query to generate DataCube:

- with 'cube by' keyword:

select size, color, count(*)
from sales
where p-id = 'shirt'
cube by size, color

DataCubes

DataCube issues:

Q1: How to store them (and/or materialize portions on demand)

Q2: Which operations to allow

DataCubes

DataCube issues:

Q1: How to store them (and/or materialize portions on demand) A: ROLAP/MOLAP

Q2: Which operations to allow A: roll-up, drill down, slice, dice

[More details: book by Han+Kamber]

DataCubes

Q1: How to store a dataCube?

C / S	S	M	L	TOT
Red	20	3	5	28
Blue	3	3	8	14
Gray	0	0	5	5
TOT	23	6	18	47

DataCubes

Q1: How to store a dataCube?

A1: Relational (R-OLAP)

Color	Size	count
'all'	'all'	47
Blue	'all'	14
Blue	M	3
…		

C / S	S	M	L	TOT
Red	20	3	5	28
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DataCubes

Q1: How to store a dataCube?

A2: Multi-dimensional (M-OLAP)

A3: Hybrid (H-OLAP)

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DataCubes

Pros/Cons:

ROLAP strong points: (DSS, Metacube)

DataCubes

Pros/Cons:

ROLAP strong points: (DSS, Metacube)

- use existing RDBMS technology
- scale up better with dimensionality

DataCubes

Pros/Cons:

MOLAP strong points: (EssBase/hyperion.com)

- faster indexing

(careful with: high-dimensionality; sparseness)

HOLAP: (MS SQL server OLAP services)

- detail data in ROLAP; summaries in MOLAP

DataCubes

Q1: How to store a dataCube

Q2: What operations should we support?

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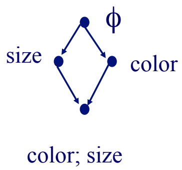
DataCubes

Q2: What operations should we support?



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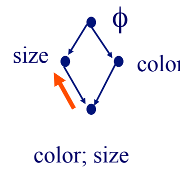
DataCubes

Q2: What operations should we support?

Roll-up



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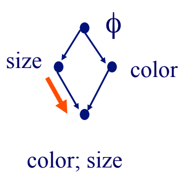
Q2: What operations should we support?

Drill-down



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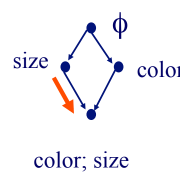
DataCubes

Q2: What operations should we support?

Slice



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Red	20	3	5	28
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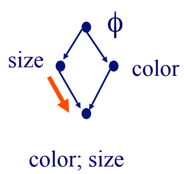
DataCubes

Q2: What operations should we support?

Dice



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Red	20	3	5	28
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DataCubes

Q2: What operations should we support?

- Roll-up
- Drill-down
- Slice
- Dice
- (Pivot/rotate; drill-across; drill-through
- top N
- moving averages, etc)

D/W - OLAP - Conclusions

- D/W: copy (summarized) data + analyze
- OLAP - concepts:
  - DataCube
  - R/M/H-OLAP servers
  - 'dimensions'; 'measures'

Outline

- Problem
- Getting the data: Data Warehouses, DataCubes, OLAP
- Supervised learning: decision trees
- Unsupervised learning
  - association rules
  - (clustering)

Decision trees - Problem

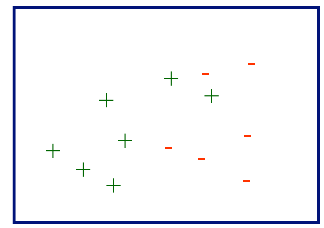
Age	Chol-level	Gender	…	CLASS-ID
30	150	M		+
				…
				-

??

Decision trees

- Pictorially, we have

num. attr#2 (eg., chol-level)

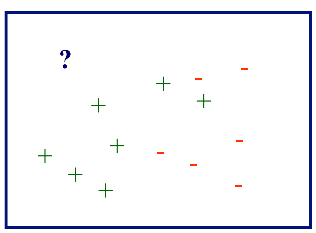


num. attr#1 (eg., 'age')

Decision trees

- and we want to label '?'

num. attr#2 (eg., chol-level)



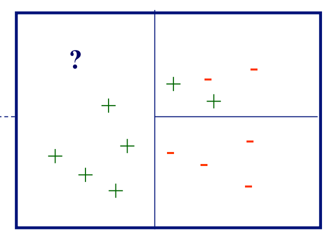
num. attr#1 (eg., 'age')

Decision trees

- so we build a decision tree:

num. attr#2 (eg., chol-level)

40



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num. attr#1 (eg., 'age')

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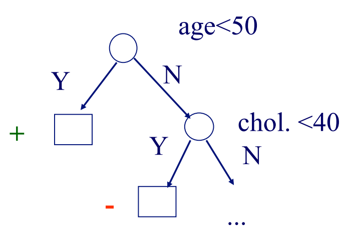
Decision trees

- so we build a decision tree:



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Outline

- Problem
- Getting the data: Data Warehouses, DataCubes, OLAP
- Supervised learning: decision trees
  - problem
  - approach
  - scalability enhancements
- Unsupervised learning
  - association rules
  - (clustering)

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Decision trees

- Typically, two steps:
  - tree building
  - tree pruning (for over-training/over-fitting)

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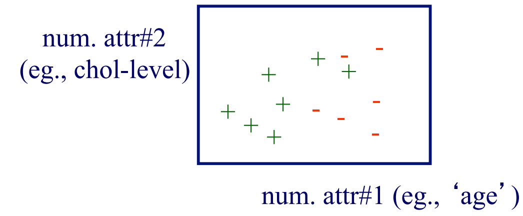
Tree building

- How?



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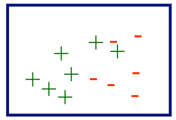
Tree building



- How?
- A: Partition, recursively - pseudocode:

  Partition (Dataset S)

  if all points in S have same label

  then return

  evaluate splits along each attribute A

  pick best split, to divide S into S1 and S2

  Partition(S1); Partition(S2)

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Tree building

- Q1: how to introduce splits along attribute A_i
- Q2: how to evaluate a split?

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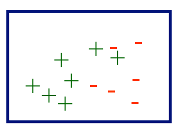
Tree building

- Q1: how to introduce splits along attribute A_i
- A1:
  - for num. attributes:
    - binary split, or
    - multiple split
  - for categorical attributes:
    - compute all subsets (expensive!), or
    - use a greedy algo



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Tree building

- Q1: how to introduce splits along attribute A_i
- Q2: how to evaluate a split?

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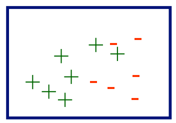
Tree building

- Q1: how to introduce splits along attribute A_i
- Q2: how to evaluate a split?
- A: by how close to uniform each subset is - ie., we need a measure of uniformity:



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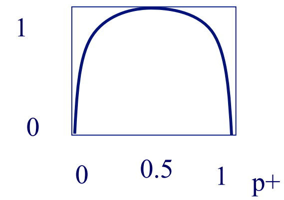
OPTIONAL

Tree building

entropy: H(p+, p-)

Any other measure?



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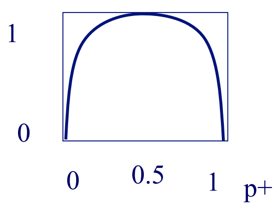
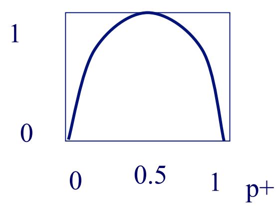
OPTIONAL

Tree building

entropy: $H(p_+, p_-)$

'gini' index: $1-p_+^2 - p_-^2$





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OPTIONAL

Tree building

entropy: $H(p_+, p_-)$

'gini' index: $1-p_+^2 - p_-^2$

(How about multiple labels?)

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OPTIONAL

Tree building

Intuition:

- entropy: #bits to encode the class label
- gini: classification error, if we randomly guess '+' with prob. p_+

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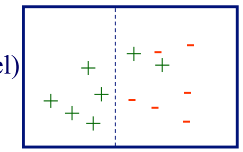
Tree building

Thus, we choose the split that reduces entropy/classification-error the most: Eg.:

num. attr#2 (eg., chol-level)



num. attr#1 (eg., 'age')

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OPTIONAL

Tree building

- Before split: we need

  $(n_+ + n_-) * H(p_+, p_-) = (7+6) * H(7/13, 6/13)$

  bits total, to encode all the class labels

- After the split we need:

  0 bits for the first half and

  $(2+6) * H(2/8, 6/8)$ bits for the second half

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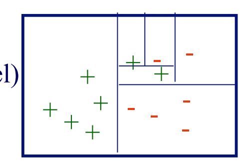
Tree pruning

- What for?

num. attr#2 (eg., chol-level)



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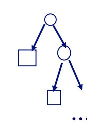

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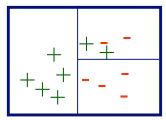
Tree pruning

Shortcut for scalability: DYNAMIC pruning:

- stop expanding the tree, if a node is 'reasonably' homogeneous
  - ad hoc threshold [Agrawal+, vldb92]
  - (Minimum Description Language (MDL) criterion (SLIQ) [Mehta+, edbt96])



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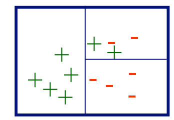
Tree pruning

- Q: How to do it?
- A1: use a 'training' and a 'testing' set - prune nodes that improve classification in the 'testing' set. (Drawbacks?)
- (A2: or, rely on MDL (= Minimum Description Language))



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OPTIONAL

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Scalability enhancements

- Interval Classifier [Agrawal+,vldb92]: dynamic pruning
- SLIQ: dynamic pruning with MDL; vertical partitioning of the file (but label column has to fit in core)
- SPRINT: even more clever partitioning

Age	Chol-level	Gender	…	CLASS-ID
30	150	M		+
				…
				-

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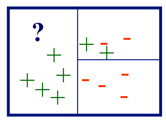
Conclusions for classifiers

- Classification through trees
- Building phase - splitting policies
- Pruning phase (to avoid over-fitting)
- For scalability:
  - dynamic pruning
  - clever data partitioning



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Association rules - idea

[Agrawal+SIGMOD93]

- Consider ‘market basket’ case:
  - (milk, bread)
  - (milk)
  - (milk, chocolate)
  - (milk, bread)
- Find ‘interesting things’, eg., rules of the form:
  - milk, bread -> chocolate | 90%

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Association rules - idea

In general, for a given rule

Ij, Ik, ... Im -> Ix | c

‘c’ = ‘confidence’ (how often people by Ix, given that they have bought Ij, ... Im

‘s’ = support: how often people buy Ij, ... Im, Ix

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Association rules - idea

Problem definition:

- given
  - a set of 'market baskets' (=binary matrix, of N rows/ baskets and M columns/products)
  - min-support 's' and
  - min-confidence 'c'
- find
  - all the rules with higher support and confidence

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Association rules - idea

Closely related concept: "large itemset"

Ij, Ik, ... Im, Ix

is a 'large itemset', if it appears more than 'min-support' times

Observation: once we have a 'large itemset', we can find out the qualifying rules easily (how?)

Thus, let's focus on how to find 'large itemsets'

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Association rules - idea

Naive solution: scan database once; keep 2**|I| counters

Drawback?

Improvement?

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Association rules - idea

Naive solution: scan database once; keep 2**|I| counters

Drawback? 2**1000 is prohibitive...

Improvement? scan the db |I| times, looking for 1-, 2-, etc itemsets

Eg., for |I|=3 items only (A, B, C), we have

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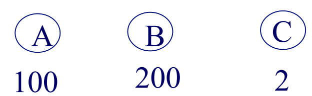
Association rules - idea



first pass

min-sup:10

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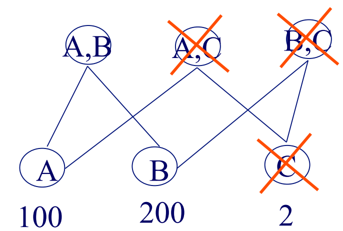
Association rules - idea



first pass

min-sup:10

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Association rules - idea

Anti-monotonicity property:

if an itemset fails to be 'large', so will every superset of it (hence all supersets can be pruned)

Sketch of the (famous!) 'a-priori' algorithm

Let *L(i-1)* be the set of large itemsets with *i-1* elements

Let *C(i)* be the set of candidate itemsets (of size *i*)

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Association rules - idea

Compute L(1), by scanning the database.

repeat, for i=2,3...,

- '**join**' L(i-1) with itself, to generate C(i)
  - two itemset can be joined, if they agree on their first *i-2* elements
- **prune** the itemsets of C(i) (how?)
- scan the db, finding the counts of the C(i) itemsets - set this to be L(i)
- unless L(i) is empty, repeat the loop

CMU SCS

Association rules - Conclusions

Association rules: a great tool to find patterns

- easy to understand its output
- fine-tuned algorithms exist

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Outline

- Problem
- Getting the data: Data Warehouses, DataCubes, OLAP
- Supervised learning: decision trees
  - problem
  - approach
  - scalability enhancements
- Unsupervised learning
  - association rules
  - clustering

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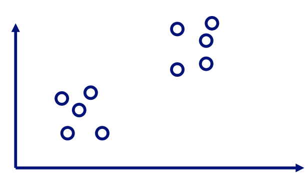
CMU SCS

Clustering

- Problem:
  - given N points in V dimensions,
  - group them



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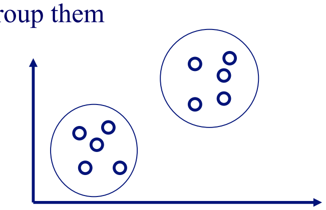
Clustering

- Problem:
  - given N points in V dimensions,
  - group them



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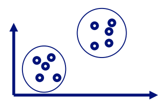
Clustering

- Problem:
  - given N points in V dimensions,
  - group them



- MANY algorithms:
  - K-means, X-means, BIRCH, OPTICS

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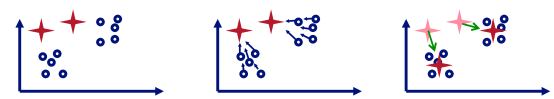
Clustering

Easiest to describe: k-means

- User gives # clusters 'k'
- Start with 'k' random seeds
- Assign each point to its nearest seed
- Move seed towards center, and repeat



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Overall Conclusions

- Data Mining = ``Big Data'' Analytics = Business Intelligence:
  - of **high** commercial, government and research interest
- DM = DB+ ML+ Stat+Sys

- Data warehousing / OLAP: to get the data
- Tree classifiers (SLIQ, SPRINT)
- Association Rules - 'a-priori' algorithm
- clustering: k-means (& BIRCH, CURE, OPTICS)

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Reading material

- Agrawal, R., T. Imielinski, A. Swami, *'Mining Association Rules between Sets of Items in Large Databases'*, SIGMOD 1993.
- M. Mehta, R. Agrawal and J. Rissanen, `*SLIQ: A Fast Scalable Classifier for Data Mining*', Proc. of the Fifth Int'l Conference on Extending Database Technology (EDBT), Avignon, France, March 1996

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Additional references

- Agrawal, R., S. Ghosh, et al. (Aug. 23-27, 1992). *An Interval Classifier for Database Mining Applications*. VLDB Conf. Proc., Vancouver, BC, Canada.
- Jiawei Han and Micheline Kamber, *Data Mining* , Morgan Kaufman, 2001, chapters 2.2-2.3, 6.1-6.2, 7.3.5