CMU SCS

15-826: Multimedia Databases and Data Mining

Data Mining - trees + assoc. rules

C. Faloutsos

CMU SCS

Outline

Goal: 'Find similar / interesting things'

- Intro to DB
- Indexing - similarity search
- Data Mining

CMU SCS

Data Mining - Detailed outline

- Statistics
- AI - decision trees
- DB
  - data warehouses; data cubes; OLAP
  - classifiers
  - association rules
  - misc. topics:
    - reconstruction of info
    - network databases; time sequence forecasting

CMU SCS

Classifiers - outline

- Case study: 'Interval Classifier' ('IC')
- recent developments and variations

CMU SCS

Tree Classifiers

Database issues: how about huge (training) datasets?

Case study: Interval Classifier [Agrawal+92]
Goal: build a classifier (eg., for target mailing)
Differences from AI/ML:

- retrieval efficiency (could use DBMS indices!)
- generation efficiency (large training dataset)

CMU SCS

Tree Classifiers - 'IC'

Proposed method: use classification tree, but

- split a range (= num. attribute) into *k* sub-ranges, as opposed to just 2
- do 'dynamic pruning' (ie., don't expand a node that is fairly homogeneous)

CMU SCS

Tree Classifiers - 'IC'

Sketch of algorithm

make-tree():

- partition set in groups by label
- obtain histograms for each group and each attribute
- Apply goodness function to pick winning attribute A'
- Partition the domain of A' into "strong" and "weak" intervals
- For each "strong" interval: assign it to majority label
- For each "weak" interval: make-tree()

CMU SCS

Tree Classifiers - 'IC'

- "strong" interval: = homogeneous (or close enough)
- *k*: depends on # of distinct values
- 'interval' = 'range' for a continuous attribute;
- 'interval' = 'value' for a categorical one
- histograms: equi-width

Classification accuracy: comparable to standard algorithms (ID3, C4)

CMU SCS

Tree Classifiers - 'IC'

Conclusions: compared to standard algorithms (ID3, C4):

- Faster, because of
  - *k*-way splitting and
  - dynamic pruning
- comparable classification accuracy

CMU SCS

Classifiers - outline

- Case study: 'Interval Classifier' ('IC')
- newer developments and variations

CMU SCS

Classifiers - newer methods

- SLIQ [Mehta+96]
- SPRINT [Shafer+,vldb96]
- PUBLIC [Rastogi+Shim, vldb98]
- RainForest [Gehrke+,2000]

Goal: how to make build decision trees, when the training set does not fit in memory

CMU SCS

Classifiers - newer methods

Goal: how to make build decision trees, when the training set does not fit in memory

SLIQ: use vertical partitioning (att-value, record-id) for each attribute; keep the (label, record-id) list in main memory

SPRINT: like SLIQ, but attach 'label' on each attribute list: (attr-value, label, record-id)

CMU SCS

Classifiers - conclusions

Recent methods: try to improve scalability/speed with

- 'dynamic' pruning
- elaborate file structures / data placement
- parallelism

CMU SCS

Data Mining - Detailed outline

- Statistics
- AI - decision trees
- DB
  - data warehouses; data cubes; OLAP
  - classifiers
  - association rules
  - misc. topics:
    - reconstruction of info
    - network databases; time sequence forecasting

CMU SCS

Association rules - outline

- Main idea [Agrawal+SIGMOD93]
- performance improvements
- Variations / Applications
- Follow-up concepts

CMU SCS

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%

CMU SCS

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

CMU SCS

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

CMU SCS

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'

CMU SCS

Association rules - idea

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

CMU SCS

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

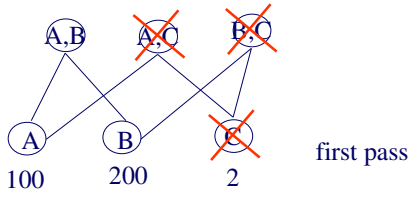
Eg., for |I|=3 items only (A, B, C), we have

CMU SCS

Association rules - idea

CMU SCS

Association rules - idea



CMU SCS

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*)

CMU SCS

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

(see example 6.1 in [Han+Kamber])

CMU SCS

Association rules - outline

- Main idea [Agrawal+SIGMOD93]
- performance improvements
- Variations / Applications
- Follow-up concepts

CMU SCS

Association rules - improvements

- Use the independence assumption, to second-guess large itemsets a few steps ahead
- eliminate 'market baskets', that don't contain any more large itemsets
- Partitioning (eg., for parallelism): find 'local large itemsets', and merge.
- Sampling
- report only 'maximal large itemsets' (dfn?)
- FP-tree (seems to be the fastest)

CMU SCS

Association rules - improvements

- FP-tree: no candidate itemset generation - only two passes over dataset
- Main idea: build a TRIE in main memory

Specifically:

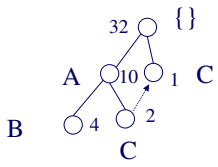
- first pass, to find counts of each item - sort items in decreasing count order
- second pass: build the TRIE, and update its counts

(eg., let A,B, C, D be the items in frequency order:)

CMU SCS

Association rules - improvements

- eg., let A,B, C, D be the items in frequency order:)



32 records
10 of them have A
4 have AB
2 have AC
1 has C

CMU SCS

Association rules - improvements

- Traversing the TRIE, we can find the large itemsets (details: in [Han+Kamber, §6.2.4])
- Result: much faster than 'a-priori' (order of magnitude)

CMU SCS

Association rules - outline

- Main idea [Agrawal+SIGMOD93]
- performance improvements
- Variations / Applications
- Follow-up concepts

CMU SCS

Association rules - variations

1) Multi-level rules: given concept hierarchy

- 'bread', 'milk', 'butter'-> foods;
- 'aspirin', 'tylenol' -> pharmacy

look for rules across any level of the hierarchy, eg

'aspirin' -> foods

(similarly, rules across dimensions, like 'product', 'time', 'branch':

'bread', '12noon', 'PGH-branch' -> 'milk'

CMU SCS

Association rules - variations

2) Sequential patterns:

'car', 'now' -> 'tires', '2 months later'

Also: given a stream of (time-stamped) events:

A A B A C A B A C .....

find rules like

B, A -> C

[Manilla+KDD97]

CMU SCS

Association rules - variations

3) Spatial rules, eg:

'house close to lake' -> 'expensive'

CMU SCS

Association rules - variations

4) Quantitative rules, eg:

'age between 20 and 30', 'chol. level <150' -> 'weight > 150lb'

Ie., given **numerical** attributes, how to find rules?

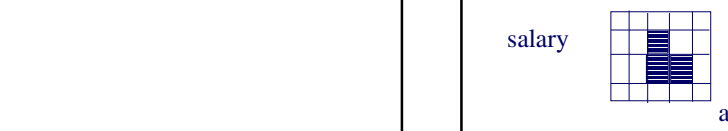
CMU SCS

Association rules - variations

4) Quantitative rules

Solution:

- bucketize the (numerical) attributes
- find (binary) rules
- stitch appropriate buckets together:



CMU SCS

Association rules - outline

- Main idea [Agrawal+SIGMOD93]
- performance improvements
- Variations / Applications
- Follow-up concepts

CMU SCS

Association rules - follow-up concepts

Associations rules vs. correlation.

Motivation: if

milk, bread

is a 'large itemset', does this means that there is a positive correlation between 'milk' and 'bread' sales?

CMU SCS

Association rules - follow-up concepts

What to do, then?

CMU SCS

Association rules - follow-up concepts

What to do, then?

A: report only pairs of items that are indeed correlated - ie, they pass the Chi-square test

The idea can be extended to 3-, 4- etc itemsets (but becomes more expensive to check)

See [Han+Kamber, §6.5], or [Brin+,SIGMOD97]

CMU SCS

Association rules - Conclusions

Association rules: a new tool to find patterns

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

CMU SCS

Reference

- Agrawal, R., S. Ghosh, et al. (Aug. 23-27, 1992). An Interval Classifier for Database Mining Applications. VLDB Conf. Proc., Vancouver, BC, Canada.
- Han + Kamber, chapter 6; chapter 7.3.5
- Mehta, M., R. Agrawal, et al. (1996). SLIQ: A Fast Scalable Classifier for Data Mining. EDBT, Avignon, France.