Mining Frequent Patterns Without Candidate Generation

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(Part of the slides are due to Jiawei Han)

Can We Do Better? Mining frequent patterns without candidate generation

- Database projection and compression
  - Project the database based on its frequent patterns
  - Compress a database into a compact, Frequent-Pattern tree (FP-tree)
  - condensed, but complete for frequent pattern mining
  - no candidate generation: test projected database only!
- Divide-and-conquer
  - decompose both the task and DB according to the frequent patterns obtained so far

Benefits of the FP-tree Structure

- Completeness
  - Preserves complete information for frequent pattern mining
- Compactness
  - Reducing irrelevant info: infrequent items are gone
  - Items in frequency descent order: the more frequently occurring, the more likely to be shared
  - Never be larger than the original database (not count node-links and the count field)
  - For Connect-4 DB, compression ratio could be over 100

Is Apriori Efficient Enough? Performance Bottlenecks!!

- Basic Idea: Candidate generation-and-test
  - Use frequent (k-1)-itemsets to generate candidate frequent k-itemsets
  - Use database scan and pattern matching to test (i.e., collect counts for the candidate itemsets)
- Bottleneck:
  - Generation may lead to huge candidate sets
    - n frequent 1-itemset will generate n(n-1)/2 candidate 2-itemsets
    - To discover a frequent pattern of length 100, e.g., {a1, a2, ..., a100}, we need to generate 2100 ≈ 1030 candidates.
  - Test involves multiple scans of the entire database
    - Needs (n + 1) scans, n is the length of the longest pattern

Construction of FP-tree from a Transaction Database

- Scan DB once, find frequent 1-itemset (single item pattern)
- Order frequent items in frequency descending order
- Scan DB again, construct FP-tree

Mining Frequent Patterns with FP-trees

- Idea: Frequent pattern growth
  - Recursively grow frequent patterns by pattern and database partition
- Method
  - For each frequent item, construct its conditional pattern-base, and then its conditional FP-tree
  - Repeat the process on each newly created conditional FP-tree
  - Until the resulting FP-tree is empty, or it contains only one path: single path will generate all the combinations of its sub-paths, each of which is a frequent pattern
From FP-tree to Conditional Pattern-Base

Starting at the frequent item header table in the FP-tree
Traverse the FP-tree by following the link of each
frequent item \( p \)
Accumulate all of transformed prefix paths of item \( p \) to
form \( p \)'s conditional pattern base

Header Table

<table>
<thead>
<tr>
<th>Item</th>
<th>Frequency</th>
<th>Head</th>
</tr>
</thead>
<tbody>
<tr>
<td>f</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>3</td>
<td></td>
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<tr>
<td>b</td>
<td>3</td>
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<tr>
<td>m</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>p</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

Conditional pattern bases

item cond. pattern base

\( c \checkmark \) f:3
\( a \checkmark \) fc:3
\( b \checkmark \) fca:1, f:1, c:1
\( m \checkmark \) fcw:2, fcab:1
\( p \checkmark \) fcwm:2, cb:1

\( \{\} \)

f:4
\( c \checkmark \)
\( b \checkmark \)
\( p \checkmark \)

f:3
\( c \checkmark \)
\( b \checkmark \)
\( p \checkmark \)

Transformed Prefix Paths

Derive the transformed prefix paths of item \( p \)
For each item \( p \) in the tree, collect \( p \)'s prefix path
with count \( p \)'s frequency

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\( \{\} \)

f:4
\( c \checkmark \)
\( b \checkmark \)
\( p \checkmark \)

Recursion: Mining Each Conditional FP-tree Until \( \{\} \)

Cond. pattern base of \( \checkmark am \) :: (f:3)
\( \checkmark cm \) :: (f:3)
\( \checkmark cam \) :: (f:3)

A Special Case: Single FP-tree Path

Suppose a (conditional) FP-tree \( T \) has a single path \( P \)
The complete set of frequent patterns of \( T \) can be
generated by enumeration of all the combinations of the
sub-paths of \( P \)

\( \{\} \)
\( f:3 \)
\( a:3 \)

All frequent patterns concerning \( m \)
\( m, f, c, a, fcm, fam, fam, fcam \)

m-conditional FP-tree

FP-Growth vs. Apriori: Scalability

With the Support Threshold

Data set T25I20D10K
FP-Growth vs. Apriori: Scalability With the Number of Transactions

Data set T25I20D100K (1.5%)

Run time (sec.)

FP-growth
Apriori

Number of transactions (K)

Run time (sec.)

FP-growth
Apriori

Data set T25I20D100K

Support threshold (%)

FP-Growth vs. Tree-Projection: Scalability with the Support Threshold

Why Is FP-Growth the Winner?

1. decompose both the mining task and DB according to the frequent patterns obtained so far
2. no redundant counting
3. leads to focused search of smaller databases
4. no candidate generation, no candidate test
5. compressed database: FP-tree structure
6. no repeated scan of entire database

I/O-Bound FP-Growth: Scaling FP-Growth by DB Projection

FP-tree cannot fit in memory?

1. first partition a database into a set of projected DBs
2. then construct and mine FP-tree for each projected DB

Alternative methods

1. Construction of a disk-resident FP-tree
2. Materialization and incremental update of an FP-tree

Partition-Based Projection
Thank you !!!