H-Mine: Hyper-Structure Mining of Frequent Patterns in Large Databases

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Paper's goals

- Introduce a new data structure: **H-struct**
- Introduce a new mining algorithm: **H-mine**
- Introduce a new data mining methodology: **space-preserving mining**

Why a new algorithm ?

- Two current algorithm categories:
  - Candidate generation-and-test approach:
    - E.g., Apriori algorithm
  - Pattern growth methods:
    - E.g., FP-growth, TreeProjection
- They have performance bottlenecks:
  - Huge space required for mining
  - Real databases contain all the cases
  - Large applications need more scalability

H-mine characteristics

- It has limited and precisely predictable space overhead.
- It can scale up to very large databases by using database partitioning
- When the data sets are dense, it can switch to use FP-trees to continue the mining process

Frequent pattern mining introduction

- set of items: $I = \{x_1,\ldots,x_n\}$
- itemset X: subset of items ($X \subseteq I$)
- transaction: T=(tid, X)
- transaction database: TBD
- support(X): number of transactions in TDB containing X

Frequent pattern mining definitions

Frequent pattern: For a transaction database TDB and a support threshold *min_sup*, X is a frequent pattern if and only if *sup(X)≥min_sup*

Frequent pattern mining: Finding the complete set of frequent patterns in a given transaction database with respect to a given support threshold.

H-mine algorithm

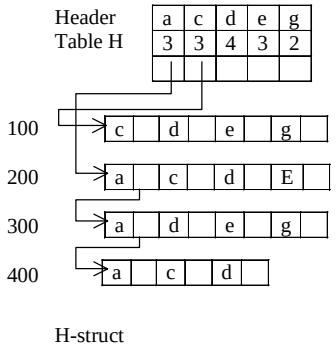
1. H-mine(Mem) – memory based, efficient pattern-growth algorithm
2. H-mine based on H-mine(Mem) for large databases by first partitioning the database
3. For dense data sets, H-mine is integrated with FP-growth dynamically

H-mine(Mem) – Example

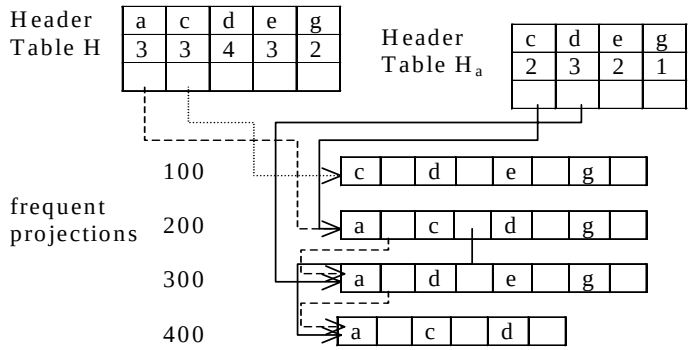
minimum support threshold is 2

Trans ID	Items	Frequent-item projection
100	c,d,e,f,g,i	c,d,e,g
200	a,c,d,e,m	a,c,d,e
300	a,b,d,e,g,k	a,d,e,g
400	a,c,d,h	a,c,d

F-list: a-c-d-e-g

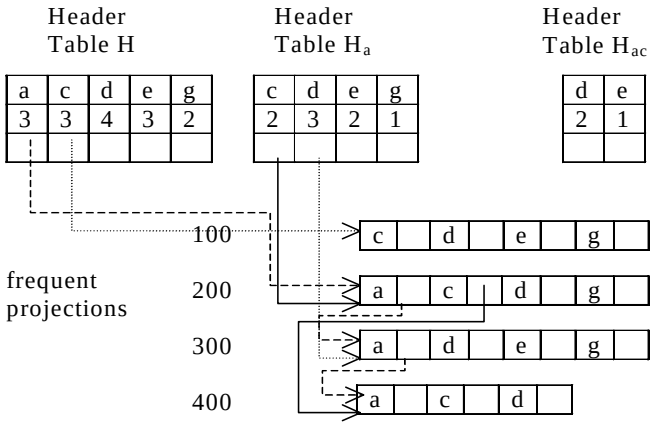


H-mine(Mem) – Example



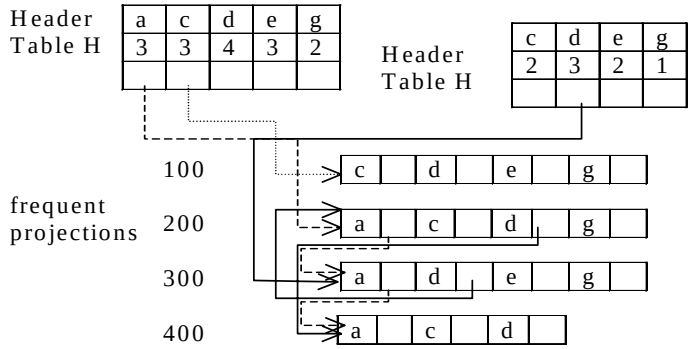
Header table H_a and ac-queue

H-mine(Mem) – Example



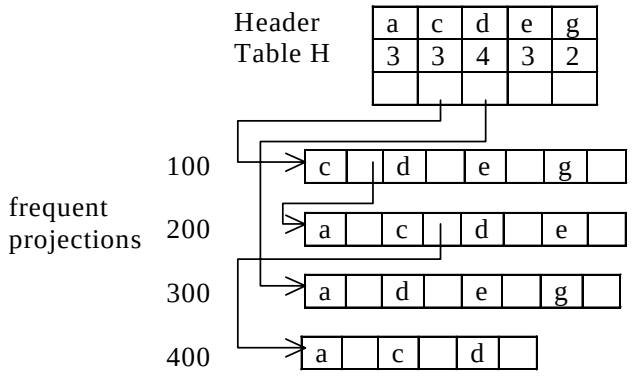
Header table H_{ac}

H-mine(Mem) – Example



Header table H_a and ad-queue

H-mine(Mem) – Example



Adjusted hyper-links after mining
a-projected database

H-mine: Mining large databases

- TDB transaction database (size *n*)
- Minimum support threshold *min_sup*
- Find L, the set of frequent items
- TDB partitioned in *k* parts (TDB_i, $1 \le i \le k$)

H-mine: Mining large databases

- Apply H-mine(Mem) to TDB_i with minimum support threshold

$$\lfloor min\_sup * n_i/n \rfloor$$

- Combine F_i, set of locally frequent pattern in TDB_i, to get the globally frequent patterns.

H-mine – Example

- TDB split in P_1,P_2,P_3,P_4
- Minimum support threshold 100

Local freq. pat.	Partitions	Accumulated sup.cnt
ab	P_1,P_2,P_3,P_4	280
ac	P_1,P_2,P_3,P_4	320
ad	P_1,P_2,P_3,P_4	260
abc	P_1,P_3,P_4	120
abcd	P_1,P_4	40
…	…	…

- Frequent patterns: ab, ac, ad, abc

Performance

- H-mine has better runtime performance on both sparse and dense data than FP-growth and Apriori
- H-mine has better space usage on both sparse and dense data than FP-growth and Apriori
- H-mine performs well with very large databases too

Conclusions

H-mine:

- has high performance
- is scalable in all kinds of data
- has very small space overhead
- can dynamically adapt to input data
- introduces *structure- and space-preserving mining* methodology

Bibliography

- "H-Mine: Hyper-Structure Mining of Frequent Patterns in Large Databases", J. Pei, J. Han, H. Lu, S. Nishio, S. Tang, and D. Yang, Int. Conf. on Data Mining (ICDM'01), San Jose, CA, Nov. 2001.
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