Mining Locally Trending High Utility Itemsets

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Outline

- Introduction
- Definition
- LTHUI-Miner
- Experiment
- Conclusion

High Utility Itemset Mining

Input:

A transaction database

TID	Items
T_1	b(2),c(2),e(1)
T_2	b(4),c(3),d(2),e(1)
T_3	b(5),c(1),e(1)
T_4	a(2),b(10),c(2)
T_5	a(2),c(6),e(2)
T_6	b(4),c(3)
T_7	b(16),c(2)
T_8	a(2),c(6),e(2)
T_9	b(5),c(2),e(1)

a unit profit table

Item	Unit profit
a	5$
b	2$
c	1$
d	2$
e	3$

a $minutil$ threshold

Output:

High-utility itemsets (with utility≥ $minutil$)

if $minutil = 40\$,$ the $HUIs$ are:

$\{a, c, e\}: 44\$$	$\{a, c\}: 44\$$	$\{b, e\}: 44\$$
$\{b, c, e\}: 52\$$	$\{c, e\}: 44\$$	$\{b\}: 92\$$
$\{b, c\}: 107\$$		

Trending High Utility Itemset Mining

☐ Time is considered

Ackman et al. (2018) proposed to discover **trending high utility itemsets**, i.e. itemsets that yield a high profit that follows an increasing or decreasing trend in the whole database.

A Transaction Database with Time

TID	Items	Time
T_1	b(2),c(2),e(1)	d1
T_2	b(4),c(3),d(2),e(1)	d3
T_3	b(5),c(1),e(1)	d4
T_4	a(2),b(10),c(2)	d5
T_5	a(2),c(6),e(2)	d6
T_6	b(4),c(3)	d7
T_7	b(16),c(2)	d9
T_8	a(2),c(6),e(2)	d10
T_9	b(5),c(2),e(1)	d12

- Transactions T_1, T_2 … T_9 have **timestamps** d_1, d_3 … d_{12}.
- Transactions can be simultaneous.

Limitation

- Trending High Utility Itemset Mining
  - This problem only focuses on discovering itemsets that have trends spanning over the whole database.
  - Rely on the unrealistic assumption that trends must be stable over the whole database.

- We propose a new type of pattern: locally trending high utility itemsets (LTHUI)
  - eg. {*schoolbag, pen, notebook*} yields a high profit and have an upward trend during the back-to-school shopping season rather than the whole year.

Binned Database

A Transaction Database With Time

TID	Items	Time
T_1	b(2),c(2),e(1)	d1
T_2	b(4),c(3),d(2),e(1)	d3
T_3	b(5),c(1),e(1)	d4
T_4	a(2),b(10),c(2)	d5
T_5	a(2),c(6),e(2)	d6
T_6	b(4),c(3)	d7
T_7	b(16),c(2)	d9
T_8	a(2),c(6),e(2)	d10
T_9	b(5),c(2),e(1)	d12

$B_{1,3}$

$B_{4,6}$

$B_{7,9}$

$B_{10,12}$

average time *at*

average utility *au* for itemset X

A **bin** denoted as $B_{i,j}$ is the set of transactions from time i to j, i.e. $B_{i,j} = \{T | i \leq t(T) \leq j\}$

A **binned database** denoted as BS is the sequence of **consecutive non-overlapping bins** of length $binlen$ in the database,

eg, $BS =< B_{1,3}, B_{4,6}, B_{7,9}, B_{10,12} >$

Window

TID	Items	Time
T_1	b(2),c(2),e(1)	d1
T_2	b(4),c(3),d(2),e(1)	d3
T_3	b(5),c(1),e(1)	d4
T_4	a(2),b(10),c(2)	d5
T_5	a(2),c(6),e(2)	d6
T_6	b(4),c(3)	d7
T_7	b(16),c(2)	d9
T_8	a(2),c(6),e(2)	d10
T_9	b(5),c(2),e(1)	d12

$B_{1,3}$

$B_{4,6}$

$B_{7,9}$

$B_{10,12}$

$W_{[1,2]} = \{B_{1,3}, B_{4,6}\}$

A **window** denoted as $W_{[i,j]}$ is the set of bins from i-th bin to the j-th bin of the sequence BS, i.e. $W_{[i,j]} = \{BS[k] | i \leq k \leq j\}$.

Slope

- Let $BN_{[i,j]}$ be the **sequence of bins** that are contained in $W_{[i,j]}$.
- Let $AN(X)_{[i,j]}$ denotes the **sequence of average utilities** of an itemset X for the bins of $BN_{[i,j]}$.
- Let $AT_{[i,j]}$ denotes the **sequence of average timestamps** corresponding to bins in $BN_{[i,j]}$.
- The **slope** of an itemset X in a sliding window W is denoted as $Slope(X, W)$, i.e. $slope(X, W) = \frac{\sum_{k=1\ldots|BN|}(AU(X)[k]-avg(AU(X)))\times(AT[k]-avg(AT))}{\sum_{t\in AT}(t-avg(AT))^2}$ iff the itemset X appears in each bin of the sliding window W, i.e., $AU(X)[k] \neq 0$.

Problem Definition

An itemset X is a **locally trending high utility itemset (LTHUI)** if there exists a window $W_{[i,j]}$ such that $length(W_{[i,j]}) = winlen$, $u_{[i,j]}(X) \geq minutil$ and $slope(X, W_{[i,j]}) \geq minslope$.

TID	Items	Time
T_1	b(2),c(2),e(1)	d1
T_2	b(4),c(3),d(2),e(1)	d3
T_3	b(5),c(1),e(1)	d4
T_4	a(2),b(10),c(2)	d5
T_5	a(2),c(6),e(2)	d6

$$at(B_{1,3}) = \frac{1+3}{2} = 2$$

$$au(\{b,c\}, B_{1,3}) = \frac{17}{3} = 5.67$$

$$at(B_{4,6}) = \frac{4+6}{2} = 5$$

$$au(\{b,c\}, B_{4,6}) = \frac{33}{3} = 11$$

$W_{[1,2]} = \{B_{1,3}, B_{4,6}\}$

$u_{[1,2]}(\{b,c\}) = 50 \geq 20$

$$slope(\{b,c\}, W_{[1,2]}) = \frac{(5.67 - 8.33) \times (2 - 3.5) + (11 - 8.33) \times (5 - 3.5)}{(2 - 3.5)^2 + (5 - 3.5)^2} = 1.78 > 0.15$$

e.g. for $binlen = 3$, $winlen = 6$, $minutil = 20$ and $minslope = 0.15$, then $\{b,c\}$ is a LTHUI.

Problem Definition

For an itemset X, a window $W_{i,j}$ is a **trending high utility period (THUP)** if for each window $W_{k,l} \subseteq W_{i,j}$ where $length(W_{[k,l]}) = winlen$, $u(X, W_{[k,l]}) \geq minutil$ and $slope(X, W_{[k,l]}) \geq minslope$.

TID	Items	Time
T_1	b(2),c(2),e(1)	d1
T_2	b(4),c(3),d(2),e(1)	d3
T_3	b(5),c(1),e(1)	d4
T_4	a(2),b(10),c(2)	d5
T_5	a(2),c(6),e(2)	d6
T_6	b(4),c(3)	d7
T_7	b(16),c(2)	d9

$u_{[1,2]}(\{b,c\}) = 50 \geq 20$

$slope(\{b,c\}, W_{[1,2]}) = 1.78 \geq 0.15$

$u_{[2,3]}(\{b,c\}) = 78 \geq 20$

$slope(\{b,c\}, W_{[2,3]}) = 1.33 \geq 0.15$

e.g. for $binlen = 3$, $winlen = 6$, $minutil = 20$ and $minslope = 0.15$, $W_{[1,3]}$ is a THUP of $\{b,c\}$

Problem Definition

The problem of **Locally Trending High Utility Itemset Mining (LTHUIM)** is to find **all Locally Trending High Utility Itemsets (LTHUIs)**, and **their maximum Trending High Utility Periods (THUPs)** given parameters $binlen$, $winlen$, $minutil$ and $minslope$.

- **For example**, given the database as mentioned before, and set the **parameters** $binlen$=3, $winlen$=6, $minutil$=20 and $minslope$=0.15

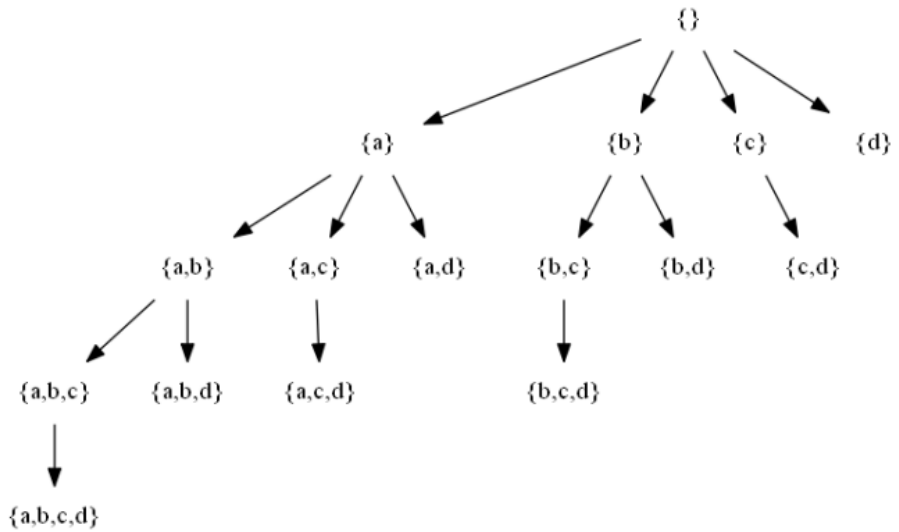
3 LTHUIs can be found

$\{b\}$: $[d_1, d_9]$	$\{b, c\}$: $[d_1, d_9]$
$\{c, e\}$: $[d_1, d_9]$	

LTHUI-Miner

The LTHUI-Miner Algorithm

- Based on HUI-Miner, find larger itemsets with **depth-first search.**
- Create a vertical structure named **TU-List** for each itemset.



TU-List of $\{b\}$

utility of itemset in a transaction

remaining utility

Utility-list		
tid	$iutil$	$rutil$
T_1	4	2
T_2	8	3
T_3	10	1
T_4	20	2
T_6	8	3
T_7	32	2
T_9	10	2
$trendPeriods$		
$W_{[1,3]}$		
$promisingPeriods$		
$W_{[1,4]}$		

maximum trending high utility periods

promising LTHUI periods

utility of itemset in a bin

remaining utility of itemset in a bin

	$binUtils$	$binRutils$
$B_{1,3}$	12	5
$B_{4,6}$	30	3
$B_{7,9}$	40	5
$B_{10,12}$	10	2

Construction of TU-List

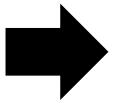
- The Utility-list of a **single item** can be constructed by scanning the database, and others can be obtained by joning their child itemset's Utility-lists.

Utility-list $\{b\}$

tid	$iutil$	$rutil$
T_1	4	2
T_2	8	3
T_3	10	1
T_4	20	2
T_6	8	3
T_7	32	2
T_9	10	2

Utility-list $\{c\}$

tid	$iutil$	$rutil$
T_1	2	0
T_2	3	0
T_3	1	0
T_4	2	0
T_5	6	0
T_6	3	0
T_7	2	0
T_8	6	0
T_9	2	0



Utility-list $\{b, c\}$

tid	$iutil$	$rutil$
T_1	6	0
T_2	11	0
T_3	11	0
T_4	22	0
T_6	11	0
T_7	34	0
T_9	12	0

Construction of TU-List

The $binUtils$ and $binRutils$ can be constructed by sanning the Utility-list.

Utility-list $\{b\}$		
tid	$iutil$	$rutil$
T_1	4	2
T_2	8	3
T_3	10	1
T_4	20	2
T_6	8	3
T_7	32	2
T_9	10	2

$B_{1,3}$

$B_{4,6}$

$B_{7,9}$

$B_{10,12}$

	binUtils	***binRutils***
$B_{1,3}$	12	5
$B_{4,6}$	30	3
$B_{7,9}$	40	5
$B_{10,12}$	10	2

T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9
d_1	d_3	d_4	d_5	d_6	d_7	d_9	d_{10}	d_{12}

Construction of TU-List

- Consider that $a \prec e \prec b \prec c$, $binlen = 3$, $winlen = 6$, $minutil = 20$ and $minslope = 0.15$, using **sliding window** to get periods information.

	$binUtils$	$binRutils$
$B_{1,3}$	12	5
$B_{4,6}$	30	3
$B_{7,9}$	40	5
$B_{10,12}$	10	2

$sumIUtils = 42$
$sumRUtils = 8$
upperbound is 50
$slope = 0.67$

$sumIUtils = 70$
$sumRUtils = 8$
upperbound is 78
$slope = 0.37$

$sumIUtils = 50$
$sumRUtils = 7$
upperbound is 57
$slope = -1.11$

$trendPeriods$
$W_{[1,3]}$
$promisingPeriods$
$W_{[1,4]}$

Optimizations

- **Pruning a low-TWU item in a database**
  - Remove an item i, if for any window $W_{i,j}$ of $winlen$, $TWU(i) < minutil$.
- **Pruning an unpromising itemset using its remaining utility in a database**
  - Remove an itemset X and its transitive extensions, if $u(X) + reu(X) < minutil$.
- **Pruning an unpromising itemset using its remaining utility in a sliding window**
  - Remove an itemset X and its transitive extensions in a sliding window W, if $u(X, W) + reu(X, W) < minutil$

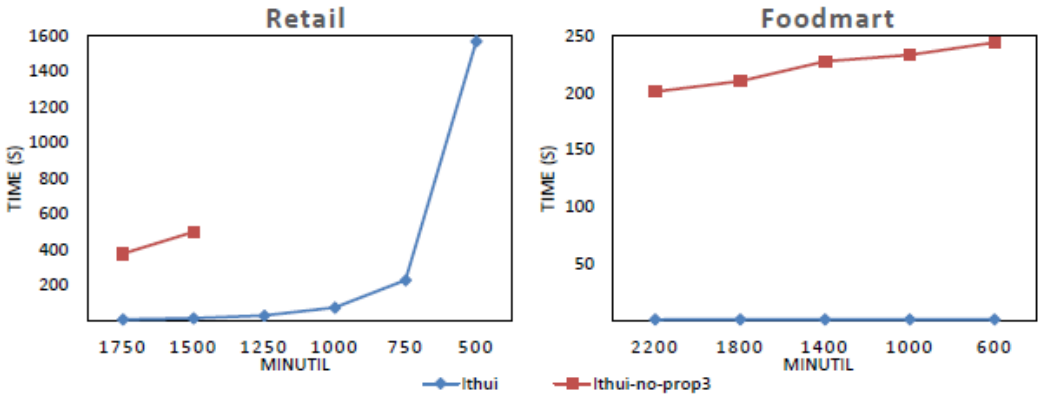
Experiment

Experimental Evaluation

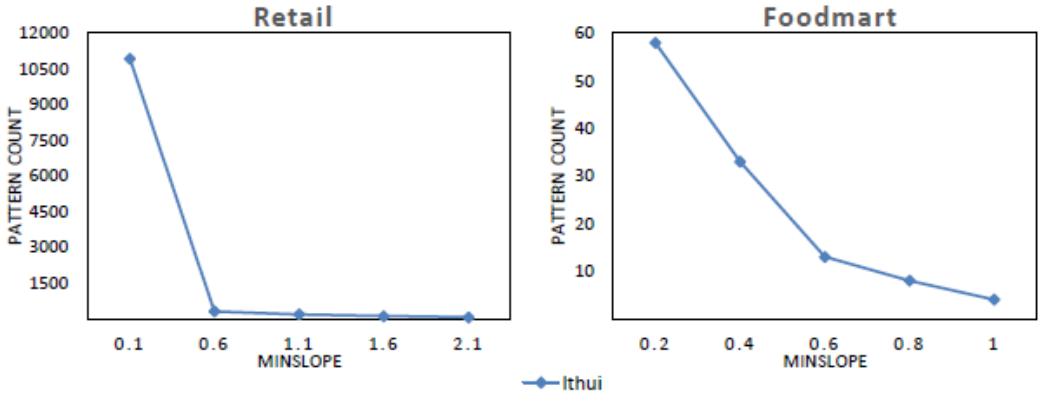
Dataset	Trans count	Item count	Average length
$retail$	88,162	16,470	10.30
$foodmart$	4141	1559	4.40

- We compared the execution time of the algorithm with and without the optimizations
- Experiments were done by varying the $minutil$ and $minslope$ parameters to see their influence on runtime and pattern count
- Java, Windows 10, 64 GB RAM, Intel Xeon E3-1270 v5

Experimental Evaluation



(a) Influence of *minutil* on runtime



(b) Influence of *minslope* on the number of patterns found

- In some cases, the optimized algorithm is over **150** times faster than the non-optimized algorithm.
- It is observed that as $minutil$ is decreased, runtime increases.
- It is observed that as $minslope$ increases, the number of patterns decreases.
- Some patterns having a strong trend were found.
  e.g., on $retail$ and $foodmart$ dataset, 179 and 13 patterns have slope values greater than 1.1 and 0.6 respectively.

Conclusion

Conclusion

- A new type of patterns named **Locally Trending High Utility Itemset**;
- A new algorithm with three optimizations;
- Results:
  - the optimizations can reduce running time over 150 times in some cases;
  - some patterns having a strong trend were found.

Open source Java data mining software, 150 algorithms
http://www.phillippe-fournier-viger.com/spmf/

Q & A