Frequent Itemset Mining

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Association Rules Example

Transaction	Items
t_1	Bread, Jelly, Butter
t_2	Bread, Butter
t_3	Bread, Milk, Butter
t_4	Apple, Bread
t_5	Apple, Milk

I = {Apple, Bread, Jelly, Milk, Butter}

Bread => Butter happens pretty frequently

Association rule mining

- Find which item sets are associated
- Association denotes accessing together
- Dataset D is set of transactions T_i
- Each T_i is set of items $I_{ij} \in I$
- Find itemsets A and B such that accessing A implies accessing B

$$A \implies B$$

- Extremely rare that this will happen always
- Not useful if such itemsets occur rarely

Parameters of an Association Rule

- For both A and B to occur, $A \cup B$ must occur
- Two thresholds or parameters
- Support: A and B should occur in at least s (ratio of) transactions

$$P(A, B) = \frac{|A \cup B|}{|T|} \geq s$$

- Confidence: If A occurs, B should occur in at least c (ratio of) transactions

$$P(B|A) = \frac{|A \cup B|}{|A|} \geq c$$

Transaction Id	Itemsets
1	A, C, D
2	B, C, E
3	A, B, C, E
4	B, E

Rule	Support	Confidence
$B \implies E$		
$C \implies E$		
$B, C \implies E$		
$E \implies B$		
$E \implies C$		
$E \implies B, C$		
$A \implies D$		
$D \implies A$		

Mining Association Rules

- Given a support threshold *s* and confidence threshold *c*
  - Mine all frequent itemsets, i.e., support of the itemset is above *s*
  - For association rules from frequent itemsets, i.e., each rule has confidence above *c*

How difficult is the problem?

- What is the naïve approach?
- Generate a candidate itemset
- Test its support
- If frequent, accept
- Else, throw away
- Total number of possible itemsets is $2^n - 1$
- Checking each itemset requires scanning the entire transaction database
- Too impractical

Apriori Principle

- Candidate-generation-and-test paradigm
- Apriori principle: If an itemset is frequent, all its subsets must also be frequent
- Conversely, if an itemset X is infrequent, all its supersets are also infrequent
- This is an *anti-monotonic* property: if a set fails, its supersets fail as well

Apriori Algorithm

- Generates candidate itemsets in order of length
- Tests each such candidate itemset for support threshold
- Uses all frequent itemsets of a particular length to generate candidates having length one more

Transaction Id	Itemsets
0	1, 2, 5
1	2, 4
2	2, 3
3	1, 2, 4
4	1, 3
5	2, 3
6	1, 3
7	1, 2, 3, 5
8	1, 2, 3
9	6

Support threshold $s = 2$

Candidate set C_1

Itemset	Frequency
1	6
2	7
3	6
4	2
5	2
6	1

$\rightarrow$

Frequent set F_1

Itemset	Frequency
1	6
2	7
3	6
4	2
5	2

$\rightarrow$

Candidate set C_2

Itemset	Frequency
1, 2	4
1, 3	4
1, 4	1
1, 5	2
2, 3	4
2, 4	2
2, 5	2
3, 4	0
3, 5	1
4, 5	0

$\rightarrow$

Frequent set F_2

Itemset	Frequency
1, 2	4
1, 3	4
1, 5	2
2, 3	4
2, 4	2
2, 5	2

$\rightarrow$

Candidate set C_3

Itemset	Frequency
1, 2, 3	2
1, 2, 5	2
(1, 3, 5)	subset
(2, 3, 4)	subset
(2, 3, 5)	subset
(2, 4, 5)	subset

$\rightarrow$

Frequent set F_3

Itemset	Frequency
1, 2, 3	2
1, 2, 5	2

Candidate set C_4

Itemset	Frequency
(1, 2, 3, 5)	subset

Do we need to count support of all generated candidates?

- F_3 = {{1, 2, 3}, {1, 2, 4}, {1, 3, 4},
  {1, 3, 5}, {2, 3, 4}}

- After join
  - C_4 = {{1, 2, 3, 4}, {1, 3, 4, 5}, {1,2,3,5}}
- After pruning:
  - C_4 = {{1, 2, 3, 4}}
    because {1, 4, 5} and {1, 2, 5 } are not in F_3 ({1, 3, 4, 5} and {1, 2, 3, 5} are removed)

Ordering Itemsets

- The items in I are sorted in lexicographic order (which is a total order).
- The order is used throughout the algorithm in each itemset.
- $\{w[1], w[2], \ldots, w[k]\}$ represents a k-itemset w consisting of items $w[1], w[2], \ldots, w[k]$, where $w[1] < w[2] < \ldots < w[k]$ according to the total order.

Details: the algorithm

Algorithm Apriori(*T*)

$C_1 \leftarrow$ init-pass(T);

$F_1 \leftarrow \{f \mid f \in C_1, f\text{.count}/n \geq \mathit{minsup}\}$; // n: no. of transactions in T

for (k = 2; $F_{k-1} \neq \emptyset$; k++) **do**

$C_k \leftarrow$ candidate-gen(F_{k-1});

for each transaction $t \in T$ **do**

for each candidate $c \in C_k$ **do**

if c is contained in t **then**

$c.\mathit{count}$++;

end

end

$F_k \leftarrow \{c \in C_k \mid c.\mathit{count}/n \geq \mathit{minsup}\}$

end

return $F \leftarrow \bigcup_k F_k$;

Candidate-gen function

Function candidate-gen(F_{k-1})
    $C_k \leftarrow \emptyset$;
    forall $f_1, f_2 \in F_{k-1}$
            with $f_1 = \{i_1, \ldots, i_{k-2}, i_{k-1}\}$
            and $f_2 = \{i_1, \ldots, i_{k-2}, i'_{k-1}\}$
            and $i_{k-1} < i'_{k-1}$ **do**
        $c \leftarrow \{i_1, \ldots, i_{k-1}, i'_{k-1}\}$; // join f_1 and f_2
        $C_k \leftarrow C_k \cup \{c\}$;
        for each (k-1)-subset s of c **do**
            if ($s \notin F_{k-1}$) **then**
                delete c from C_k; // prune
        end
    end
    return C_k;

Step 2: Generating rules from frequent itemsets

- Frequent itemsets $\neq$ association rules
- One more step is needed to generate association rules
- For each frequent itemset *X*,

  For each proper nonempty subset *A* of *X*,
  - Let *B* = X - *A*
  - A $\rightarrow$ B is an association rule if
    - Confidence(A $\rightarrow$ B) $\geq$ minconf,

      support(A $\rightarrow$ B) = support(A$\cup$B) = support(X)

      confidence(A $\rightarrow$ B) = support(A $\cup$ B) / support(A)

Generating rules: an example

- Suppose {2,3,4} is frequent
- Proper nonempty subsets:
  - {2,3}, {2,4}, {3,4}, {2}, {3}, {4}
- These generate these association rules:
  - 2,3 $\rightarrow$ 4,
  - 2,4 $\rightarrow$ 3,
  - 3,4 $\rightarrow$ 2,
  - 2 $\rightarrow$ 3,4,
  - 3 $\rightarrow$ 2,4,
  - 4 $\rightarrow$ 2,3,

Frequent Pattern Tree

- Frequent pattern (FP)-growth
- Compact representation of entire transaction database as a tree
- FP-tree
- Resembles a prefix tree

Jiawei Han, Jian Pei, and Yiwen Yin. 2000. Mining frequent patterns without candidate generation. In *Proceedings of the 2000 ACM SIGMOD*. ***[Citations: 9670]***

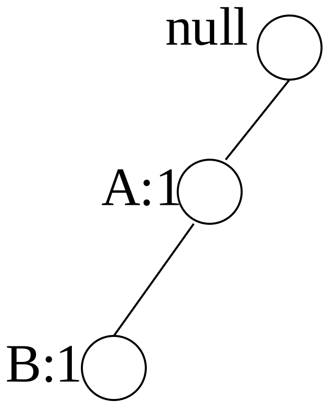
Algorithm

- First finds support of all 1-itemsets
- Items in *descending* order of support forms flist order
- Re-arranges items in every transaction in *flist* order
- Root is “null”
- Nodes are items with corresponding count
- Each transaction is added as a path in the tree
- Count of common prefixes are incremented
- Nodes of same item are linked using node links
- Two database scans

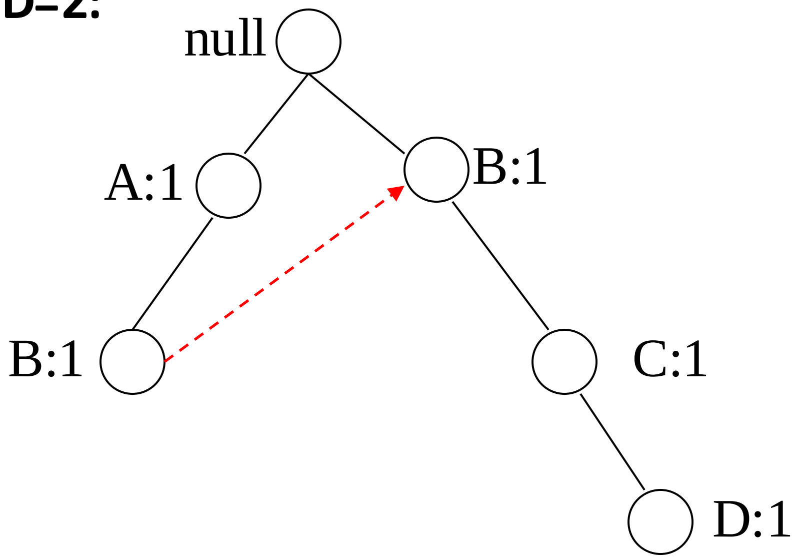
FP-Tree Construction

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

After reading TID=1:



After reading TID=2:



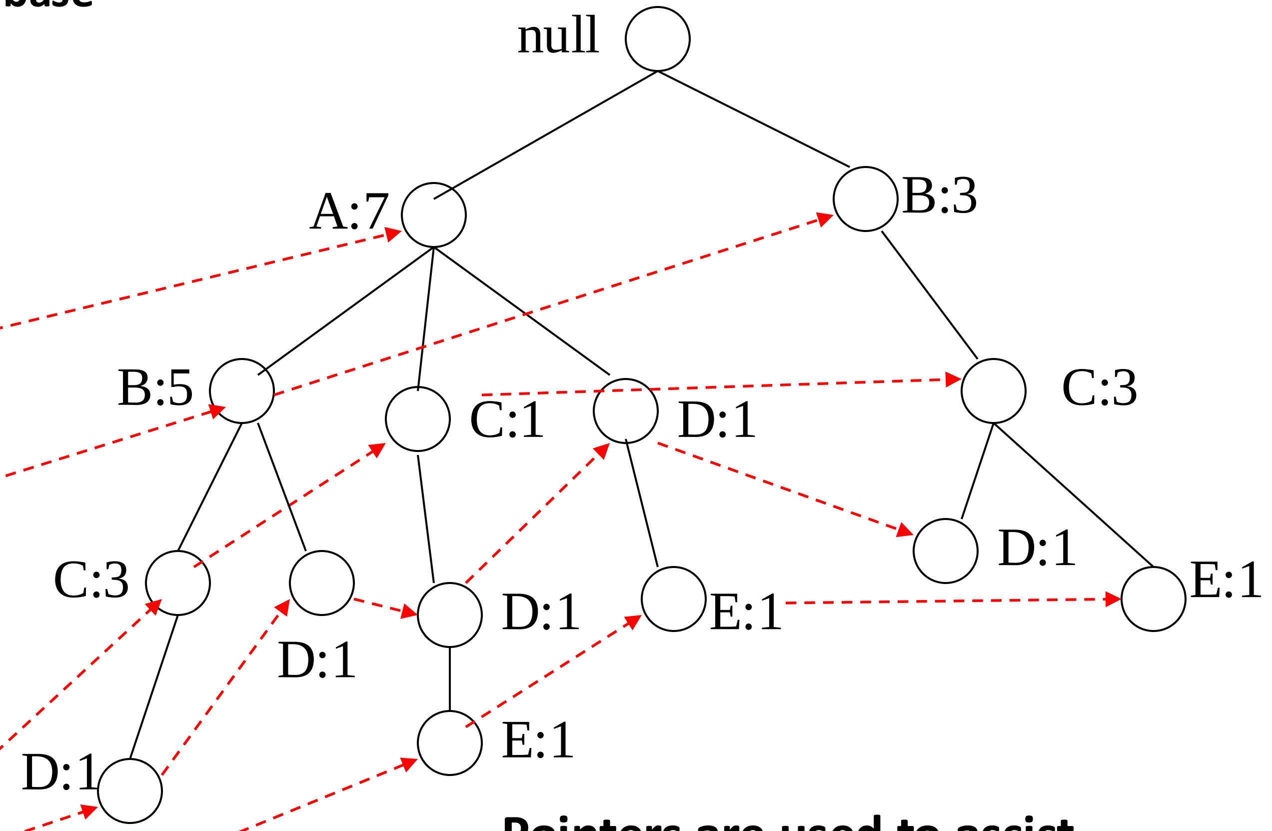
FP-Tree Construction

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

Transaction Database

Header table

Item	Pointer
A	
B	
C	
D	
E	

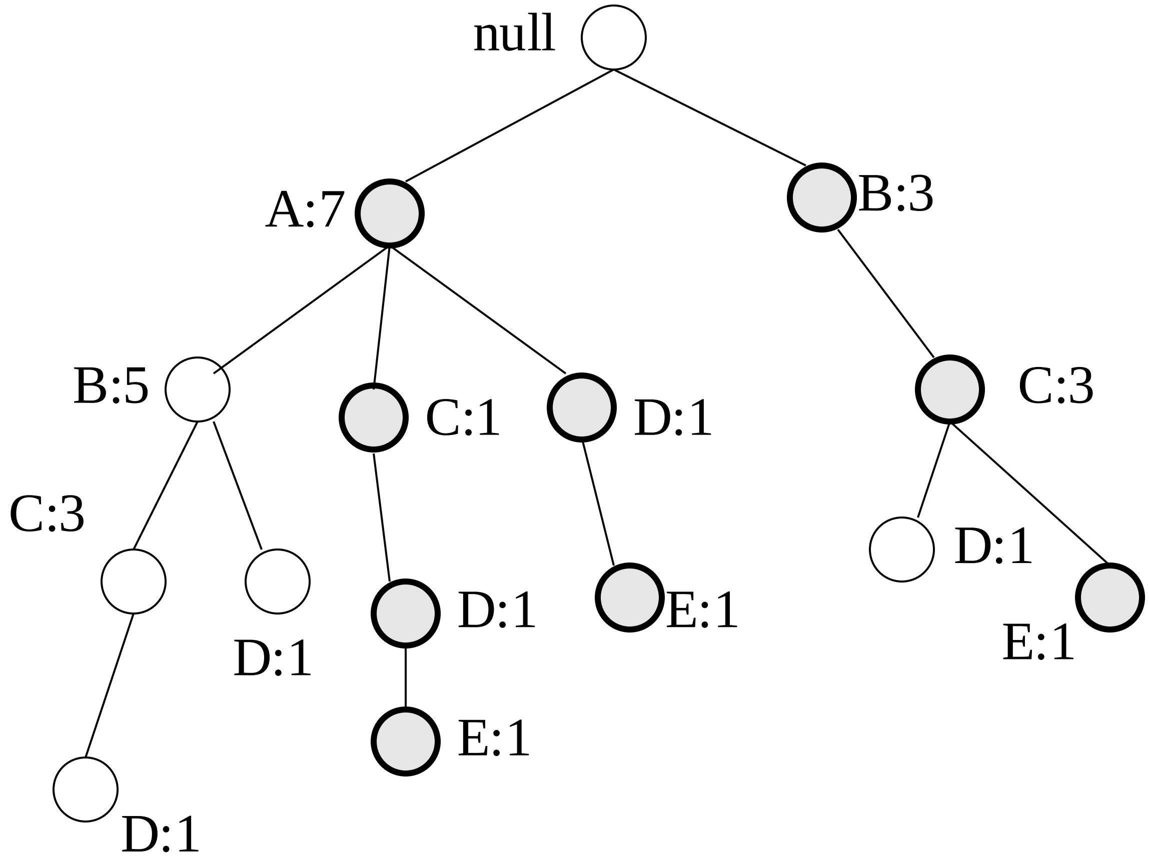


Pointers are used to assist frequent itemset generation

FP-growth

To mine frequent itemsets containing E (starts with the least frequent item)

1. Identify paths containing E
2. Build conditional pattern base



Build conditional pattern base for E:

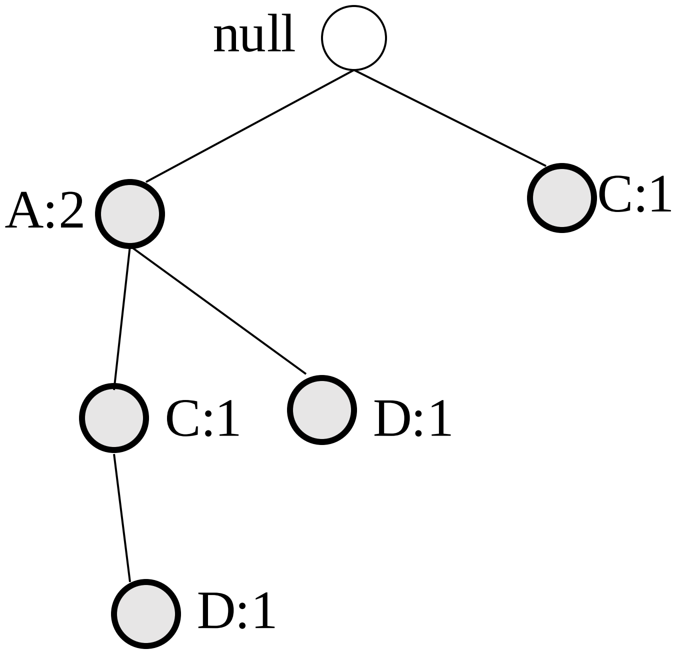
P = {(A:1,C:1,D:1),
(A:1,D:1),
(B:1,C:1)}

Recursively apply FP-growth on P

FP-growth

<u>Conditional tree for E:</u>

Assume minSup=2



Conditional Pattern base for E:

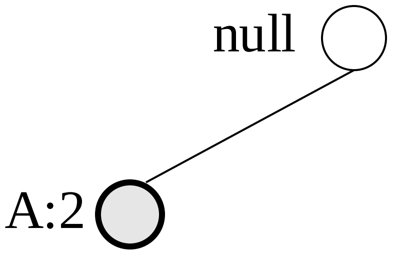
P = {(A:1,C:1,D:1,E:1),
(A:1,D:1,E:1),
(B:1,C:1,E:1)}

Count for E is 3: {E} is frequent itemset

Recursively apply FP-growth on P

FP-growth

<u>Conditional tree for D within conditional tree for E:</u>



Conditional pattern base for D within conditional base for E:

P = {(A:1,C:1,D:1),
(A:1,D:1)}

Count for D is 2: {D,E} is frequent itemset

Recursively apply FP-growth on P

FP-growth

<u>Conditional tree for A within D within E:</u>

Count for A is 2: {A,D,E} is frequent itemset

Next step:

This recursion stops

Construct conditional tree C within conditional tree E

Continue until exploring conditional tree for A (which has only node A)

FP-growth

<u>Conditional tree for C within E:</u>

Assume minSup=2

Conditional Pattern base for CE:

P = {(A:1,C:1,E:1),
(C:1,E:1)}

Output 2:{C,E}

Return since no further recursion

FP-growth

<u>Conditional tree for A within conditional of E:</u>

Assume minSup=2

Conditional Pattern base for E:

P = {(A:2, E:2)}

Output 2:{A,E}

No further recursion.