Frequent Pattern Growth (FP-Growth) Algorithm

An Introduction

Outline

Introduction

FP-Tree data structure

Step 1: FP-Tree Construction

Step 2: Frequent Itemset Generation

Discussion

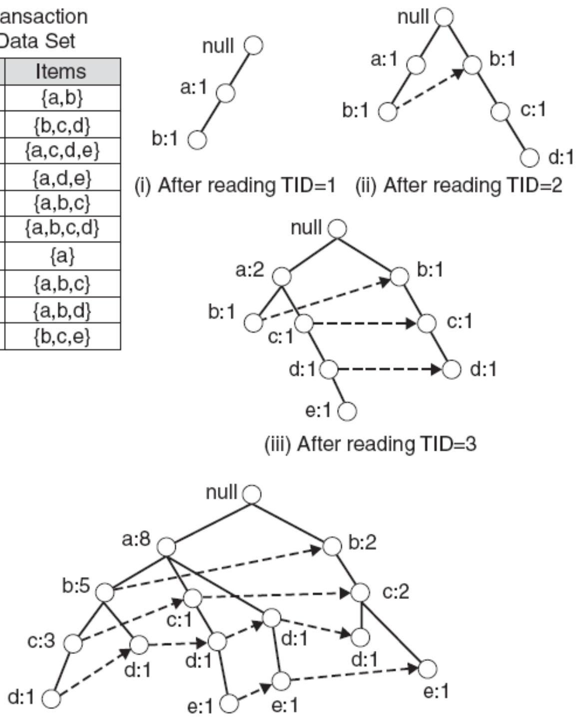
Introduction

- **Apriori:** uses a generate-and-test approach – generates candidate itemsets and tests if they are frequent
  - Generation of candidate itemsets is expensive (in both space and time)
  - Support counting is expensive
    - Subset checking (computationally expensive)
    - Multiple Database scans (I/O)
- **FP-Growth:** allows frequent itemset discovery without candidate itemset generation. Two step approach:
  - **Step 1**: Build a compact data structure called the *FP-tree*
    - Built using 2 passes over the data-set.
  - **Step 2**: Extracts frequent itemsets directly from the FP-tree
    - Traversal through FP-Tree

Core Data Structure: FP-Tree

Transaction Data Set

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	{a}
8	{a,b,c}
9	{a,b,d}
10	{b,c,e}



(i) After reading TID=1 (ii) After reading TID=2

(iii) After reading TID=3

(iv) After reading TID=10

- Nodes correspond to items and have a counter
- FP-Growth reads 1 transaction at a time and maps it to a path
- Fixed order is used, so paths can overlap when transactions share items (when they have the same prefix).
- In this case, counters are incremented
- Pointers are maintained between nodes containing the same item, creating singly linked lists (dotted lines)
- The more paths that overlap, the higher the compression. FP-tree may fit in memory.
- Frequent itemsets extracted from the FP-Tree.

Step 1: FP-Tree Construction (Example)

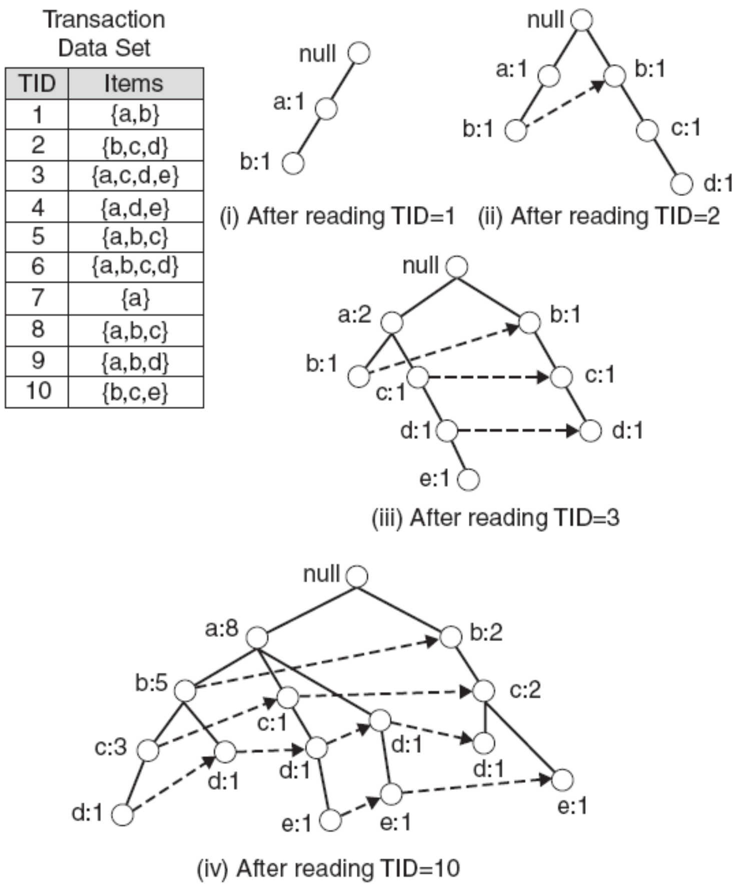
FP-Tree is constructed using 2 passes over the data-set:

- **Pass 1**:
  - Scan data and find support for each item.
  - Discard infrequent items.
  - Sort frequent items in decreasing order based on their support.
    - For our example: a, b, c, d, e
    - Use this order when building the FP-Tree, so common prefixes can be shared.

Step 1: FP-Tree Construction (Example)

- **Pass 2**: construct the FP-Tree (see diagram on next slide)
  - Read transaction 1: $\{a, b\}$
    - Create 2 nodes a and b and the path $null \rightarrow a \rightarrow b$. Set counts of a and b to 1.
  - Read transaction 2: $\{b, c, d\}$
    - Create 3 nodes for b, c and d and the path $null \rightarrow b \rightarrow c \rightarrow d$. Set counts to 1.
    - Note that although transaction 1 and 2 share b, the paths are disjoint as they don't share a common prefix. Add the link between the b's.
  - Read transaction 3: $\{a, c, d, e\}$
    - It shares common prefix item a with transaction 1 so the path for transaction 1 and 3 will overlap and the frequency count for node a will be incremented by 1. Add links between the c's and d's.
  - Continue until all transactions are mapped to a path in the FP-tree.

Step 1: FP-Tree Construction (Example)



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	{a}
8	{a,b,c}
9	{a,b,d}
10	{b,c,e}

(i) After reading TID=1 (ii) After reading TID=2

(iii) After reading TID=3

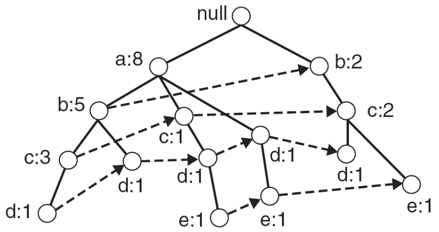
(iv) After reading TID=10

FP-Tree size

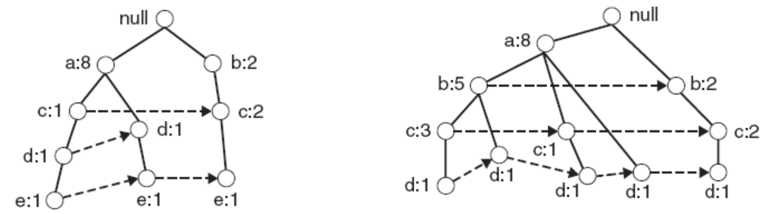
- The FP-Tree usually has a smaller size than the uncompressed data – typically many transactions share items (and hence prefixes).
  - *Best case scenario*: all transactions contain the same set of items.
    - 1 path in the FP-tree
  - *Worst case scenario*: every transaction has a unique set of items (no items in common)
    - Size of the FP-tree is *at least* as large as the original data.
    - Storage requirements for the FP-tree are higher – need to store the pointers between the nodes and the counters.
  - The size of the FP-tree depends on how the items are ordered
    - Ordering by decreasing support is typically used but it does not always lead to the smallest tree (it's a heuristic).

Step 2: Frequent Itemset Generation

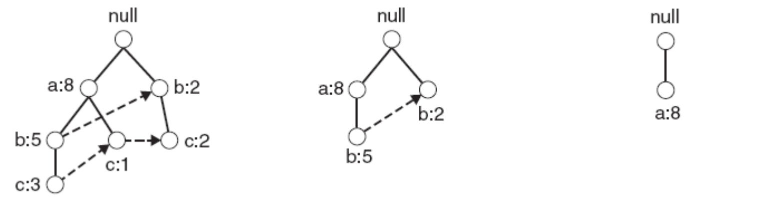
- FP-Growth extracts frequent itemsets from the FP-tree.
- Bottom-up algorithm – from the leaves towards the root
  - Divide and conquer: first look for frequent itemsets ending in *e*, then *de*, etc. . . then *d*, then *cd*, etc. . .
- First, extract prefix path sub-trees ending in an item(set). (*hint*: use the linked lists)



↑ Complete FP-tree
→ **Example:** prefix path sub-trees



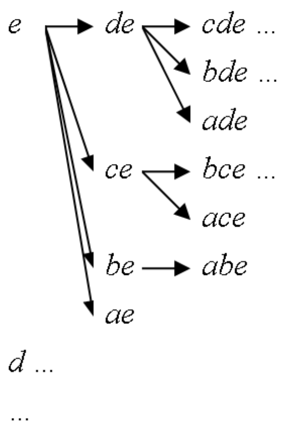
(a) Paths containing node e
(b) Paths containing node d

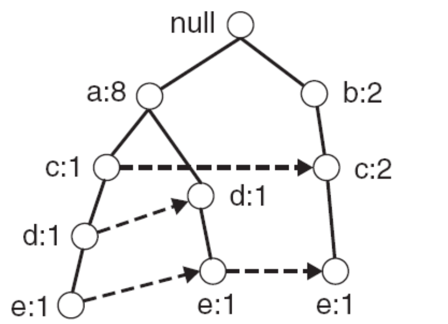


(c) Paths containing node c
(d) Paths containing node b
(e) Paths containing node a

Step 2: Frequent Itemset Generation

- Each prefix path sub-tree is processed recursively to extract the frequent itemsets. Solutions are then merged.
  - **E.g.** the *prefix path sub-tree* for *e* will be used to extract frequent itemsets ending in *e*, then in *de*, *ce*, *be* and *ae*, then in *cde*, *bde*, *cde*, etc.
  - Divide and conquer approach



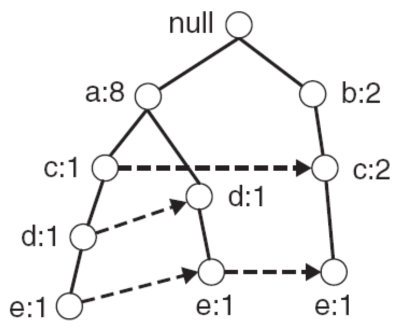


Prefix path sub-tree ending in *e*.

Example

Let $minSup = 2$ and extract all frequent itemsets containing e.

- 1. Obtain the prefix path sub-tree for e:

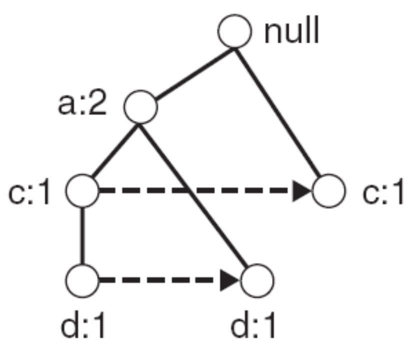


- 2. Check if e is a frequent item by adding the counts along the linked list (dotted line). If so, extract it.
  - Yes, count =3 so $\{e\}$ is extracted as a frequent itemset.
- 3. As e is frequent, find frequent itemsets ending in e. i.e. de, ce, be and ae.
  - i.e. decompose the problem recursively.
  - To do this, we must first to obtain the conditional FP-tree for e.

Conditional FP-Tree

- The FP-Tree that would be built if we only consider transactions containing a particular itemset (and then removing that itemset from all transactions).
- **Example**: FP-Tree conditional on e.

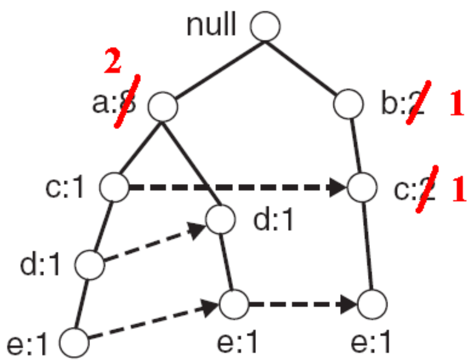
TID	Items
~~1~~	~~{a,b}~~
~~2~~	~~{b,c,d}~~
3	{a,c,d,~~e~~}
4	{a,d,~~e~~}
~~5~~	~~{a,b,e}~~
~~6~~	~~{a,b,c,d}~~
~~7~~	~~{a}~~
~~8~~	~~{a,b,c}~~
~~9~~	~~{a,b,d}~~
10	{b,c,~~e~~}



Conditional FP-Tree

To obtain the *conditional FP-tree* for *e* from the *prefix sub-tree* ending in *e*:

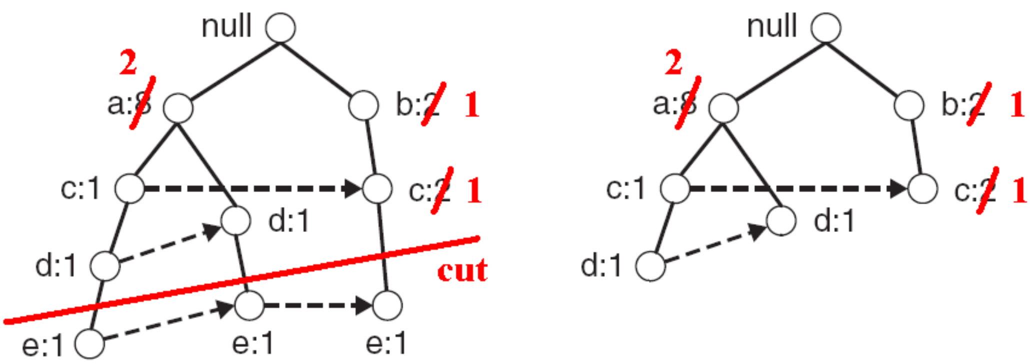
- Update the support counts along the prefix paths (from *e*) to reflect the number of transactions containing *e*.
  - *b* and *c* should be set to 1 and *a* to 2.



Conditional FP-Tree

To obtain the *conditional FP-tree* for *e* from the *prefix sub-tree* ending in *e*:

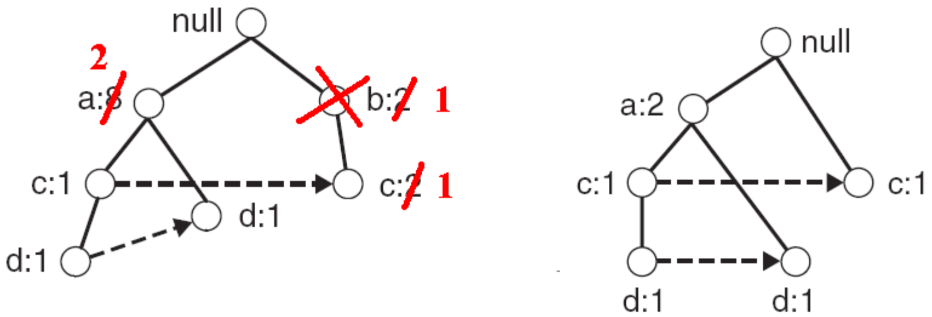
- Remove the nodes containing *e* – information about node *e* is no longer needed because of the previous step



Conditional FP-Tree

To obtain the *conditional FP-tree* for *e* from the *prefix sub-tree* ending in *e*:

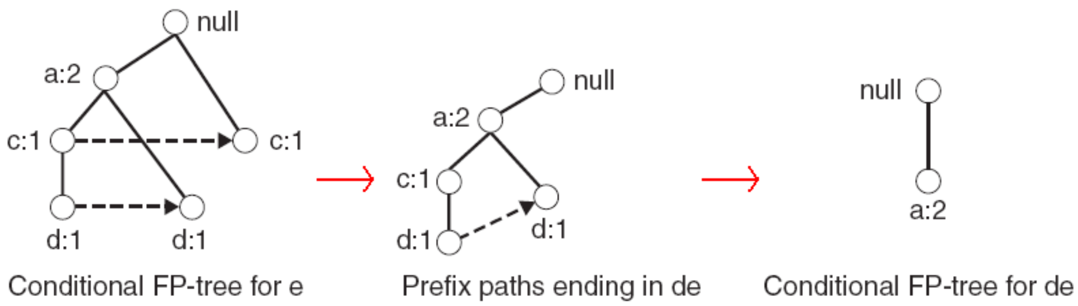
- Remove infrequent items (nodes) from the prefix paths
- **E.g.** *b* has a support of 1 (note this really means *be* has a support of 1). i.e. there is only 1 transaction containing *b and e* so *be* is infrequent – can remove b.



Question: why were *c* and *d* not removed?

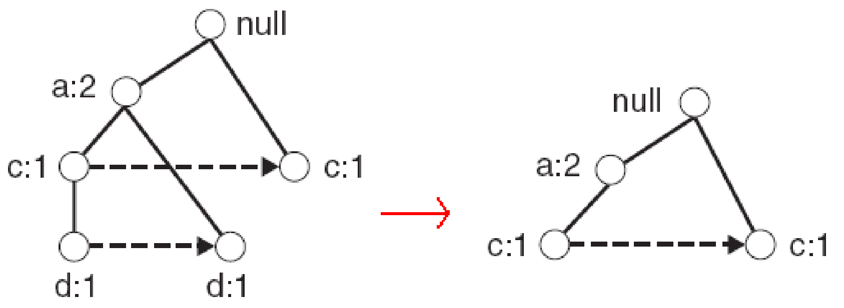
Example (continued)

- 4. Use the the conditional FP-tree for *e* to find frequent itemsets ending in *de*, *ce* and *ae*
  - Note that *be* is not considered as *b* is not in the conditional FP-tree for *e*.
  - For each of them (e.g. *de*), find the prefix paths from the conditional tree for *e*, extract frequent itemsets, generate conditional FP-tree, etc... (recursive)
  - **Example:** $e \rightarrow de \rightarrow ade$ ($\{d, e\}$,$\{a, d, e\}$ are found to be frequent)



Example (continued)

- 4. Use the the conditional FP-tree for e to find frequent itemsets ending in de, ce and ae
  - **Example:** $e \rightarrow ce$ ($\{c, e\}$ is found to be frequent)



Conditional FP-tree for e   Prefix paths ending in ce

- etc... (ae, then do the whole thing for b,... etc)

Result

- Frequent itemsets found (ordered by suffix and order in which they are found):

Suffix	Frequent Itemsets
e	{e}, {d,e}, {a,d,e}, {c,e},{a,e}
d	{d}, {c,d}, {b,c,d}, {a,c,d}, {b,d}, {a,b,d}, {a,d}
c	{c}, {b,c}, {a,b,c}, {a,c}
b	{b}, {a,b}
a	{a}

Discussion

- Advantages of FP-Growth
  - only 2 passes over data-set
  - "compresses" data-set
  - no candidate generation
  - much faster than Apriori
- Disadvantages of FP-Growth
  - FP-Tree may not fit in memory!!
  - FP-Tree is expensive to build
    - Trade-off: takes time to build, but once it is built, frequent itemsets are read off easily.
    - Time is wasted (especially if support threshold is high), as the only pruning that can be done is on *single items*.
    - support can only be calculated once the entire data-set is added to the FP-Tree.

References

- [1] Pang-Ning Tan, Michael Steinbach, Vipin Kumar: *Introduction to Data Mining*, Addison-Wesley.
  - Chapter 6: *Association Analysis: Basic Concepts and Algorithms.*
  - Available from

  `http://www-users.cs.umn.edu/~kumar/dmbook/index.php`