# 732A75 Advanced Data Mining
# TDDD41 Data Mining - Clustering and Association Analysis
## Lecture 7: FP Grow Algorithm

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# Outline

- Content
  - Frequent Pattern (FP) Grow Algorithm
  - Exercise
  - Summary
- Literature
  - Course book. Second edition: 5.2.4. Third edition: 6.2.4.
  - Han, J., Pei, J. and Yin, Y. Mining Frequent Patterns without Candidate Generation. In Proc. of the 2000 ACM SIGMOD Int. Conf. on Management of Data, 2000.

# FP Grow Algorithm

- Assume that we have access to some transactional data, e.g.

| Transaction id | Items bought |
|---|---|
| 1 | F, A, C, D, G, I, M, P |
| 2 | A, B, C, F, L, M, O |
| 3 | B, F, H, J, O, W |
| 4 | B, C, K, S, P |
| 5 | A, F, C, E, L, P, M, N |

- The FP grow algorithm returns all the frequent itemsets without candidate generation and, thus, it may save time and space.
- First, it finds frequent 1-itemsets and **sorts the frequent items within each transaction in support descending order**, e.g. with *minsup* = 3

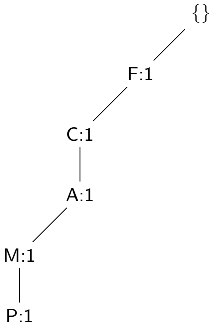
| Transaction id | Items bought |
|---|---|
| 1 | F, C, A, M, P |
| 2 | F, C, A, B, M |
| 3 | F, B |
| 4 | C, B, P |
| 5 | F, C, A, M, P |

- Then, it outputs the frequent 1-itemsets, i.e. F, C, A, B, M, and P.

# FP Grow Algorithm

- Then, it constructs a so-called FP tree.

| Transaction id | Items bought |
|---|---|
| 1 | F, C, A, M, P |
| 2 | F, C, A, B, M |
| 3 | F, B |
| 4 | C, B, P |
| 5 | F, C, A, M, P |



# FP Grow Algorithm

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| 2 | F, C, A, B, M |
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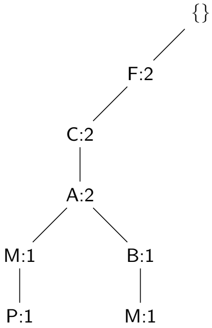
| 4 | C, B, P |
| 5 | F, C, A, M, P |



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|---|---|
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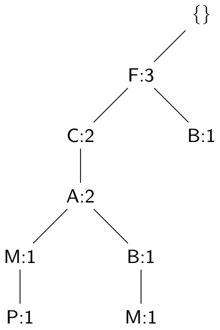

# FP Grow Algorithm

- Then, it constructs a so-called FP tree.

| Transaction id | Items bought |
|---|---|
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| 2 | F, C, A, B, M |
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| 4 | C, B, P |
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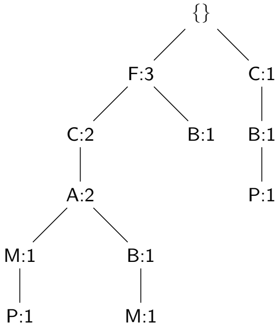
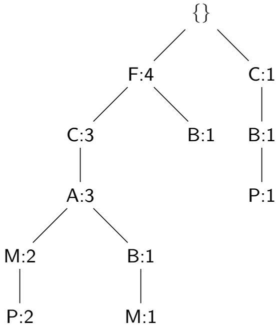


# FP Grow Algorithm

- Then, it constructs a so-called FP tree.

| Transaction id | Items bought |
|---|---|
| 1 | F, C, A, M, P |
| 2 | F, C, A, B, M |
| 3 | F, B |
| 4 | C, B, P |
| 5 | F, C, A, M, P |




- Finally, it mines the FP tree for frequent itemsets instead of the original database, since the former is typically much smaller.

# FP Grow Algorithm

**Algorithm**: FP-tree($D$, $minsup$)
**Input**: A transactional database $D$, and the minimum support $minsup$.
**Output**: The FP tree for $D$ and $minsup$.

Count support for each item in $D$
Remove the infrequent items from the transactions in $D$
Sort the items in each transaction in $D$ in support descending order
Create a FP tree with a single node $T$ with $T.name = NULL$
for each transaction $I \in D$ do
    insert-tree($I$, $T$)

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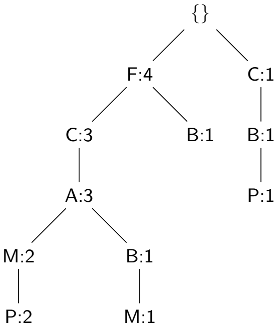
**Algorithm**: insert-tree($I_1, \ldots I_m$, $T$)
**Input**: An itemset $I_1, \ldots, I_m$, and a node $T$ in the FP tree.
**Output**: Modified FP tree.

if $T$ has a child $N$ such that $N.name = I_1.name$ then
    $N.count{+}{+}$
else
    create a new child $N$ of $T$ with $N.name = I_1.name$ and $N.count = 1$
if $m > 1$ then
    insert-tree ($I_2, \ldots, I_m, N$)

## FP Grow Algorithm

- Given an item X, the X-conditional database consists of all the prefix paths leading to X in the FP tree.




| Item | Conditional database |
|---|---|
| F | - |
| C | F:3 |
| A | FC:3 |
| B | FCA:1, F:1, C:1 |
| M | FCA:2, FCAB:1 |
| P | FCAM:2, CB:1 |

- The support of each prefix path in the X-conditional database is equal to the count of X for that prefix path.
- The X-conditional database contains all the itemsets in $D$ that end with X.
- So, it suffices to mine the X-conditional database to find all the frequent itemsets in $D$ that end with X.
- So, re-start the whole process for the X-conditional database, i.e. call the FP grow algorithm recursively.

# FP Grow Algorithm

- For instance, the M-conditional database is {FCA:2, FCAB:1}, or

| Tid | Items bought |
|---|---|
| 1 | F, C, A |
| 2 | F, C, A |
| 3 | F, C, A, B |

- After finding the frequent 1-itemsets and sorting the transactions accordingly, we have

| Tid | Items bought |
|---|---|
| 1 | F, C, A |
| 2 | F, C, A |
| 3 | F, C, A |

- Output the frequent 1-itemsets, adding M as suffix, i.e. FM, CM, and AM.
- Build the FP tree and the conditional databases.


| Item | Conditional database |
|---|---|
| F | - |
| C | F:3 |
| A | FC:3 |

- Re-start the process for the FM-, CM-, and AM-conditional databases.

# FP Grow Algorithm

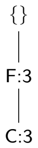
- For instance, the AM-conditional database is $\{$FC:3$\}$, or

| Tid | Items bought |
|---|---|
| 1 | F, C |
| 2 | F, C |
| 3 | F, C |

- After finding the frequent 1-itemsets and sorting the transactions accordingly, we have

| Tid | Items bought |
|---|---|
| 1 | F, C |
| 2 | F, C |
| 3 | F, C |

- Output the frequent 1-itemsets, adding AM as suffix, i.e. FAM, and CAM.
- Build the FP tree and the conditional databases.




| Item | Conditional database |
|---|---|
| F | - |
| C | F:3 |

- Re-start the process for the FAM-, and CAM-conditional databases.

# FP Grow Algorithm

- For instance, the CAM-conditional database is {F:3}, or

| Tid | Items bought |
|---|---|
| 1 | F |
| 2 | F |
| 3 | F |

- After finding the frequent 1-itemsets and sorting the transactions accordingly, we have

| Tid | Items bought |
|---|---|
| 1 | F |
| 2 | F |
| 3 | F |

- Output the frequent 1-itemsets, adding CAM as suffix, i.e. FCAM.
- Build the FP tree and the conditional databases.


| Item | Conditional database |
|---|---|
| F | - |

- Backtrack.

# FP Grow Algorithm

- To mine the FP tree *Tree*, call FP-grow(*Tree*, NULL, *minsup*).

**Algorithm**: FP-grow(*Tree*, $\alpha$, *minsup*)
**Input**: A FP tree *Tree*, an itemset $\alpha$, and the minimum support *minsup*.
**Output**: All the itemsets in *Tree* that end with $\alpha$ and have *minsup*.

for each item $X$ in *Tree* do
    output the itemset $\beta = X \cup \alpha$ with support$=X.count$
    build the $\beta$ conditional database and the corresponding FP tree $Tree_\beta$
    if $Tree_\beta$ is not empty then call FP-grow($Tree_\beta$, $\beta$, *minsup*)

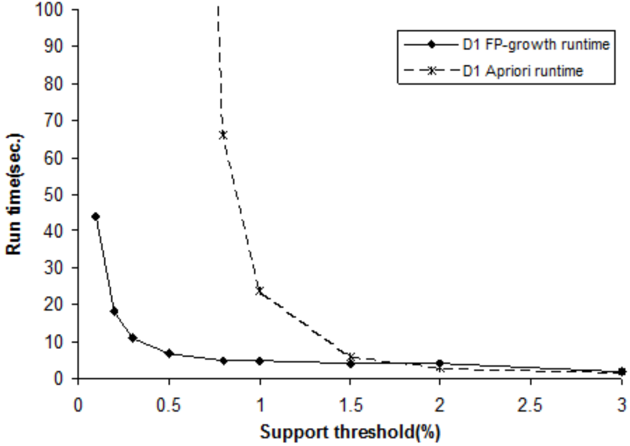
- The algorithm above can be made more efficient by adding the lines below.

if *Tree* has a single branch then
    for each combination $\beta$ of the nodes in the branch do
        output the itemset $\beta \cup \alpha$ with support $= \min_{X \in \beta} X.count$
else

- The FP grow algorithm is correct, i.e. it misses no frequent itemset.

# FP Grow Algorithm

- With small values for *minsup*, there are many and long candidates, which implies long runtime due to expensive operations such as pattern matching, subset checking, storing, etc.



# Exercise

- Run the FP grow algorithm on the database below with mininum support equal to two transactions.

| Tid | Items bought |
|---|---|
| 1 | A, B, E |
| 2 | B, D |
| 3 | B, C |
| 4 | A, B, D |
| 5 | A, C |
| 6 | B, C |
| 7 | A, C |
| 8 | A, B, C, E |
| 9 | A, B, C |

- Show the execution details (i.e. FP tree construction, conditional databases, recursive calls), not just the frequent itemsets found.

# Summary

- Mining transactions to find rules of the form

$$Item_1, \ldots, Item_m \rightarrow Item_{m+1}, \ldots, Item_n$$

  with user-defined minimum support and confidence.
- Two-step solution:
  1. Find all the large itemsets.
  2. Generate all the rules with minimum confidence from the large itemsets.
- We have seen one solution for step 2, and two solutions for step 1, i.e. with and without candidate generation: Apriori and FP grow algorithms.
- Their runtime can differ substantially for small values of *minsup*.