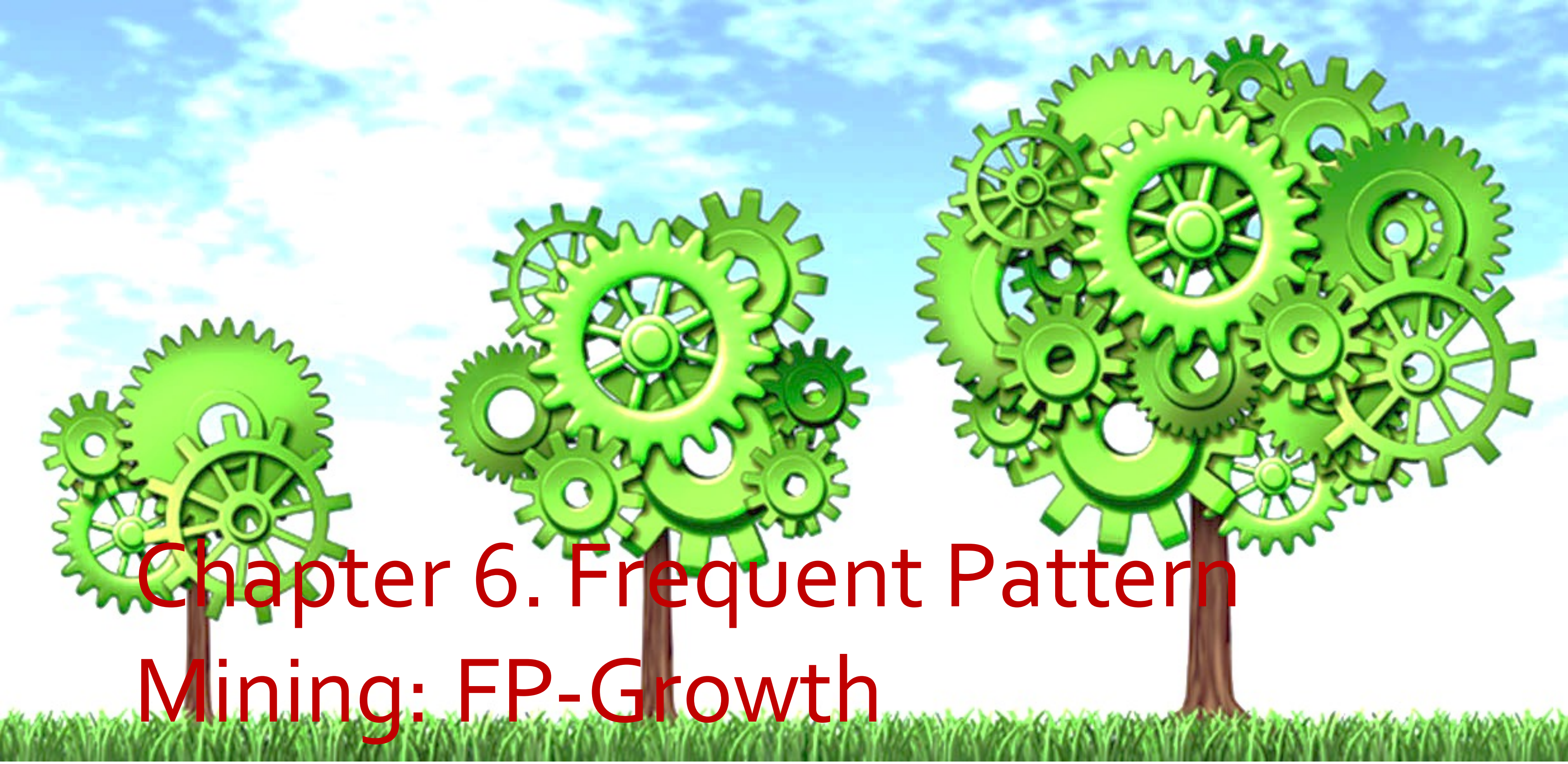

Chapter 6. Frequent Pattern Mining: FP-Growth

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Introduction to Data Mining

Frequent Pattern Mining Methods

- Apriori
- **ECLAT**
- **FP-Growth**

Exploring Vertical Data Format: ECLAT

- ECLAT (Equivalence Class Transformation): A depth-first search algorithm using set intersection [Zaki et al. @KDD'97]
- Tid-List: List of transaction-ids containing an itemset
- Vertical format: $t(e) = \{T_{10}, T_{20}, T_{30}\}$; $t(a) = \{T_{10}, T_{20}\}$; $t(ae) = \{T_{10}, T_{20}\}$
- **Deriving frequent patterns based on vertical intersections**

A transaction DB in Horizontal Data Format

Tid	Itemset
10	a, c, d, e
20	a, b, e
30	b, c, e

The transaction DB in Vertical Data Format

Item	TidList
a	10, 20
b	20, 30
c	10, 30
d	10
e	10, 20, 30

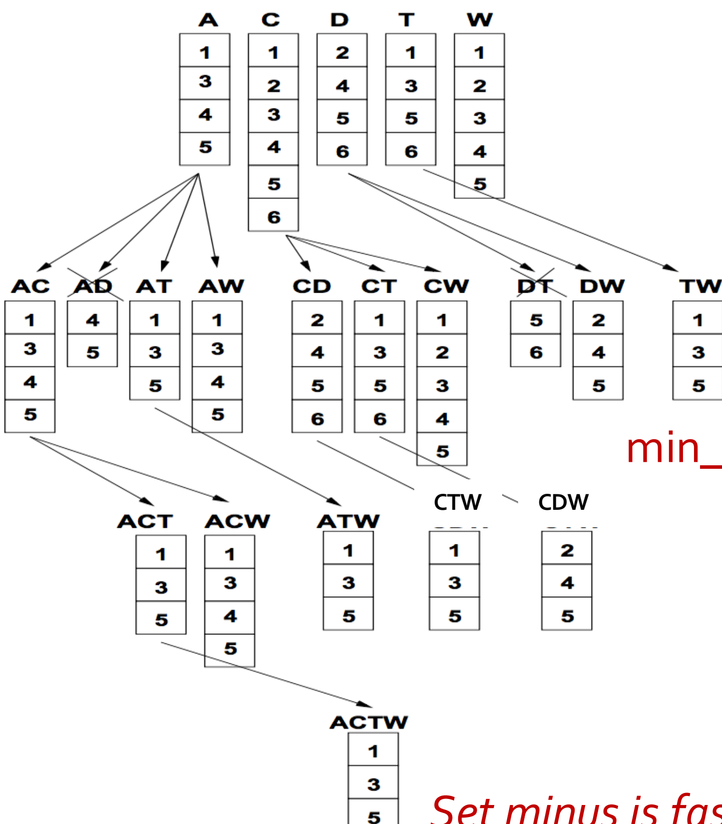
http://www.cs.rpi.edu/~zaki/PaperDir/SIGKDD03-diffsets.pdf

ECLAT: Diffset Based Mining

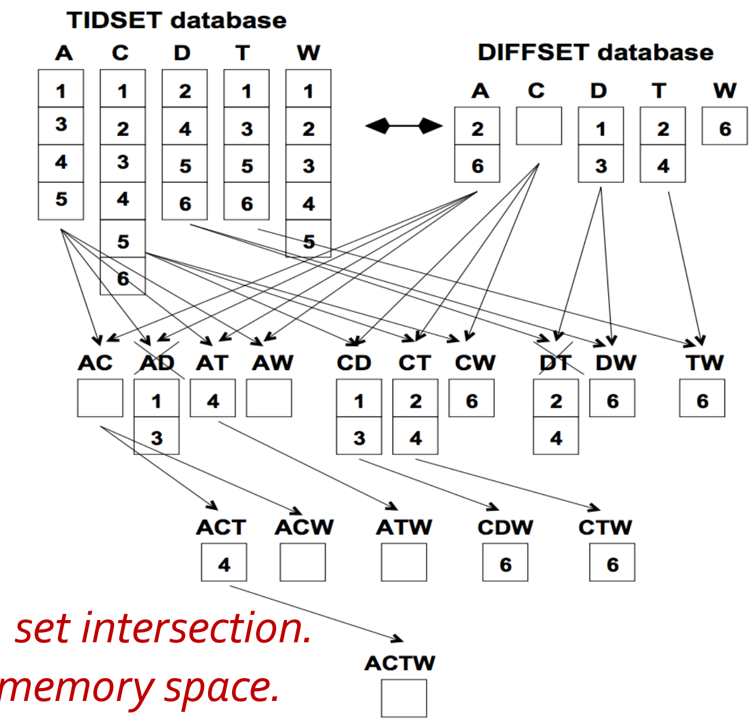
- Using diffset to accelerate mining
  - Only keep track of differences of tids

P: itemset; X, Y: items; d: diffset;
t: transaction set/list; σ: support

$d(XY) = t(X) - t(Y)$
$\quad = d(Y) - d(X)$
$d(PXY) = t(PX) - t(PY)$
$\quad = d(PY) - d(PX)$
$\sigma(PX) = \sigma(P) - |d(PX)|$



min_sup = 3



Set minus is faster than set intersection.
Set minus requires less memory space.

FPGrowth: Mining Frequent Patterns by Pattern Growth

- Idea: Frequent pattern growth (FPGrowth)
  - Find frequent single items and partition the database based on each such item
  - Recursively grow frequent patterns by doing the above for each partitioned database (also called *conditional database*)
  - To facilitate efficient processing, an efficient data structure, FP-tree, can be constructed
- Mining becomes
  - Recursively construct and mine (conditional) FP-trees
  - Until the resulting FP-tree is empty, or until it contains only one path—single path will generate all the combinations of its sub-paths, each of which is a frequent pattern

YouTube: https://www.youtube.com/watch?v=LXx1xKF9oDg

Example: Construct FP-tree from a Transactional DB

TID	Items in the Transaction	Ordered, frequent items
100	*{f, a, c, d, g, i, m, p}*	*{f, c, a, m, p}*
200	*{a, b, c, f, l, m, o}*	*{f, c, a, b, m}*
300	*{b, f, h, j, o, w}*	*{f, b}*
400	*{b, c, k, s, p}*	*{c, b, p}*
500	*{a, f, c, e, l, p, m, n}*	*{f, c, a, m, p}*

Answer:
f:4, a:3, c:4, b:3, m:3, p:3;
fm: 3, cm: 3, am: 3, cp:3;
fcm: 3, fam:3, cam: 3;
fcam: 3.

1. Scan DB once, find single item frequent pattern:

Let min_support = 3

f:4, a:3, c:4, b:3, m:3, p:3

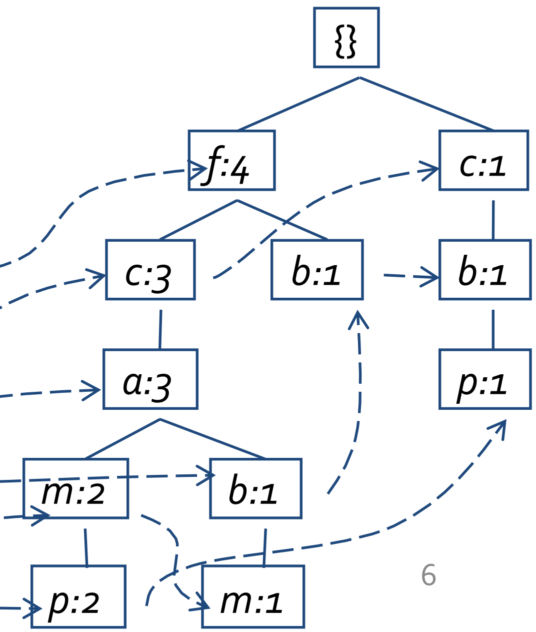
2. Sort frequent items in frequency descending order, f-list

F-list = f-c-a-b-m-p

3. Scan DB again, construct FP-tree

Header Table

Item	Frequency	Header
f	4	
c	4	
a	3	
b	3	
m	3	
p	3	

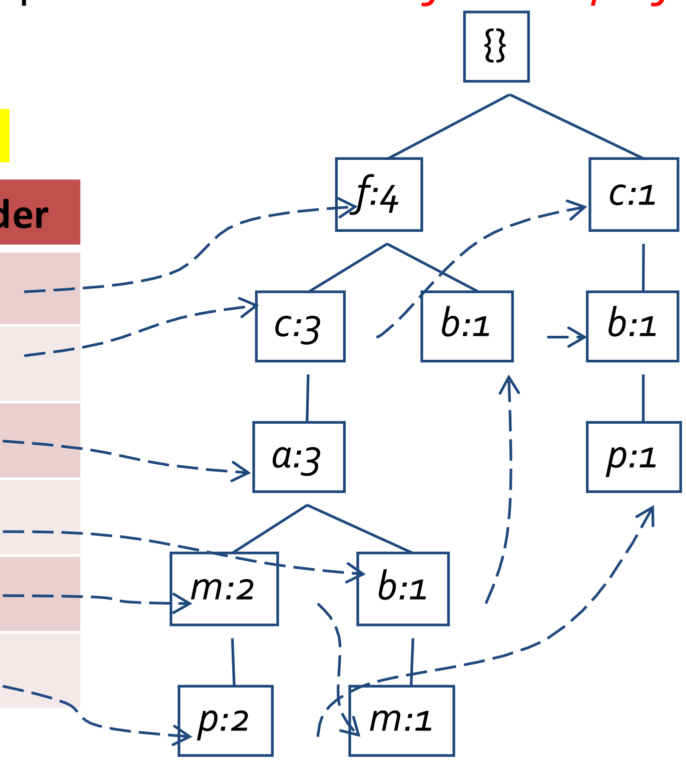


Divide and Conquer Based on Patterns and Data

- Pattern mining can be partitioned according to current patterns
  - Patterns containing p: p's conditional database: *fcam:2, cb:1*
  - Patterns having m but no p: m's conditional database: *fca:2, fcab:1*
  - …… ……
- *p*'s conditional pattern base: *transformed prefix paths* of item *p*

min_support = 3

Item	Frequency	Header
f	4	
c	4	
a	3	
b	3	
m	3	
p	3	



Conditional **pattern bases**

Item	*Conditional pattern base*
c	*f:3*
a	*fc:3*
b	*fca:1, f:1, c:1*
m	*fca:2, fcab:1*
p	*fcam:2, cb:1*

Mine Each Conditional Pattern-Base Recursively

Conditional **pattern bases**

item	*cond. pattern base*
c	*f:3*
a	*fc:3*
b	*fca:1, f:1, c:1*
m	*fca:2, fcab:1*
p	*fcam:2, cb:1*

min_support = 3

For each conditional pattern-base

- Mine single-item patterns
- Construct its **cond. FP-tree** & mine it

p-conditional PB: ***fcam:2, cb:1 → c: 3***

m-conditional PB: ***fca:2, fcab:1 → fca: 3***

b-conditional PB: ***fca:1, f:1, c:1 → ϕ***

a-conditional PB: ***fc:3 → fc:3***

c-conditional PB: ***f:3 → f:3***

Mine Each Conditional Pattern-Base Recursively

Conditional pattern bases

item	*cond. pattern base*
c	*f:3*
a	*fc:3*
b	*fca:1, f:1, c:1*
m	*fca:2, fcab:1*
p	*fcam:2, cb:1*

min_support = 3

For each conditional pattern-base

- Mine single-item patterns
- Construct its **cond. FP-tree** & **mine** it

p-conditional PB: ***fcam:2, cb:1 → c: 3***

m-conditional PB: ***fca:2, fcab:1 → fca: 3***

b-conditional PB: ***fca:1, f:1, c:1 → ϕ***

a-conditional PB: ***fc:3 → fc:3***

c-conditional PB: ***f:3 → f:3***

{} — *f:3* — *c:3* — *a:3*
m-cond. FP-tree

{} — *f:3* — *c:3*
am-cond. FP-tree

{} — *f:3*
cm-cond. FP-tree

{} — *f:3*
cam-cond. FP-tree

mine(<f:3, c:3, a:3>|m)

→ (am:3) + mine(<f:3, c:3>|am)

→ (cam:3) + (fam:3) + mine (<f:3>|cam)

→ (fcam:3)

→ (cm:3) + mine(<f:3>|cm)

→ (fcm:3)

→ (fm:3)

Mine Each Conditional Pattern-Base Recursively

Conditional pattern bases

item	*cond. pattern base*
c	***f:3***
a	***fc:3***
b	***fca:1, f:1, c:1***
m	***fca:2, fcab:1***
p	***fcam:2, cb:1***

min_support = 3

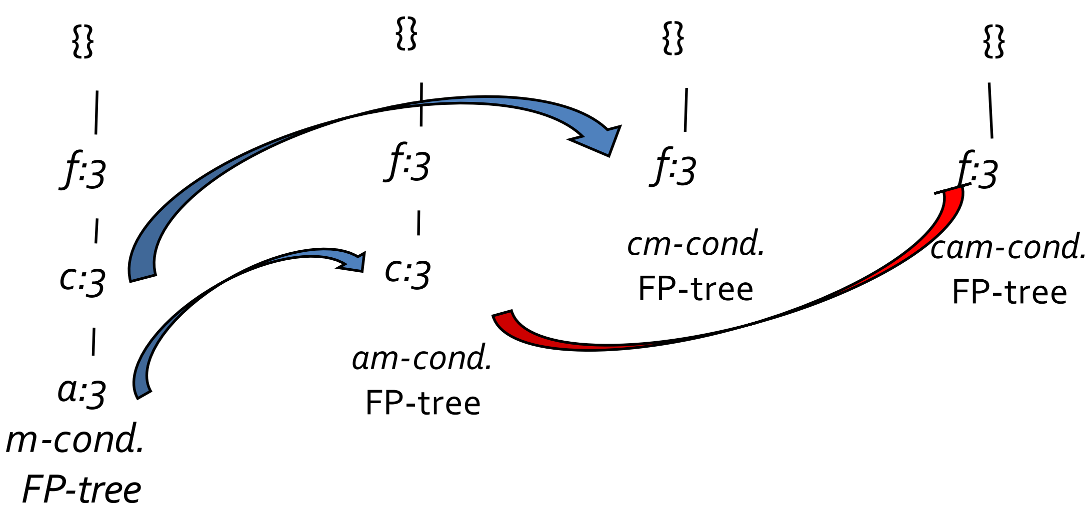
For each conditional pattern-base

- Mine single-item patterns
- Construct its cond. FP-tree & mine it

p-conditional PB: ***fcam:2, cb:1*** → ***c: 3***

m-conditional PB: ***fca:2, fcab:1*** → ***fca: 3***

b-conditional PB: ***fca:1, f:1, c:1*** → ***ϕ***



Actually, for single branch FP-tree, all frequent patterns can be generated in one shot

m: 3
fm: 3, cm: 3, am: 3
fcm: 3, fam:3, cam: 3
fcam: 3

Mine Each Conditional Pattern-Base Recursively

***Conditional* pattern bases**

item	*cond. pattern base*
c	***f:3***
a	***fc:3***
b	***fca:1, f:1, c:1***
m	***fca:2, fcab:1***
p	***fcam:2, cb:1***

min_support = 3

For each conditional pattern-base

- Mine single-item patterns
- Construct its **cond. FP-tree** & **mine** it

p-conditional PB: ***fcam:2, cb:1*** → ***c: 3***

m-conditional PB: ***fca:2, fcab:1*** → ***fca: 3***

b-conditional PB: ***fca:1, f:1, c:1*** → ***ϕ***

a-conditional PB: ***fc:3*** → ***fc:3***

c-conditional PB: ***f:3*** → ***f:3***

Mine Each Conditional Pattern-Base Recursively

Conditional **pattern bases**

item	***cond. pattern base***
c	***f:3***
a	***fc:3***
b	***fca:1, f:1, c:1***
m	***fca:2, fcab:1***
p	***fcam:2, cb:1***

min_support = 3

For each conditional pattern-base

- Mine single-item patterns
- Construct its **cond. FP-tree** & **mine** it

p-conditional PB: ***fcam:2, cb:1* → *c: 3***

m-conditional PB: ***fca:2, fcab:1* → *fca: 3***

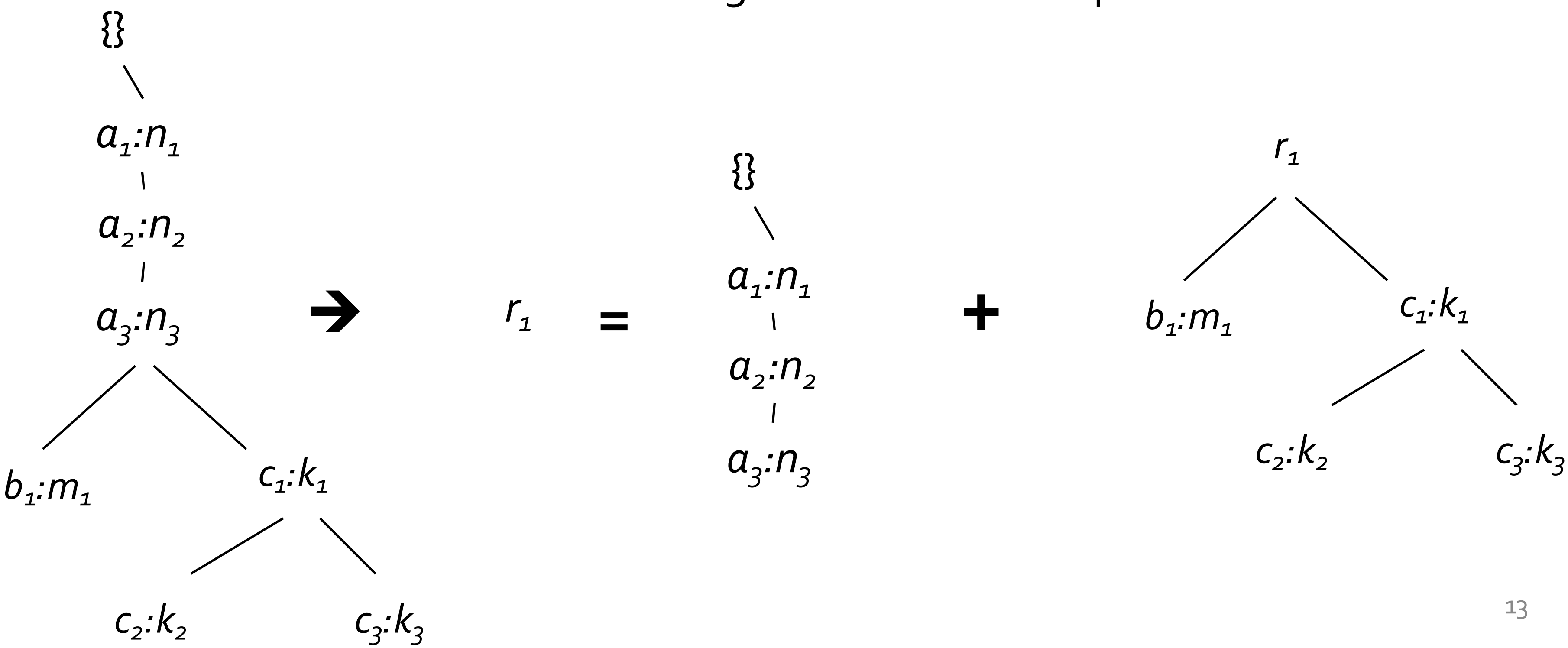
b-conditional PB: ***fca:1, f:1, c:1* → *ϕ***

a-conditional PB: ***fc:3* → *fc:3***

c-conditional PB: ***f:3* → *f:3***

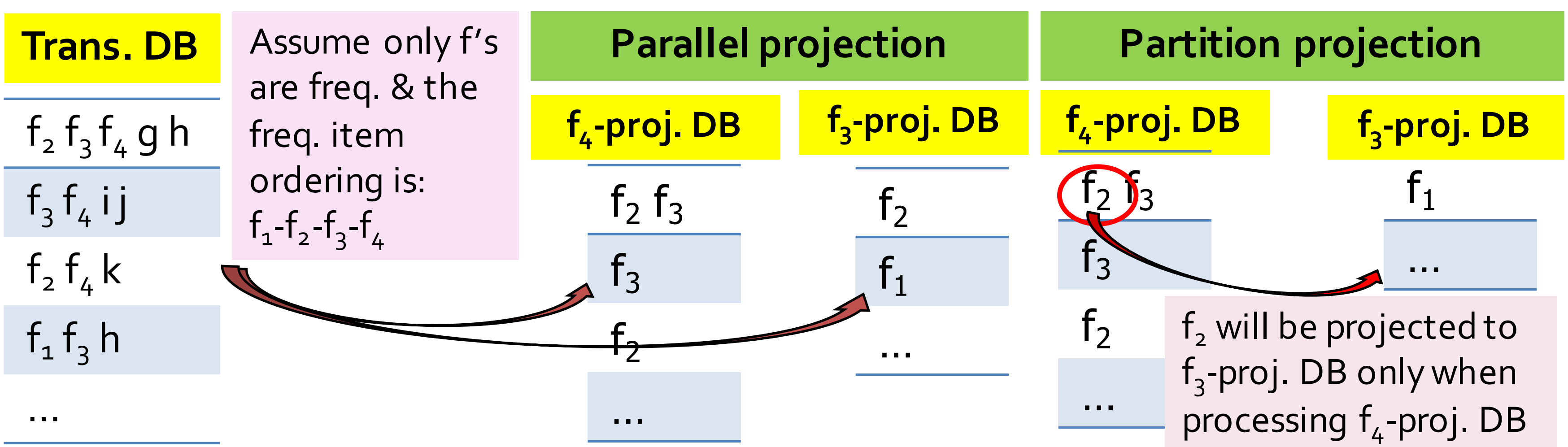
A Special Case: Single Prefix Path in FP-tree

- Suppose a (conditional) FP-tree T has a shared single prefix-path P
- Mining can be decomposed into two parts
  - Reduction of the single prefix path into one node
  - Concatenation of the mining results of the two parts



Scaling FP-growth by Database Projection

- What if FP-tree cannot fit in memory? — DB projection
  - Project the DB based on patterns
  - Construct & mine FP-tree for each projected DB
- Parallel projection vs. partition projection
  - Parallel projection: Project the DB on each frequent item
    - Space costly, all partitions can be processed in parallel
  - Partition projection: Partition the DB in order
    - Passing the unprocessed parts to subsequent partitions



Discussion

- Compare Apriori, ECLAT, and FP-Growth.
  - Strong points of each
  - Weak points of each

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