

The background features a complex, abstract design. It includes a network of thin, intersecting lines in shades of red, orange, and grey, creating a web-like structure. Scattered throughout are small, colored dots in green, blue, and orange. A prominent white banner with a slight 3D effect and a drop shadow is positioned horizontally across the upper middle of the image. The banner contains the title text. On the left side of the banner, there is a small, square inset image showing a cluster of orange and red dots on a light background, with a faint grid pattern overlaid. The overall aesthetic is technical and data-oriented.

FPGrowth: A Pattern Growth Approach

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

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}

去除不频繁的
项之后

顺序要按 F-list.

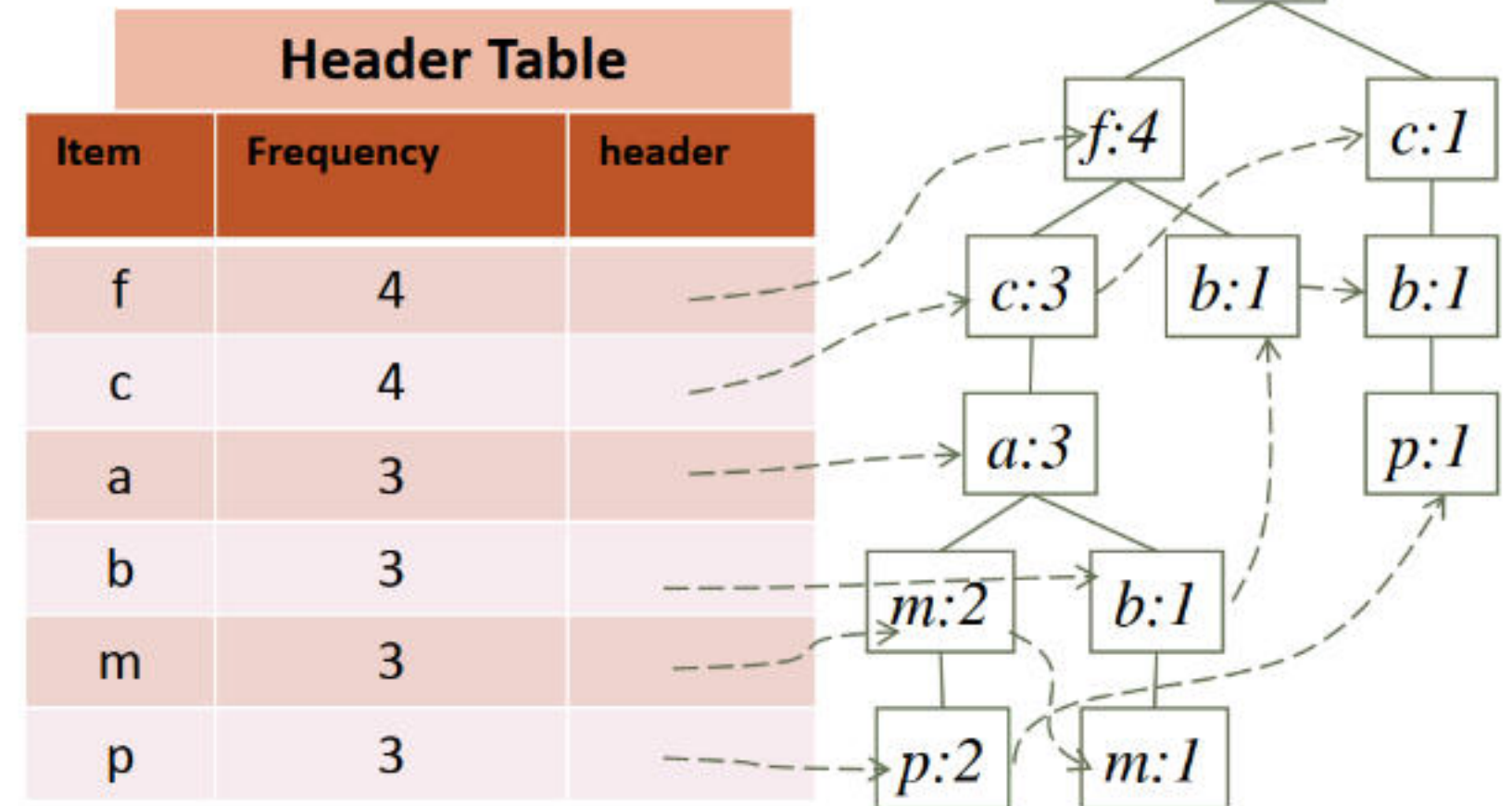
1. Scan DB once, find single item frequent pattern: **Let min_support = 3**

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

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

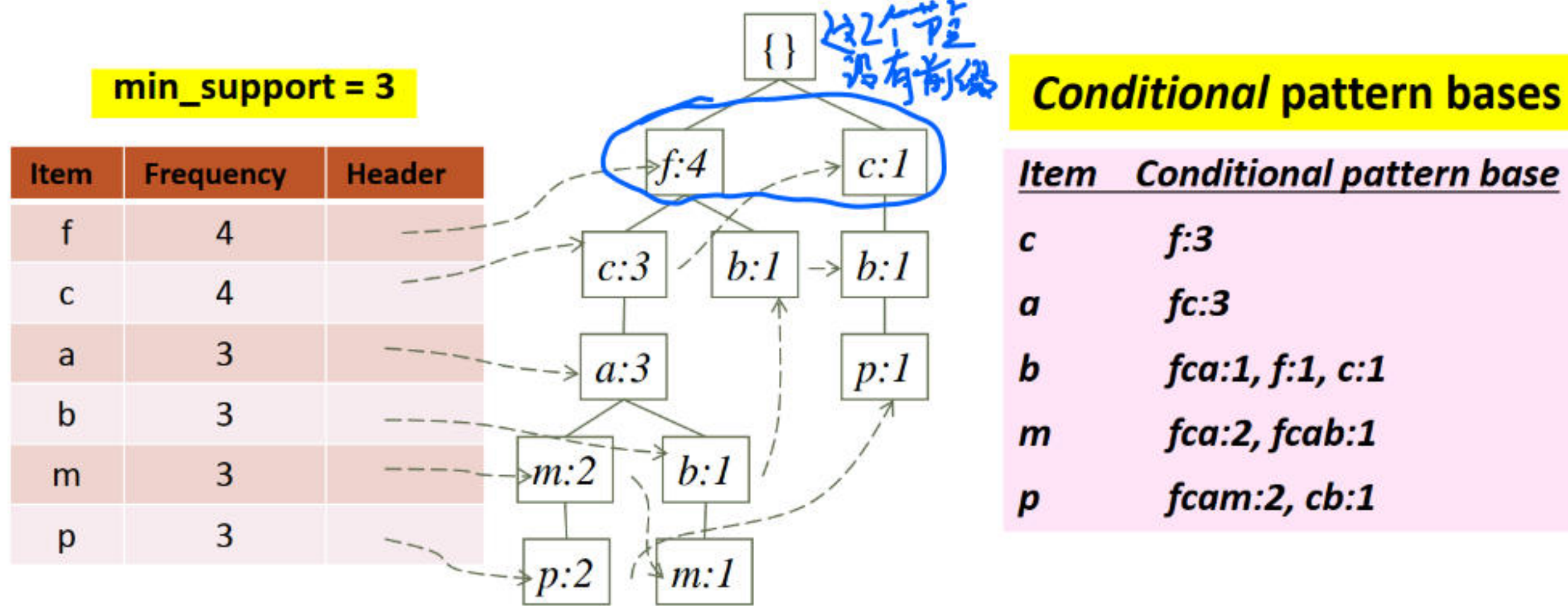
F-list = f-c-a-b-m-p

3. Scan DB again, construct FP-tree



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



Mine Each Conditional Pattern-Base Recursively

Conditional pattern bases

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

- For each conditional pattern-base
 - Mine single-item patterns
 - Construct its FP-tree & mine it

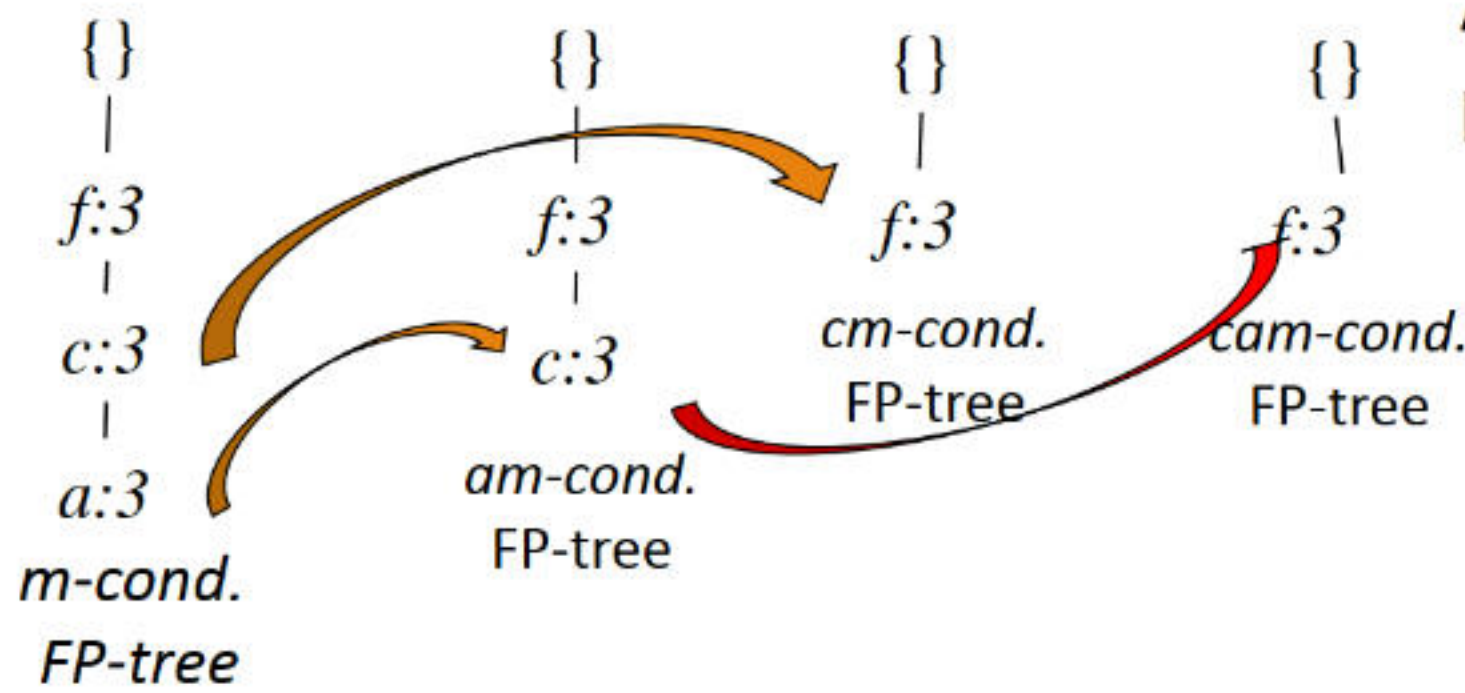
p-conditional PB: $fcam:2, cb:1 \rightarrow c: 3$ *c出现了3次*

m-conditional PB: $fca:2, fcab:1 \rightarrow fca: 3$ *fca出现了3次.*

b-conditional PB: $fca:1, f:1, c:1 \rightarrow \phi$ *没有出现3次的.*

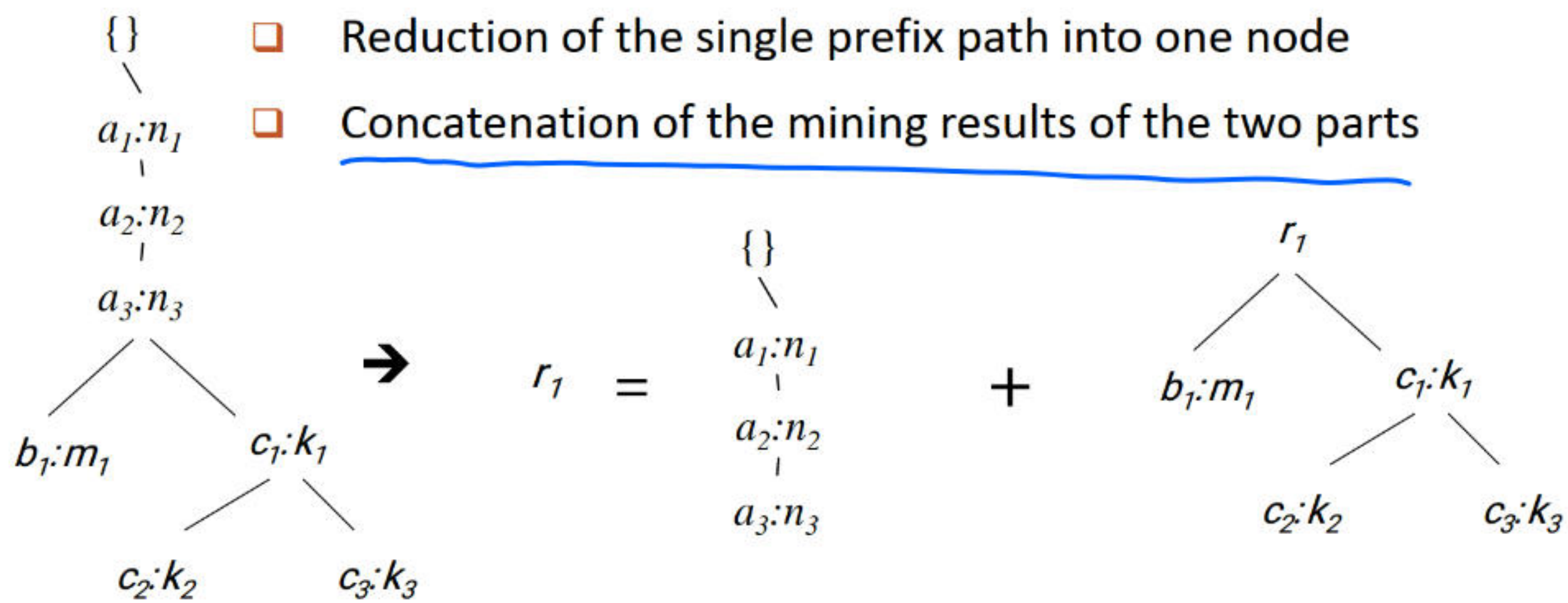
Actually, for single branch FP-tree, all frequent patterns can be generated in one shot

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



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

