



University of Colorado
Boulder

CSCI 4502/5502

Data Mining

Fall 2020
Lecture 09 (Sep 22)

Reminders

- ◆ Homework 3

- ◆ due at 9:30am, Th, Sep 24

- ◆ Temporary 2-week remote instruction

- ◆ Wed Sep 23 to Wed Oct 7

- ◆ Stay healthy! Take good care!

Announcements

◆ Homework 1

- ◆ grades posted in Canvas, please check
- ◆ contact GSS first with grading questions
- ◆ Homework 2 is being graded
- ◆ No new homework this Thursday
- ◆ work on course project proposal

Review

♦ Chapter 6: Mining Frequent Patterns

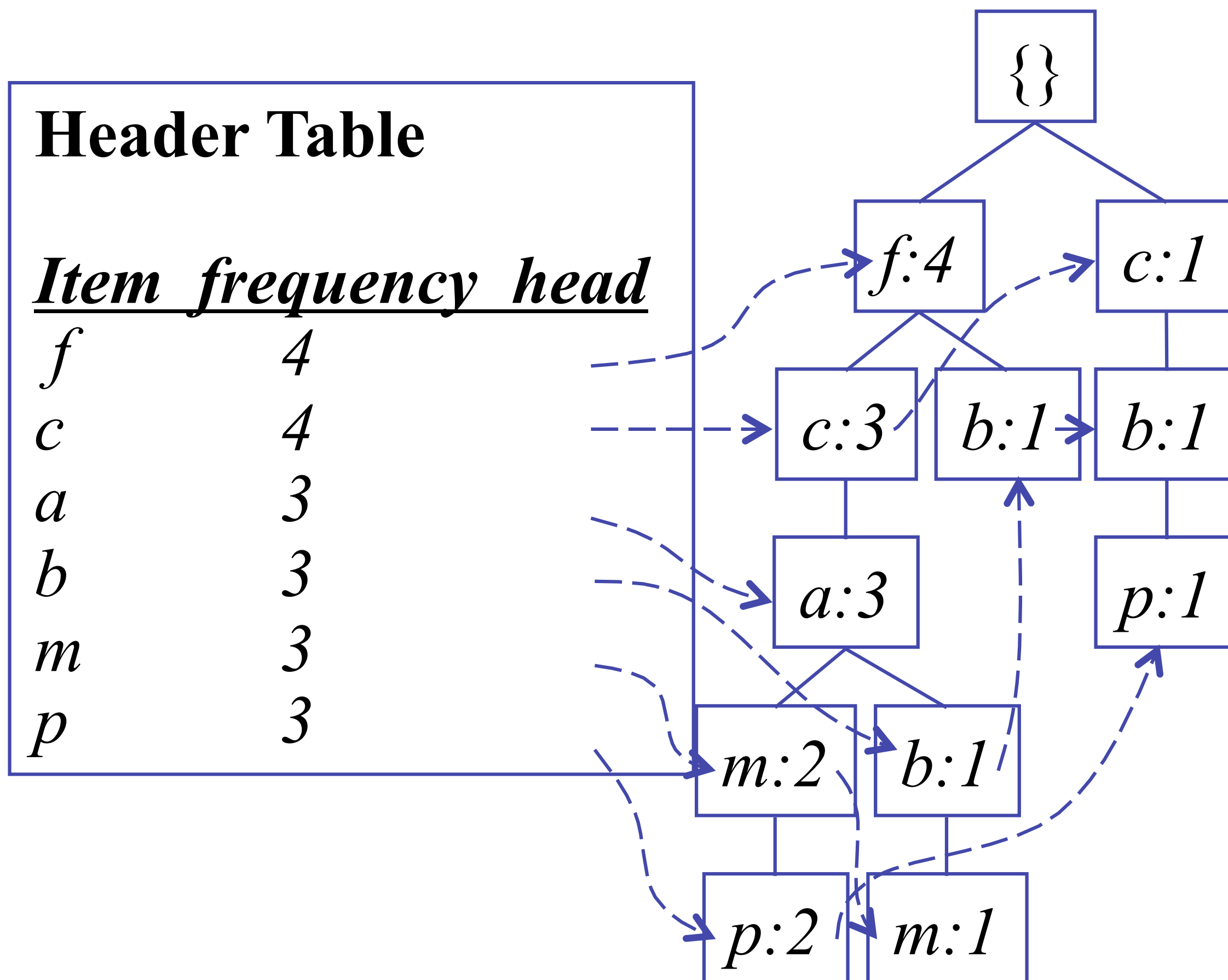
- ♦ basic concepts, Apriori algorithm, correlation: lift
- ♦ improve the efficiency of Apriori
 - ♦ #scans, #candidates, support counting
- ♦ FP-growth: grow patterns w/o generating candidates
 - ♦ if c is frequent in $DB|ab$, then abc is frequent

FP-tree Construction

<i>TID</i>	<i>Items bought</i>	<i>(ordered) frequent items</i>
100	{ <i>f, a, c, d, g, i, m, p</i> }	{ <i>f, c, a, m, p</i> }
200	{ <i>a, b, c, f, l, m, o</i> }	{ <i>f, c, a, b, m</i> }
300	{ <i>b, f, h, j, o, w</i> }	{ <i>f, b</i> }
400	{ <i>b, c, k, s, p</i> }	{ <i>c, b, p</i> }
500	{ <i>a, f, c, e, l, p, m, n</i> }	{ <i>f, c, a, m, p</i> }

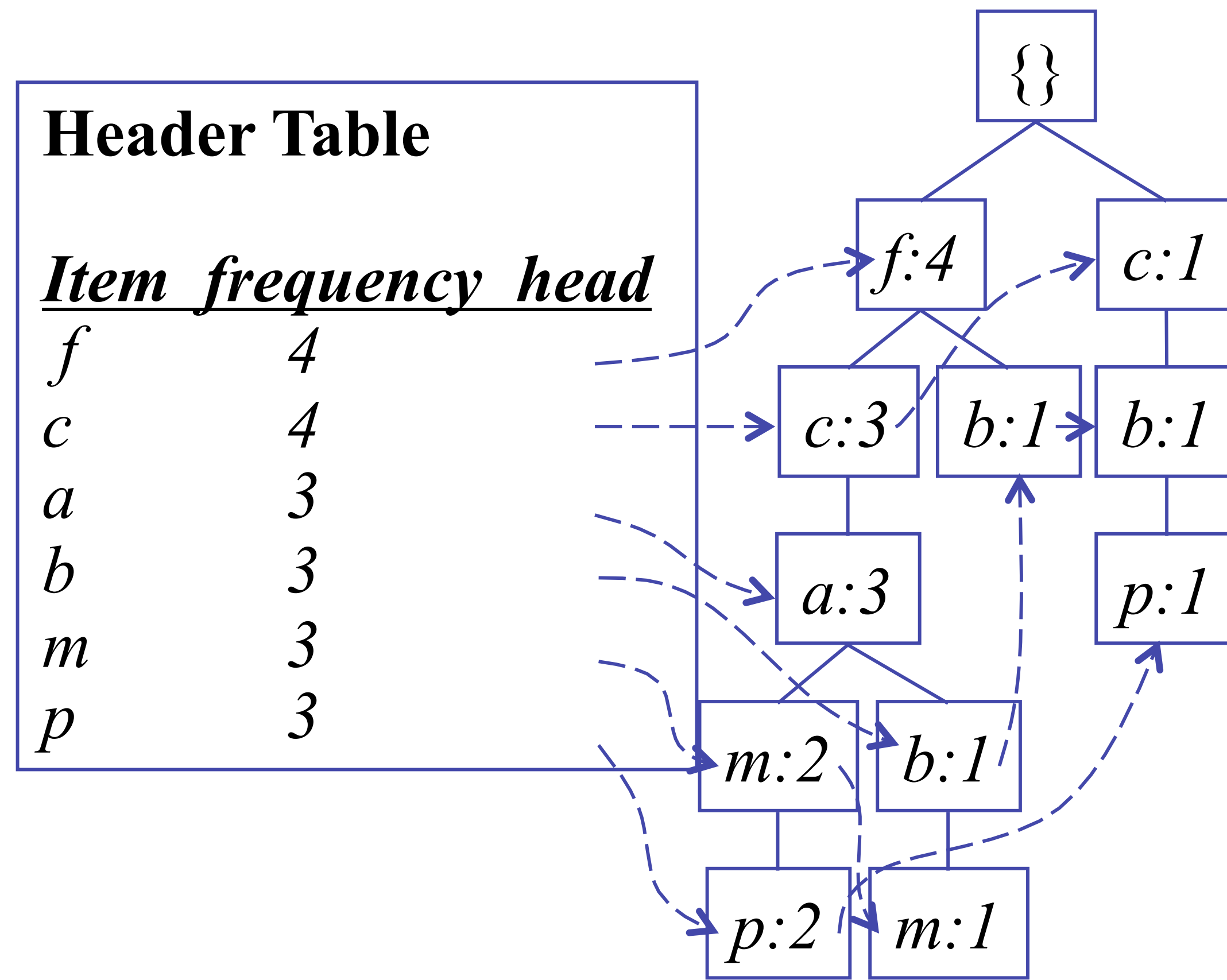
min_sup = 0.6

- ♦ Scan, find freq. 1-itemset
- ♦ Sort freq. items in descending frequency
- ♦ Scan, construct FP-tree



Conditional Pattern Base

- ✦ Traverse links of each frequent item, prefix paths



Conditional pattern bases

item *cond. pattern base*

c *f:3*

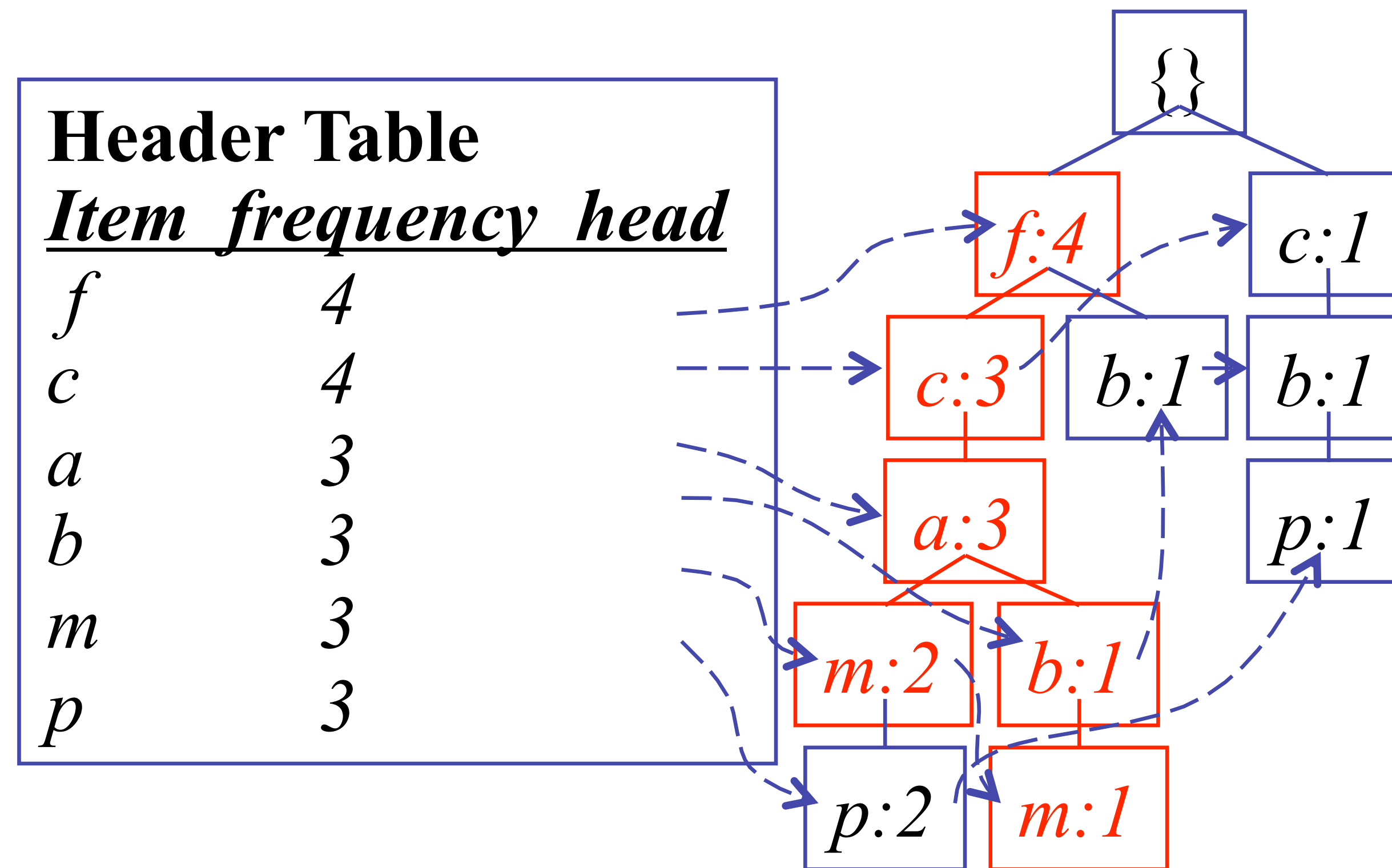
a *fc:3*

b *fca:1, f:1, c:1*

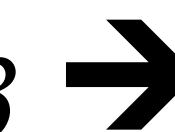
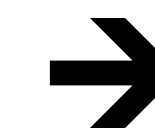
m *fca:2, fcab:1*

p *fcam:2, cb:1*

Conditional FP-trees



m-conditional pattern base:
fca:2, fcab:1



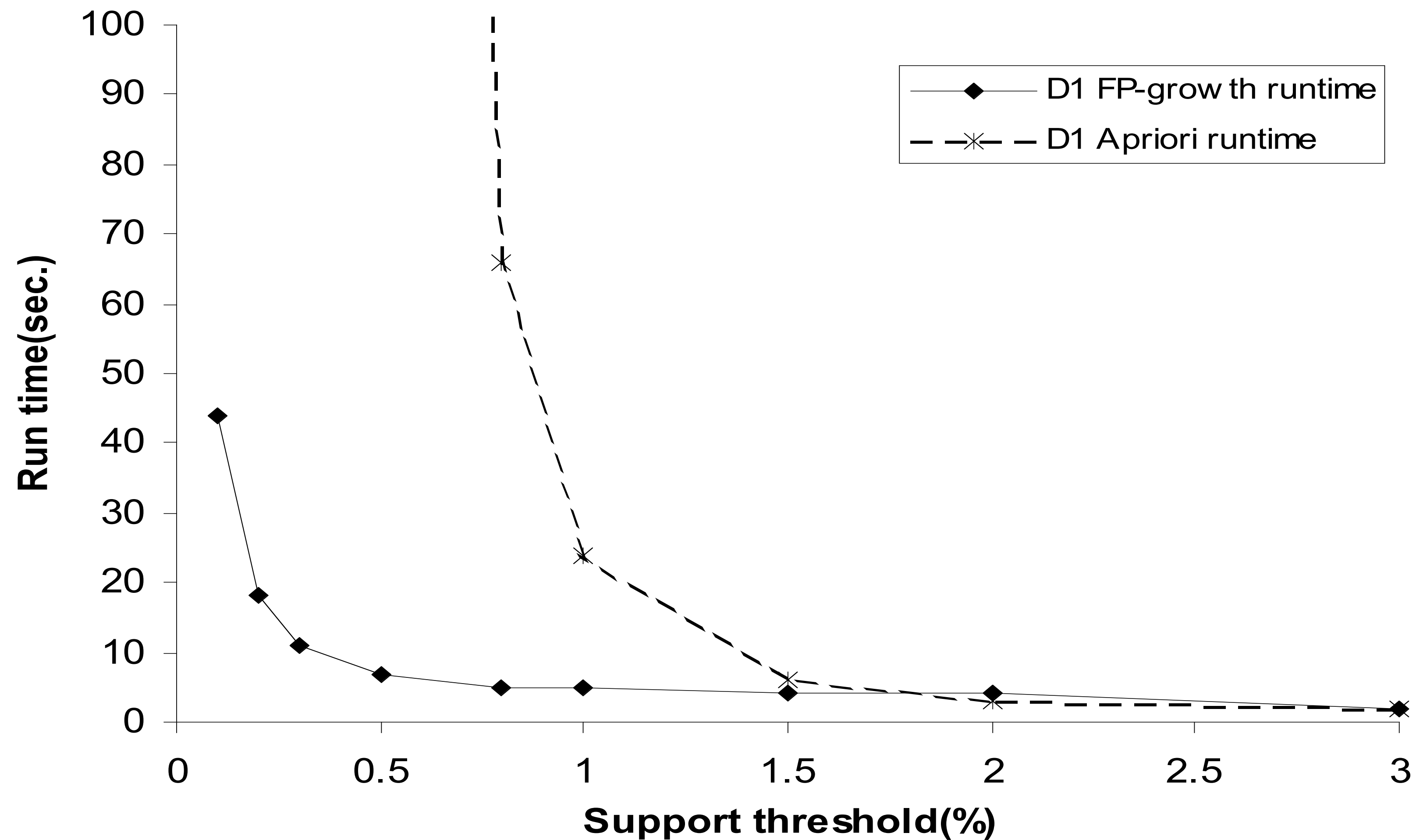
All frequent
 patterns relate to *m*
m,
fm, cm, am,
fcm, fam, cam,
fcam

m-conditional FP-tree

FP-growth

- ♦ Idea: Frequent pattern growth
 - ♦ recursively grow freq. patterns by pattern and data partition
- ♦ Method
 - ♦ freq. item \Rightarrow conditional pattern base \Rightarrow conditional FP-tree
 - ♦ repeat on each newly created FP-tree
 - ♦ until FP-tree is empty or single path

FP-growth vs. Apriori



Correlation Rules

- ◆ Correlation rule

- ◆ $A \Rightarrow B$ [support, confidence, correlation]

- ◆ Measure of dependent/correlated events

$$lift(A, B) = \frac{P(A \cup B)}{P(A)P(B)}$$

- ◆ lift = 1? independent
 - ◆ lift < 1? negatively dependent
 - ◆ lift > 1? positively dependent

$$lift(A, B) = \frac{P(A \cup B)}{P(A)P(B)}$$

	basketball	not basketball	sum (row)
cereal	2000	1750	3750
not cereal	1000	250	1250
sum (col)	3000	2000	5000

$$lift(B, C) = \frac{2000/5000}{(3000/5000) \times (3750/5000)} = 0.89$$

$$lift(B, \bar{C}) = \frac{1000/5000}{(3000/5000) \times (1250/5000)} = 1.33$$

$$\chi^2 = \sum_{i=1}^c \sum_{j=1}^r \frac{(o_{ij} - e_{ij})^2}{e_{ij}} \quad e_{ij} = \frac{\text{count}(A = a_i) \times \text{count}(B = b_j)}{N}$$

	basketball	not basketball	sum (row)
cereal	2000	1750	3750
not cereal	1000	250	1250
sum (col)	3000	2000	5000

♦ $e_{cb} = 3750 * 3000 / 5000 = 2250$

♦ $\chi^2 = (2000 - 2250)^2 / 2250 + (1750 - 1500)^2 / 1500 + (1000 - 750)^2 / 750 + (250 - 500)^2 / 500 = 227.78$ (correlated)

♦ $o_{cb} = 2000 < e_{cb} = 2250$ (negative)

Other Correlation Measures

$$all_conf(A, B) = \frac{sup(A \cup B)}{\max\{sup(A), sup(B)\}} = \min\{P(A|B), P(B|A)\}$$

$$max_conf(A, B) = \max\{P(A|B), P(B|A)\}$$

$$Kulc(A, B) = \frac{1}{2}(P(A|B) + P(B|A))$$

$$\begin{aligned} cosine(A, B) &= \frac{P(A \cup B)}{\sqrt{P(A) \times P(B)}} = \frac{sup(A \cup B)}{\sqrt{sup(A) \times sup(B)}} \\ &= \sqrt{P(A|B) \times P(B|A)}. \end{aligned}$$

Comparison (I)

<i>Data</i>										
<i>Set</i>	<i>mc</i>	\overline{mc}	$m\overline{c}$	$\overline{m\overline{c}}$	χ^2	<i>lift</i>	<i>all_conf.</i>	<i>max_conf.</i>	<i>Kulc.</i>	<i>cosine</i>
D_1	10,000	1000	1000	100,000	90557	9.26	0.91	0.91	0.91	0.91
D_2	10,000	1000	1000	100	0	1	0.91	0.91	0.91	0.91
D_3	100	1000	1000	100,000	670	8.44	0.09	0.09	0.09	0.09
D_4	1000	1000	1000	100,000	24740	25.75	0.5	0.5	0.5	0.5
D_5	1000	100	10,000	100,000	8173	9.18	0.09	0.91	0.5	0.29
D_6	1000	10	100,000	100,000	965	1.97	0.01	0.99	0.5	0.10

- ♦ **Null-transaction:** e.g., $\neg m \neg c$
- ♦ **Null-variant:** lift and χ^2
- ♦ **Null-invariant:** all_conf, max_conf, Kulc, cosine

Comparison (2)

<i>Data</i>										
<i>Set</i>	<i>mc</i>	\overline{mc}	$m\overline{c}$	$\overline{m\overline{c}}$	χ^2	<i>lift</i>	<i>all_conf.</i>	<i>max_conf.</i>	<i>Kulc.</i>	<i>cosine</i>
D_1	10,000	1000	1000	100,000	90557	9.26	0.91	0.91	0.91	0.91
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D_6	1000	10	100,000	100,000	965	1.97	0.01	0.99	0.5	0.10

◆ Imbalance ratio

$$IR(A, B) = \frac{|sup(A) - sup(B)|}{sup(A) + sup(B) - sup(A \cup B)}$$