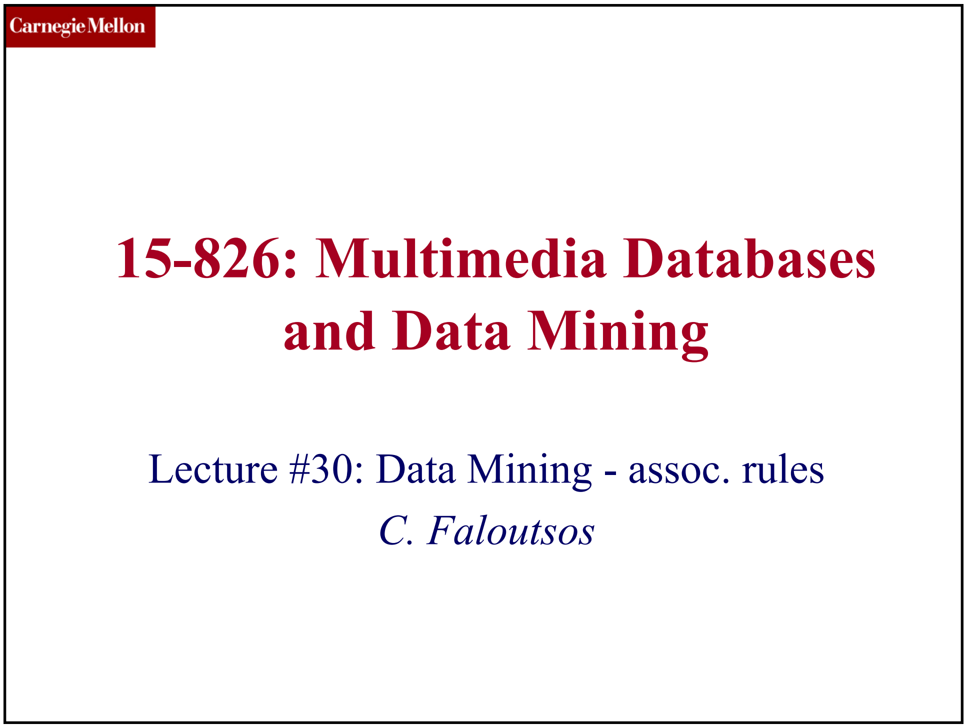

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# 15-826: Multimedia Databases and Data Mining

Lecture #30: Data Mining - assoc. rules

*C. Faloutsos*

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## Problem

- Given many market baskets
- Find which products sell together

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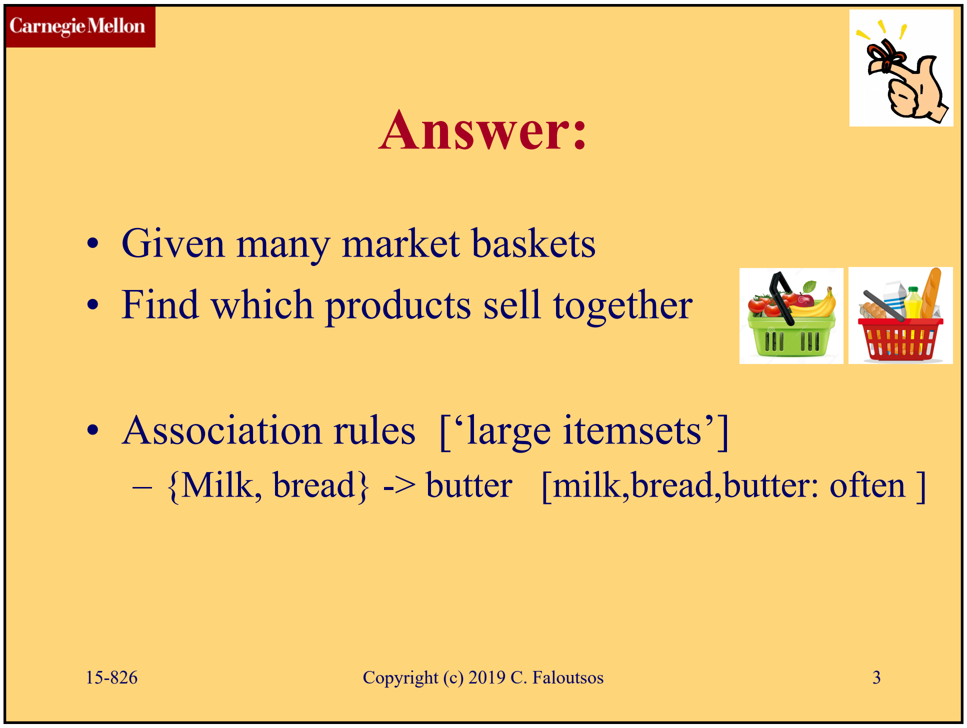

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## Answer:

- Given many market baskets
- Find which products sell together

- Association rules ['large itemsets']
  - {Milk, bread} -> butter [milk,bread,butter: often ]

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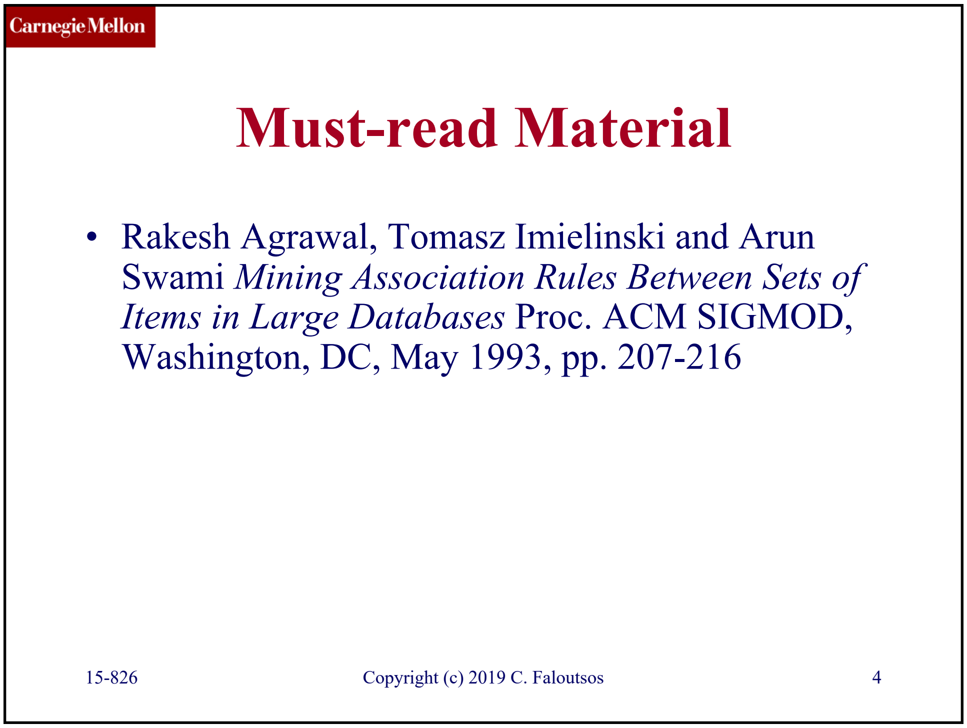

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## Must-read Material

- Rakesh Agrawal, Tomasz Imielinski and Arun Swami *Mining Association Rules Between Sets of Items in Large Databases* Proc. ACM SIGMOD, Washington, DC, May 1993, pp. 207-216

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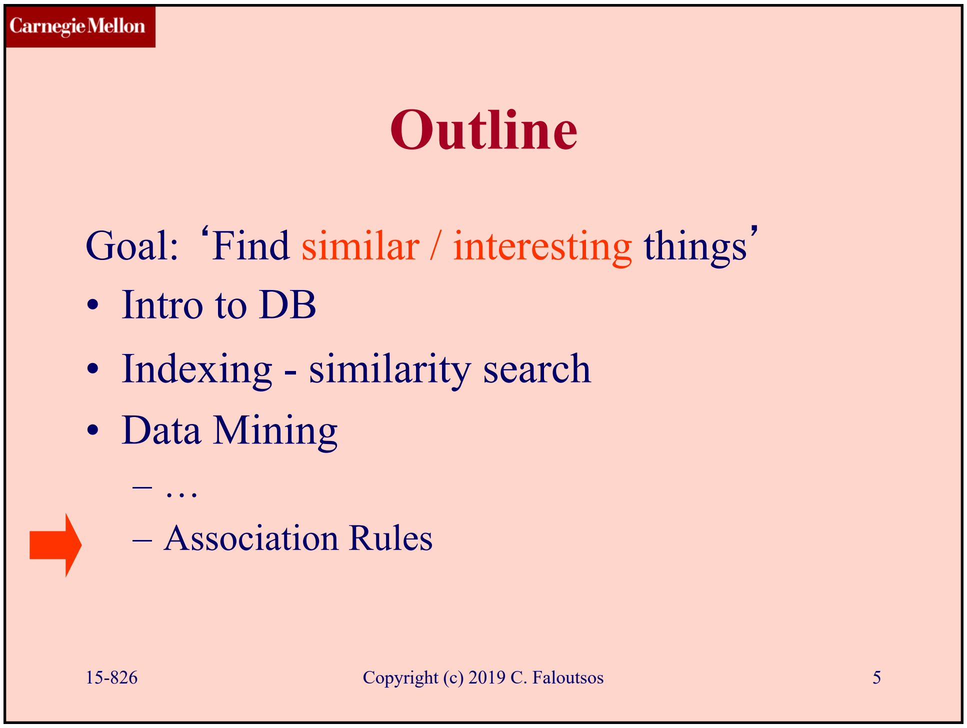

# Outline

Goal: ‘Find similar / interesting things’

- Intro to DB
- Indexing - similarity search
- Data Mining
  - …
  - Association Rules

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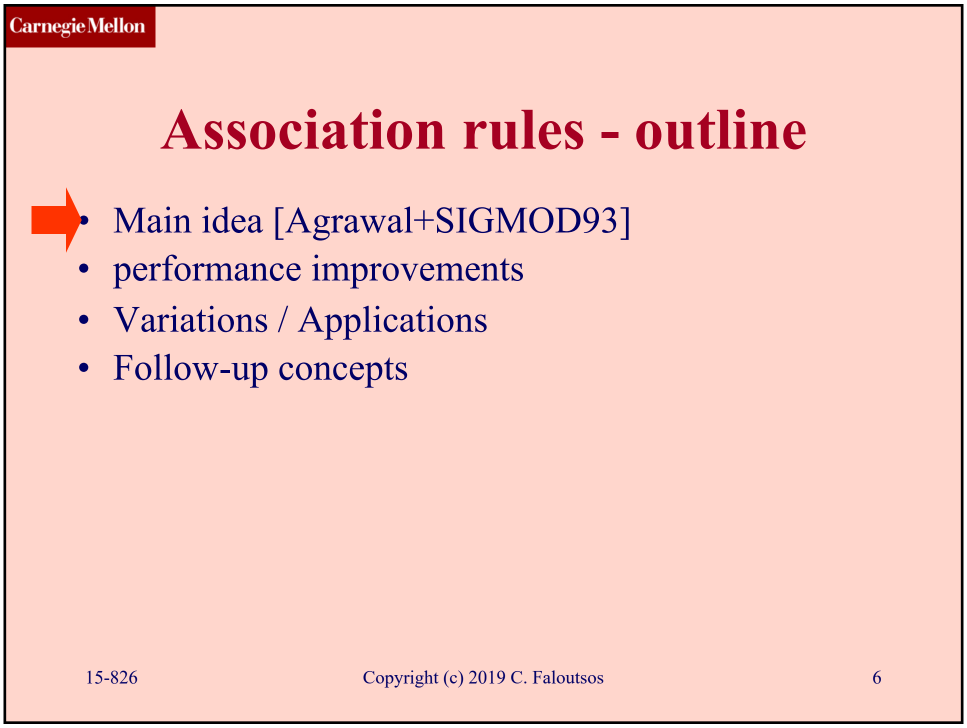

# Association rules - outline

- Main idea [Agrawal+SIGMOD93]
- performance improvements
- Variations / Applications
- Follow-up concepts

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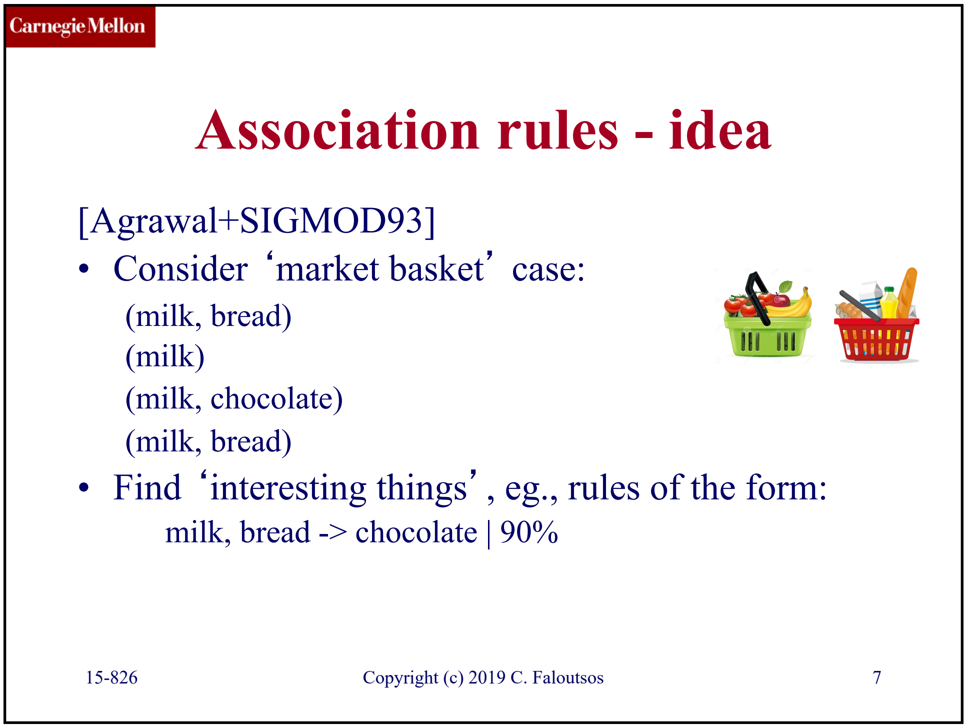

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## Association rules - idea

[Agrawal+SIGMOD93]

- Consider ‘market basket’ case:
  - (milk, bread)
  - (milk)
  - (milk, chocolate)
  - (milk, bread)
- Find ‘interesting things’, eg., rules of the form:
  - milk, bread -> chocolate | 90%

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## Other settings?

- Market baskets - products

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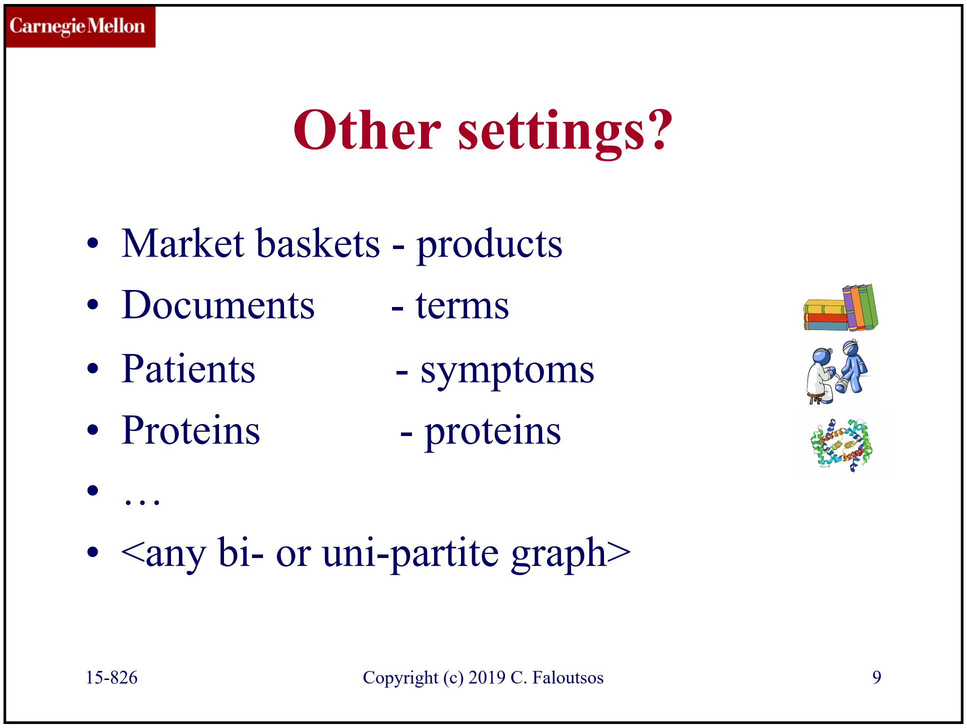

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## Other settings?

- Market baskets - products
- Documents - terms
- Patients - symptoms
- Proteins - proteins
- …
- <any bi- or uni-partite graph>

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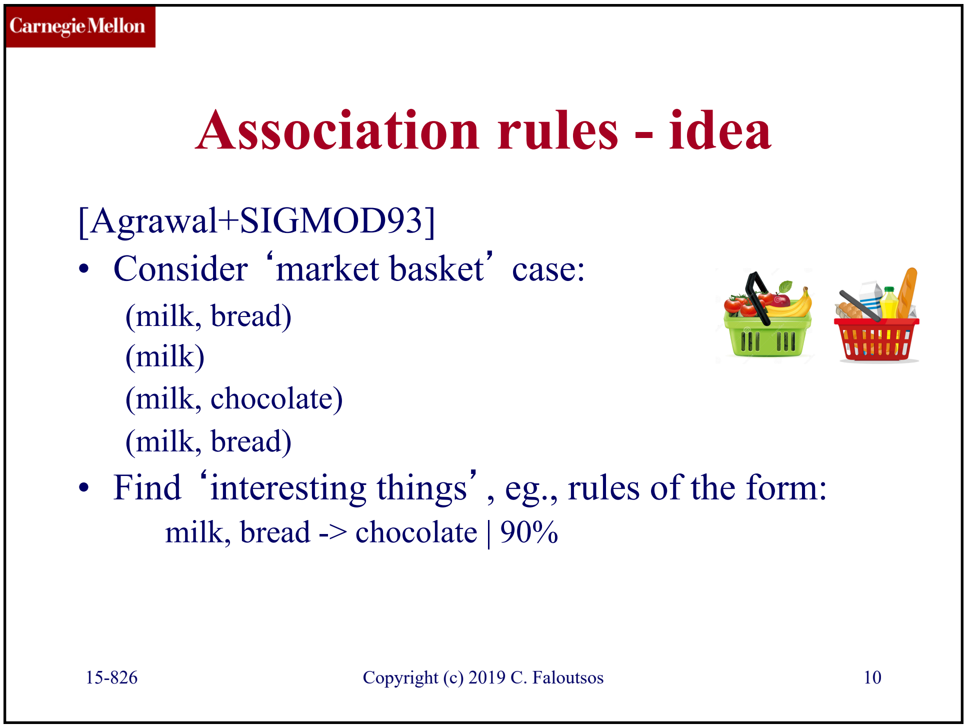

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## Association rules - idea

[Agrawal+SIGMOD93]

- Consider ‘market basket’ case:
  (milk, bread)
  (milk)
  (milk, chocolate)
  (milk, bread)
- Find ‘interesting things’, eg., rules of the form:
  milk, bread -> chocolate | 90%

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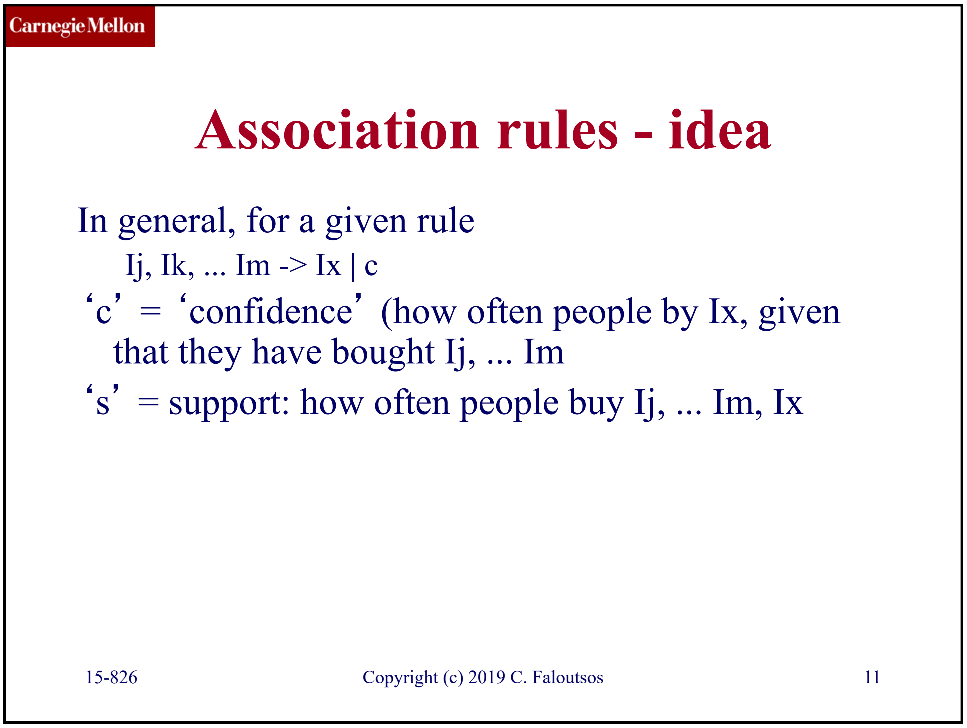

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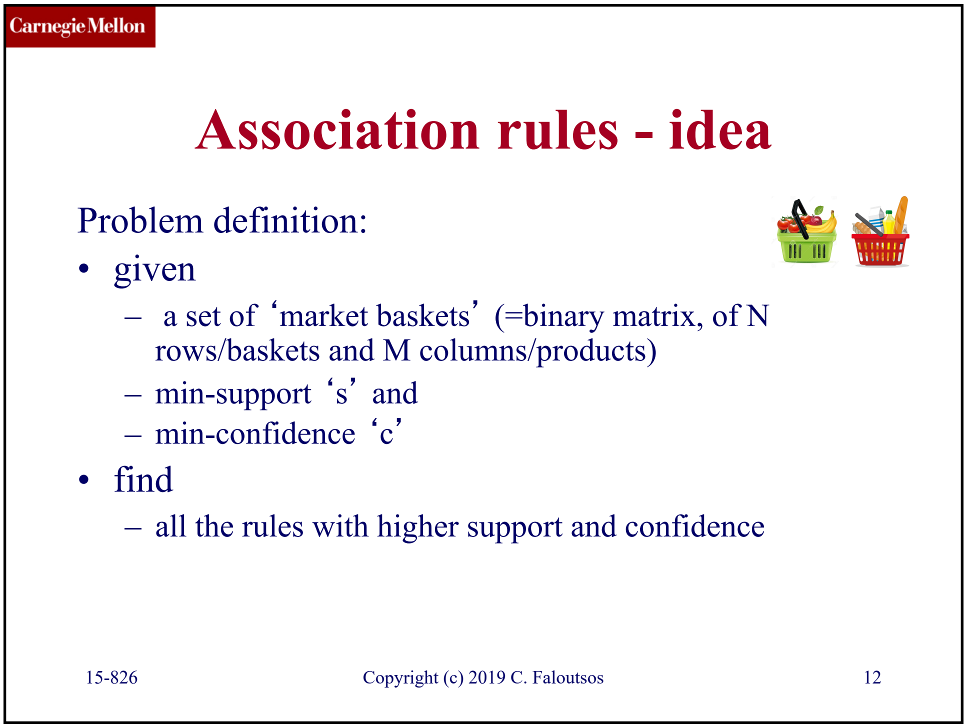
## Association rules - idea

In general, for a given rule

Ij, Ik, ... Im -> Ix | c

'c' = 'confidence' (how often people by Ix, given that they have bought Ij, ... Im

's' = support: how often people buy Ij, ... Im, Ix



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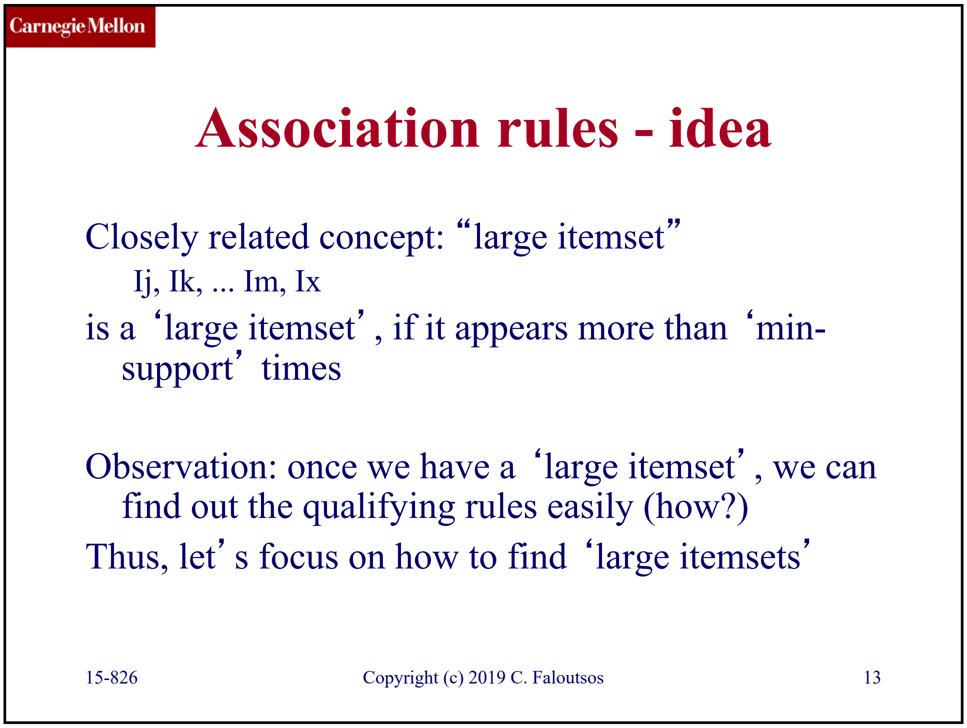
## Association rules - idea

Problem definition:

- given
  - a set of 'market baskets' (=binary matrix, of N rows/baskets and M columns/products)
  - min-support 's' and
  - min-confidence 'c'
- find
  - all the rules with higher support and confidence



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## Association rules - idea

Closely related concept: “large itemset”

Ij, Ik, ... Im, Ix

is a ‘large itemset’, if it appears more than ‘min-support’ times

Observation: once we have a ‘large itemset’, we can find out the qualifying rules easily (how?)

Thus, let’s focus on how to find ‘large itemsets’

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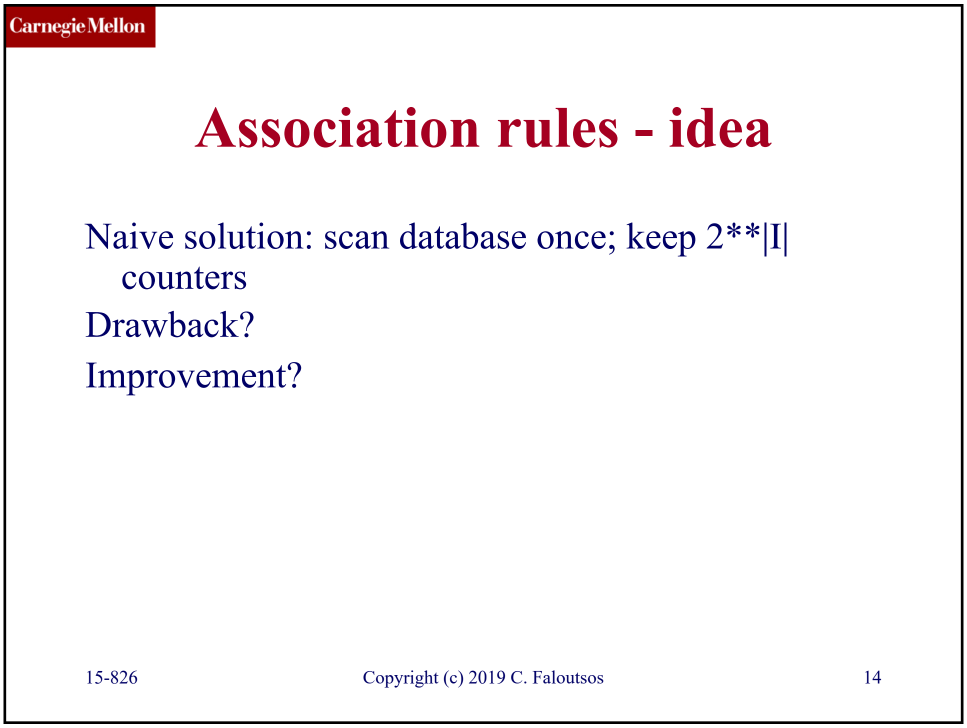

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## Association rules - idea

Naive solution: scan database once; keep 2**|I| counters

Drawback?

Improvement?

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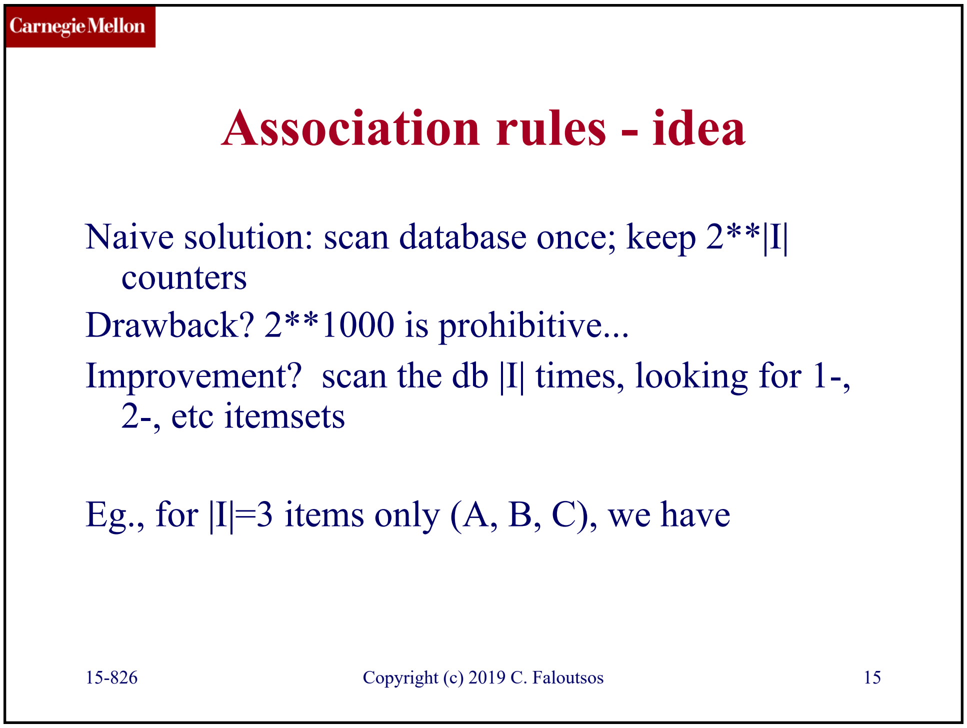

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## Association rules - idea

Naive solution: scan database once; keep 2**|I| counters

Drawback? 2**1000 is prohibitive...

Improvement? scan the db |I| times, looking for 1-, 2-, etc itemsets

Eg., for |I|=3 items only (A, B, C), we have

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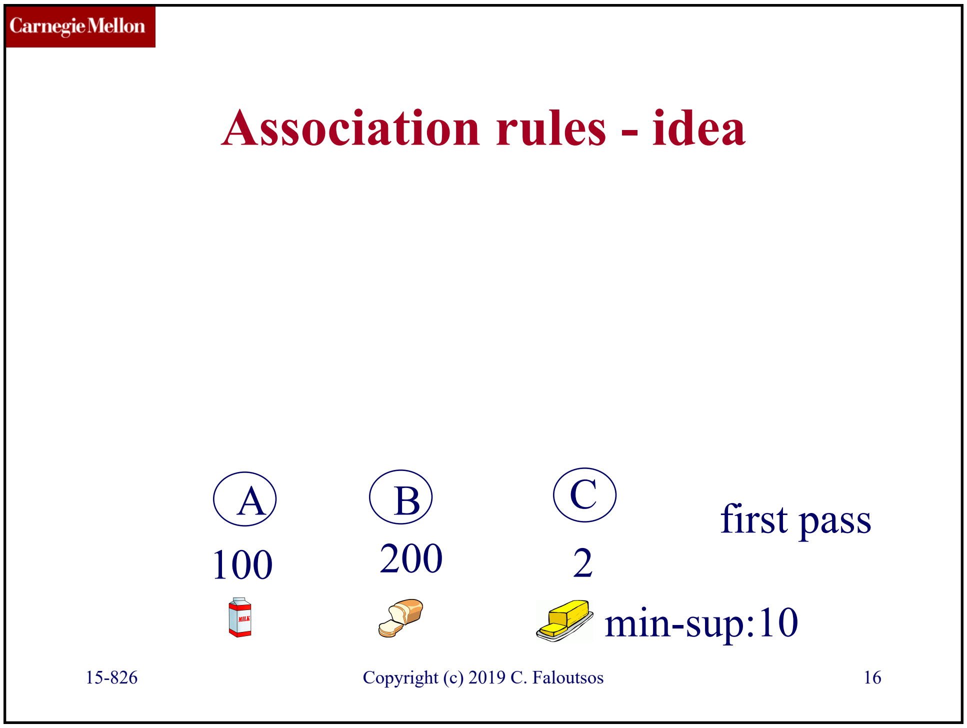

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## Association rules - idea

| A | B | C | first pass |
|---|---|---|---|
| 100 | 200 | 2 | |
| | | | min-sup:10 |

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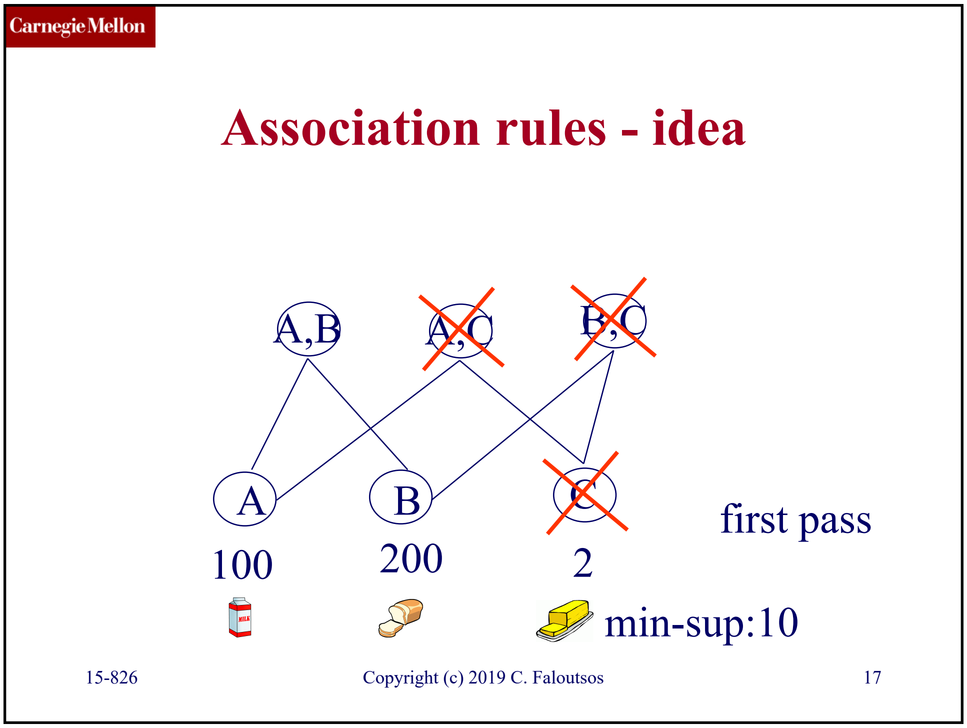

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## Association rules - idea

A,B

~~A,C~~

~~B,C~~

A

B

~~C~~

first pass

100

200

2

min-sup:10

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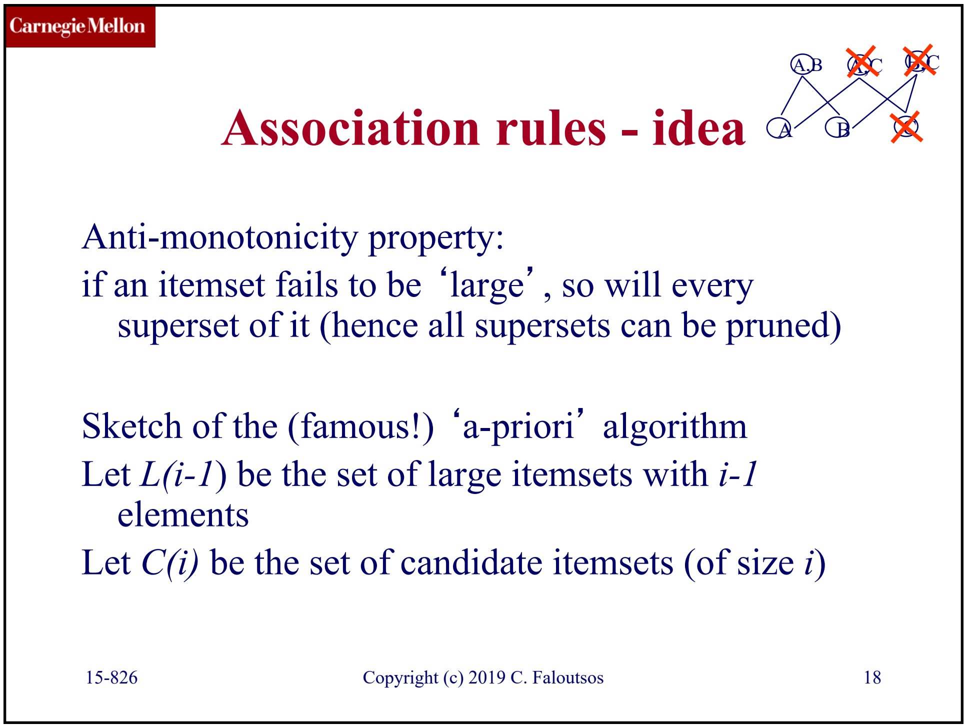

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## Association rules - idea

Anti-monotonicity property:

if an itemset fails to be ‘large’, so will every superset of it (hence all supersets can be pruned)

Sketch of the (famous!) ‘a-priori’ algorithm

Let *L(i-1)* be the set of large itemsets with *i-1* elements

Let *C(i)* be the set of candidate itemsets (of size *i*)

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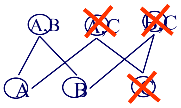
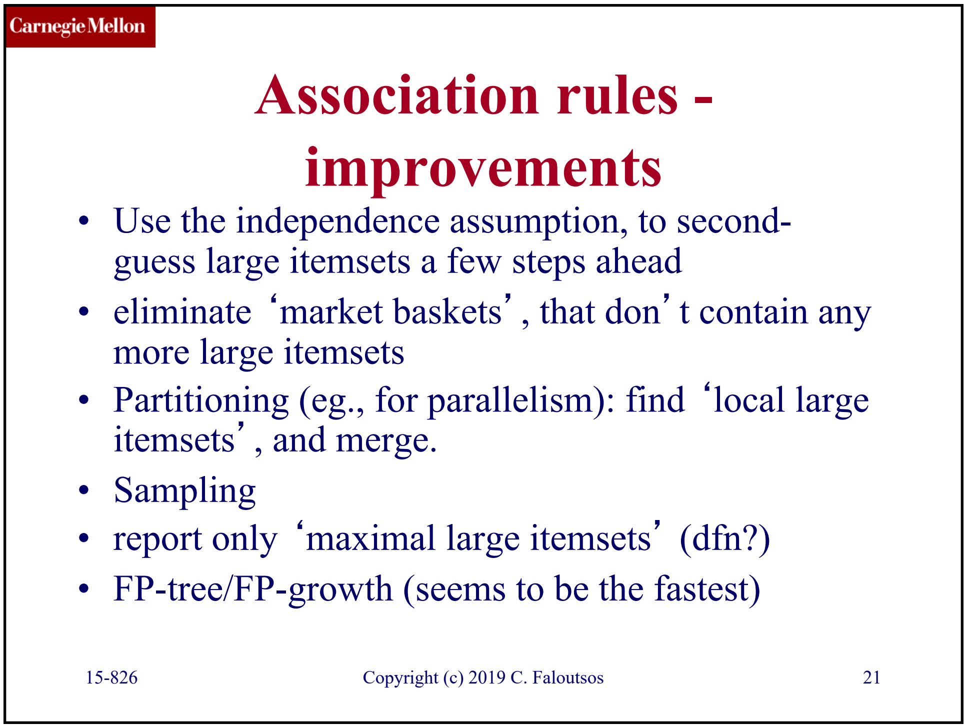
## Association rules - idea



```
Compute L(1), by scanning the database.
repeat, for i=2,3...,
    'join' L(i-1) with itself, to generate C(i)
        two itemset can be joined, if they agree on their first i-2 elements
    prune the itemsets of C(i) (how?)
    scan the db, finding the counts of the C(i) itemsets - set
      this to be L(i)
    unless L(i) is empty, repeat the loop
(see example 6.1 in [Han+Kamber])
```

## Association rules - outline

- Main idea [Agrawal+SIGMOD93]
- performance improvements
- Variations / Applications
- Follow-up concepts



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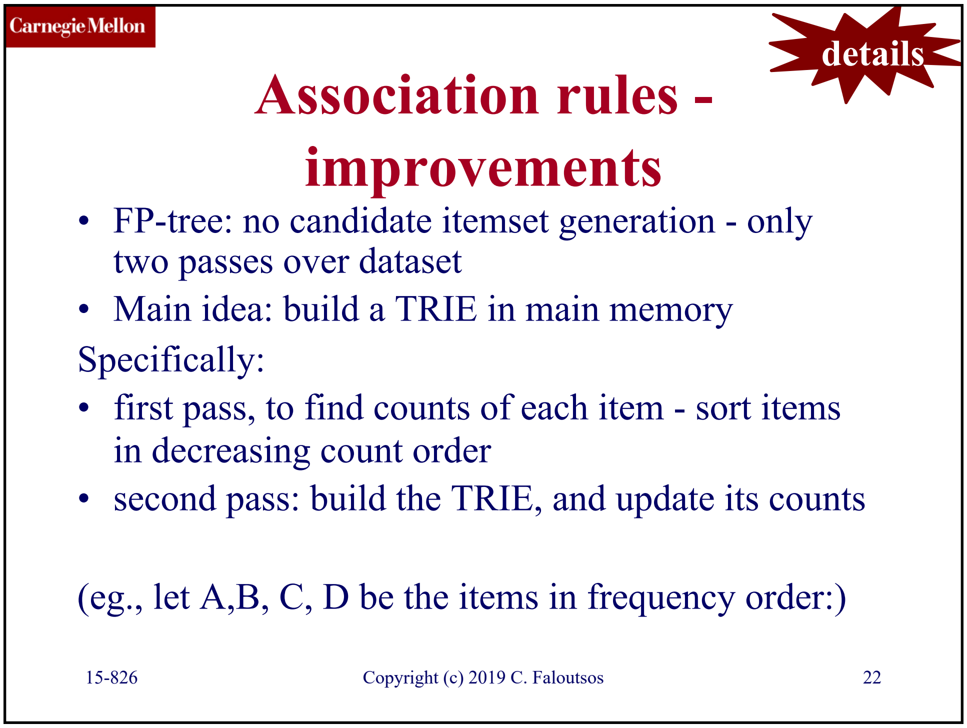
## Association rules - improvements

- Use the independence assumption, to second-guess large itemsets a few steps ahead
- eliminate ‘market baskets’, that don’t contain any more large itemsets
- Partitioning (eg., for parallelism): find ‘local large itemsets’, and merge.
- Sampling
- report only ‘maximal large itemsets’ (dfn?)
- FP-tree/FP-growth (seems to be the fastest)



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details

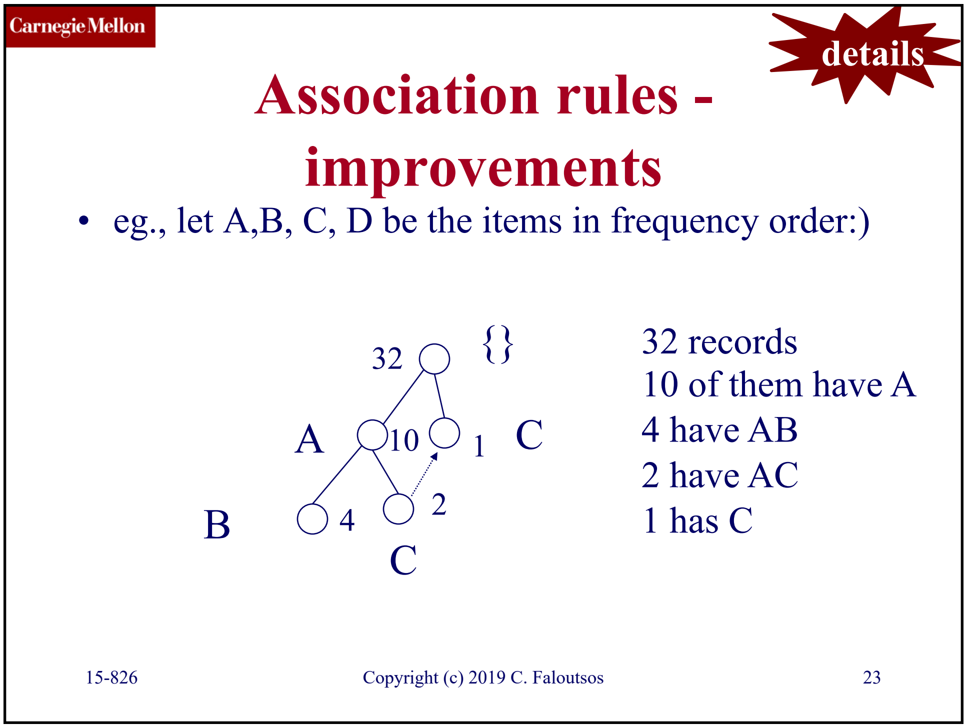
## Association rules - improvements

- FP-tree: no candidate itemset generation - only two passes over dataset
- Main idea: build a TRIE in main memory

Specifically:

- first pass, to find counts of each item - sort items in decreasing count order
- second pass: build the TRIE, and update its counts

(eg., let A,B, C, D be the items in frequency order:)



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## Association rules - improvements

- eg., let A,B, C, D be the items in frequency order:)

32 records
10 of them have A
4 have AB
2 have AC
1 has C

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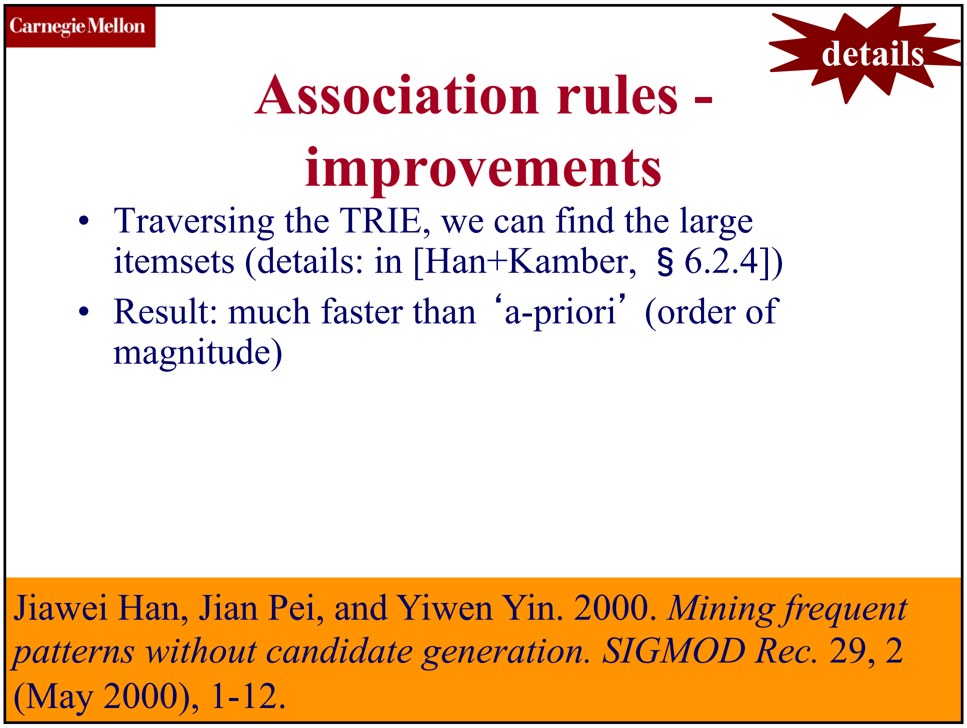

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details

## Association rules - improvements

- Traversing the TRIE, we can find the large itemsets (details: in [Han+Kamber, § 6.2.4])
- Result: much faster than ʻa-prioriʼ (order of magnitude)

Jiawei Han, Jian Pei, and Yiwen Yin. 2000. *Mining frequent patterns without candidate generation. SIGMOD Rec.* 29, 2 (May 2000), 1-12.

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# Association rules - outline

- Main idea [Agrawal+SIGMOD93]
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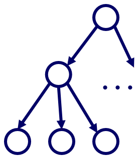
# Association rules - variations



1) Multi-level rules: given concept hierarchy

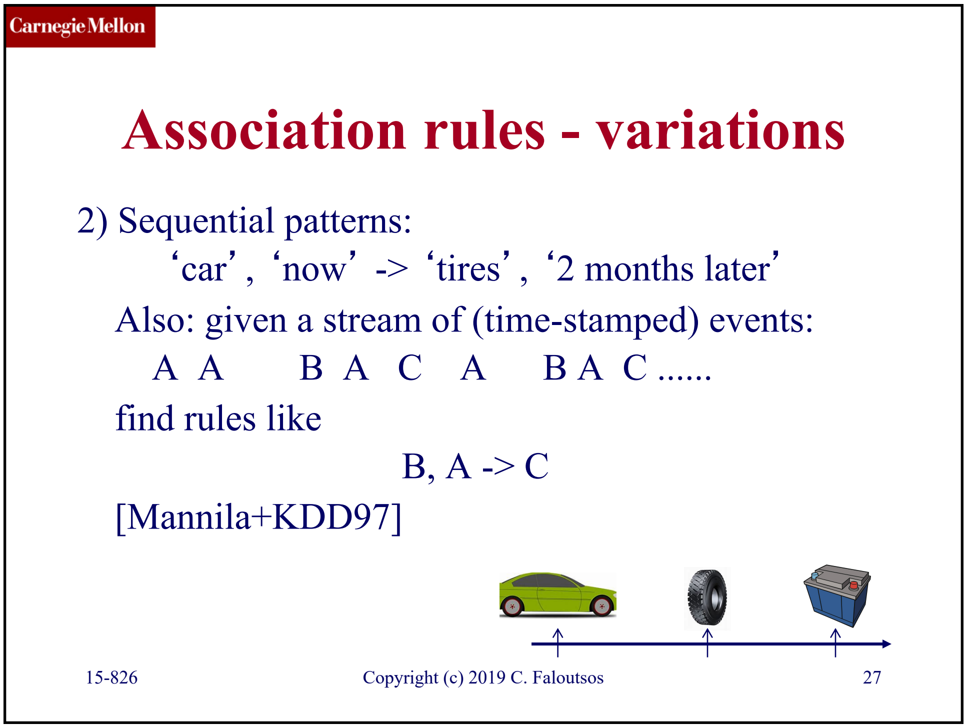
- 'bread', 'milk', 'butter' -> foods;
- 'aspirin', 'tylenol' -> pharmacy

look for rules across any level of the hierarchy, eg

'aspirin' -> foods

(similarly, rules across dimensions, like 'product', 'time', 'branch':

'bread', '12noon', 'PGH-branch' -> 'milk'



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## Association rules - variations

2) Sequential patterns:

‘car’ , ‘now’ -> ‘tires’ , ‘2 months later’

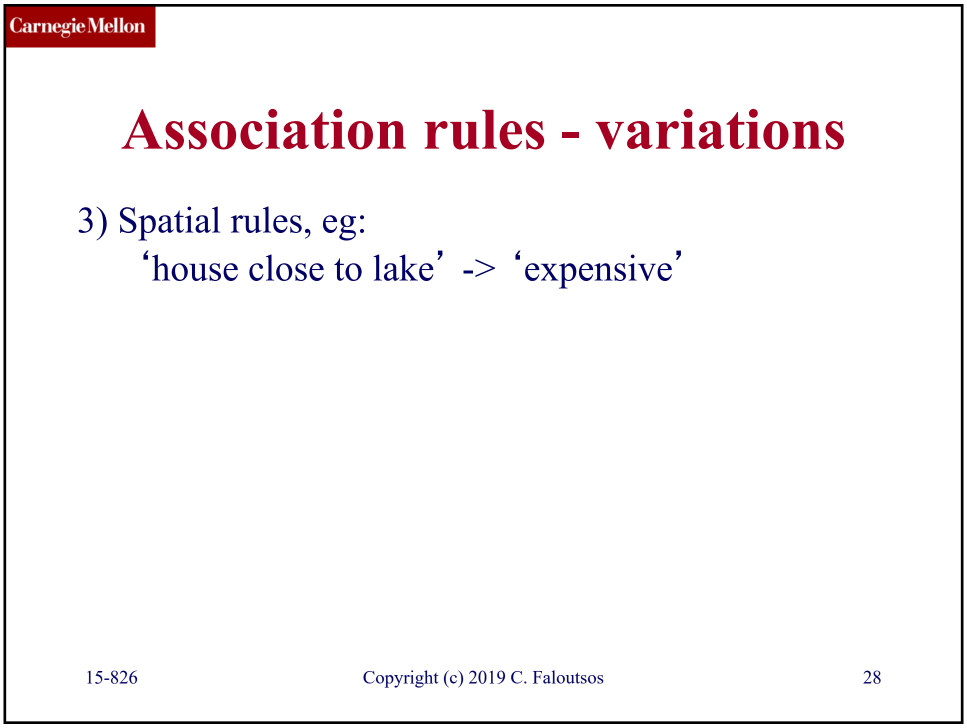
Also: given a stream of (time-stamped) events:

A A B A C A B A C ......

find rules like

B, A -> C

[Mannila+KDD97]



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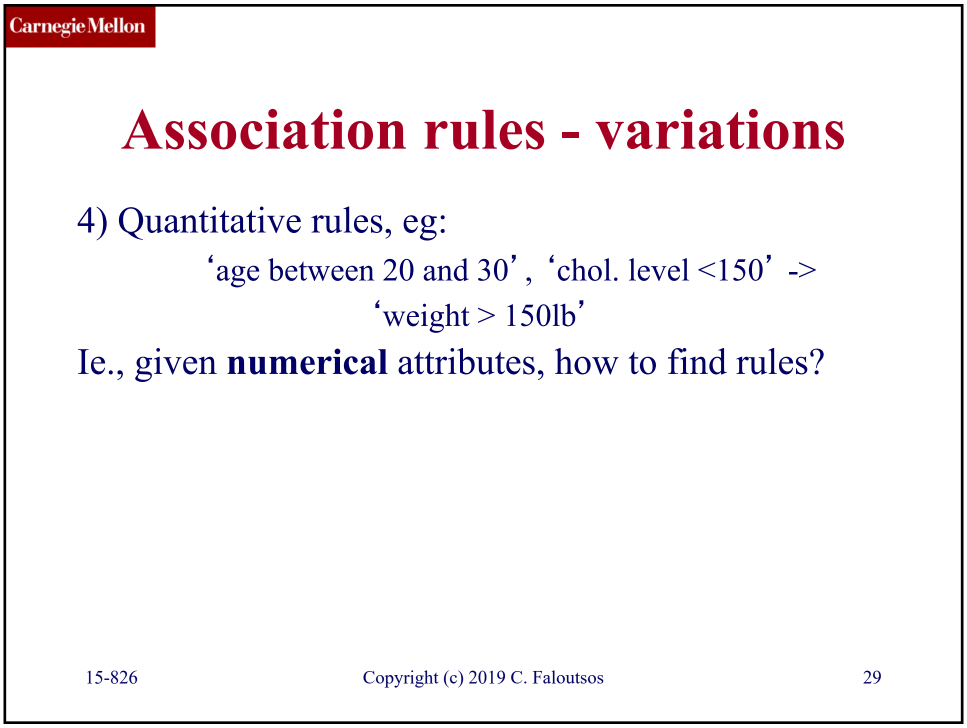
## Association rules - variations

3) Spatial rules, eg:

‘house close to lake’ -> ‘expensive’



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# Association rules - variations

4) Quantitative rules, eg:

‘age between 20 and 30’, ‘chol. level <150’ ->
‘weight > 150lb’

Ie., given **numerical** attributes, how to find rules?

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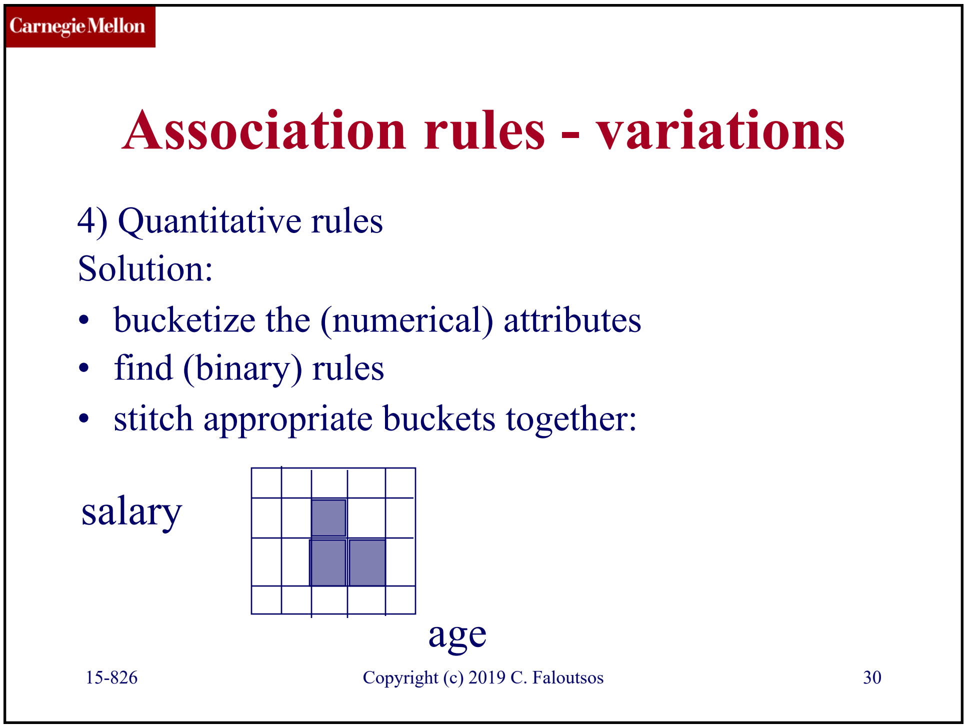

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# Association rules - variations

4) Quantitative rules

Solution:

- bucketize the (numerical) attributes
- find (binary) rules
- stitch appropriate buckets together:

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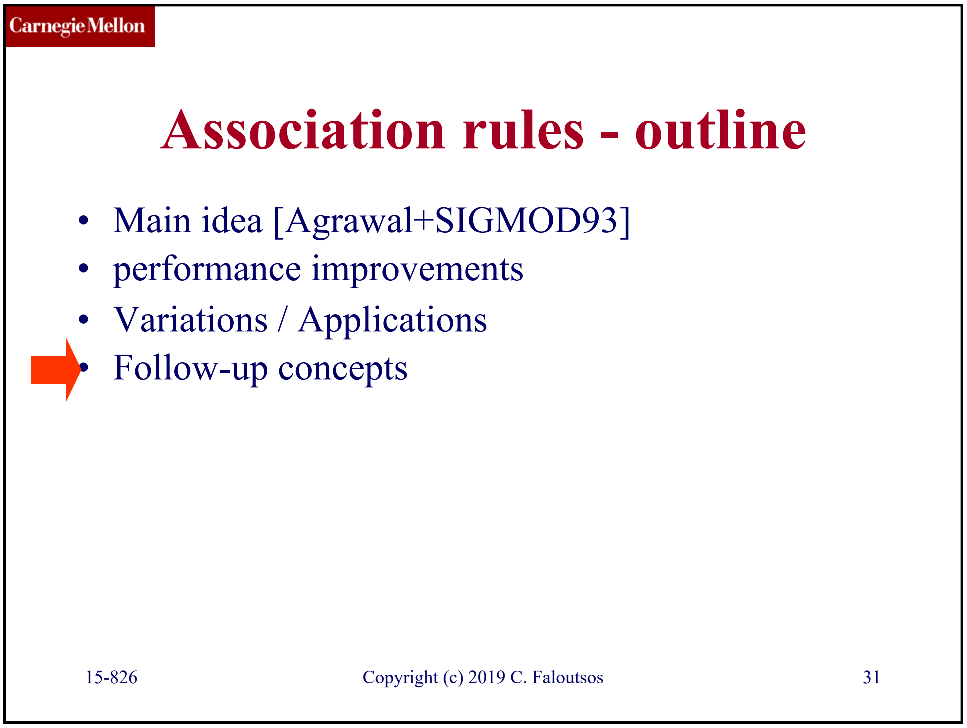

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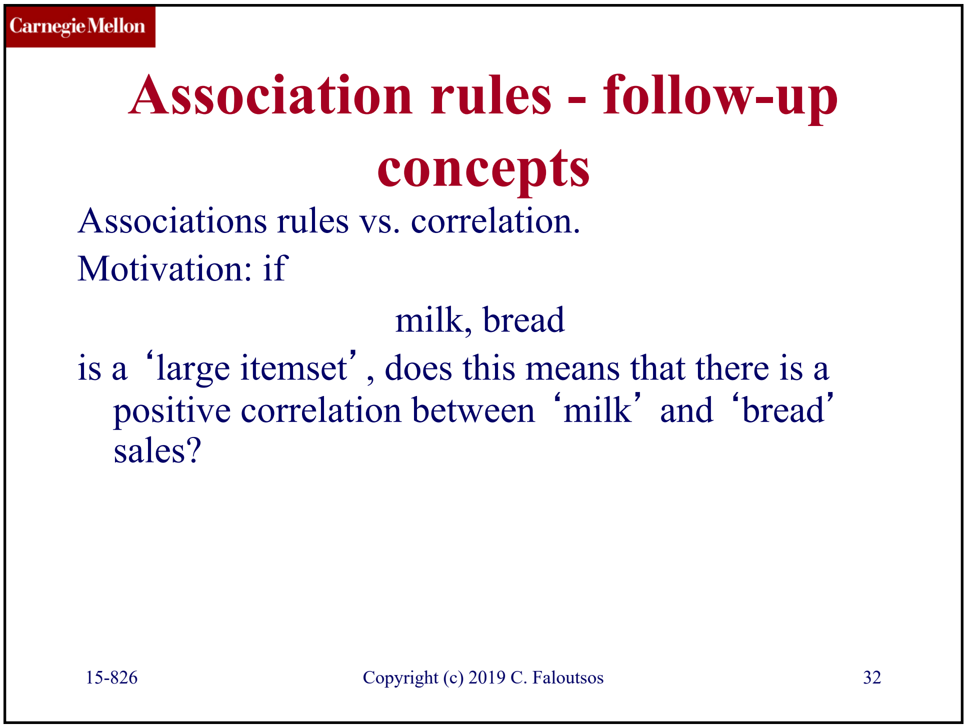
## Association rules - outline

- Main idea [Agrawal+SIGMOD93]
- performance improvements
- Variations / Applications
- Follow-up concepts



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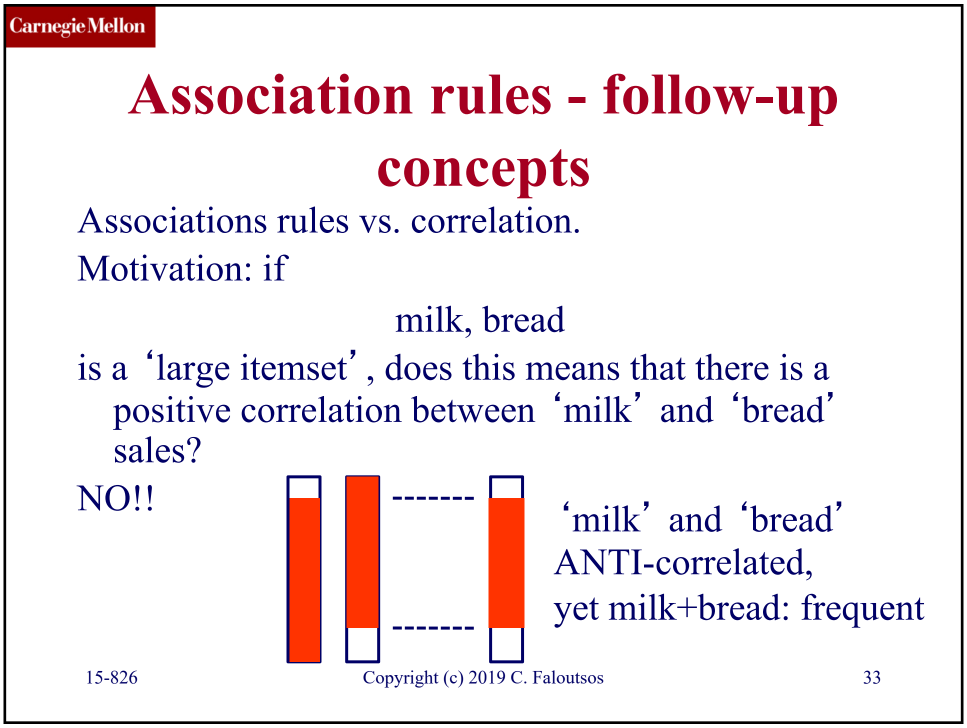
## Association rules - follow-up concepts

Associations rules vs. correlation.

Motivation: if

milk, bread

is a ‘large itemset’, does this means that there is a positive correlation between ‘milk’ and ‘bread’ sales?



# Association rules - follow-up concepts

Associations rules vs. correlation.

Motivation: if

milk, bread

is a ‘large itemset’, does this means that there is a positive correlation between ‘milk’ and ‘bread’ sales?

NO!!

‘milk’ and ‘bread’ ANTI-correlated, yet milk+bread: frequent

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# Association rules - follow-up concepts

What to do, then?

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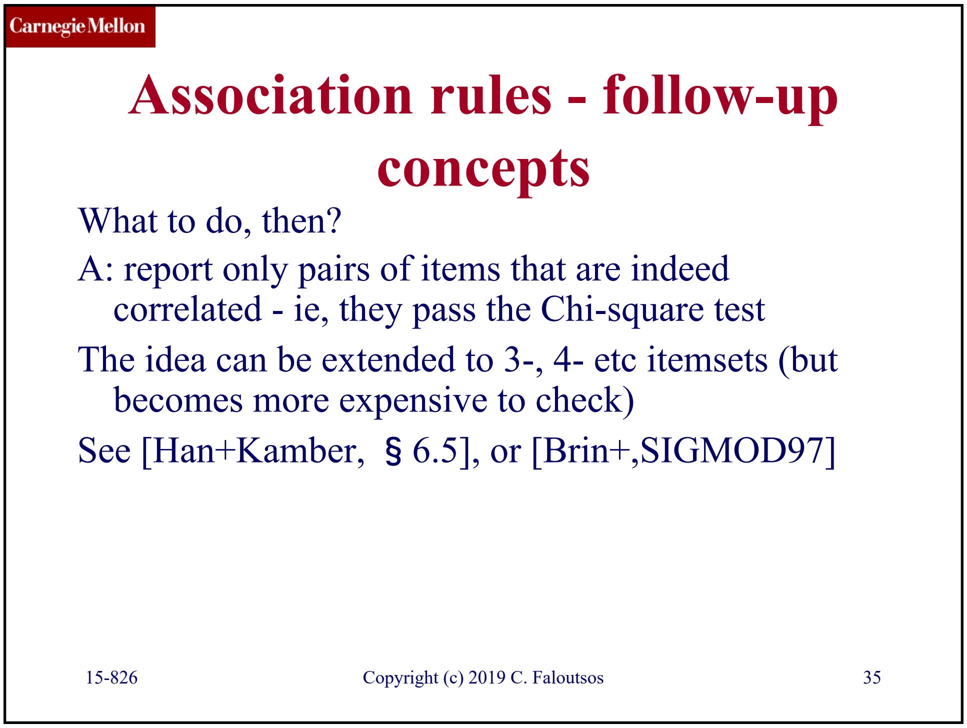

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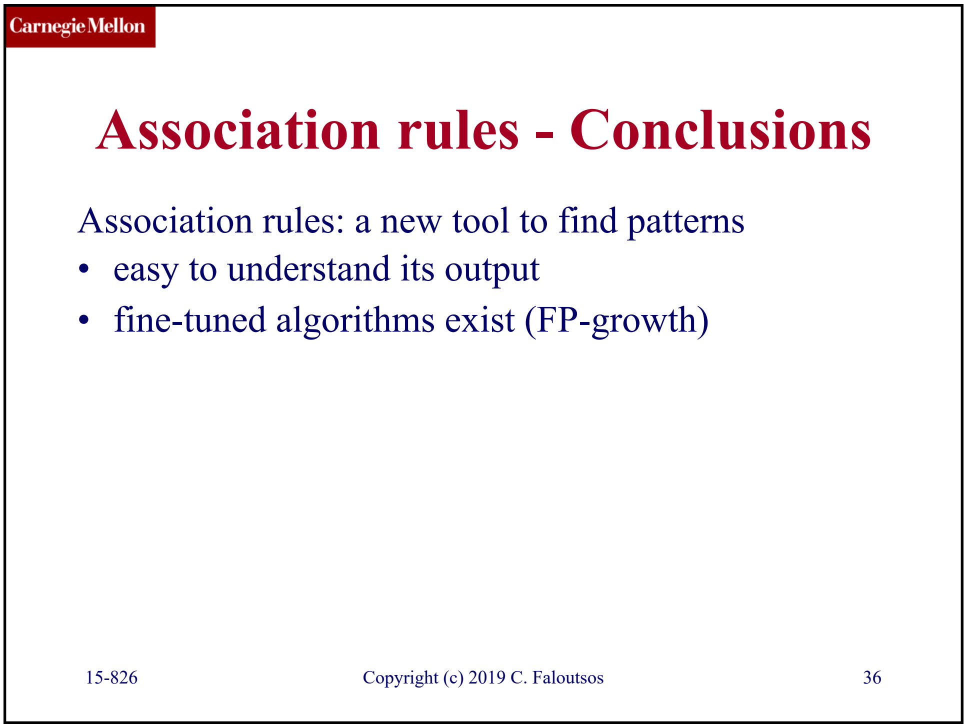
## Association rules - follow-up concepts

What to do, then?

A: report only pairs of items that are indeed correlated - ie, they pass the Chi-square test

The idea can be extended to 3-, 4- etc itemsets (but becomes more expensive to check)

See [Han+Kamber, § 6.5], or [Brin+,SIGMOD97]



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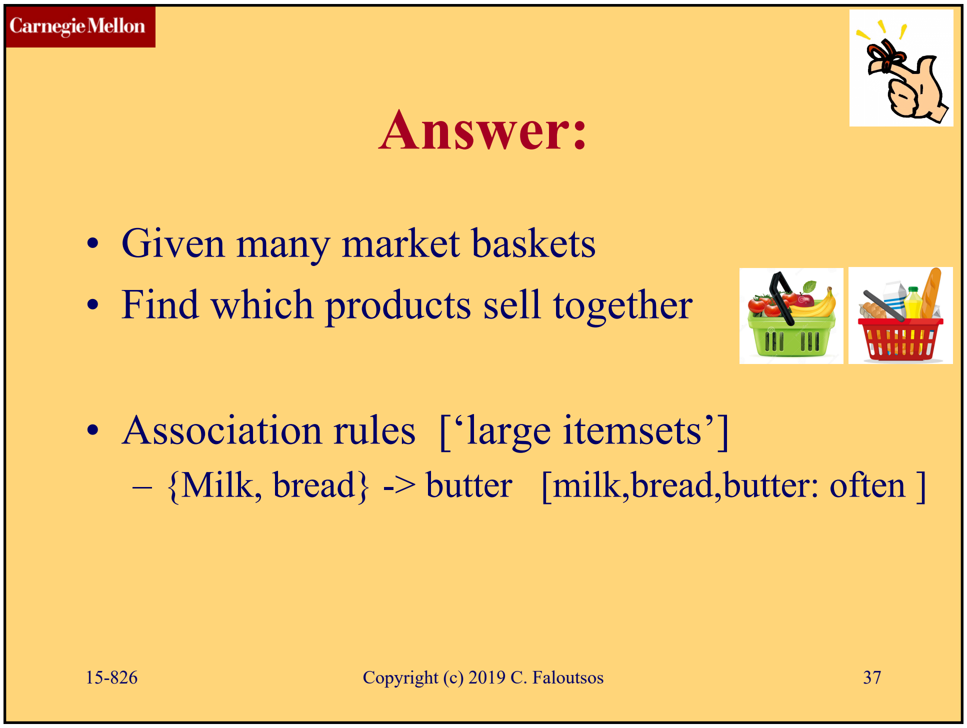
## Association rules - Conclusions

Association rules: a new tool to find patterns

- easy to understand its output
- fine-tuned algorithms exist (FP-growth)



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# Answer:

- Given many market baskets
- Find which products sell together

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  - {Milk, bread} -> butter [milk,bread,butter: often ]

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