# Market Basket Analysis
# and
# Mining Association Rules

# Mining Association Rules

- **Market Basket Analysis**
- What is Association rule mining
- Apriori Algorithm
- Measures of rule interestingness

# Market Basket Analysis

- One basket tells you about what one customer purchased at one time.
- A loyalty card makes it possible to tie together purchases by a single customer (or household) over time.

# Market Basket Analysis

- Retail – each customer purchases different set of products, different quantities, different times
- MBA uses this information to:
  - Identify who customers are (not by name)
  - Understand why they make certain purchases
  - Gain insight about its merchandise (products):
    - Fast and slow movers
    - Products which are purchased together
    - Products which might benefit from promotion
  - Take action:
    - Store layouts
    - Which products to put on specials, promote, coupons…
- Combining all of this with a customer loyalty card it becomes even more valuable

# more than just the contents of shopping carts

- It is also about what customers do not purchase, and why.
- If customers purchase baking powder, but no flour, what are they baking?
- If customers purchase a mobile phone, but no case, are you missing an opportunity?
- It is also about key drivers of purchases; for example, the gourmet mustard that seems to lie on a shelf collecting dust until a customer buys that particular brand of special gourmet mustard in a shopping excursion that includes hundreds of dollars' worth of other products. Would eliminating the mustard (to replace it with a better-selling item) threaten the entire customer relationship?

# Market Basket Analysis

- association rules can be applied on other types of “baskets.”
  - Items purchased on a credit card, such as rental cars and hotel rooms, provide insight into the next product that customers are likely to purchase,
  - Optional services purchased by telecommunications customers (call waiting, call forwarding, DSL, speed call, and so on) help determine how to bundle these services together to maximize revenue.
  - Banking products used by retail customers (money market accounts, certificate of deposit, investment services, car loans, and so on) identify customers likely to want other products.
  - Unusual combinations of insurance claims can be a sign of fraud and can spark further investigation.
  - Medical patient histories can give indications of likely complications based on certain combinations of treatments.

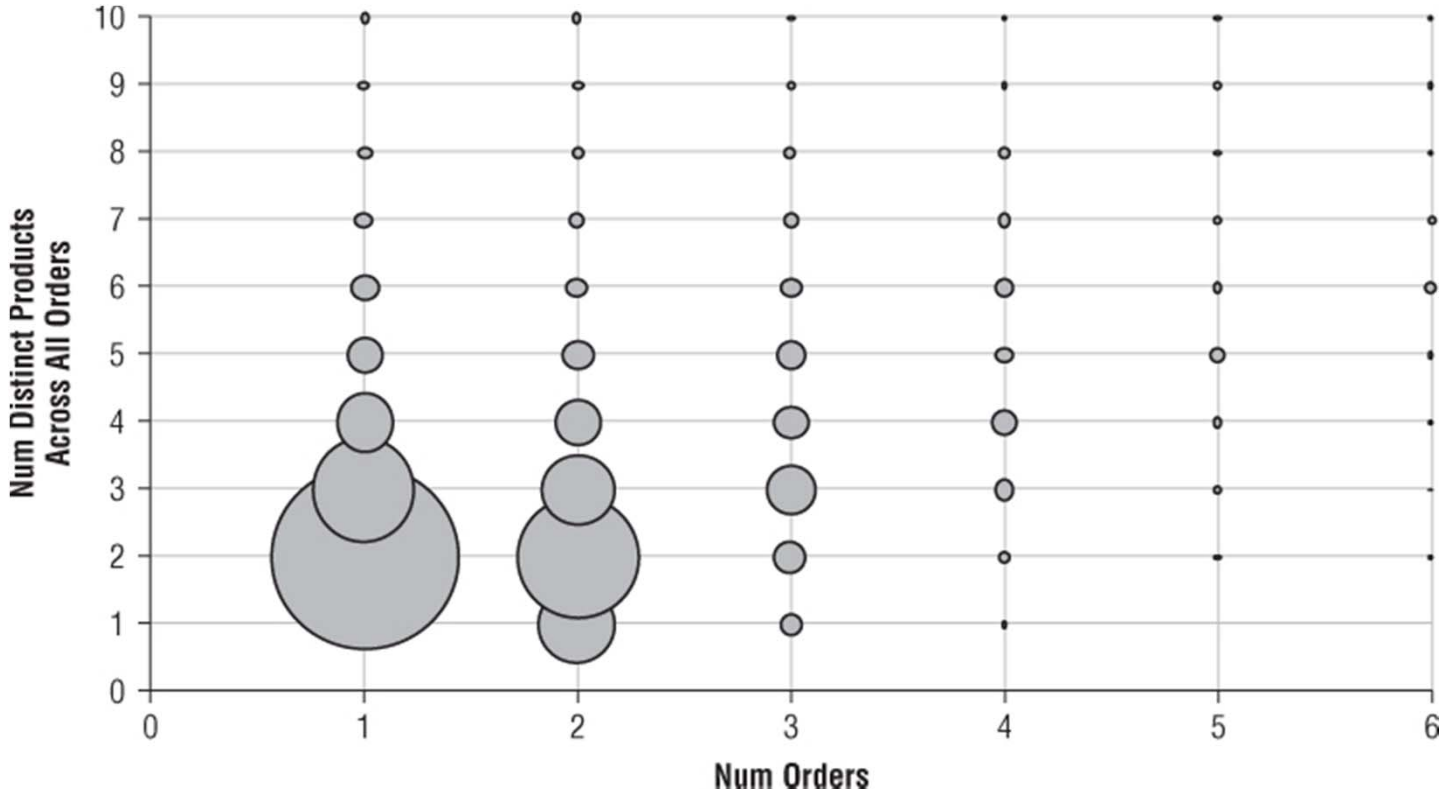
# Market Basket Analysis

- The *order* is the fundamental data structure for market basket data. An order represents a single purchase event by a customer.
- The *customer* entity is optional and should be available when a customer can be identified over time.
- Tracking customers over time makes it possible to determine, for instance, which grocery shoppers “bake from scratch”
  - interesting to the makers of flour as well as prepackaged cake mixes and the makers of aprons and kitchen appliances.
- The *store* entity provides information about where the products are purchased.

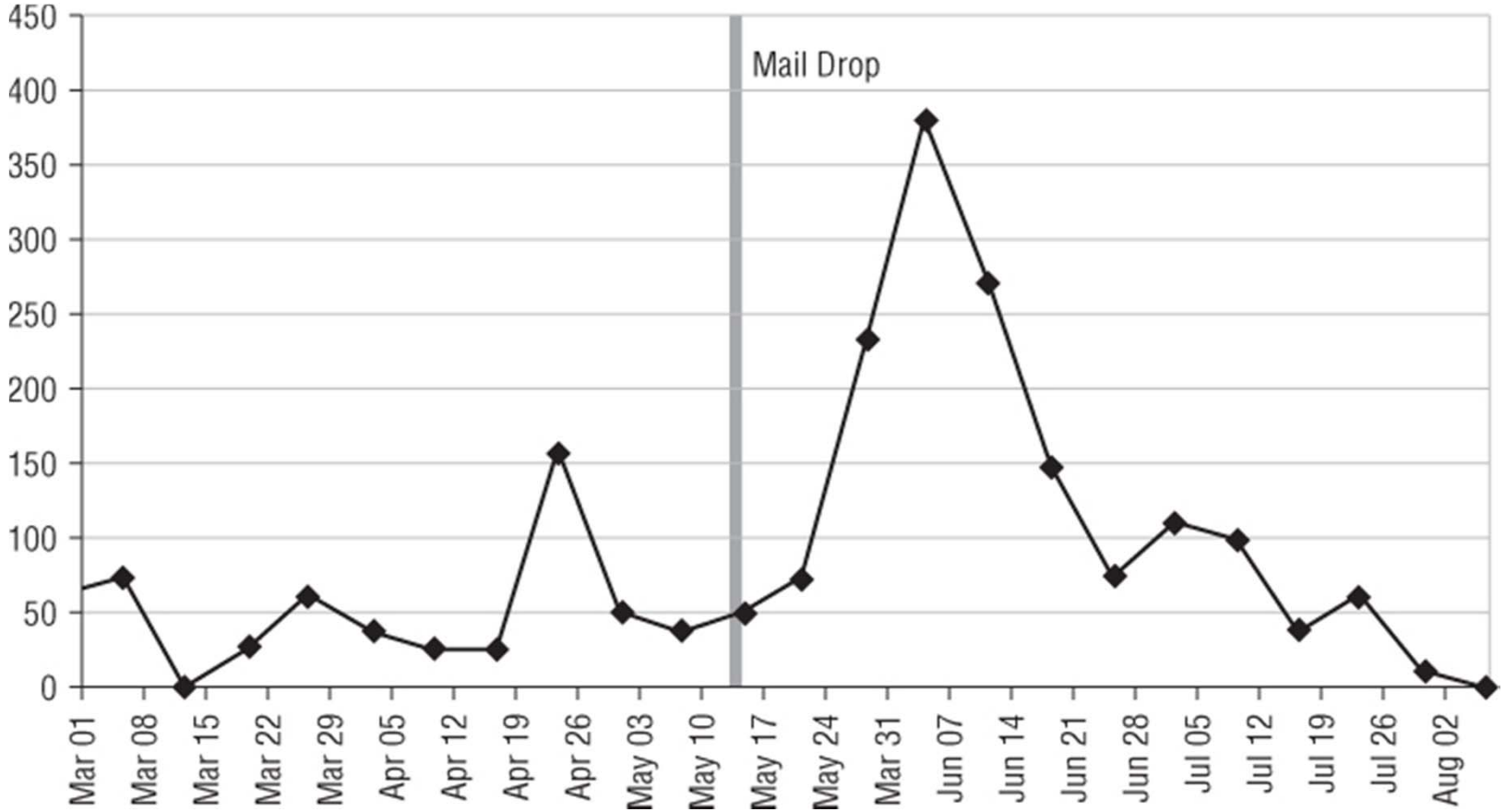
# Market Basket Analysis: Basic Measures

- Ex. of questions to ask before starting with fancy techniques:
  - Average number of orders per customer
  - Change in average number of orders per customer over time
  - Average number of unique items per order
  - Change in average number of unique items per order over time
  - Proportion of customers and average purchase size of customers who purchase the most popular products
  - Proportion of customers and average purchase size of customers who purchase the least popular products
  - Average order size
  - Changes in average order size over time
  - Average order size by important dimensions, such as geography, method of payment, time of year, and so on

- In some cases, few customers have multiple purchases, so the proportion of orders per customer is close to one, suggesting a business opportunity to increase the number of sales per customer.
- The Figure represents the number of unique items ever purchased by the depth of the relationship (the number of orders) for customers who purchased more than one item from a small specialty retailer.



- Tracking Marketing Interventions



# Mining Association Rules

- Market Basket Analysis
- **What is Association rule mining**
- Apriori Algorithm
- Measures of rule interestingness

# What Is Association Rule Mining?

- Association rule mining
  - Finding frequent patterns, associations, correlations, or causal structures among sets of items in transaction databases
  - Understand customer buying habits by finding associations and correlations between the different items that customers place in their "shopping basket"

- Applications
  - Basket data analysis, cross-marketing, catalog design, loss-leader analysis, web log analysis, fraud detection (supervisor->examiner)

# How can Association Rules be used?

## Stories – Beer and Diapers

- Diapers and Beer. Most famous example of market basket analysis for the last few years. If you buy diapers, you tend to buy beer.
  - T. Blischok headed Terradata's Industry Consulting group.
  - K. Heath ran self joins in SQL (1990), trying to find two itemsets that have baby items, which are particularly profitable.
  - Found this pattern in their data of 50 stores/90 day period.
  - Unlikely to be significant, but it's a nice example that explains associations well.

*Ronny Kohavi ICML 1998*

Probably mom was calling dad at work to buy diapers on way home and he decided to buy a six-pack as well.

The retailer could move diapers and beers to separate places and position high-profit items of interest to young fathers along the path.

# What Is Association Rule Mining?

- Rule form

  Antecedent → Consequent [support, confidence]

  *(support and confidence are user defined measures of interestingness)*

- Examples
  - buys(x, “computer”) → buys(x, “financial management software”) [0.5%, 60%]
  - age(x, “30..39”) ^ income(x, “42..48K”) → buys(x, “car”) [1%,75%]

# How can Association Rules be used?

- Let the rule discovered be

  {Bagels,...} → {Potato Chips}

- Potato chips as consequent => Can be used to determine what should be done to boost its sales

- Bagels in the antecedent => Can be used to see which products would be affected if the store discontinues selling bagels

- Bagels in antecedent and Potato chips in the consequent => Can be used to see what products should be sold with Bagels to promote sale of Potato Chips

| Customer | Items |
|---|---|
| 1 | Orange juice, soda |
| 2 | Milk, orange juice, window cleaner |
| 3 | Orange juice, detergent |
| 4 | Orange juice, detergent, soda |
| 5 | Window cleaner, soda |

| | OJ | WINDOW CLEANER | MILK | SODA | DETERGENT |
|---|---|---|---|---|---|
| OJ | 4 | 1 | 1 | 2 | 1 |
| Window Cleaner | 1 | 2 | 1 | 1 | 0 |
| Milk | 1 | 1 | 1 | 0 | 0 |
| Soda | 2 | 1 | 0 | 3 | 1 |
| Detergent | 1 | 0 | 0 | 1 | 2 |

Orange juice and soda are more likely to be purchased together than any other two items.
Detergent is never purchased with window cleaner or milk.
Milk is never purchased with soda or detergent.

# Association rule types

- Actionable Rules
  - contain high-quality, actionable information
- Trivial Rules
  - information already well-known by those familiar with the business
- Inexplicable Rules
  - no explanation and do not suggest action
- Trivial and Inexplicable Rules occur most often

# Rules

- Wal-Mart customers who purchase Barbie dolls have a 60% likelihood of also purchasing one of three types of candy bars [*Forbes*, Sept 8, 1997]

- Customers who purchase maintenance agreements are very likely to purchase large appliances (Linoff and Berry experience)

- When a new hardware store opens, one of the most commonly sold items is toilet bowl cleaners (Linoff and Berry experience)

# Basic Concepts

- Given:
  - (1) database of transactions,
  - (2) each transaction is a list of items purchased by a customer in a visit
- Find:
  - all rules that correlate the presence of one set of items (itemset) with that of another set of items
  - E.g., 35% of people who buys salmon also buys cheese

# Rule Basic Measures

$$A \Rightarrow B\ [\ s,\ c\ ]$$

**Support:** denotes the frequency of the rule within transactions. A high value means that the rule involves a great part of database.

$$\text{support}(A \Rightarrow B\ [\ s,\ c\ ]) = p(A \cup B)$$

**Confidence:** denotes the percentage of transactions containing A which also contain B. It is an estimation of conditioned probability .

$$\text{confidence}(A \Rightarrow B\ [\ s,\ c\ ]) = p(B|A) = \text{sup}(A,B)/\text{sup}(A).$$

| | |
|---|---|
| Tr1 | Shoes, *Socks*, Tie, Belt |
| Tr2 | Shoes, *Socks*, Tie, Belt, Shirt, Hat |
| Tr3 | Shoes, Tie |
| Tr4 | Shoes, *Socks*, Belt |

| Transaction | Shoes | Socks | Tie | Belt | Shirt | Scarf | Hat |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | | 0 | 0 | 0 |
| 2 | 1 | 1 | 1 | 1 | 1 | 0 | 1 |
| 3 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 4 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| ... | | | | | | | |

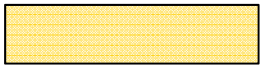
$Socks \Rightarrow Tie$

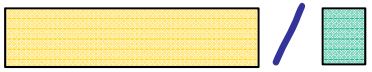
- Support is 50% (2/4)
- Confidence is 66.67% (2/3)

transactions

| A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| 1 | 1 | 1 | 0 | 1 | 1 | 0 |
| 1 | 0 | 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 0 | 1 | 0 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| 1 | 1 | 0 | 1 | 1 | 1 | 0 |
| 1 | 1 | 1 | 0 | 1 | 0 | 1 |
| 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 0 | 0 | 1 | 0 |

Rule C => D

support 

confidence 

# Example

| Trans. Id | Purchased Items |
|---|---|
| 1 | A,D |
| 2 | A,C |
| 3 | A,B,C |
| 4 | B,E,F |

## Definitions:

Itemset:

A,B or B,E,F

Support of an itemset:

Sup(A,B)=1

Sup(A,C)=2

Frequent pattern:

Given min. sup=2, {A,C} is a frequent pattern

For minimum support = 50% and minimum confidence = 50%, we have the following rules

A => C with 50% support and 66% confidence

C => A with 50% support and 100% confidence

# Other Applications

- "Baskets" = documents
- "items" = words in those documents
  - Lets us find words that appear together unusually frequently, i.e., linked concepts.

| | Word 1 | Word 2 | Word 3 | Word 4 |
|---|---|---|---|---|
| Doc 1 | 1 | 0 | 1 | 1 |
| Doc 2 | 0 | 0 | 1 | 1 |
| Doc 3 | 1 | 1 | 1 | 0 |

Word 4 => Word 3

When word 4 occurs in a document there a big probability of word 3 occurring

# Other Applications

- "Baskets" = sentences
- "items" = documents containing those sentences
  - Items that appear together too often could represent plagiarism.

| | Doc 1 | Doc 2 | Doc 3 | Doc 4 |
|---|---|---|---|---|
| Sent 1 | 1 | 0 | 1 | 1 |
| Sent 2 | 0 | 0 | 1 | 1 |
| Sent 3 | 1 | 1 | 1 | 0 |

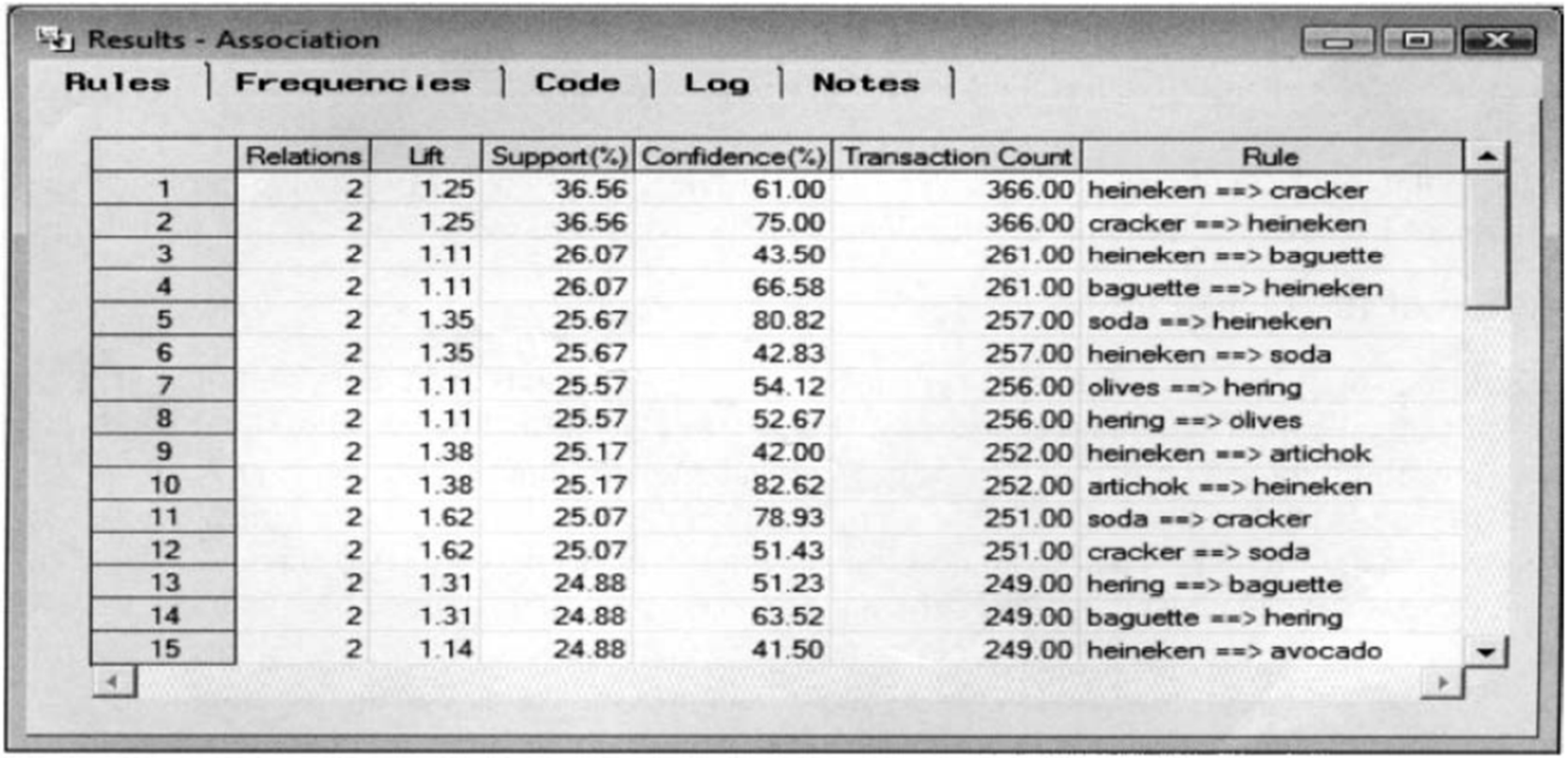
Doc 4 => Doc 3

When a sentence occurs in document 4 there is a big probability of occurring in document 3

# Other Applications

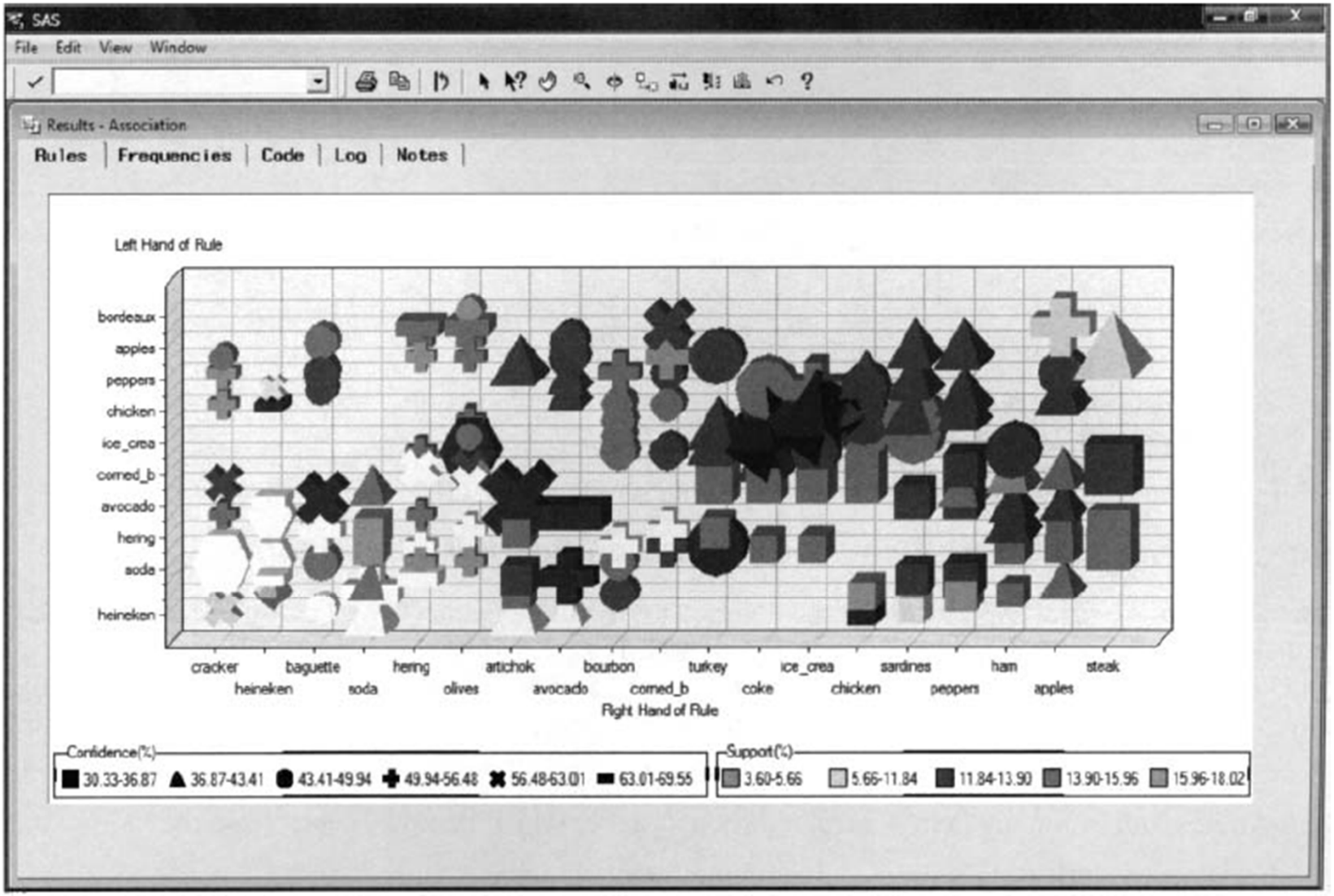
- "Baskets" = Web pages;
- "items" = linked pages.
  - Pairs of pages with many common references may be about the same topic.
- "Baskets" = Web pages $p_i$;
- "items" = pages that link to $p_i$
  - Pages with many of the same links may be mirrors or about the same topic.

| | wp a | wp b | wp c | wp d |
|---|---|---|---|---|
| wp1 | | | | |
| wp2 | | | | |



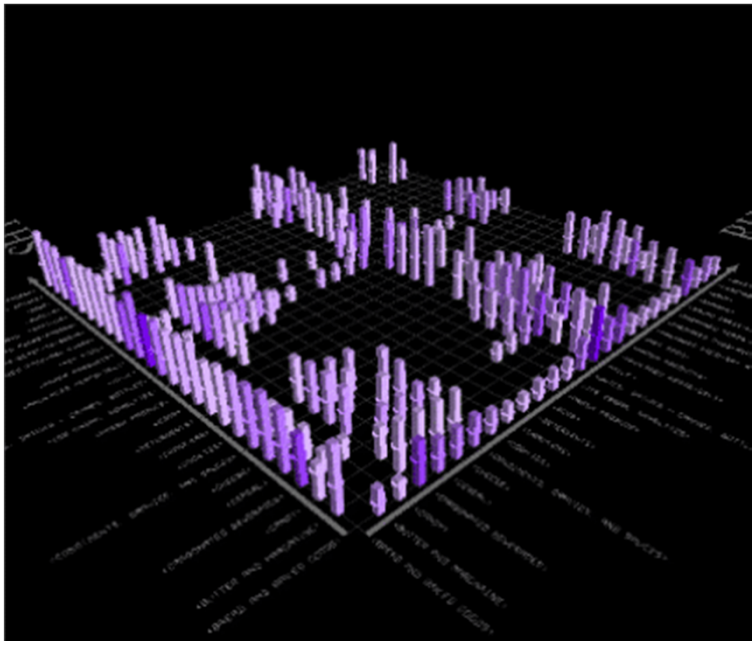

| | Relations | Lift | Support(%) | Confidence(%) | Transaction Count | Rule |
|---|---|---|---|---|---|---|
| 1 | 2 | 1.25 | 36.56 | 61.00 | 366.00 | heineken ==> cracker |
| 2 | 2 | 1.25 | 36.56 | 75.00 | 366.00 | cracker ==> heineken |
| 3 | 2 | 1.11 | 26.07 | 43.50 | 261.00 | heineken ==> baguette |
| 4 | 2 | 1.11 | 26.07 | 66.58 | 261.00 | baguette ==> heineken |
| 5 | 2 | 1.35 | 25.67 | 80.82 | 257.00 | soda ==> heineken |
| 6 | 2 | 1.35 | 25.67 | 42.83 | 257.00 | heineken ==> soda |
| 7 | 2 | 1.11 | 25.57 | 54.12 | 256.00 | olives ==> hering |
| 8 | 2 | 1.11 | 25.57 | 52.67 | 256.00 | hering ==> olives |
| 9 | 2 | 1.38 | 25.17 | 42.00 | 252.00 | heineken ==> artichok |
| 10 | 2 | 1.38 | 25.17 | 82.62 | 252.00 | artichok ==> heineken |
| 11 | 2 | 1.62 | 25.07 | 78.93 | 251.00 | soda ==> cracker |
| 12 | 2 | 1.62 | 25.07 | 51.43 | 251.00 | cracker ==> soda |
| 13 | 2 | 1.31 | 24.88 | 51.23 | 249.00 | hering ==> baguette |
| 14 | 2 | 1.31 | 24.88 | 63.52 | 249.00 | baguette ==> hering |
| 15 | 2 | 1.14 | 24.88 | 41.50 | 249.00 | heineken ==> avocado |

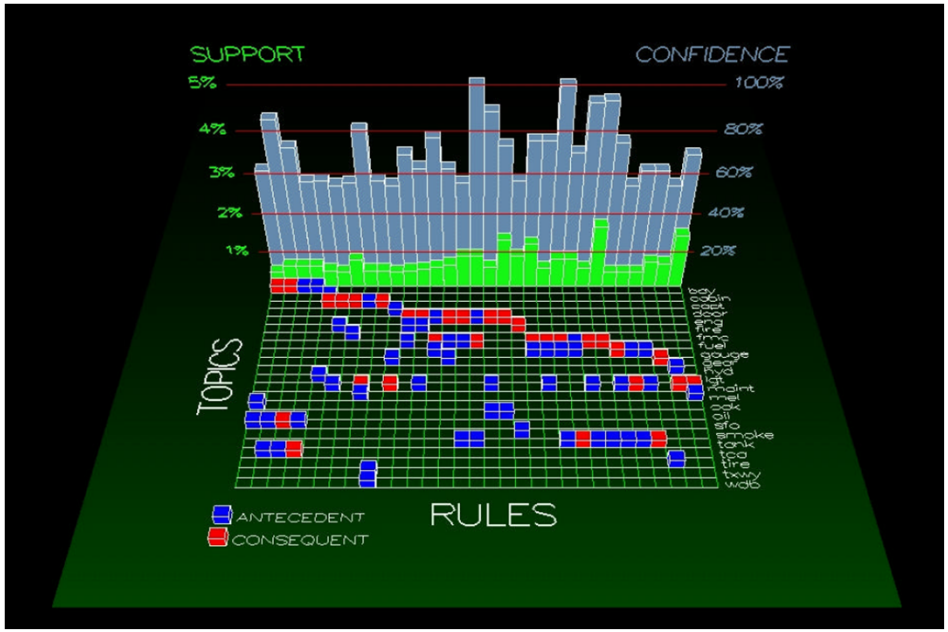
Randall Matignon 2007, Data Mining Using SAS Enterprise Miner, Wiley (book).




The support probability of each rule is identified by the color of the symbols and the confidence probability of each rule is identified by the shape of the symbols. The items that have the highest confidence are Heineken beer, crackers, chicken, and peppers.

Randall Matignon 2007, Data Mining Using SAS Enterprise Miner, Wiley (book).




SUPPORT
CONFIDENCE
5%
4%
3%
2%
1%
100%
80%
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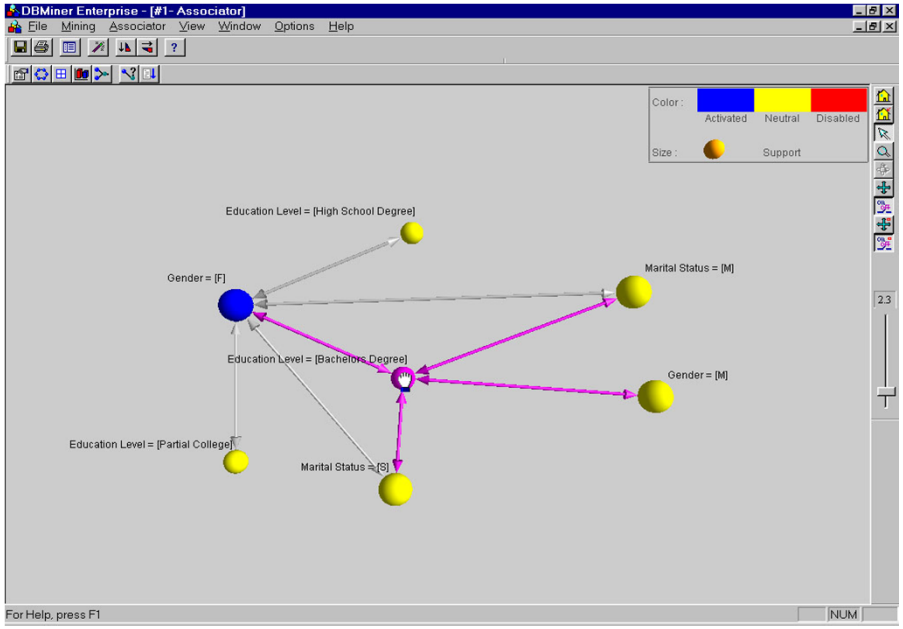
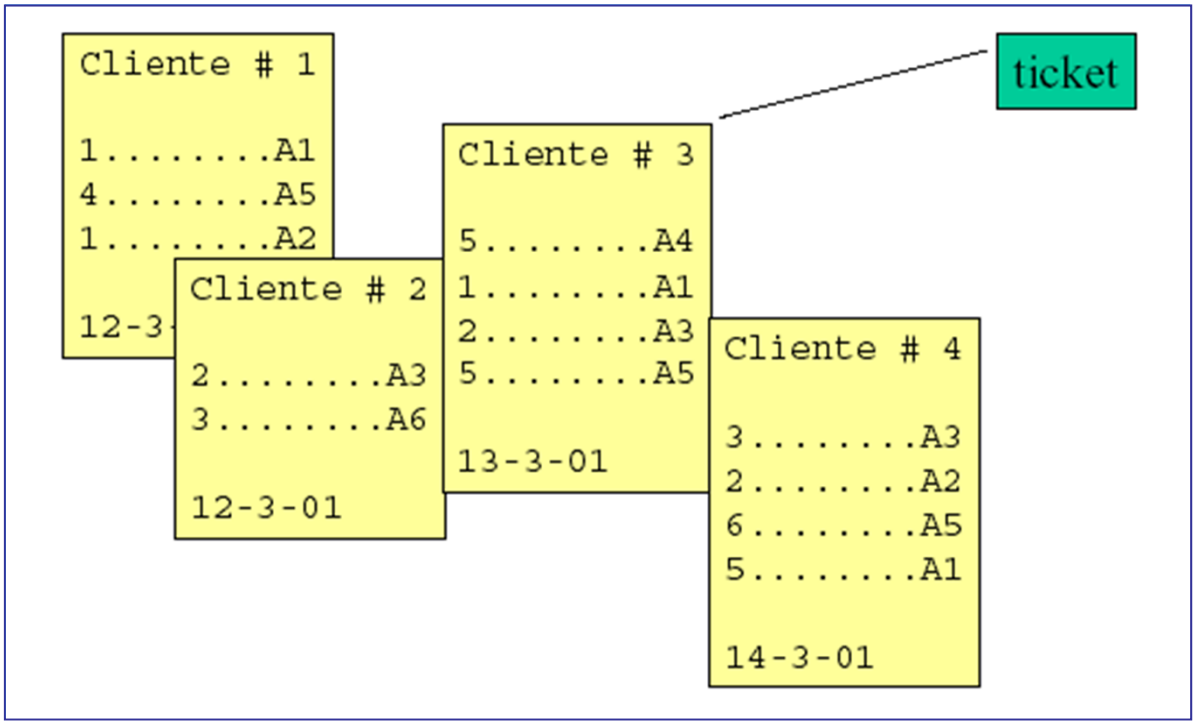
40%
20%
TOPICS
RULES
ANTECEDENT
CONSEQUENT


DBMiner Enterprise - [#1- Associator]
File Mining Associator View Window Options Help
Color :
Activated
Neutral
Disabled
Size :
Support
Education Level = [High School Degree]
Gender = [F]
Marital Status = [M]
Education Level = [Bachelors Degree]
Gender = [M]
Education Level = [Partial College]
Marital Status = [S]
2.3
For Help, press F1
NUM

# Mining Association Rules

- Market Basket Analysis
- What is Association rule mining
- **Apriori Algorithm**
- Measures of rule interestingness

# Boolean association rules




**Each transaction is converted to a Boolean vector**

| Cliente | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 | A9 | A10 | A11 | A12 | A13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| 6 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 |
| 8 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |

# Finding Association Rules

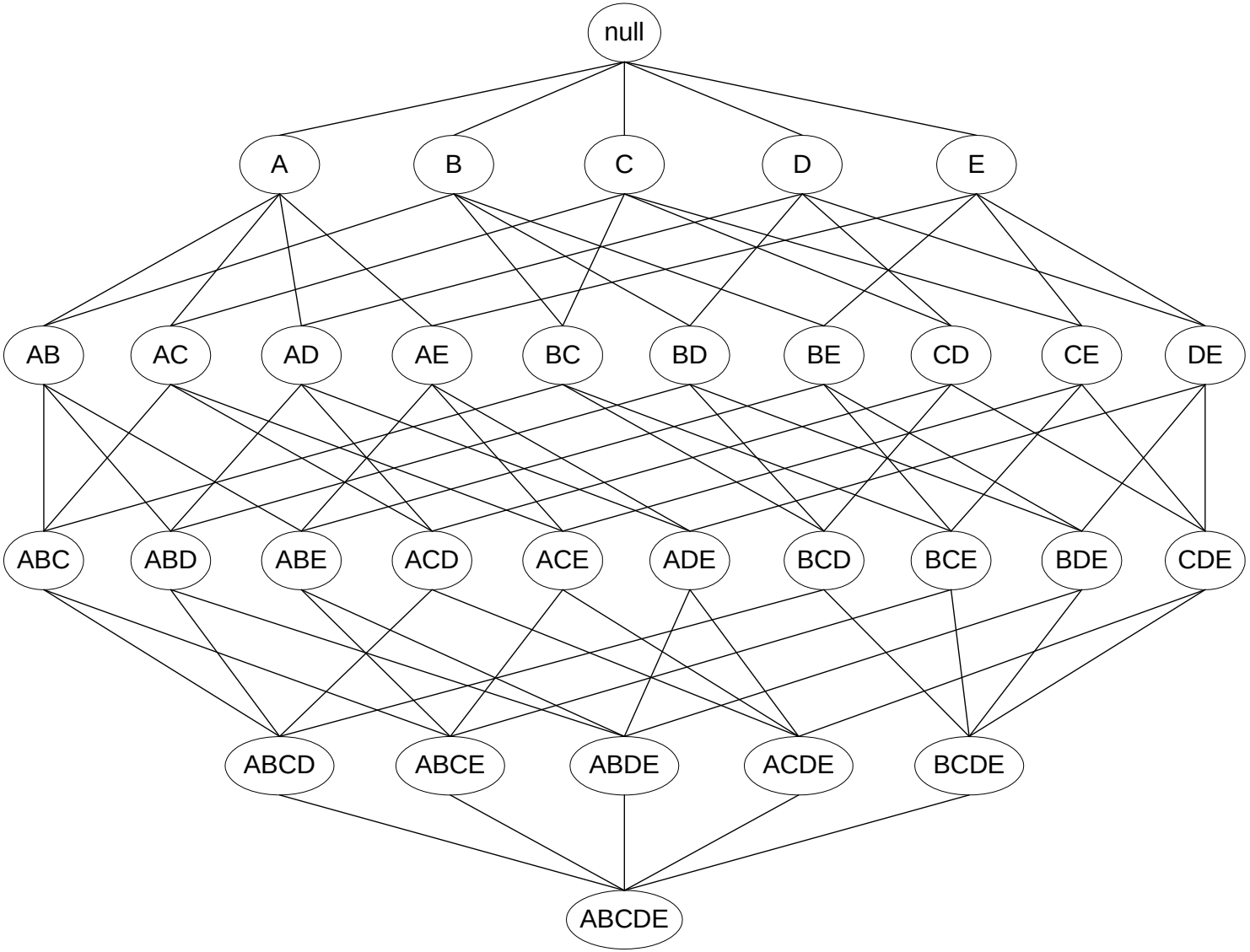
Approach:

1) Find all itemsets that have high support

- These are known as frequent itemsets

2) Generate association rules from frequent itemsets

# Itemset Lattice for 5 products



# Apriori principle

**Any subset of a frequent itemset must be frequent**

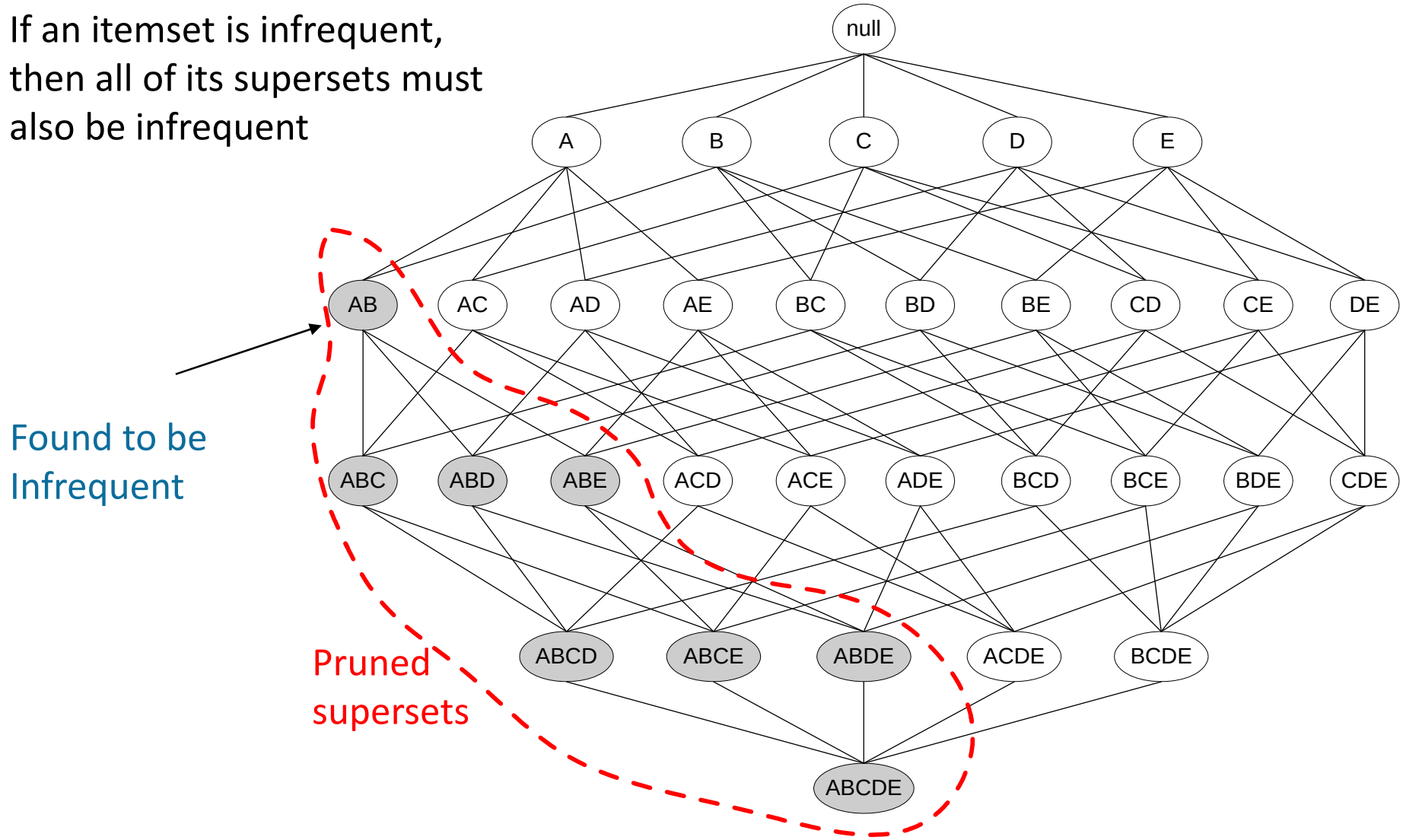
- A transaction containing {beer, diaper, nuts} also contains {beer, diaper}
- {beer, diaper, nuts} is frequent → {beer, diaper} must also be frequent

# Apriori principle

- No superset of any infrequent itemset should be generated or tested
  - Many item combinations can be pruned

# Apriori principle for pruning candidates

If an itemset is infrequent, then all of its supersets must also be infrequent



# Mining Frequent Itemsets (the Key Step)

- Find the *frequent itemsets:* the sets of items that have (at least) minimum support
  - A subset of a frequent itemset must also be a frequent itemset
    - Generate length (k+1) candidate itemsets from length k frequent itemsets, and
    - Test the candidates against DB to determine which are in fact frequent

# How to Generate Candidates? - step 1

- The items in $L_{k-1}$ are listed in an order
- Step 1: self-joining $L_{k-1}$

  insert into $C_k$

  select $p.item_1, p.item_2, \ldots, p.item_{k-1}, q.item_{k-1}$

  from $L_{k-1}\ p, L_{k-1}\ q$

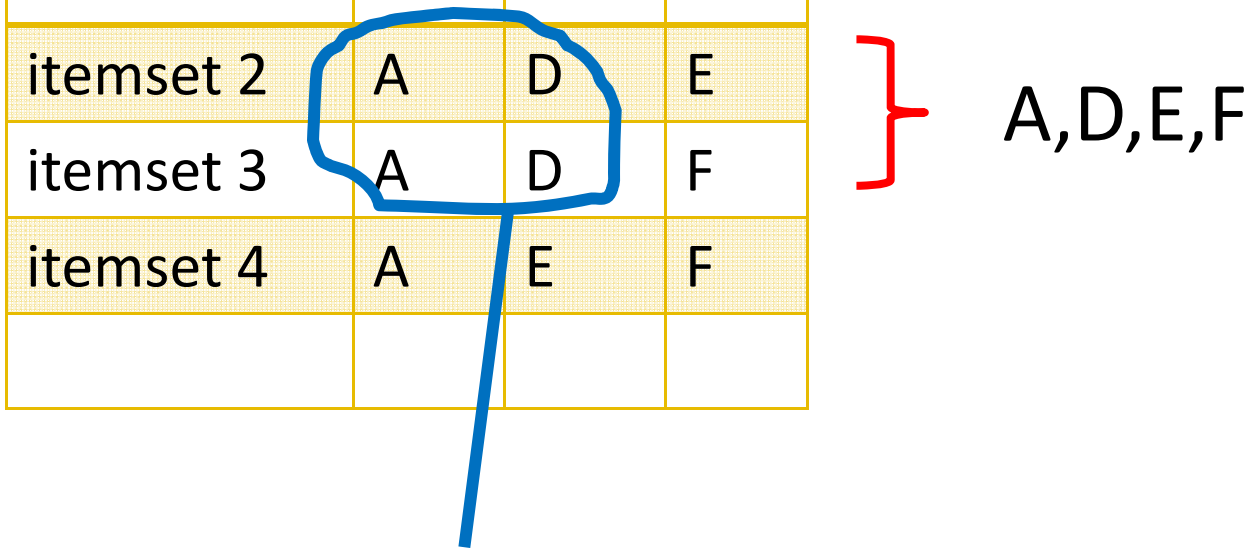
  where $p.item_1=q.item_1, \ldots, p.item_{k-2}=q.item_{k-2}, p.item_{k-1} < q.item_{k-1}$

| A | D | E |
|---|---|---|
| = | = | ^ |
| A | D | F |

L3 – set of itemsets of size 3 that are frequent

***(itemsets need to be sorted)***

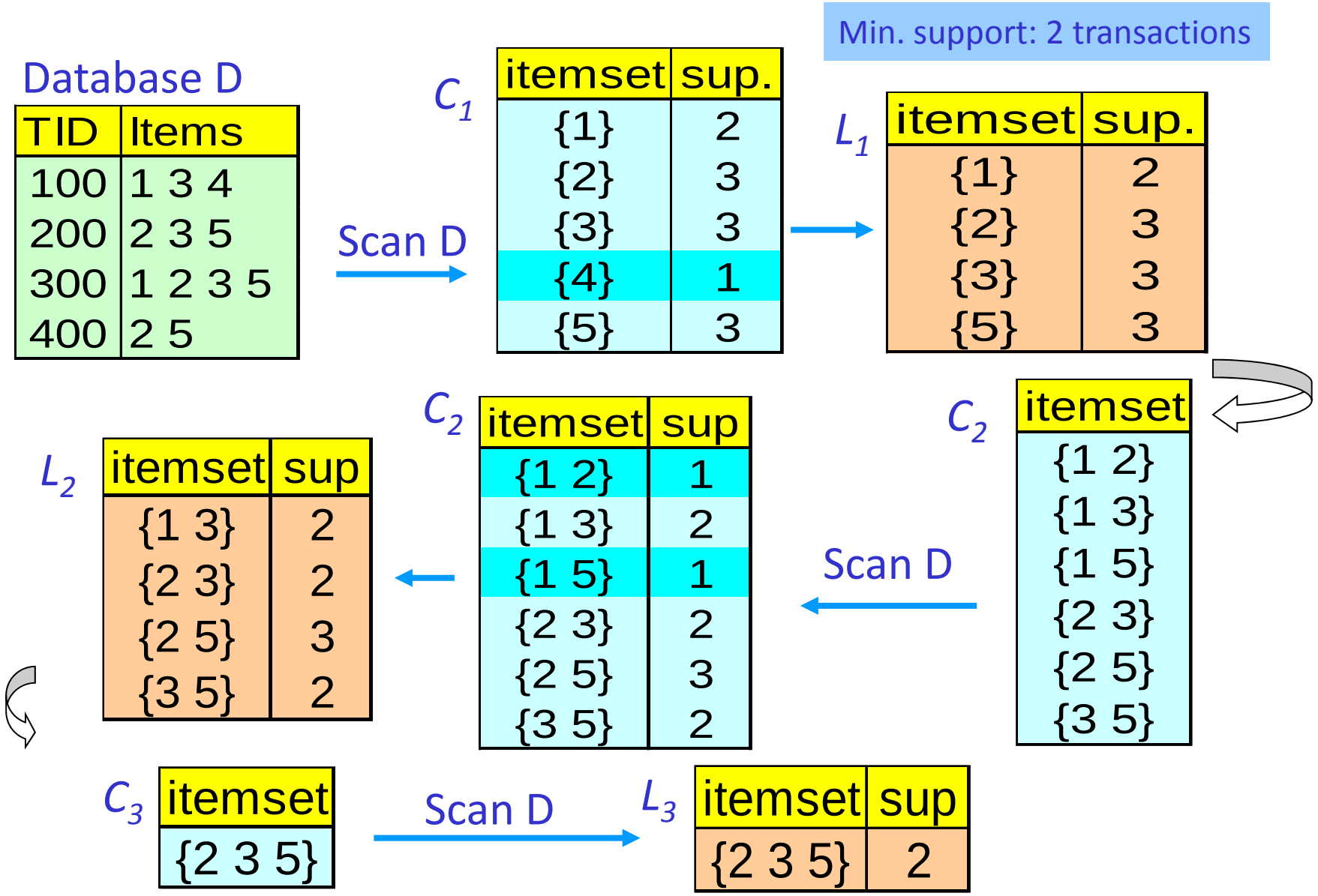
| | | | |
|---|---|---|---|
| itemset 1 | A | B | C |
| itemset 2 | A | D | E |
| itemset 3 | A | D | F |
| itemset 4 | A | E | F |
| | | | |




Two itemsets with the same k-1 = 3-1 elements are merged and inserted in C4 (the set of candidate itemsets of size 4).

Those in C4 that have support above the threshold are inserted in L4.

# The Apriori Algorithm — Example



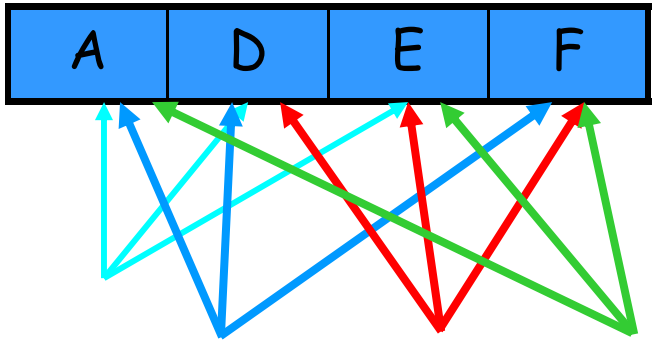
# How to Generate Candidates? – step 2

- Step 2: pruning

  for all *itemsets c in* $C_k$ do

    for all *(k-1)-subsets s of c* do

      if *(s is not in* $L_{k-1}$*)* then delete *c* from $C_k$




**Note:** In step 1 we may generate candidates that include itemsets of size k-1 that are not frequent.

The pruning step may be able to eliminate some candidates without counting their support.

Counting support is a computationally demanding task.

# Example of Generating Candidates – step 1

- $L_3$ = {*abc, abd, acd, ace, bcd*}
- **Self-joining**: $L_3 * L_3$
  - joining *abc* and *abd* gives *abcd*
  - joining *acd* and *ace* gives *acde*

# Example of Generating Candidates – step 2

- $L_3$ = {*abc, abd, acd, ace, bcd*}
- **Pruning** *(before counting its support)*:
  - *abcd:* check if *abc, abd, acd, bcd,* are in *L3*
  - *acde:* check if *acd, ace, ade, cde* are *in L3*
  - *acde* is removed because *ade* is not in $L_3$
- *Thus* $C_4$={*abcd*}

# The Apriori Algorithm

- $C_k$: Candidate itemset of size k $L_k$ : frequent itemset of size k
- Join Step: $C_k$ is generated by joining $L_{k-1}$ with itself
- Prune Step: Any (k-1)-itemset that is not frequent cannot be a subset of a frequent k-itemset
- Algorithm:

$L_1$ = {frequent items};
**for** ($k$ = 1; $L_k$ !=∅; $k$++) **do begin**
$C_{k+1}$ = candidates generated from $L_k$;
**for each** transaction $t$ in database do
increment the count of all candidates in $C_{k+1}$ that are contained in $t$
$L_{k+1}$ = candidates in $C_{k+1}$ with min_support
**end**
**return** L = $\cup_k L_k$;

# Generating AR from frequent intemsets

- Confidence ($A \Rightarrow B$) = $P(B|A)$ = $\frac{support\_count(\{A,B\})}{support\_count(\{A\})}$

- For every frequent itemset x, generate all non-empty subsets of x

- For every non-empty subset s of x, output the rule

  " $s \Rightarrow (x-s)$ " if $\frac{support\_count(\{x\})}{support\_count(\{s\})} \geq min\_conf$

# Rule Generation

- How to efficiently generate rules from frequent itemsets?
  - In general, confidence does not have an anti-monotone property
  - But confidence of rules generated from the same itemset has an anti-monotone property
  - L = {A,B,C,D}:

$$c(ABC \rightarrow D) \geq c(AB \rightarrow CD) \geq c(A \rightarrow BCD)$$

    - Confidence is non-increasing as number of items in rule consequent increases

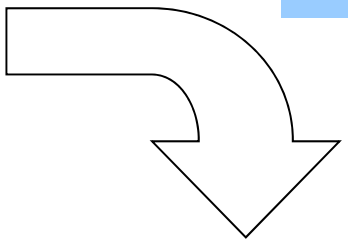
## From Frequent Itemsets to Association Rules

- *Q: Given frequent set {A,B,E}, what are possible association rules?*
  - A => B, E
  - A, B => E
  - A, E => B
  - B => A, E
  - B, E => A
  - E => A, B
  - __ => A,B,E (empty rule), or true => A,B,E

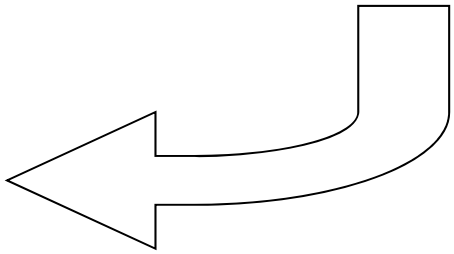
# Generating Rules: example

| Trans-ID | Items |
|---|---|
| 1 | ACD |
| 2 | BCE |
| 3 | ABCE |
| 4 | BE |
| 5 | ABCE |

Min_support: 60%
Min_confidence: 75%



| Frequent Itemset | Support |
|---|---|
| {BCE},{AC} | 60% |
| {BC},{CE},{A} | 60% |
| {BE},{B},{C},{E} | 80% |



| Rule | Conf. |
|---|---|
| {BC} =>{E} | 100% |
| {BE} =>{C} | 75% |
| {CE} =>{B} | 100% |
| {B} =>{CE} | 75% |
| {C} =>{BE} | 75% |
| {E} =>{BC} | 75% |

# Exercice

| TID | Items |
|---|---|
| 1 | Bread, Milk, Chips, Mustard |
| 2 | Beer, Diaper, Bread, Eggs |
| 3 | Beer, Coke, Diaper, Milk |
| 4 | Beer, Bread, Diaper, Milk, Chips |
| 5 | Coke, Bread, Diaper, Milk |
| 6 | Beer, Bread, Diaper, Milk, Mustard |
| 7 | Coke, Bread, Diaper, Milk |

Converta os dados para o formato booleano e para um suporte de 40%, aplique o algoritmo apriori.

| Bread | Milk | Chips | Mustard | Beer | Diaper | Eggs | Coke |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |

**0.4*7= 2.8**

| C1 | |
|---|---|
| Bread | 6 |
| Milk | 6 |
| Chips | 2 |
| Mustard | 2 |
| Beer | 4 |
| Diaper | 6 |
| Eggs | 1 |
| Coke | 3 |

| L1 | |
|---|---|
| Bread | 6 |
| Milk | 6 |
| Beer | 4 |
| Diaper | 6 |
| Coke | 3 |

| C2 | |
|---|---|
| Bread,Milk | 5 |
| Bread,Beer | 3 |
| Bread,Diaper | 5 |
| Bread,Coke | 2 |
| Milk,Beer | 3 |
| Milk,Diaper | 5 |
| Milk,Coke | 3 |
| Beer,Diaper | 4 |
| Beer,Coke | 1 |
| Diaper,Coke | 3 |

| L2 | |
|---|---|
| Bread,Milk | 5 |
| Bread,Beer | 3 |
| Bread,Diaper | 5 |
| Milk,Beer | 3 |
| Milk,Diaper | 5 |
| Milk,Coke | 3 |
| Beer,Diaper | 4 |
| Diaper,Coke | 3 |

| C3 | |
|---|---|
| Bread,Milk,Beer | 2 |
| Bread,Milk,Diaper | 4 |
| Bread,Beer,Diaper | 3 |
| Milk,Beer,Diaper | 3 |
| Milk,Beer,Coke | |
| Milk,Diaper,Coke | 3 |

| L3 | |
|---|---|
| Bread,Milk,Diaper | 4 |
| Bread,Beer,Diaper | 3 |
| Milk,Beer,Diaper | 3 |
| Milk,Diaper,Coke | 3 |

$$8 + C_2^8 + C_3^8 = 92 \quad >> \quad 24$$

# Mining Association Rules

- Market Basket Analysis
- What is Association rule mining
- Apriori Algorithm
- **Measures of rule interestingness**

# Interestingness Measurements

- **How good is the association Rule?**
- Are all of the strong association rules discovered interesting enough to present to the user?
- How can we measure the interestingness of a rule?
- Subjective measures
  - A rule (pattern) is interesting if
  - it is *unexpected* (surprising to the user); and/or
  - *actionable* (the user can do something with it)
  - (only the user can judge the interestingness of a rule)

# Objective measures of rule interest

- Support
- Confidence or strength
- Lift or Interest or Correlation
- Conviction
- Leverage or Piatetsky-Shapiro

# Criticism to Support and Confidence

- Example 1: (Aggarwal & Yu, PODS98)
  - Among 5000 students
    - 3000 play basketball
    - 3750 eat cereal
    - 2000 both play basket ball and eat cereal

| | basketball | not basketball | sum(row) | |
|---|---|---|---|---|
| cereal | 2000 | 1750 | 3750 | 75% |
| not cereal | 1000 | 250 | 1250 | 25% |
| sum(col.) | 3000 | 2000 | 5000 | |
| | 60% | 40% | | |

*play basketball* $\Rightarrow$ *eat cereal* [40%, 66.7%]

misleading because the overall percentage of students eating cereal is 75% which is higher than 66.7%.

*play basketball* $\Rightarrow$ *not eat cereal* [20%, 33.3%]

is more accurate, although with lower support and confidence

# Lift of a Rule

$$LIFT(A \rightarrow B) = \frac{\sup(A,B)}{\sup(A)\sup(B)} = \frac{p(B \mid A)}{p(B)}$$

- *play basketball* $\Rightarrow$ *eat cereal* [40%, 66.7%]

$$LIFT = \frac{\frac{2000}{5000}}{\frac{3000}{5000} \times \frac{3750}{5000}} = 0.89$$

- *play basketball* $\Rightarrow$ *not eat cereal* [20%, 33.3%]

$$LIFT = \frac{\frac{1000}{5000}}{\frac{3000}{5000} \times \frac{1250}{5000}} = 1.33$$

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

# Problems With Lift

- Rules that hold 100% of the time may not have the highest possible lift. For example, if 5% of people are Vietnam veterans and 90% of the people are more than 5 years old, we get a lift of 0.05/(0.05*0.9)=1.11 which is only slightly above 1 for the rule
- Vietnam veterans -> more than 5 years old.
- And, lift is symmetric:
- *not eat cereal* $\Rightarrow$ *play basketball* [20%, 80%]

$$LIFT = \frac{\frac{1000}{5000}}{\frac{1250}{5000} \times \frac{3000}{5000}} = 1.33$$

# Conviction of a Rule

$$Conv(A \rightarrow B) = \frac{\sup(A) \cdot \sup(\bar{B})}{\sup(A, \bar{B})} = \frac{P(A) \cdot P(\bar{B})}{P(A, \bar{B})} = \frac{P(A)(1 - P(B))}{P(A) - P(A, B)}$$

- Conviction is a measure of the implication and has value 1 if items are unrelated.

- *play basketball* $\Rightarrow$ *eat cereal* [40%, 66.7%]
- *eat cereal* $\Rightarrow$ *play basketball* conv:0.85

$$Conv = \frac{\frac{3000}{5000}\left(1 - \frac{3750}{5000}\right)}{\frac{3000}{5000} - \frac{2000}{5000}} = 0.75$$

- *play basketball* $\Rightarrow$ *not eat cereal* [20%, 33.3%]
- *not eat cereal* $\Rightarrow$ *play basketball* conv:1.43

$$Conv = \frac{\frac{3000}{5000}\left(1 - \frac{1250}{5000}\right)}{\frac{3000}{5000} - \frac{1000}{5000}} = 1.125$$

# Conviction

- conviction of X=>Y can be interpreted as the
- ratio of the expected frequency that X occurs without Y (that is to say, the frequency that the rule makes an incorrect prediction) if X and Y were independent
- divided by the observed frequency of incorrect predictions.
- A conviction value of 1.2 shows that the rule would be incorrect 20% more often (1.2 times as often) if the association between X and Y was purely random chance.

# Leverage of a Rule

- **Leverage or Piatetsky-Shapiro**

$$PS(A \rightarrow B) = \sup(A,B) - \sup(A) \cdot \sup(B)$$

  - PS (or Leverage):
  - is the proportion of additional elements covered by both the premise and consequence above the expected if independent.

# Comments

- Traditional methods such as database queries:
  - support hypothesis verification about a relationship such as the co-occurrence of diapers & beer.

- Data Mining methods automatically discover significant associations rules from data.
  - Find whatever patterns exist in the database, without the user having to specify in advance what to look for (data driven).
  - Therefore allow finding unexpected correlations

# Choosing the Right Set of Items

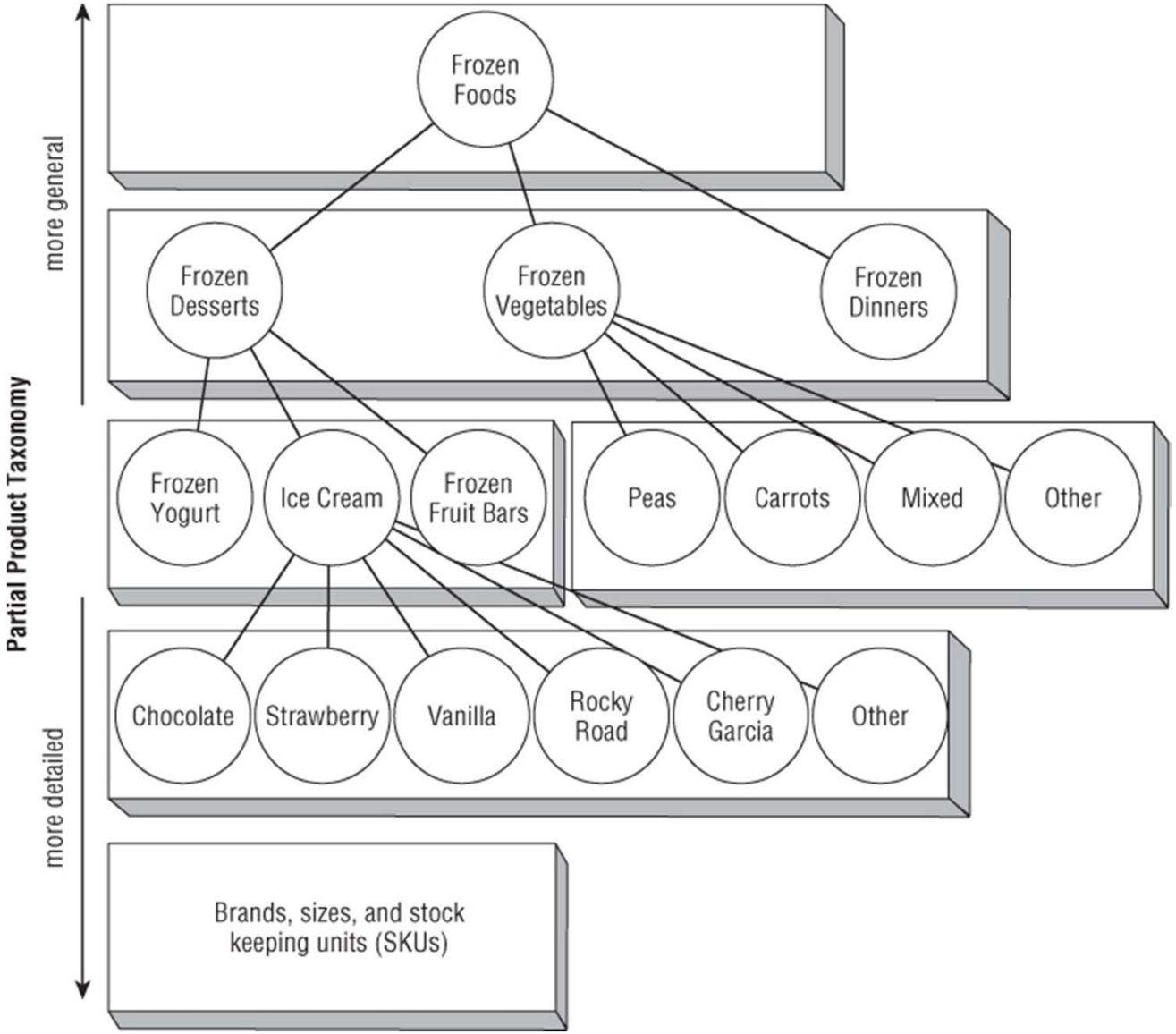
| CUSTOMER | PIZZA | MILK | SUGAR | APPLES | COFFEE |
|---|---|---|---|---|---|
| 1 | X | | | | |
| 2 | | X | X | | |
| 3 | X | | | X | X |
| 4 | | X | | | X |
| 5 | X | | X | X | X |

| CUSTOMER | EXTRA CHEESE | ONIONS | PEPPERS | MUSHROOMS | OLIVES |
|---|---|---|---|---|---|
| 1 | X | X | | | X |
| 2 | | | X | | |
| 3 | X | X | | X | |
| 4 | | X | | | X |
| 5 | X | | X | X | X |

# Product Hierarchies Help to Generalize Items

- Are large fries and small fries the same product?
- Is the brand of ice cream more relevant than its flavor?
- Which is more important: the size, style, pattern, or designer of clothing?
- Is the energy-saving option on a large appliance indicative of customer behavior?

- **Market basket analysis produces the best results when the items occur in roughly the same number of transactions in the data. This helps prevent rules from being dominated by the most common items. Product hierarchies can help here. Roll up rare items to higher levels in the hierarchy, so they become more frequent. More common items may not have to be rolled up at all.**


Partial Product Taxonomy
more general
more detailed
Frozen Foods
Frozen Desserts
Frozen Vegetables
Frozen Dinners
Frozen Yogurt
Ice Cream
Frozen Fruit Bars
Peas
Carrots
Mixed
Other
Chocolate
Strawberry
Vanilla
Rocky Road
Cherry Garcia
Other
Brands, sizes, and stock keeping units (SKUs)

# *Virtual Items Go Beyond the Product Hierarchy*

- The purpose of virtual items is to enable the analysis to take advantage of information that goes beyond the product hierarchy.
- Examples of virtual items might be
  - designer labels, such as Calvin Klein, that appear in both apparel departments and perfumes
  - low-fat and no-fat products in a grocery store
  - energy-saving options on appliances
  - whether the purchase was made with cash, a credit card, or check
  - the day of the week or the time of day the transaction occurred
  - *virtual items* can also be used to specify which group, such as an existing location or a new location, generates the transaction.

# Application Difficulties

- Wal-Mart knows that customers who buy Barbie dolls (it sells one every 20 seconds) have a 60% likelihood of buying one of three types of candy bars. What does Wal-Mart do with information like that?
- 'I don't have a clue,' says Wal-Mart's chief of merchandising, Lee Scott.

- See - KDnuggets 98:01 for many ideas
  www.kdnuggets.com/news/98/n01.html

# Some Suggestions

- By increasing the price of Barbie doll and giving the type of candy bar free, wal-mart can reinforce the buying habits of that particular types of buyer
- Highest margin candy to be placed near dolls.
- Special promotions for Barbie dolls with candy at a slightly higher margin.
- Take a poorly selling product X and incorporate an offer on this which is based on buying Barbie and Candy. If the customer is likely to buy these two products anyway then why not try to increase sales on X?
- Probably they can not only bundle candy of type A with Barbie dolls, but can also introduce new candy of Type N in this bundle while offering discount on whole bundle. As bundle is going to sell because of Barbie dolls & candy of type A, candy of type N can get free ride to customers houses. And with the fact that you like something, if you see it often, Candy of type N can become popular.

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- **Vipin Kumar and Mahesh Joshi,** "Tutorial on High Performance Data Mining ", 1999
- **Rakesh Agrawal, Ramakrishnan Srikan**, "Fast Algorithms for Mining Association Rules", Proc VLDB, 1994

  (http://www.cs.tau.ac.il/~fiat/dmsem03/Fast%20Algorithms%20for%20Mining%20Association%20Rules.ppt)