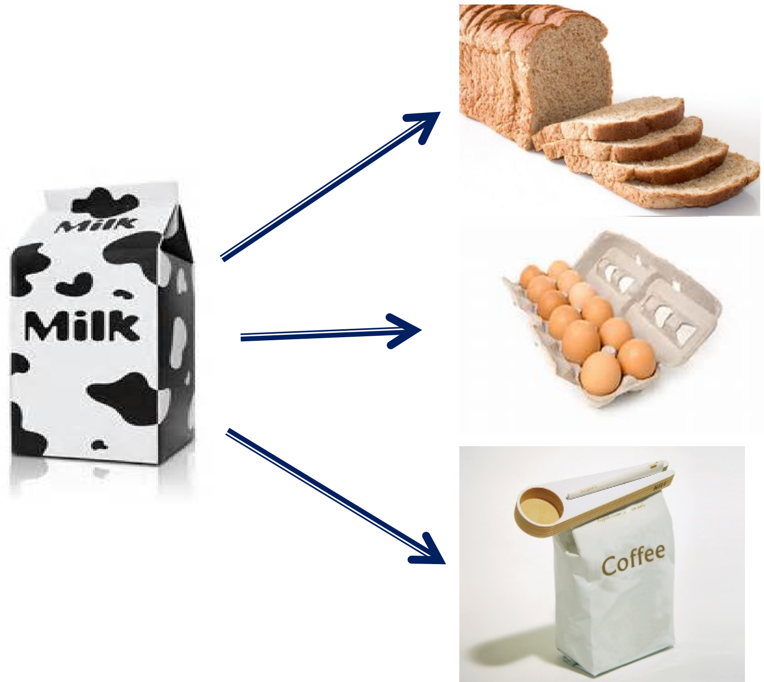
Association Rule Learning

Learning Algorithm Implementations

Finding Patterns

Is there any insight in these baskets?

What % of customers that buy milk buy eggs?



Out of the Customers who bought milk
71% bought bread
43% bought eggs
26% included coffee

Market Basket Analysis

What % of customers that buy milk buy eggs?

26 %

What % of customers that buy milk and eggs bought cake mix?

What kinds of questions can we answer?

Is cereal typically purchased with bananas?

Does the brand/type of cereal matters?

- How are the demographics of the neighborhood affecting what customers are buying?

Huggies and Chuggies

Mining Association Rules

- **Association rule learning** is a method for discovering interesting relations between variables in large databases It is intended to identify strong rules/patterns discovered in databases using some measures of interestingness

What are Item sets?

Item

One attribute–value pair

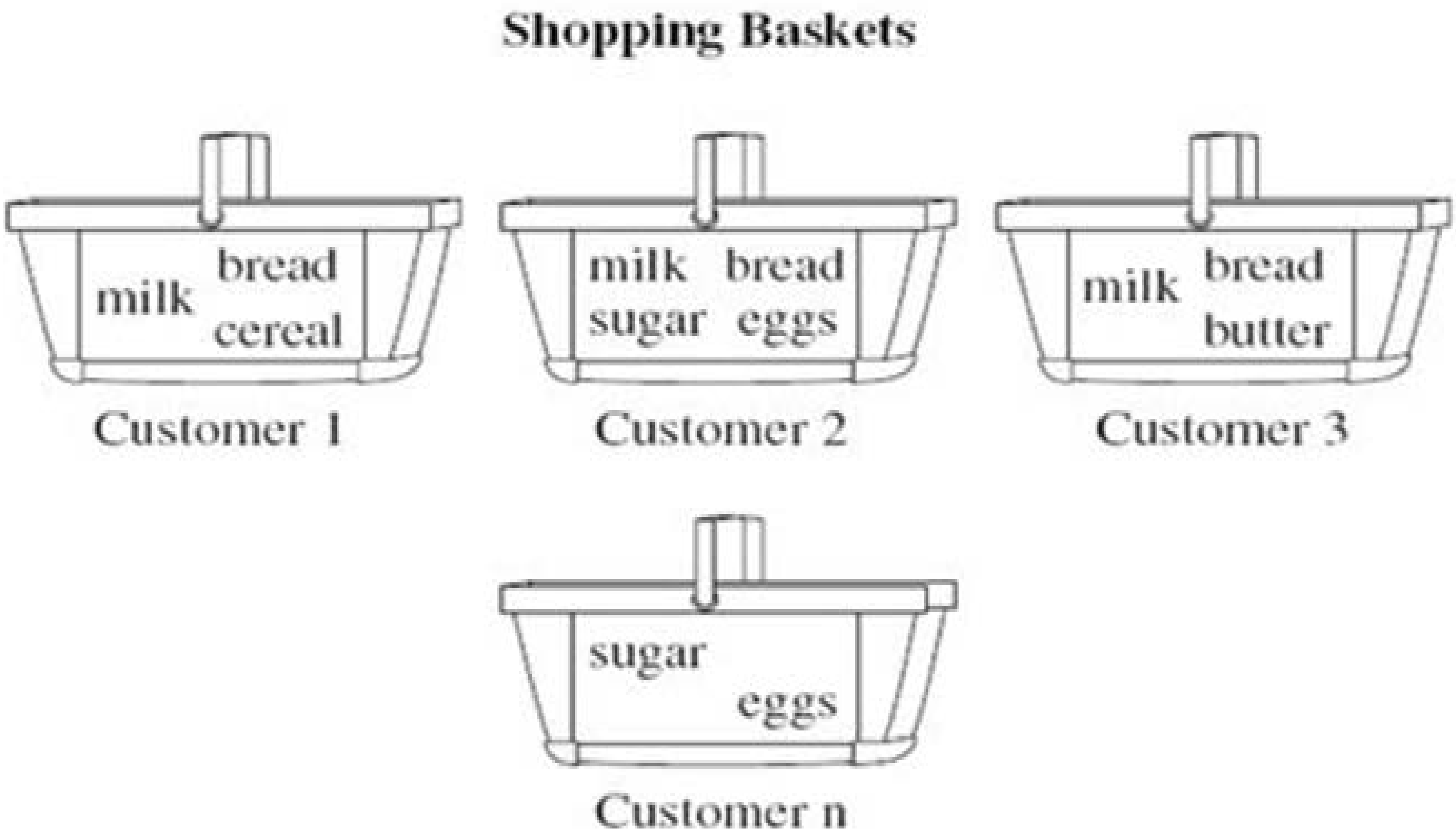
Item set

All items occurring in a rule

Attribute=Bought diapers
Value=Low, Medium, High

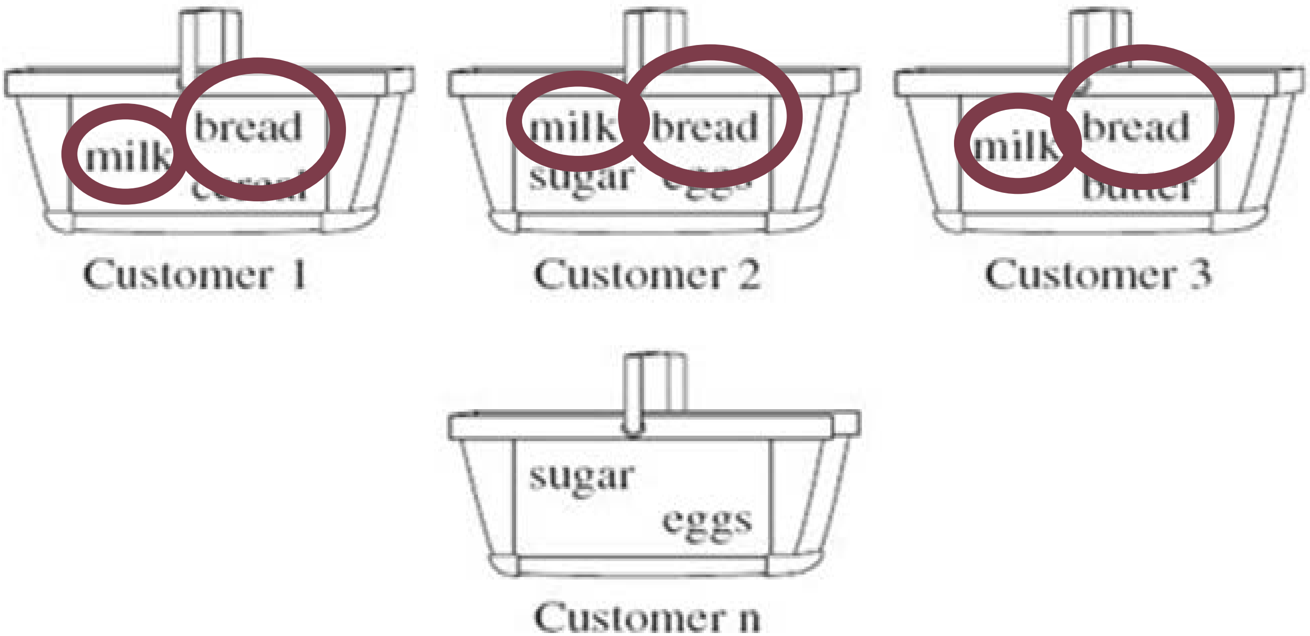
Item Sets

- Coverage = Support
  - Number of instances rule predicts correctly
- Accuracy = Confidence
  - proportion of the number of instances that the rule applies to
- Produce only rules that exceed pre-defined support

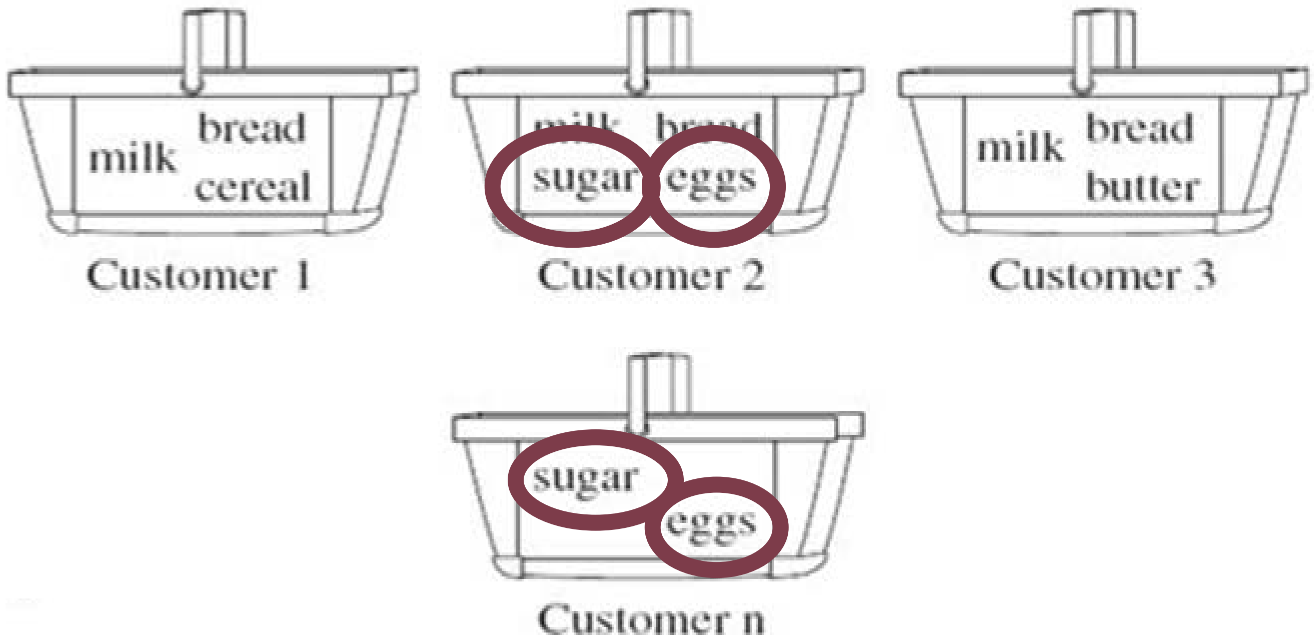


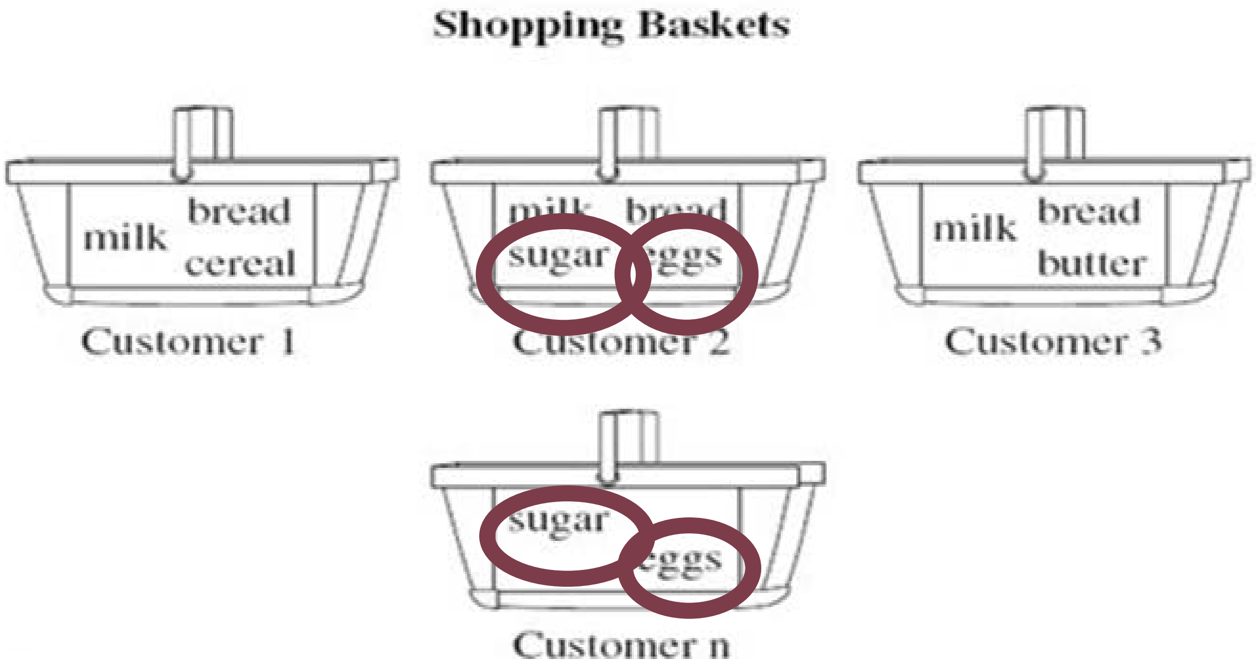
Shopping Baskets
milk
bread
cereal
Customer 1
milk
bread
bread
sugar
eggs
Customer 2
milk
bread
butter
Customer 3
sugar
eggs
Customer n

Shopping Baskets



Shopping Baskets





What is the Support and Accuracy for sugar and eggs?

Basket	Milk	Bread	Cereal	Sugar	Eggs	Butter
Customer 1	1	1	1			
Customer 2	1	1		1	1	
Customer 3	1	1				1
Customer 4				1	1	

Rule Examples:

Sugar->Eggs
Sugar, Eggs -> Milk
Milk - >Bread, Butter
Milk - >Bread, Cereal

Mining Association Rules

- Standard separate-and-conquer method
- Looking at every possible combination of attributes, every combination of values on right-hand side
- Problems:
  - Computational complexity
  - Resulting in enormous number of rules
    - pruned based on support and confidence

Association Rule Learning

- Popular and well researched method for discovering interesting relations between variables in large datasets
- It is intended to identify strong rules discovered in databases using different measures of interestingness
- Market Basket Analyses
    - Promotional pricing, product placement, web usage mining, intrusion detection, bioinformatics
- Does not consider order (sequence mining)

Item sets

- Coverage = Support
  - Number of instances rule predicts correctly
- Accuracy = Confidence
  - proportion of the number of instances that the rule applies to
- Item: one attribute–value pair
- Item set: all items occurring in a rule

Goal

- Produce only rules that exceed pre-defined support
  - Find all item sets with the given minimum support
  - generating rules from these item sets
- Generate one item sets, two item sets, etc.

Weather data example

One-item sets	Two-item sets	Three-item sets	Four-item sets
Outlook = Sunny (5)	Outlook = Sunny Temperature = Mild (2)	Outlook = Sunny Temperature = Hot Humidity = High (2)	Outlook = Sunny Temperature = Hot Humidity = High Play = No (2)
Temperature = Cool (4)	Outlook = Sunny Humidity = High (3)	Outlook = Sunny Humidity = High Windy = False (2)	Outlook = Rainy Temperature = Mild Windy = False Play = Yes (2)
…	…	…	…

Total number of item sets

- With minimum support = 2
  - 12 one-item sets
  - 47 two-item sets
  - 39 three-item sets
  - 6 four-item sets
  - 0 five-item sets
- Once all item sets with minimum support have been generated they are turned into association rules

Association rules

- Example: 3 item set with coverage=4
  Humidity = Normal, Windy = False, Play = Yes (4)

- Produces seven (2N-1) potential rules: Accuracy

If Humidity=Normal and Windy=False then Play=Yes	4/4
If Humidity=Normal and Play=Yes then Windy=False	4/6
If Windy=False and Play=Yes then Humidity=Normal	4/6
If Humidity=Normal then Windy=False and Play=Yes	4/7
If Windy=False then Humidity=Normal and Play=Yes	4/8
If Play=Yes then Humidity=Normal and Windy=False	4/9
If True then Humidity=Normal and Windy=False and Play=Yes	4/14

Accuracy = coverage/# of instances where condition in the antecedent is true

Rules with support > 1 and confidence = 100%

	Association rule		Sup.	Conf.
1	Humidity=Normal Windy=False	⇒Play=Yes	4	100%
2	Temperature=Cool	⇒Humidity=Normal	4	100%
3	Outlook=Overcast	⇒Play=Yes	4	100%
4	Temperature=Cold Play=Yes	⇒Humidity=Normal	3	100%
...	...	...	...	...
58	Outlook=Sunny Temperature=Hot	⇒Humidity=High	2	100%

- Total
  - 3 rules with support four
  - 5 with support three
  - 50 with support two

Generating rules from the same item set

- Item set
  - Temperature = Cool, Humidity = Normal, Windy = False, Play = Yes (2)

- Sub-sets with coverage of (2):

Temperature = Cool, Windy = False	(2)
Temperature = Cool, Humidity = Normal, Windy = False	(2)
Temperature = Cool, Windy = False, Play = Yes	(2)

- Resulting rules (coverage=2 & confidence=100%):

Temperature = Cool, Windy = False Than Humidity = Normal, Play = Yes
Temperature = Cool, Windy = False, Humidity = Normal Than Play = Yes
Temperature = Cool, Windy = False, Play = Yes Than Humidity = Normal

How to efficiently find all frequent item sets?

- First find one-item sets
  - Use them to generate two-item sets
  - use two-item sets to generate three-item sets …
- If (A B) is frequent item set then
  - (A) and (B) have to be frequent item sets as well
- if X is frequent k-item set than
  - all (k-1)- item subsets of X are also frequent
  - compute k-item set by merging (k-1)-item sets

Efficient item set generation

- Given: five three-item sets

`(A B C), (A B D), (A C D), (A C E), (B C D)`

- Candidate four-item sets:
- `(A B C D) OK because of (B C D)`
- `(A C D E) Not OK because of (C D E)`
- Second stage:
  - take each item and generate rules – checking minimum accuracy

Summary

- Practical issue need to generate a certain number of rules
  - by incrementally reducing min. support required
- ARFF format very inefficient for typical market basket data
  - Attributes represent items in a basket and most items are usually missing