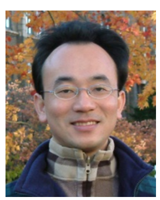
Tamkang University

Big Data Mining

Unsupervised Learning: Association Analysis

1071BDM08
TLVXM1A (M2244) (8619) (Fall 2018)
(MBA, DBETKU) (3 Credits, Required) [Full English Course]
(Master's Program in Digital Business and Economics)
Mon, 9, 10, 11, (16:10-19:00) (B206)



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Course Schedule (1/2)

Tamkang University

Week	Date	Subject/Topics
1	2018/09/10	Course Orientation for Big Data Mining
2	2018/09/17	ABC: AI, Big Data, Cloud Computing
3	2018/09/24	Mid-Autumn Festival (Day off)
4	2018/10/01	Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data
5	2018/10/08	Fundamental Big Data: MapReduce Paradigm, Hadoop and Spark Ecosystem
6	2018/10/15	Foundations of Big Data Mining in Python
7	2018/10/22	Supervised Learning: Classification and Prediction
8	2018/10/29	Unsupervised Learning: Cluster Analysis
9	2018/11/05	Unsupervised Learning: Association Analysis

Course Schedule (2/2)

Tamkang University

Week	Date	Subject/Topics
10	2018/11/12	Midterm Project Report
11	2018/11/19	Machine Learning with Scikit-Learn in Python
12	2018/11/26	Deep Learning for Finance Big Data with TensorFlow
13	2018/12/03	Convolutional Neural Networks (CNN)
14	2018/12/10	Recurrent Neural Networks (RNN)
15	2018/12/17	Reinforcement Learning (RL)
16	2018/12/24	Social Network Analysis (SNA)
17	2018/12/31	Bridge Holiday (Extra Day Off)
18	2019/01/07	Final Project Presentation

Unsupervised Learning: Association Analysis

Outline

- **Association Analysis**
- **Apriori algorithm**
  – Frequent Itemsets
  – **Association Rules**

Data Mining Tasks and Machine Learning

Unsupervised Learning: Association Analysis

Data Mining Tasks & Methods	Data Mining Algorithms	Learning Type
Prediction		
Classification	Decision Trees, Neural Networks, Support Vector Machines, kNN, Naïve Bayes, GA	Supervised
Regression	Linear/Nonlinear Regression, ANN, Regression Trees, SVM, kNN, GA	Supervised
Time series	Autoregressive Methods, Averaging Methods, Exponential Smoothing, ARIMA	Supervised
Association		
Market-basket	Apriori, OneR, ZeroR, Eclat, GA	Unsupervised
Link analysis	Expectation Maximization, Apriori Algorithm, Graph-Based Matching	Unsupervised
Sequence analysis	Apriori Algorithm, FP-Growth, Graph-Based Matching	Unsupervised
Segmentation		
Clustering	*k*-means, Expectation Maximization (EM)	Unsupervised
Outlier analysis	*k*-means, Expectation Maximization (EM)	Unsupervised

Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Transaction Database

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

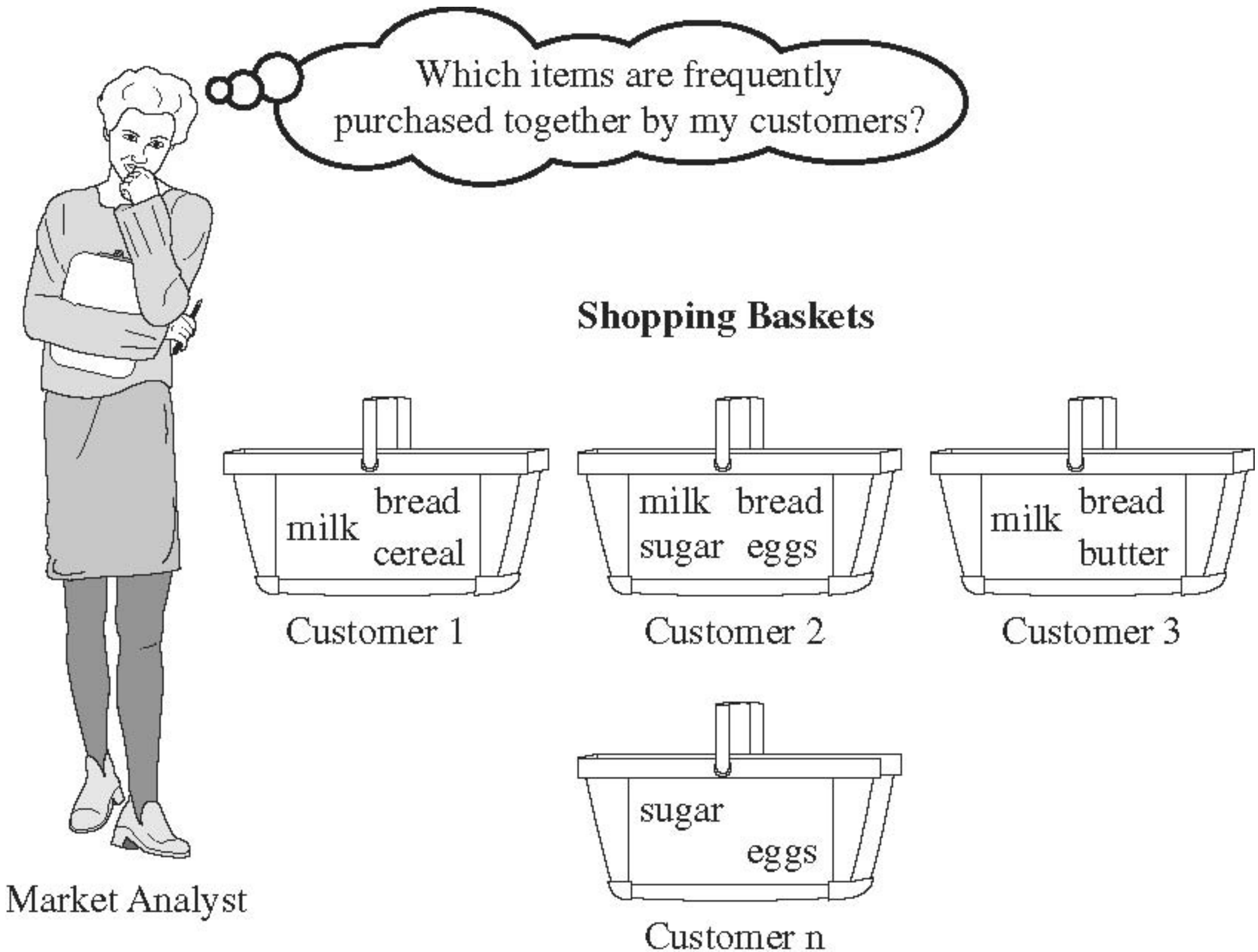
Association Analysis

Association Analysis: Mining Frequent Patterns, Association and Correlations

- Association Analysis
- Mining Frequent Patterns
- Association and Correlations
- Apriori Algorithm

Source: Han & Kamber (2006)

Market Basket Analysis



Source: Han & Kamber (2006)

Association Rule Mining

- Apriori Algorithm

Raw Transaction Data

Transaction No	SKUs (Item No)
1	1, 2, 3, 4
1	2, 3, 4
1	2, 3
1	1, 2, 4
1	1, 2, 3, 4
1	2, 4

One-item Itemsets

Itemset (SKUs)	Support
1	3
2	6
3	4
4	5

Two-item Itemsets

Itemset (SKUs)	Support
1, 2	3
1, 3	2
1, 4	3
2, 3	4
2, 4	5
3, 4	3

Three-item Itemsets

Itemset (SKUs)	Support
1, 2, 4	3
2, 3, 4	3

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Association Rule Mining

- A very popular DM method in business
- Finds interesting relationships (affinities) between variables (items or events)
- Part of machine learning family
- Employs unsupervised learning
- There is no output variable
- Also known as market basket analysis
- Often used as an example to describe DM to ordinary people, such as the famous “relationship between diapers and beers!”

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Association Rule Mining

- Input: the simple point-of-sale transaction data
- Output: Most frequent affinities among items
- Example: according to the transaction data…

  "Customer who bought a laptop computer and a virus protection software, also bought extended service plan 70 percent of the time."
- How do you use such a pattern/knowledge?
  - Put the items next to each other for ease of finding
  - Promote the items as a package (do not put one on sale if the other(s) are on sale)
  - Place items far apart from each other so that the customer has to walk the aisles to search for it, and by doing so potentially seeing and buying other items

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Association Rule Mining

- A representative applications of association rule mining include
  - In business: cross-marketing, cross-selling, store design, catalog design, e-commerce site design, optimization of online advertising, product pricing, and sales/promotion configuration
  - In medicine: relationships between symptoms and illnesses; diagnosis and patient characteristics and treatments (to be used in medical DSS); and genes and their functions (to be used in genomics projects)…

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Association Rule Mining

- Are all association rules interesting and useful?

A Generic Rule: **X $\Rightarrow$ Y [S%, C%]**

X, Y: products and/or services

X: Left-hand-side (LHS)

Y: Right-hand-side (RHS)

S: Support: how often **X** and **Y** go together

C: Confidence: how often **Y** go together with the **X**

Example: {Laptop Computer, Antivirus Software} $\Rightarrow$ {Extended Service Plan} [30%, 70%]

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Association Rule Mining

- Algorithms are available for generating association rules
  - Apriori
  - Eclat
  - FP-Growth
  - + Derivatives and hybrids of the three
- The algorithms help identify the frequent item sets, which are, then converted to association rules

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

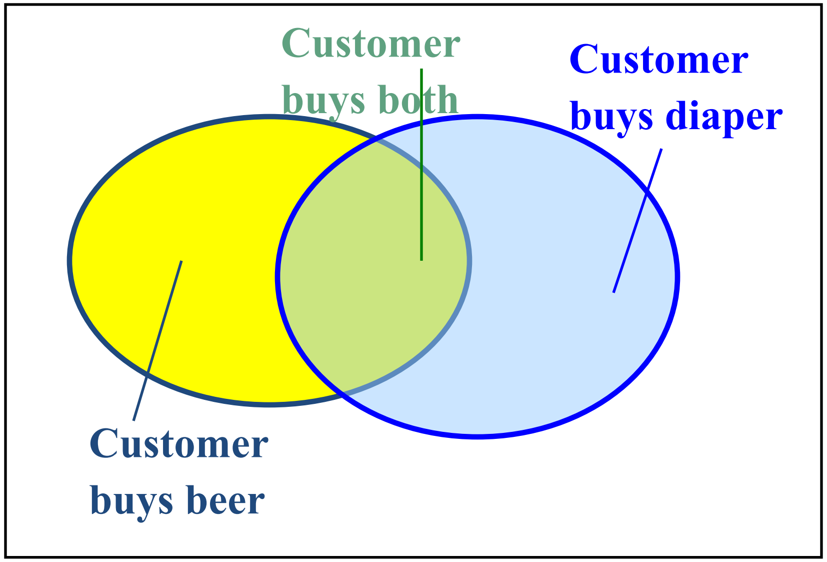
Association Rule Mining

- Apriori Algorithm
  - Finds subsets that are common to at least a minimum number of the itemsets
  - uses a bottom-up approach
    - frequent subsets are extended one item at a time (the size of frequent subsets increases from one-item subsets to two-item subsets, then three-item subsets, and so on), and
    - groups of candidates at each level are tested against the data for minimum

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Basic Concepts: Frequent Patterns and Association Rules

Transaction-id	Items bought
10	A, B, D
20	A, C, D
30	A, D, E
40	B, E, F
50	B, C, D, E, F



- Itemset X = $\{x_1, \ldots, x_k\}$
- Find all the rules $X \rightarrow Y$ with minimum support and confidence
  - support, *s*, probability that a transaction contains $X \cup Y$
  - confidence, *c*, conditional probability that a transaction having X also contains *Y*

Let $sup_{min} = 50\%$, $conf_{min} = 50\%$

Freq. Pat.: {A:3, B:3, D:4, E:3, AD:3}

Association rules:

$A \rightarrow D$ (60%, 100%)

$D \rightarrow A$ (60%, 75%)

$A \rightarrow D$ (support = 3/5 = 60%, confidence = 3/3 =100%)

$D \rightarrow A$ (support = 3/5 = 60%, confidence = 3/4 = 75%)

Source: Han & Kamber (2006)

Market basket analysis

- Example
  - Which groups or sets of items are customers likely to purchase on a given trip to the store?
- Association Rule
  - *Computer → antivirus_software [support = 2%; confidence = 60%]*
    - A support of 2% means that 2% of all the transactions under analysis show that computer and antivirus software are purchased together.
    - A confidence of 60% means that 60% of the customers who purchased a computer also bought the software.

Source: Han & Kamber (2006)

Association rules

- Association rules are considered interesting if they satisfy both
  - a minimum support threshold and
  - a minimum confidence threshold.

Source: Han & Kamber (2006)

Frequent Itemsets, Closed Itemsets, and Association Rules

Let $I = \{I_1, I_2, \ldots, I_m\}$ be a set of items. Let D, the task-relevant data, be a set of database transactions where each transaction T is a set of items such that $T \subseteq I$. Each transaction is associated with an identifier, called TID. Let A be a set of items. A transaction T is said to contain A if and only if $A \subseteq T$. An association rule is an implication of the form $A \Rightarrow B$, where $A \subset I$, $B \subset I$, and $A \cap B = \phi$. The rule $A \Rightarrow B$ holds in the transaction set D with **support** s, where s is the percentage of transactions in D that contain $A \cup B$ (i.e., the *union* of sets A and B, or say, both A and B). This is taken to be the probability, $P(A \cup B)$.[1] The rule $A \Rightarrow B$ has **confidence** c in the transaction set D, where c is the percentage of transactions in D containing A that also contain B. This is taken to be the conditional probability, $P(B|A)$. That is,

$$\textit{Support}\ (A \rightarrow B) = P(A \cup B)$$

$$\textit{Confidence}\ (A \rightarrow B) = P(B|A)$$

Source: Han & Kamber (2006)

Support (A → B) = P(A ∪ B)
Confidence (A → B) = P(B|A)

- The notation *P(A ∪ B) indicates the probability that a transaction contains the union of set A and set B*
  - *(i.e., it contains every item in A and in B).*
- *This should not be confused with P(A or B),* which indicates the probability that a transaction contains either *A or B.*

Source: Han & Kamber (2006)

Does diaper purchase predict beer purchase?

- Contingency tables

	Beer: Yes	Beer: No	
No diapers	6	94	100
diapers	40	60	100

DEPENDENT (yes)

	Beer: Yes	Beer: No
No diapers	23	77
diapers	23	77

INDEPENDENT (no predictability)

Source: Dickey (2012) http://www4.stat.ncsu.edu/~dickey/SAScode/Encore_2012.ppt

$$Support\ (A \rightarrow B) = P(A \cup B)$$

$$Confidence\ (A \rightarrow B) = P(B|A)$$

$$Conf\ (A \rightarrow B) = Supp\ (A \cup B) / Supp\ (A)$$

$$Lift\ (A \rightarrow B) = Supp\ (A \cup B) / (Supp\ (A) \times Supp\ (B))$$

Lift (Correlation)

$$Lift\ (A \rightarrow B) = Confidence\ (A \rightarrow B) / Support(B)$$

Source: Dickey (2012) http://www4.stat.ncsu.edu/~dickey/SAScode/Encore_2012.ppt

Lift

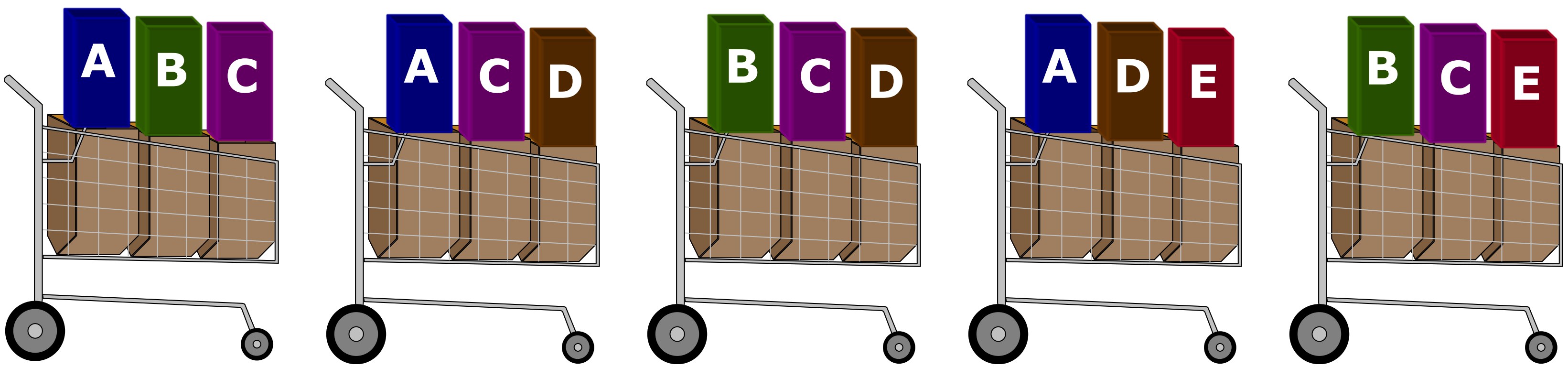
Lift = Confidence / Expected Confidence if Independent

Checking → Saving ↓	No (1500)	Yes (8500)	(10000)
No	500	3500	4000
Yes	1000	5000	6000

SVG=>CHKG Expect 8500/10000 = 85% if independent
Observed Confidence is 5000/6000 = 83%
Lift = 83/85 < 1.
Savings account holders actually LESS likely than others to have checking account !!!

Source: Dickey (2012) http://www4.stat.ncsu.edu/~dickey/SAScode/Encore_2012.ppt

Support & Confidence



Rule	Support	Confidence
$A \Rightarrow D$	2/5	2/3
$C \Rightarrow A$	2/5	2/4
$A \Rightarrow C$	2/5	2/3
$B \& C \Rightarrow D$	1/5	1/3

Source: SAS Enterprise Miner Course Notes, 2014, SAS

Support & Confidence & Lift

Checking Account

Saving Account		No	Yes	
	No	500	3500	4,000
	Yes	1000	5000	6,000
				10,000

Support(SVG $\Rightarrow$ CK) = 50%=5,000/10,000

Confidence(SVG $\Rightarrow$ CK) = 83%=5,000/6,000

Expected Confidence(SVG $\Rightarrow$ CK) = 85%=8,500/10,000

Lift (SVG → CK) = Confidence/Expected Confidence = 0.83/0.85 < 1

Source: SAS Enterprise Miner Course Notes, 2014, SAS

Support (A→B)
Confidence (A→B)
Expected Confidence (A→B)
Lift (A→B)

$$Support\ (A \rightarrow B) = P(A \cup B)$$

Count(A&B)/Count(Total)

$$Confidence\ (A \rightarrow B) = P(B|A)$$

$$Conf\ (A \rightarrow B) = Supp\ (A \cup B) / Supp\ (A)$$

Count(A&B)/Count(A)

$$Expected\ Confidence\ (A \rightarrow B) = Support(B)$$

Count(B)

$$Lift\ (A \rightarrow B) = Confidence\ (A \rightarrow B)\ /\ Expected\ Confidence\ (A \rightarrow B)$$

$$Lift\ (A \rightarrow B) = Supp\ (A \cup B)\ /\ (Supp\ (A) \times Supp\ (B))$$

Lift (Correlation)

$$Lift\ (A \rightarrow B) = Confidence\ (A \rightarrow B)\ /\ Support(B)$$

Lift (A→B)

- Lift (A→B)
  = Confidence (A→B) / Expected Confidence (A→B)
  = Confidence (A→B) / Support(B)
  = (Supp (A&B) / Supp (A)) / Supp(B)
  = Supp (A&B) / Supp (A) x Supp (B)

Minimum Support and Minimum Confidence

- Rules that satisfy both a minimum support threshold (*min_sup*) and a minimum confidence threshold (*min_conf*) are called **strong**.
- By convention, we write support and confidence values so as to occur between 0% and 100%, rather than 0 to 1.0.

Source: Han & Kamber (2006)

K-itemset

- itemset
  - A set of items is referred to as an itemset.
- K-itemset
  - An itemset that contains *k items is a k*-itemset*.*
- Example:
  - The set {*computer, antivirus software*} is a 2-itemset.

Absolute Support and Relative Support

- Absolute Support
  - The occurrence frequency of an itemset is the number of transactions that contain the itemset
    - frequency, support count, or count of the itemset
  - Ex: 3
- Relative support
  - Ex: 60%

Frequent Itemset

- If the relative support of an itemset *I satisfies a prespecified minimum support threshold, then I is a* frequent itemset.
  - *i.e., the absolute* support of *I satisfies the corresponding minimum support count threshold*
- The set of frequent *k-itemsets is commonly denoted by* L_K

Confidence

$$confidence(A \Rightarrow B) = P(B|A) = \frac{support(A \cup B)}{support(A)} = \frac{support\_count(A \cup B)}{support\_count(A)}$$

- the confidence of rule $A \rightarrow B$ *can be easily derived from the* support counts of *A and* $A \cup B$.
- once the support counts of *A, B, and* $A \cup B$ *are* found, it is straightforward to derive the corresponding association rules $A \rightarrow B$ *and* $B \rightarrow A$ and check whether they are strong.
- Thus the problem of mining association rules can be reduced to that of mining frequent itemsets.

Source: Han & Kamber (2006)

Association rule mining: Two-step process

1. Find all frequent itemsets
   - By definition, each of these itemsets will occur at least as frequently as a predetermined minimum support count, *min_sup.*
2. Generate strong association rules from the frequent itemsets
   - By definition, these rules must satisfy minimum support and minimum confidence.

Source: Han & Kamber (2006)

Efficient and Scalable Frequent Itemset Mining Methods

- The Apriori Algorithm
  - Finding Frequent Itemsets Using Candidate Generation

Apriori Algorithm

- **Apriori** is a seminal algorithm proposed by R. Agrawal and R. Srikant in 1994 for mining frequent itemsets for Boolean association rules.
- The name of the algorithm is based on the fact that the algorithm uses *prior knowledge of frequent itemset properties, as we shall* see following.

Source: Han & Kamber (2006)

Apriori Algorithm

- Apriori employs an iterative approach known as a *level-wise search, where k-itemsets are used to explore (k+1)-itemsets.*
- *First, the set of frequent 1-itemsets is found* by scanning the database to accumulate the count for each item, and collecting those items that satisfy minimum support. The resulting set is denoted L_1.
- *Next,* L_1 *is used to find* L_2, the set of frequent 2-itemsets, which is used to find L_3, *and so on, until no more frequent k-itemsets can be found.*
- *The finding of each* L_k *requires one full scan of the database.*

Source: Han & Kamber (2006)

Apriori Algorithm

- To improve the efficiency of the level-wise generation of frequent itemsets, an important property called the Apriori property.
- Apriori property
  - *All nonempty subsets of a frequent itemset must also be frequent.*

Apriori algorithm
(1) Frequent Itemsets
(2) Association Rules

Transaction Database

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

Table 1 shows a database with 10 transactions.
Let *minimum support = 20%* and *minimum confidence = 80%*.
Please use **Apriori algorithm** for generating **association rules** from frequent itemsets.

Table 1: Transaction Database

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

Apriori Algorithm
$C_1 \rightarrow L_1$

Step **1-1**

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

C_1

Itemset	Support Count
A	6
B	7
C	6
D	7
E	3

minimum support = 20% = 2 / 10
Min. Support Count = 2

L_1

Itemset	Support Count
A	6
B	7
C	6
D	7
E	3

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

Apriori Algorithm

$C_2 \rightarrow L_2$

Step 1-2

L_1

Itemset	Support Count
A	6
B	7
C	6
D	7
E	3

C_2

Itemset	Support Count
A, B	3
A, C	4
A, D	3
A, E	2
B, C	3
B, D	6
B, E	2
C, D	3
C, E	3
D, E	1

minimum support = 20% = 2 / 10

Min. Support Count = 2

L_2

Itemset	Support Count
A, B	3
A, C	4
A, D	3
A, E	2
B, C	3
B, D	6
B, E	2
C, D	3
C, E	3

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

Apriori Algorithm
$C_3 \rightarrow L_3$

Step **1-3**

L_2

Itemset	Support Count
A, B	3
A, C	4
A, D	3
A, E	2
B, C	3
B, D	6
B, E	2
C, D	3
C, E	3

C_3

Itemset	Support Count
A, B, C	1
A, B, D	2
A, B, E	1
A, C, D	1
A, C, E	2
B, C, D	2
B, C, E	2

minimum support = 20% = 2 / 10
Min. Support Count = 2

L_3

Itemset	Support Count
A, B, D	2
A, C, E	2
B, C, D	2
B, C, E	2

Generating Association Rules

Step 2-1

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

minimum confidence = 80%

L_1

Itemset	Support Count
A	6
B	7
C	6
D	7
E	3

L_2

Itemset	Support Count
A, B	3
A, C	4
A, D	3
A, E	2
B, C	3
B, D	6
B, E	2
C, D	3
C, E	3

Association Rules Generated from L_2

A→B: 3/6	B→A: 3/7
A→C: 4/6	C→A: 4/6
A→D: 3/6	D→A: 3/7
A→E: 2/6	E→A: 2/3
B→C: 3/7	C→B: 3/6
B→D: 6/7=85.7% *	D→B: 6/7=85.7% *
B→E: 2/7	E→B: 2/3
C→D: 3/6	D→C: 2/7
C→E: 3/6	E→C: 3/3=100% *

Generating Association Rules

Step 2-2

minimum confidence = 80%

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

Association Rules Generated from L_3

A→BD: 2/6	B→CD: 2/7
B→AD: 2/7	C→BD: 2/6
D→AB: 2/7	D→BC: 2/7
AB→D: 2/3	BC→D: 2/3
AD→B: 2/3	BD→C: 2/6
BD→A: 2/6	CD→B: 2/3
A→CE: 2/6	B→CE: 2/7
C→AE: 2/6	C→BE: 2/6
E→AC: 2/3	E→BC: 2/3
AC→E: 2/4	BC→E: 2/3
AE→C: 2/2=100%*	BE→C: 2/2=100%*
CE→A: 2/3	CE→B: 2/3

L_1

Itemset	Support Count
A	6
B	7
C	6
D	7
E	3

L_2

Itemset	Support Count
A, B	3
A, C	4
A, D	3
A, E	2
B, C	3
B, D	6
B, E	2
C, D	3
C, E	3

L_3

Itemset	Support Count
A, B, D	2
A, C, E	2
B, C, D	2
B, C, E	2

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

Frequent Itemsets and Association Rules

L_1

Itemset	Support Count
A	6
B	7
C	6
D	7
E	3

L_2

Itemset	Support Count
A, B	3
A, C	4
A, D	3
A, E	2
B, C	3
B, D	6
B, E	2
C, D	3
C, E	3

L_3

Itemset	Support Count
A, B, D	2
A, C, E	2
B, C, D	2
B, C, E	2

minimum support = 20%
minimum confidence = 80%

Association Rules:

B→D (60%, 85.7%) (Sup.: 6/10, Conf.: 6/7)
D→B (60%, 85.7%) (Sup.: 6/10, Conf.: 6/7)
E→C (30%, 100%) (Sup.: 3/10, Conf.: 3/3)
AE→C (20%, 100%) (Sup.: 2/10, Conf.: 2/2)
BE→C (20%, 100%) (Sup.: 2/10, Conf.: 2/2)

Table 1 shows a database with 10 transactions.
Let *minimum support = 20%* and *minimum confidence = 80%*.
Please use **Apriori algorithm** for generating **association rules** from frequent itemsets.

Transaction ID	Items bought
T01	A, B, D
T02	A, C, D
T03	B, C, D, E
T04	A, B, D
T05	A, B, C, E
T06	A, C
T07	B, C, D
T08	B, D
T09	A, C, E
T10	B, D

Association Rules:

B→D (60%, 85.7%) (Sup.: 6/10, Conf.: 6/7)
D→B (60%, 85.7%) (Sup.: 6/10, Conf.: 6/7)
E→C (30%, 100%) (Sup.: 3/10, Conf.: 3/3)
AE→C (20%, 100%) (Sup.: 2/10, Conf.: 2/2)
BE→C (20%, 100%) (Sup.: 2/10, Conf.: 2/2)

Association Analysis in Google Colab

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

AssociationAnalysis.ipynb

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Association Rules Generation from Frequent Itemsets

Source: https://rasbt.github.io/mlxtend/user_guide/frequent_patterns/association_rules/

```
# ! pip install mlxtend
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules

dataset = [['Milk', 'Onion', 'Nutmeg', 'Kidney Beans', 'Eggs', 'Yogurt'],
           ['Dill', 'Onion', 'Nutmeg', 'Kidney Beans', 'Eggs', 'Yogurt'],
           ['Milk', 'Apple', 'Kidney Beans', 'Eggs'],
           ['Milk', 'Unicorn', 'Corn', 'Kidney Beans', 'Yogurt'],
           ['Corn', 'Onion', 'Onion', 'Kidney Beans', 'Ice cream', 'Eggs']]

te = TransactionEncoder()
te_ary = te.fit(dataset).transform(dataset)
df = pd.DataFrame(te_ary, columns=te.columns_)
frequent_itemsets = apriori(df, min_support=0.6, use_colnames=True)

frequent_itemsets
```

	support	itemsets
0	0.8	(Eggs)
1	1.0	(Kidney Beans)
2	0.6	(Milk)
3	0.6	(Onion)
4	0.6	(Yogurt)
5	0.8	(Eggs, Kidney Beans)
6	0.6	(Onion, Eggs)

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

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           ['Dill', 'Onion', 'Nutmeg', 'Kidney Beans', 'Eggs', 'Yogurt'],
           ['Milk', 'Apple', 'Kidney Beans', 'Eggs'],
           ['Milk', 'Unicorn', 'Corn', 'Kidney Beans', 'Yogurt'],
           ['Corn', 'Onion', 'Onion', 'Kidney Beans', 'Ice cream', 'Eggs']]

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           ['Dill', 'Onion', 'Nutmeg', 'Kidney Beans', 'Eggs', 'Yogurt'],
           ['Milk', 'Apple', 'Kidney Beans', 'Eggs'],
           ['Milk', 'Unicorn', 'Corn', 'Kidney Beans', 'Yogurt'],
           ['Corn', 'Onion', 'Onion', 'Kidney Beans', 'Ice cream', 'Eggs']]

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frequent_itemsets
```

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```python
frequent_itemsets = apriori(df,
min_support=0.6,
use_colnames=True)
```

	support	itemsets
0	0.8	(Eggs)
1	1.0	(Kidney Beans)
2	0.6	(Milk)
3	0.6	(Onion)
4	0.6	(Yogurt)
5	0.8	(Eggs, Kidney Beans)
6	0.6	(Onion, Eggs)
7	0.6	(Milk, Kidney Beans)
8	0.6	(Onion, Kidney Beans)
9	0.6	(Yogurt, Kidney Beans)
10	0.6	(Onion, Eggs, Kidney Beans)

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

association_rules(frequent_itemsets, metric="confidence", min_threshold=0.7)

```
1 association_rules(frequent_itemsets, metric="confidence", min_threshold=0.7)
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(Eggs)	(Kidney Beans)	0.8	1.0	0.8	1.00	1.00	0.00	inf
1	(Kidney Beans)	(Eggs)	1.0	0.8	0.8	0.80	1.00	0.00	1.000000
2	(Onion)	(Eggs)	0.6	0.8	0.6	1.00	1.25	0.12	inf
3	(Eggs)	(Onion)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000
4	(Milk)	(Kidney Beans)	0.6	1.0	0.6	1.00	1.00	0.00	inf
5	(Onion)	(Kidney Beans)	0.6	1.0	0.6	1.00	1.00	0.00	inf
6	(Yogurt)	(Kidney Beans)	0.6	1.0	0.6	1.00	1.00	0.00	inf
7	(Onion, Eggs)	(Kidney Beans)	0.6	1.0	0.6	1.00	1.00	0.00	inf
8	(Onion, Kidney Beans)	(Eggs)	0.6	0.8	0.6	1.00	1.25	0.12	inf
9	(Eggs, Kidney Beans)	(Onion)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000
10	(Onion)	(Eggs, Kidney Beans)	0.6	0.8	0.6	1.00	1.25	0.12	inf
11	(Eggs)	(Onion, Kidney Beans)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

```
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1.2)
rules
```

```
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1.2)
rules
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(Onion)	(Eggs)	0.6	0.8	0.6	1.00	1.25	0.12	inf
1	(Eggs)	(Onion)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000
2	(Onion, Kidney Beans)	(Eggs)	0.6	0.8	0.6	1.00	1.25	0.12	inf
3	(Eggs, Kidney Beans)	(Onion)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000
4	(Onion)	(Eggs, Kidney Beans)	0.6	0.8	0.6	1.00	1.25	0.12	inf
5	(Eggs)	(Onion, Kidney Beans)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

```
rules["antecedent_len"] = rules["antecedents"].apply(lambda x: len(x))
rules
```

```
rules["antecedent_len"] = rules["antecedents"].apply(lambda x: len(x))
rules
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	antecedent_len
0	(Onion)	(Eggs)	0.6	0.8	0.6	1.00	1.25	0.12	inf	1
1	(Eggs)	(Onion)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000	1
2	(Onion, Kidney Beans)	(Eggs)	0.6	0.8	0.6	1.00	1.25	0.12	inf	2
3	(Eggs, Kidney Beans)	(Onion)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000	2
4	(Onion)	(Eggs, Kidney Beans)	0.6	0.8	0.6	1.00	1.25	0.12	inf	1
5	(Eggs)	(Onion, Kidney Beans)	0.8	0.6	0.6	0.75	1.25	0.12	1.600000	1

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

```
rules[ (rules['antecedent_len'] >= 2) &
       (rules['confidence'] > 0.75) &
       (rules['lift'] > 1.2) ]
```

```
rules[ (rules['antecedent_len'] >= 2) &
       (rules['confidence'] > 0.75) &
       (rules['lift'] > 1.2) ]
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	antecedent_len
2	(Onion, Kidney Beans)	(Eggs)	0.6	0.8	0.6	1.0	1.25	0.12	inf	2

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

```
rules[rules['antecedents'] == {'Eggs', 'Kidney Beans'}]
```

```
rules[rules['antecedents'] == {'Eggs', 'Kidney Beans'}]
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	antecedent_len
3	(Eggs, Kidney Beans)	(Onion)	0.8	0.6	0.6	0.75	1.25	0.12	1.6	2

https://colab.research.google.com/drive/1dkZITXbEM9hZykd5qyWZ2rljri1Pdtud

Summary

- **Association Analysis**
- **Apriori algorithm**
  - Frequent Itemsets
  - **Association Rules**

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