

Association Analysis

Data Mining

Bidur Devkota, PhD

Gandaki College of Engineering and Science
Pokhara, Nepal

Association Analysis

Popular story about using data mining to identify a relation between sales of **beer and diapers**?

In the early 1990s, a group of data analysts working for a large grocery chain in the United States stumbled upon an intriguing pattern in their sales data. Here's how it unfolded:

The Discovery:

*The team noticed that on **Friday evenings**, there was a **significant increase in the sales of both diapers and beer**.*

Initially, this seemed counterintuitive. Why would these seemingly unrelated products be purchased together?

<https://t.ly/cmH2U>

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Association Analysis

Popular story about using data mining to identify a relation between sales of **beer and diapers**?

Their Findings was as follows:

New fathers often made late-night diaper runs for their infants.

Leveraging the findings :

Armed with this insight, the grocery chain decided to experiment.

They strategically placed beer near the diaper aisle to encourage this combined purchase behaviour.

*The result? A **boost** in sales for both products.*

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Association Analysis

- ▶ Uncovering Hidden Patterns: Association Rule Mining & Market Basket Analysis
- ▶ What is it?
 - ▶ A rule-based machine learning method to discover interesting relationships between variables in large databases.
- ▶ Popular Analogy:
 - ▶ Market Basket Analysis (MBA) - Figuring out what products customers buy together.
- ▶ Core Question:
 - ▶ "If a customer buys item X, how likely are they to also buy item Y?"
- ▶ Goal:
 - ▶ Translate vast transactional data into actionable business intelligence.

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Association Analysis

- ▶ Association Analysis has been extensively studied in the data mining community.
- ▶ What is Association?
 - ▶ causal connection (as per the interest, behavior, activity, purpose, etc)
- ▶ What is association Analysis/Mining?
- ▶ Finding frequent patterns, associations, correlations, or causal structures among sets of items or objects in transaction databases, relational databases, and other information repositories
- ▶ Applications
 - ▶ Basket basket analysis
 - ▶ Cross-marketing,

Association Analysis

- ▶ **Itemset**: A collection of items (e.g., {Diapers, Beer, Chips}).
- ▶ **Association Rule**: An implication of the form $X \rightarrow Y$ (e.g., "If Diapers, then Beer").
- ▶ **Support(X)**: How frequently does the itemset appear?
 - ▶ Support = $\text{Freq}(X, Y) / \text{Total Transactions}$
 - ▶ "What % of all transactions contain both diapers and beer?"
- ▶ **Confidence($X \rightarrow Y$)**: How reliable is the rule?
 - ▶ Confidence = $\text{Support}(X, Y) / \text{Support}(X)$
 - ▶ "When someone buys diapers, what % of the time do they also buy beer?"
- ▶ **Lift($X \rightarrow Y$)**: How much more likely is Y bought with X?
 - ▶ Lift = $\text{Support}(X, Y) / (\text{Support}(X) * \text{Support}(Y))$
 - ▶ Lift = 1: No association. Lift > 1: Positive association. Lift < 1: Negative association.

Association Analysis

- ▶ Finding Rules Efficiently: The Apriori Algorithm
- ▶ Steps:
 - ▶ Step 1: Scan transactions, find Frequent Itemsets (meet min. Support).
 - ▶ Step 2: Join frequent itemsets to form candidates for larger itemsets.
 - ▶ Step 3: Prune candidates using the Apriori Principle: "All subsets of a frequent itemset must also be frequent."
 - ▶ Repeat Steps 2 & 3 until no new frequent itemsets.
 - ▶ Generate Rules from frequent itemsets that meet min. Confidence & Lift.
- ▶ Basic Apriori Principle:
 - ▶ If {Diapers, Beer, Chips} is frequent, then {Diapers, Beer} must also be frequent. This reduces the search space.

Association Analysis

Retail Store Sales Data Analysis

- ▶ Question: Which products are frequently bought together to improve shelf placement and marketing?

Transaction_ID	Customer	Product	Quantity	Date
1	C001	Bread	1	2025-01-01
2	C002	Bread	1	2025-01-02
3	C002	Butter	1	2025-01-02
4	C003	Milk	?	2025-01-03
5	C004	Bread	1	2025-01-04
6	C004	Butter	1	2025-01-04
7	C004	Jam	1	2025-01-04
8	C002	Butter	1	2025-01-02

Retail Store Sales Data Analysis

- Question: Which products are frequently bought together to improve shelf placement and marketing?

Transaction_ID	Customer	Product	Quantity	Date	Remarks
1	C001	Bread	1	2025-01-01	-
2	C002	Bread	1	2025-01-02	-
3	C002	Butter	1	2025-01-02	-
4	C003	Milk	?	2025-01-03	Missing Quantity
5	C004	Bread	1	2025-01-04	-
6	C004	Butter	1	2025-01-04	-
7	C004	Jam	1	2025-01-04	-
8	C002	Butter	1	2025-01-02	Duplicate Entry

Retail Store Sales Data Analysis

► Data Cleaning:

- Remove noise, fix errors, handle missing values
 - Remove duplicate (Transaction 8)
 - Fill missing quantity (Transaction 4 → 1)

► Output:

- Cleaned table with consistent, valid data

Transaction_ID	Customer	Product	Quantity	Date
1	C001	Bread	1	2025-01-01
2	C002	Bread	1	2025-01-02
3	C002	Butter	1	2025-01-02
4	C003	Milk	1	2025-01-03
5	C004	Bread	1	2025-01-04
6	C004	Butter	1	2025-01-04
7	C004	Jam	1	2025-01-04

Retail Store Sales Data Analysis

► Data Integration:

- Combine data from multiple sources
 - Merge customer data (demographics, region) with transaction table

► Output:

- Unified dataset with fields like Customer_Age, Location

Transaction_ID	Customer	Age	Address	Product	Quantity	Date
1	C001	52	Pokhara	Bread	1	2025-01-01
2	C002	53	Kathmandu	Bread	1	2025-01-02
3	C002	53	Kathmandu	Butter	1	2025-01-02
4	C003	33	Dharan	Milk	1	2025-01-03
5	C004	54	Dharan	Bread	1	2025-01-04
6	C004	67	Birgunj	Butter	1	2025-01-04
7	C004	22	Pokhara	Jam	1	2025-01-04

Retail Store Sales Data Analysis

► Data Selection:

- Select relevant subset for analysis
 - Choose only columns: Customer, Product, Quantity

► Output:

- Reduced table focused on purchase patterns

Customer	Product	Quantity
C001	Bread	1
C002	Bread	1
C002	Butter	1
C003	Milk	1
C004	Bread	1
C004	Butter	1
C004	Jam	1

Retail Store Sales Data Analysis

► Data Transformation:

- Convert or encode data into useful form
 - Convert transactions into “basket format” per customer:
 - C001 → {Bread}
 - C002 → {Bread, Butter}
 - C004 → {Bread, Butter, Jam}

► Output:

- Transaction list ready for pattern mining

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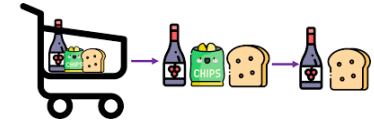
Retail Store Sales Data Analysis

► Data Mining:

- Extract useful patterns or associations
 - Apply **Apriori** algorithm → find frequent itemsets

► Output:

- Pattern found: {**Bread, Butter**} appears frequently
- C001 → {Bread}
- C002 → {**Bread, Butter**}
- C004 → {**Bread, Butter**, Jam}



<https://t.ly/T55x7>

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Retail Store Sales Data Analysis

► Pattern Evaluation:

- Identify meaningful, interesting patterns
 - Evaluate rule confidence:
 - Bread → Butter (Support = 50%, Confidence = 80%)

► Output:

- Keep only high-confidence patterns

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Retail Store Sales Data Analysis

► Knowledge Presentation:

- Present results in user-friendly format
 - Create bar chart of frequent itemsets or rule list

► Output:

- Insights: “Customers who buy bread often buy butter.”

Rule Extracted:

If a customer buys **Bread**, they are likely to buy **Butter**.

Support: 50%, Confidence: 80%

► Business Use:

- Place bread and butter together on shelves.

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Apriori Algorithm - Support and Confidence

Transaction ID		Find Frequent Itemsets		
Transaction ID	Items Purchased	Itemset	Occurrence	Support = (Count / Total Txns)
T1	Bread, Butter, Milk	{Bread}	4	4/5 = 0.8
T2	Bread, Butter	{Butter}	4	4/5 = 0.8
T3	Bread, Milk	{Milk}	3	3/5 = 0.6
T4	Butter, Milk	{Bread, Butter}	3	3/5 = 0.6
T5	Bread, Butter, Jam	{Bread, Milk}	2	2/5 = 0.4
		{Butter, Milk}	2	2/5 = 0.4
		{Bread, Butter, Milk}	1	0.2

Minimum Support Threshold = 0.4 → keep itemsets ≥ 0.4

Frequent Itemsets → {Bread}, {Butter}, {Milk}, {Bread Butter}, {Bread Milk}, {Butter Milk},

Apriori Algorithm - Support and Confidence

Frequent 2 - Itemsets

Itemset	Occurrence	Support = (Count / Total Txns)
{Bread, Butter}	3	3/5 = 0.6
{Bread, Milk}	2	2/5 = 0.4
{Butter, Milk}	2	2/5 = 0.4

make rules from the frequent 2-itemsets

Rule: Bread → Butter

Support(Bread → Butter) = Support({Bread, Butter}) = 3/5 = 0.6
 Confidence(Bread → Butter) = Support({Bread, Butter}) / Support({Bread})
 = (3/5) / (4/5)
 = 3/4
 = 0.75

Rule: Butter → Bread

Support({Butter, Bread}) = 3/5 = 0.6
 Confidence(Butter → Bread) = Support({Bread, Butter}) / Support({Butter})
 = (3/5) / (4/5)
 = 3/4
 = 0.75

Apriori Algorithm - Support and Confidence

- **Support** tells *how popular a combination* is in the whole store.
- **Confidence** tells *how reliable the rule* is once the left-hand item is bought.
- With support = 0.6 and confidence = 0.75, the store can:
 - put **Bread** and **Butter** together,
 - or offer a “*buy bread, get butter 30% off*” promo.

References

- Tan, P.N., Steinbach, M. and Kumar, V., 2006. Introduction to data mining. Pearson Education, Inc. 3.
- Han, J., Kamber, M. and Mining, D., 2006. Concepts and techniques. Morgan Kaufmann
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