IN-STORE BASKET AFFINITY MODELING FOR A HOME IMPROVEMENT RETAIL CHAIN

1. Background and Problem Statement:

A national home improvement retail chain operating 120+ physical stores observed high footfall but relatively low cross-category purchases. Customers often bought only the item they came in for (e.g., a drill), overlooking essential accessories (e.g., bits, plugs, safety gear). Traditional merchandising and shelf placement were not informed by data. The management team initiated a **basket affinity modeling project** to optimize product positioning and in-store promotions by identifying frequently co-purchased items.

2. Objectives:

- To identify high-lift product combinations using point-of-sale (POS) data
- To redesign shelf placement and signage based on product affinities
- To increase the number of items per basket and improve cross-category sales
- To inform in-store marketing strategies with real-world data patterns

3. Methodology:

Data Sources and Preparation:

- 12 months of transaction-level POS data across 120 stores (~2.1 million baskets)
- Each transaction included timestamp, store ID, product IDs, and quantity sold
- Product metadata included category, price, brand, size, and safety classification

Analysis Approach:

- Built transactional matrix using SQL and cleaned data using Python (pandas)
- Performed **market basket analysis** with the Apriori algorithm
- Evaluated association rules using:
    - **Support** (frequency of combination)
    - **Confidence** (conditional probability)
    - **Lift** (strength of association; lift > 1 indicates positive relationship)

- Created affinity heatmaps and visual layouts using planogram software for simulation

4. Results:

- Identified top product pairings with high sales lift:
  - **Power Drill + Wood Drill Bits** → Lift: 2.3, Confidence: 0.66
  - **Paint Bucket + Paint Brush + Plastic Sheet (floor cover)** → Lift: 1.8
  - **Wall Mount TV Bracket + Screwdriver Kit + Cable Organizer** → Lift: 2.0
- Found that only **37% of these combinations** were placed within 2 meters of each other in-store
- Post-intervention pilot in 10 stores with revised layout and co-branded signs led to:
  - **24% increase in cross-category purchases**
  - **11.6% rise in average items per basket**
  - Positive feedback from store managers citing "easier upselling"

5. Interpretation and Insights:

- Product pairings with high lift were often spread across unrelated aisles due to legacy layout logic
- Most impulse pairings happened when signage or shelf adjacency prompted discovery
- High-margin accessories were often missed due to poor visibility near core tools
- Pairings with strong functional logic (e.g., "use together") were most effective

6. Recommendations:

- Implement **zonal adjacency plans** for top 30 pairings across all stores
- Use **in-store signage** with cross-sell prompts (e.g., "Bought a Drill? Don't forget the Bits!")
- Create **combo packaging or checkout suggestions** for bundled items
- Run **seasonal cross-merchandising campaigns** (e.g., Summer DIY kit bundles)
- Train store staff to recognize and recommend based on high-lift combinations

7. Future Work:

- Integrate loyalty card data to personalize in-store offers at POS terminals
- Use RFID or smart shelf technology to test real-time proximity-based recommendations
- Conduct A/B testing across store layouts to refine basket growth tactics
- Develop a mobile shopping assistant app that recommends pairings while shopping in-store

8. Stakeholder Relevance:

Academic:

- A robust application of association rule mining for spatial decision-making
- Suitable for coursework in retail analytics, behavioral merchandising, and operations strategy

Corporate:

- Enables brick-and-mortar retailers to optimize shelf space and drive upselling
- Provides a data-backed strategy for increasing basket value through product adjacency and co-promotion