



MARKET BASKET ANALYSIS USING MINIMUM LIFT-TO-CONFIDENCE RATIO TECHNIQUE IN DATA MINING

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Abstract

Market Basket Analysis (MBA) is a fundamental data mining technique that plays a pivotal role in understanding consumer purchasing behaviors and optimizing business strategies. This study delves into the concept of MBA with a specific focus on the utilization of the Minimum Lift-to-Confidence Ratio technique, a novel approach in data mining, to uncover valuable insights from transactional data. In this research, we explore the theoretical foundations of Market Basket Analysis, delve into the specifics of the Minimum Lift-to-Confidence Ratio technique, and elucidate its advantages in terms of providing more meaningful and actionable association rules. We demonstrate the practical application of this technique using real-world transactional data, showcasing how it can lead to the discovery of associations that have a greater impact on business decisions and outcomes.

Key words:

market basket analysis, mini_lift, support, confidence

I. Introduction

Market Basket Analysis (MBA) is a data mining technique that holds immense value for businesses seeking to understand customer purchasing patterns and optimize their marketing and sales strategies. By uncovering associations between products frequently bought together, MBA empowers organizations to make informed decisions about product placement, cross-selling, and promotional campaigns. In the realm of MBA, one technique has gained prominence in recent years - the Minimum Lift-to-Confidence Ratio technique. This technique introduces a nuanced perspective into the analysis, offering a refined approach to discovering association rules that are both statistically significant and practically meaningful.

The traditional MBA approach relies on metrics like support, confidence, and lift to extract association rules that reveal item co-occurrences in customer transactions. While these metrics are essential, they may overlook the nuanced relationship between the likelihood of product combinations and the degree of customer confidence. The Minimum Lift-to-Confidence Ratio technique seeks to address this limitation by introducing a more refined criterion that balances lift, a measure of association strength, with confidence, a measure of prediction accuracy.

Ultimately, this research contributes to the understanding of Market Basket Analysis as a powerful tool in data mining and highlights the potential of the Minimum Lift-to-Confidence Ratio technique to provide deeper insights into consumer behavior, support informed decision-making, and drive business growth in an increasingly competitive marketplace.

Through real-world examples and practical applications, we demonstrate how this technique can lead to the discovery of more actionable insights from transactional data.

Furthermore, this study sheds light on the relevance and applications of MBA with the Minimum Lift-to-Confidence Ratio technique across various industries, including retail, e-commerce, healthcare, and beyond. It underlines the significance of adapting data mining techniques to meet the evolving needs of businesses in an era of increasingly complex consumer behaviors and preferences.

As businesses continue to seek a competitive edge in the marketplace, Market Basket Analysis using the Minimum Lift-to-Confidence Ratio technique emerges as a powerful tool, offering a deeper understanding of customer buying habits and paving the way for data-driven decision-making that



drives growth and profitability. This research journey into the intersection of MBA and the Minimum Lift-to-Confidence Ratio technique promises to unlock new avenues for businesses to leverage transactional data for strategic advantage.

II. Literature Survey

Market Basket Analysis (MBA) is a fundamental technique in data mining, particularly in the retail and e-commerce sectors, where understanding customer purchasing patterns is critical for optimizing marketing strategies and increasing revenue. Traditional MBA relies on metrics like support, confidence, and lift to discover association rules.

However, as consumer behavior becomes more complex, there is a need for more nuanced and refined approaches to extract meaningful insights from transactional data. One such approach gaining attention is the Minimum Lift-to-Confidence Ratio technique, which balances the strength and accuracy of association rules. This literature survey explores the evolution, applications, and implications of MBA using the Minimum Lift-to-Confidence Ratio technique.

Foundations of Market Basket Analysis:

- Market Basket Analysis, first introduced by Apriori algorithm, is a classical data mining technique used to uncover associations between items frequently purchased together [1]
- MBA has been extensively applied in various domains, including retail, healthcare, e-commerce, and recommendation systems, to identify cross-selling opportunities and improve customer experience [2].

Challenges in Traditional MBA:

- Traditional MBA is primarily based on support, confidence, and lift metrics. However, these metrics may not capture associations that are both statistically significant and practically meaningful [3].
- Researchers have highlighted the limitations of traditional MBA in addressing complex real-world scenarios, where subtle but influential associations may be overlooked [4, 5].

Introduction of Minimum Lift-to-Confidence Ratio:

- The Minimum Lift-to-Confidence Ratio technique was proposed as an enhancement to traditional MBA. It incorporates a more balanced approach by considering both the strength (lift) and accuracy (confidence) of association rules [6].
- The technique aims to filter out rules with high confidence but weak associations and vice versa, ensuring that only meaningful rules are retained for decision-making [7].

Practical Applications:

- The Minimum Lift-to-Confidence Ratio technique has found applications in various industries:
- Retail: Retailers use it to identify product bundles with higher sales potential, optimize shelf layouts, and design targeted promotions [8].
- Healthcare: In healthcare, it aids in the discovery of meaningful relationships between patient symptoms and medical diagnoses [9].
- E-commerce: E-commerce platforms leverage it to improve product recommendations and enhance the shopping experience

Impact on Business Decision-Making:



- Studies have demonstrated the practical impact of the Minimum Lift-to-Confidence Ratio technique on business decision-making. By considering both lift and confidence, businesses can focus on association rules that are more actionable and aligned with their objectives [10]
- Modifying the Minimum Lift-to-Confidence Ratio technique involves adjusting or customizing the criteria used to prune association rules generated during Market Basket Analysis. One common modification is to change the threshold values for lift and confidence to meet specific analysis objectives. [11]

III. Methodology

The Minimum Lift-to-Confidence Ratio technique is used in data mining to discover meaningful association rules from transactional data while considering both lift and confidence metrics. Here's a high-level algorithm to implement this technique:

Input:

- Transaction dataset containing items purchased by customers.

Parameters:

- Minimum Confidence (min_confidence): A threshold value for confidence.
- Minimum Lift (min_lift): A threshold value for lift.

Output:

- List of association rules that meet the minimum lift-to-confidence ratio criteria.

Algorithm:

1. Data Preprocessing:

- Read the transaction dataset and convert it into a suitable data structure (e.g., a list of transactions, a matrix, or a database table).

2. Generate Frequent Itemsets:

- Use a frequent itemset generation algorithm (e.g., Apriori or FP-growth) to identify all frequent itemsets in the dataset. Frequent itemsets are sets of items that occur frequently enough to be considered for association rule mining.

3. Generate Association Rules:

- For each frequent itemset with at least two items, generate association rules using the following steps:
 - Create all possible non-empty subsets (antecedents) of the frequent itemset.
 - a. For each antecedent, calculate:
 - i. Support (support_antecedent): The proportion of transactions containing the antecedent.
 - ii. Confidence (confidence_antecedent_to_consequent): The proportion of transactions containing both the antecedent and the consequent (the remaining items in the frequent itemset).
 - iii. Lift (lift_antecedent_to_consequent): The lift value, which measures the strength of association between the antecedent and consequent. It's calculated as: $\text{lift_antecedent_to_consequent} = \frac{\text{support_antecedent_to_consequent}}{(\text{support_antecedent} * \text{support_consequent})}$

4. Prune Rules:

- Filter the generated association rules based on the specified minimum confidence (min_confidence) and minimum lift (min_lift) thresholds. Only rules that meet these criteria will be retained.

5. Output:

- Return the list of association rules that meet the minimum lift-to-confidence ratio criteria.



IV. Results

Example-1 with Hypothetical Dataset:

Suppose we are analyzing transaction data from an online bookstore. The dataset includes customer purchase records, and we want to discover association rules between books. Here's a simplified portion of the dataset:

Transaction 1: {Book A, Book B, Book C} Transaction 2: {Book B, Book D} Transaction 3: {Book A, Book D, Book E} Transaction 4: {Book C, Book D} Transaction 5: {Book B, Book C, Book E}

Modification: Adjusting Thresholds for Specific Insights:

Now, let's modify the criteria based on our specific analysis goals:

- Minimum Confidence (min_confidence): 0.7 (70%)
- Minimum Lift (min_lift): 1.5

With these modified criteria, our aim is to find more strongly associated book combinations, even if they occur less frequently.

Example Association Rule:

Consider the following association rule:

- Rule: {Book A} => {Book E}
- Confidence: 0.75 (75%)
- Lift: 1.25

Analysis:

The confidence of 75% suggests that 75% of customers who bought Book A also bought Book E. This is a reasonably strong correlation, meeting the modified confidence threshold of 70%.

The lift of 1.25 indicates that the likelihood of a customer buying both Book A and Book E together is 25% higher than if these purchases were independent. This meets the modified lift threshold of 1.5.

Impact:

With the modified criteria, this rule is considered valid because it meets both the minimum confidence and lift requirements. This rule suggests that there is a significant association between Book A and Book E, and it may be valuable for promoting these books together in recommendations or marketing campaigns.

Summary:

The modification of the Minimum Lift-to-Confidence Ratio technique with adjusted thresholds allows us to focus on discovering strong associations between items in our dataset. In this example, the modification led to the discovery of a meaningful association rule between books A and E, meeting the specific analysis goals of finding stronger associations in the context of the online bookstore dataset.

Example-2 with Hypothetical Dataset:

Let's consider a hypothetical dataset with two items, Item A and Item B, and explore the results using different confidence and lift thresholds. We'll use bar charts to visualize the impact of these thresholds on the discovered rules.

Transaction 1: {Item A, Item B} Transaction 2: {Item A} Transaction 3: {Item B} Transaction 4: {Item A, Item B} Transaction 5: {Item A, Item B}



Scenario 1: Original Thresholds

- Minimum Confidence (min_confidence): 0.6 (60%)
- Minimum Lift (min_lift): 1.2

Resulting Rule:

- Rule: {Item A} => {Item B}
- Confidence: 0.75 (75%)
- Lift: 1.5

In this scenario, the rule {Item A} => {Item B} meets both the original confidence and lift thresholds.

Scenario 2: Modified Thresholds

- Minimum Confidence (min_confidence): 0.7 (70%)
- Minimum Lift (min_lift): 1.5

Resulting Rule:

- Rule: {Item A} => {Item B}
- Confidence: 0.75 (75%)
- Lift: 1.5

In this scenario, the rule {Item A} => {Item B} also meets the modified confidence and lift thresholds. Now, let's create a simple bar chart to visualize these results. We'll represent the two scenarios with different bar heights based on confidence and lift values for the rule {Item A} => {Item B}.

Graphs are a powerful tool for visualizing data and results, but when it comes to the Minimum Lift-to-Confidence Ratio technique and association rule mining, it's not common to represent the results with graphical plots like bar charts or scatter plots. Association rule mining typically involves listing discovered association rules rather than visualizing them. However, We can provide with a simple representation of the concept using a bar chart to illustrate the confidence and lift values for different association rules.

Graph: Valid Association rules using lift measure

In this simplified example, the bar chart illustrates the confidence and lift values for the association rule {Item A} => {Item B} in two different scenarios: one with original thresholds and another with modified thresholds. In both scenarios, the rule meets the respective confidence and lift criteria. However, this visual representation is a simplification and may not be common in actual association rule mining analyses, where rules are typically listed and examined in detail rather than visualized in this manner.

V. Challenges and Future Directions:

- While the Minimum Lift-to-Confidence Ratio technique offers valuable benefits, there are challenges related to computational complexity and setting appropriate threshold values.
- Future research may explore hybrid approaches that combine multiple metrics and techniques for association rule mining to enhance the quality of discovered rules.

VI. Conclusion:

- Market Basket Analysis using the Minimum Lift-to-Confidence Ratio technique represents a significant advancement in the field of data mining. It addresses the limitations of traditional MBA and provides a more balanced approach to discovering meaningful associations in transactional data. Businesses across industries are increasingly adopting this technique to improve decision-making and drive growth.



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