



FINAL YEAR DISSERTATION

Market Basket Analysis with Graph Theory

April 17, 2021

Sahil M. Pattni

Bachelor of Science with Honours in Computer Science

Supervised by Dr. Neamat El Gayar

Declaration

I, Sahil Manojkumar Pattni, confirm that this work submitted for assessment is my own and is expressed in my own words. Any uses made within it of the works of other authors in any form (e.g., ideas, equations, figures, text, tables, programs) are properly acknowledged at any point of their use. A list of the references employed is included.

Date: April 17, 2021

Signed: Sahil Manojkumar Pattni

Abstract

In this digital age, data is being generated and collected at an unprecedented rate, with data analytics employed by corporations and small businesses alike to produce actionable insights, reduce costs, optimize operations and increase revenue. Association rules allow us to identify relationships between products that can provide insights into customer spending habits and product perception.

In this study, a minimum spanning tree (MST) will be generated from a transactional database such that only the strongest relationships between products remain. A clustering algorithm will be applied to this MST to identify high co-purchase segments, and association rules will then be extracted from these segments. **[ADD MORE HERE]**

Contents

1	Introduction	1
1.1	Motivation	1
1.2	Aims	2
1.3	Objectives	2
2	Background	3
2.1	Transaction and Association Representation	3
2.1.1	Binary Purchase Vectors	3
2.2	Product Association	4
2.3	Graph Theory	4
2.3.1	Minimum Spanning Trees	5
2.3.2	Prim's Algorithm	5
2.3.3	Kruskal's Algorithm	6
2.4	Related Work	7
2.4.1	Extracting Minimum Spanning Trees using K-Means	7
2.4.2	Markov Clustering	8
2.4.3	AIS Algorithm	9
2.4.4	Apriori Algorithm	12
2.4.5	Subjective Measurement of Association Rules	12
2.4.6	Association Rules from Minimum Spanning Trees	14
2.4.7	Summary	15
3	The CGRG Algorithm	18
3.1	Data Processing	18
3.2	Distance Function	18
3.3	Clustering and Rule Generation	20
3.3.1	Markov Clustering	20
3.3.2	Itemset Generation	20
3.3.3	Bi-Cluster Rule Generation	20

3.3.4	Intra-Cluster Rule Generation	21
3.3.5	Rule Pruning	22
4	Experiments and Analysis	24
4.1	Environment	24
4.2	CGRG and Apriori Algorithm	24
	References	27

Chapter 1

Introduction

1.1 Motivation

For businesses such as groceries, hypermarkets, and retail outlets that deal with the trade of heterogeneous physical assets, operations such as inventory management and product placement play an instrumental role in determining the business' financial success. These involve asking questions such as:

- Which products should be placed at the entrance of the store? Which should be placed closer to the exit?
- Which products will benefit the most by being placed at eye-level?
- Which products should be placed next to each other to maximize the purchase volume?

One way to find optimal solutions to such queries is to employ the use of Association Rule Mining (also known as Market Basket Analysis). This set of techniques assess frequent itemsets (e.g. from sales data) and generate association rules between products. A prime example of the utility of association rules is the urban legend of "*Beers and Pampers*", where a company allegedly studied their point-of-sale data and found a strong association between the purchase of diapers and a particular brand of beer during a certain time. With *diapers* as the antecedent and *beer* as the consequent, this rule can be written as:

$$\{Diapers\} \rightarrow \{Beer\}$$

This is an example of a single-element rule, where both the antecedent and consequent are sets that contain only one element each. Several algorithms exist for association rule mining, most prominently the Apriori Algorithm (**Agrawal and Srikant 1994**) and FP-Growth (**Han et al. 2000**), however these algorithms tend to generate an overwhelming amount of rules, rendering it inconvenient for the end-user to extract actionable information from the ruleset. This paper proposes to improve upon an existing method (see: Section 2.4.6) that derives association rules from minimum spanning trees.

1.2 Aims

The aim of this paper is to improve upon the aforementioned method by introducing a method that allows for the generation of multi-element association rules (i.e. rules where either/both the antecedent and consequent of the rule contain more than one element).

1.3 Objectives

The research objectives for this paper are as described below:

1. Acquire a suitable dataset upon which the study can be conducted.
2. Construct an affinity graph from the chosen dataset.
3. Explore and evaluate MST extraction algorithms.
4. Identify and evaluate methodologies for generating multi-element association rules from an MST.
5. Extract MST from the graph and generate association-rules using the chosen methodologies.
6. Evaluate the generated association rules against the rules generated by the Apriori Algorithm.

Chapter 2

Background

2.1 Transaction and Association Representation

2.1.1 Binary Purchase Vectors

Let $I = I_1, I_2, \dots, I_m$ be a set of binary attributes (i.e. items), and let T be a database of transactions. As defined in (Agrawal, Imieliński, et al. 1993), a binary purchase vector is a transaction t represented as a vector of length m , where:

$$t[k] = \begin{cases} 1 & \text{if } I_k \text{ purchased in } t \\ 0 & \text{otherwise} \end{cases}$$

For example, consider a grocer who only sells five items: milk, eggs, bread, apples and oranges. Consider the following transactions:

Transaction t_1 : Customer purchases bread and oranges.

Transaction t_2 : Customer purchases eggs, bread and apples.

Transaction t_3 : Customer purchases milk and oranges.

The binary purchase vectors for these transactions would be:

	milk	eggs	bread	apples	oranges
t_1	0	0	1	0	1
t_2	0	1	1	1	0
t_3	1	0	0	0	1

Table 2.1: Binary Purchase Vectors

2.2 Product Association

The association between products pairs across all transactions can be ascertained from the binary purchase vectors using the Pearson's Correlation Coefficient (**Pearson 1895**). Since the correlations are of two binary variables, the Pearson's Correlation Coefficient is equivalent to the Phi-Coefficient ϕ (**Ernest C and El-Sanhurry 1991**), where for n observations:

$$\phi = \sqrt{\frac{\chi^2}{n}}$$

Applying this correlation formula to the set of binary purchase vectors in Table 2.1, we get:

	milk	eggs	bread	apples	oranges
milk	1.0	-0.5	-1.0	-0.5	0.5
eggs	-0.5	1.0	0.5	1.0	-1.0
bread	-1.0	0.5	1.0	0.5	-0.5
apples	-0.5	1.0	0.5	1.0	-1.0
oranges	0.5	-1.0	-0.5	-1.0	1.0

Table 2.2: Correlation Matrix

Note that the correlation matrix is diagonally symmetrical. This is true of all correlation matrices where the items on the x-axis and y-axis are the same and in the same order. This correlation matrix can then be represented as a graph, where the nodes are the products, and the edges are the correlation values.

2.3 Graph Theory

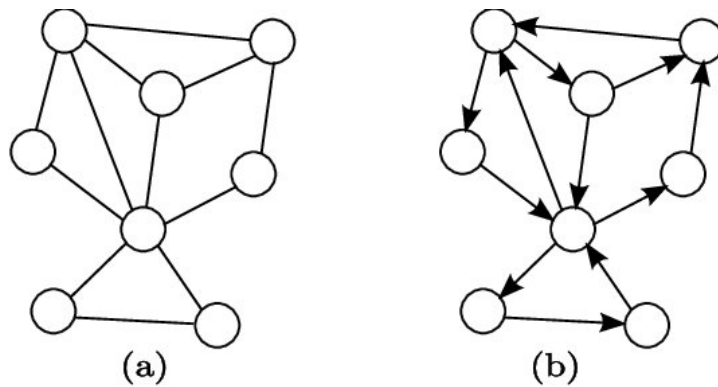


Figure 2.1: Undirected and Directed Graphs

In discrete mathematics and more specifically - graph theory, a graph is a data structure that contains a set of nodes (i.e. vertices) connected by lines (i.e. edges). These edges may be directed - such as in Figure 2.1:(a), or undirected - such as in Figure 2.1:(b). The edges may contain values (i.e. weights) between the two vertices it connects. A graph G with a set of vertices V and a set of edges E can be represented via the notation $G = (V, E)$. For the scope of this project, we will be building undirected graphs, where the weight between two vertices is the same in both directions.

2.3.1 Minimum Spanning Trees

Given an undirected $G = (V, E)$, a *spanning tree* can be described as a subgraph that is a tree which includes all the vertices V of G with the minimum number of edges required. A *minimum spanning tree* (MST) is the spanning tree with the smallest sum of edge weights. This means that if the graph has n vertices, each spanning tree - including the minimum spanning tree - will have $n - 1$ edges. Since a minimum spanning tree captures the lowest weights in a graph, with modifications it could be an excellent candidate to capture the opposite as well: the strongest associations between products. There are two widely used algorithms to extract the minimum spanning tree from a graph: Prim's algorithm and Kruskal's algorithm.

2.3.2 Prim's Algorithm

Independently discovered by three authors, Prim's algorithm (**Prim 1957**)(**Jarník 1930**)(**Dijkstra 1959**) is a greedy algorithm¹ to find the minimum spanning tree of an undirected, weighted graph G . To successfully implement the algorithm, three sets need to be maintained: a set of *discovered* edges, and two sets of vertices: a set of *undiscovered* vertices, and a set of *discovered* vertices. Figure 2.2 illustrates Prim's algorithm being applied to a graph. The algorithm is as follows:

Initialize an empty set of discovered edges: E , and two sets of vertices: an empty set D of the discovered vertices, and UD as the set of undiscovered vertices.

- Pick an arbitrary vertex as a starting point (in the case of Figure 2.2, the top right node). Add this vertex to D and remove it from UD .
- While UD is not empty:
 - Find the edge e_i with the smallest weight such that it connects together a vertex V_1 in D and V_2 in UD (to avoid forming cycles).

¹Selecting the locally optimal choice at each iteration of the solution

- Append V_2 to D and remove it from UD (i.e. V_2 is now discovered).
- Append e_i to E .

Once D contains all the vertices of G , the algorithm terminates, and the set D represents the minimum spanning tree, and $\sum_{i=1}^n e_i$ is the weight of the MST. The time complexity of this algorithm is $O(V^2)$.

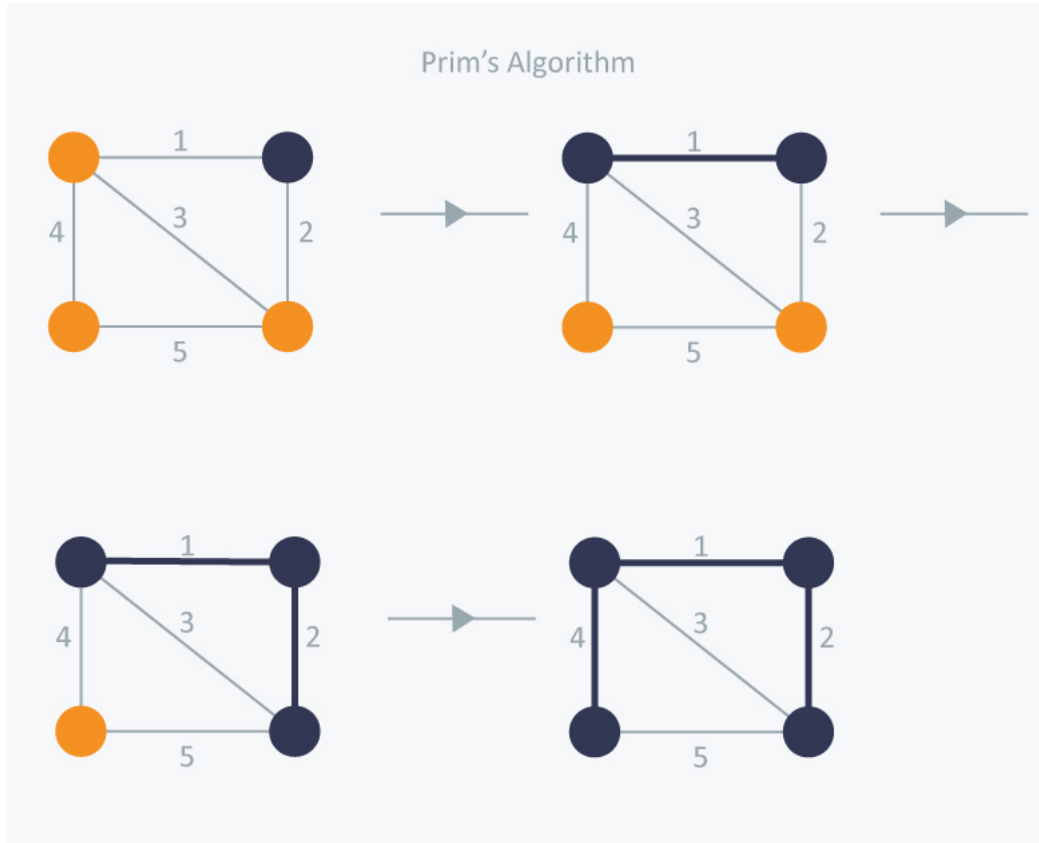


Figure 2.2: Prim's Algorithm applied to a graph (Abdelnabi 2018)

2.3.3 Kruskal's Algorithm

Another greedy algorithm, Kruskal's algorithm (Kruskal 1956) also extracts the MST from a graph. Unlike Prim's algorithm, Kruskal's doesn't select an edge that connects directly to the already built spanning tree, but rather picks the global optimal solution. The algorithm is as follows:

Maintaining a set of edges E , and an initially empty set of chosen edges C :

- Sort the set of edges E in ascending order.
- While the number of elements in C is not $n - 1$:

- Select the smallest edge e_i from E .
- If adding it does not form a cycle with the spanning tree formed so far, append e_i to C .
- Remove e_i from E .

The algorithm will terminate when $n - 1$ edges have been selected. The time complexity for this algorithm is $O(E \log E)$.

2.4 Related Work

2.4.1 Extracting Minimum Spanning Trees using K-Means

(Zhong et al. 2015) proposed a novel framework to extract the minimum spanning tree of a graph based on the K-Means clustering algorithm. Their methodology can be separated into two distinct phases. In the first phase, the data is partitioned into \sqrt{n} clusters via K-Means and the Kruskal's algorithm is applied to each of the clusters individually. Once the \sqrt{n} MSTs have been constructed, they are combined to form an approximate MST. In the second phase, new partitions are constructed based on the borders of the clusters identified in phase 1. Based on these new partitions, a second approximate MST is constructed. Finally, both graphs are merged such that the resulting graph has $2(n - 1)$ edges. The Kruskal's algorithm is run on this graph to get the final approximation of the MST.

Critical Analysis

The authors have proposed an efficient way to approximate a minimum spanning tree, with their methodology having a complexity of $O(N^{1.5})$, which is faster than the standard MST algorithm which has a complexity of $O(N^2)$. For clarity, we have illustrated the disparity between the author's algorithm and the standard algorithm on Figure 2.3.

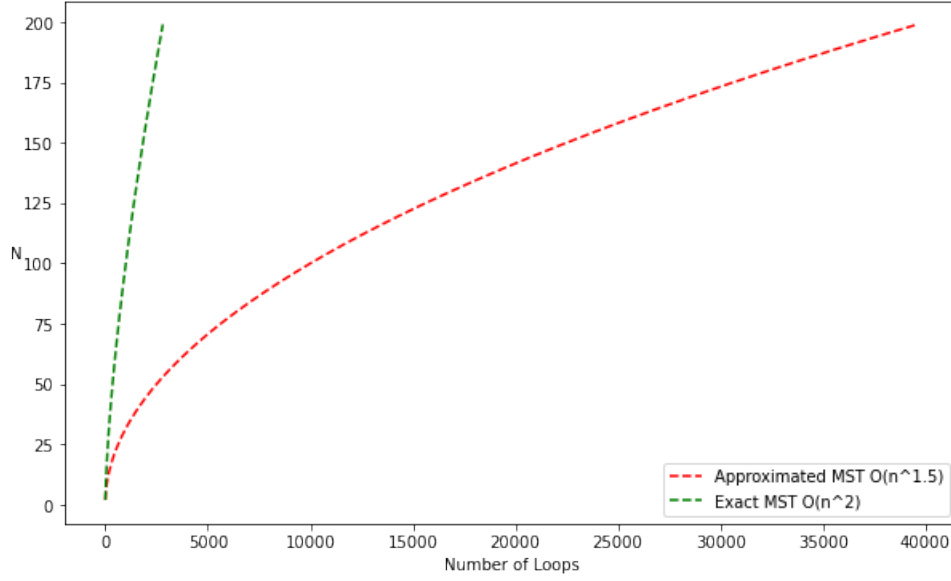


Figure 2.3: Efficiency of K-Means optimized MST vs. exact MST

The K-Means optimized algorithm is $\frac{\sqrt{n}-1}{\sqrt{n}}\%$ faster than the standard MST algorithm.

2.4.2 Markov Clustering

(Dongen 1969) introduced the novel Markov Clustering Algorithm (MCL), a graph clustering algorithm based on Markov Processes (Markov 2006) that favours sparse graphs (i.e. graphs where the average degree is smaller than the number of nodes). The reason for this follows the notion that dense regions in sparse graphs correspond with regions in which the number of k -length paths is relatively large - and therefore - paths whose beginnings and ends are in the same dense region have a higher probability for random walks² of length k as opposed to other paths. In other words, random walks originating from a node in a dense region have a high probability of ending in that same dense region. Given a non-negative weighted directional graph G , the MCL simulates flow in the graph. It does this by first mapping the graph G in a generic way onto a Markov matrix M_1 . Once completed, the set of transition probabilities (TP's) are iteratively recomputed via expansion and contraction, resulting in an array of Markov Graphs. In the expansion stage, higher TP's are calculated, whereas for the contraction phase, a new Markov Graph is created by rewarding high TP's and penalizing low TP's. The belief is that by doing so, the flow between dense regions that are sparsely connected will be removed, leaving only distinct and unconnected dense regions (i.e. clusters). The author tested the MCL

²A random walk is a stochastic process of of successively random steps along a space, in this case: a directed graph.

algorithm against randomly generated graphs which were known to possess a natural cluster structure. The authors noted that the MCL algorithm successfully managed to capture the segregation present in the graphs, and concluded that the algorithm was capable of handling graphs with large natural clusters.

Critical Analysis

The author proposed a novel way to apply the mathematics behind Markov processes to successfully segment and isolate densely connected segments of a graph. The results from this paper have inspired us to use the clustering algorithm in our own work.

2.4.3 AIS Algorithm

(Agrawal, Imieliński, et al. 1993) proposed a novel algorithm to generate all statistically significant association rules between items in a database, laying the foundation for association rule mining. Given a set of items $I = \{I_1, I_2, I_3, \dots, I_m\}$, the authors define an association rule to be of the form $X \rightarrow I_j$ where X is a set of items such that $X \subset I, I_j \notin X$. The hypothetical database stated was a list of transactions, T , where each transaction t was a binary vector of length m , as described in Section 2.1.1. The authors define two constraints for assessing association rules:

Support

The support of an association rule is the proportion of transactions in which the itemsets in the rule are present. For a set of transactions T , where $T(i)$ denotes the set of transactions in which the set of items $i \subseteq I$ was purchased:

$$\text{support}(i) = \frac{T(i)}{T}$$

Similarly, where $T(i_k, i_j)$ represents the set of transactions in which the itemsets $\{i_k \subset I, i_j \subset I\}$ were purchased, the support for the association rule $i_k \rightarrow i_j$ can be represented as:

$$\text{support}(i_k \rightarrow i_j) = \frac{T(i_k, i_j)}{T}$$

Support scores correspond with the statistical significance of a rule, and rules with low support scores may not occur frequently enough to draw reasonable conclusions from.

Confidence

Confidence is the conditional probability of an itemset i_j ; $i_j \subset I$ being present in a transaction given that itemset i_k ; $i_k \subset I$ is present in the same transaction. The confidence of the association rule $i_k \rightarrow i_j$ can be represented as:

$$\text{confidence}(i_k \rightarrow i_j) = \frac{T(i_k, i_j)}{T(i_k)} \equiv \frac{\text{support}(i_k \rightarrow i_j)}{\text{support}(i_k)}$$

The confidence of an association rule can be thought of as the rule's *strength*.

With these constraints defined, the authors state that their methodology for association rule mining can be split into two discrete steps:

1. The generation of candidate itemsets.
2. The generation of statistically significant association rules from the itemsets.

Candidate Itemset Generation

To generate candidate itemsets, the authors first generate all possible itemsets from the database, defining those whose support score was above a support constraint $\text{min}_{\text{support}}$ as *large itemsets*. The authors note that a brute-force check³ would be sub-optimal, taking up to 2^m passes of the database (where m is the number of items in the itemset I). Therefore, they introduced a methodology where they would only observe itemsets of length k on the k^{th} pass of the dataset, to see if the itemsets satisfied the support constraint. On the $(k + 1)^{\text{th}}$ pass of the dataset, they need only check itemsets that are *1-extensions* (i.e. itemsets extended by only one item) or the *large itemsets* discovered in the previous pass. Their reasoning is now commonly known as *The Apriori Principle*, where they state that if an itemset i_k is *large* (i.e. satisfies the support constraint), then any subset $i_j \subset i_k$ will also be *large*. This reasoning also applies that if an itemset i_j is found to be *small* (i.e. did not satisfy the support constraint), then any superset $i_k; i_j \subset i_k$ will also be *small*. This allows the authors to prune the number of association rules whose support scores need to be computed, as if they find i_j to be *small*, any superset $i_k; i_j \subset i_k$ need not have its support score computed as it is known to be *small*.

However, if an itemset i_j is indeed found to be *large*, then another multiple passes over the dataset will be required to check the support scores for subsets of i_j . To avoid this, the authors devised a measure to calculate the expected support \bar{s} of an itemset. The expected support is used to estimate the support of $i_j = (i_p + i_q)$, not only when i_j is expected to be *large*, but also when i_p is expected to be *large* yet $(i_p + i_q)$ is expected to be *small*. This estimation further prunes the number of rules whose support scores

³checking every possible itemset iteratively.

need to be computed.

Association Rule Generation

To generate association rules, the authors used the following technique:

for each *large* itemset $Y = \{i_1, i_2, \dots, i_k\}; k \geq 2$ from the set of non-pruned *large* itemsets, generate a set of association rules in the form $X \rightarrow i_j; X \subset Y, i_j \notin X$ such that X is of length $k - 1$. Therefore, each *large* itemset will produce k rules. From the generated rules, the authors discarded those rules whose confidence scores fell below the confidence constraint $min_{confidence}$.

Evaluation

The authors tested their methodology on a sales dataset with 46,783 transactions, with 63 distinct departments. Their configuration was composed of a support constraint of 1% (i.e. $min_{support} = 0.01$) and a confidence constraint of 50% (i.e. $min_{confidence} = 0.5$). The authors note that the rules produced follow what general intuition might suggest. For example:

$$\{\text{Auto Accessories, Tires}\} \rightarrow \{\text{Automotive Services}\}$$

Furthermore, the authors assessed the accuracy of their support estimation metric \bar{s} by observing the ratio of correctly estimated itemsets for both *small* and *large* against various values for the support constraint. They were able to conclude that their estimation accuracy was satisfactory, as their accuracy was 96% and above for support thresholds.

Critical Analysis

The authors have proposed a novel methodology that has been the bedrock of numerous research publications, including most of the papers in this literature review. Their estimation function performed with high accuracy, meaning it can reduce the number of passes through a database the algorithm has to take by a significant amount. Additionally, their pruning techniques allowed them to eliminate a large proportion of itemsets from the space. Even after the significant pruning of rules, a major drawback of this methodology is the large number of rules produced, although one could argue that only the highest performing rules need be observed in further detail. Finally, the algorithm only allows the consequent to have one item, thereby limiting the type and quality of rules produced.

2.4.4 Apriori Algorithm

(Agrawal and Srikant 1994) improved on their previous work with (Agrawal, Imieliński, et al. 1993) by introducing the Apriori algorithm, which - in addition to being faster than the AIS algorithm - can produce association rules where the consequent has more than one item. The structure for the Apriori algorithm follows closely to the AIS algorithm in that it uses *large* itemsets to generate the association rules. The algorithm generates candidate itemsets in the k^{th} pass only from the itemsets found to be *large* in the $(k - 1)^{th}$ pass, following the intuition of *The Apriori Principle*, where any subset of a *large* itemset must itself be *large*. As a result, the candidate itemsets that have k items can be generated from the *large* itemsets having $(k - 1)$ items, and any such itemsets that contain a subset that is *small* are discarded. For every *large* itemset l , all non-empty subsets of l are gathered. For every subset a , it generates a rule in the form:

$$a \rightarrow (l - a)$$

if the support and confidence constraints of the rule are met.

Critical Analysis

The authors have further improved upon their AIS algorithm in the form of the Apriori Algorithm, which is much better known than the former due to its inherent ability to generate more complex rules, and its efficiency in doing so. The ability to generate more complex rules makes it a good benchmark to test our own algorithm against, to see whether it can either serve as an alternative or even a complement to the Apriori Algorithm.

2.4.5 Subjective Measurement of Association Rules

(Zekic-Susac and Has 2015) proposed a novel measure for the *interestingness* of association rules, identifying that a dominant, universally used measure did not exist. The authors' goal was to combine objective measures such as the support, confidence and lift scores with more subjective measures. Instead of the Apriori approach, their methodology has them generate association rules via the *tree-building technique* - which compresses a large database into a Frequent-Pattern tree, citing that this technique was more efficient than the Apriori algorithm. The authors employed the heuristical unexpectedness measure⁴ and the heuristical actionability measure⁵ as their subjective measures, and a minimum confidence

⁴How significantly a rule contradicts a user's prior beliefs.

⁵If the user believes they can use the information to their advantage (e.g. a promotion).

threshold of 51% as their objective measure. Since a subjective measure would require a human subject, the authors' used the estimations of a sales manager from a Croatian retail chain, and stored his responses in binary format for the subjective measures (i.e. 0 if a rule was unexpected else 1, 0 if a rule is not useful else 1). The dataset used for this paper was a real transactional dataset with 14,012 transactions and a set of 1,230 unique items (which was later pruned to 7,006 transactions and a set of 278 products) from the same Croatian retail chain their test subject worked at. The authors then generated association rules from the first-level hierarchical grouping of items from the dataset (items with a minimum support of 25%), of which 36 rules were identified as statistically significant. From this set of rules, only two rules satisfied both subjective measures and the confidence constraint, and therefore these two rules were identified as highly interesting. The authors then generated association rules from the second-level hierarchical grouping of items, where items that represented the same product (but had different a manufacturer, brand etc.) were grouped together. Of the rules generated, 15 satisfied their confidence constraints and had a support value able 10%. 5 rules from this set satisfied both their subjective and objective measures, more than the previous experiment The authors were able to conclude that the increase in accuracy and number of interesting rules resulted from the second level of grouping which generalized the products.

Critical Analysis

Whereas the original measure of statistical significance introduced by (Agrawal, Imieliński, et al. 1993) was purely objective, the authors of this paper have presented a well thought out approach to combining the subjective metrics with objective ones to produce a human-verified association rule set. A few caveats to note, however: their study only involved one subject, which is rarely regarded to be statistically acceptable. An ideal study would require multiple, randomly chosen subjects to offset any bias that the singular subject would have had, and in addition, the larger their subject size, the closer their collective estimations will model the total population's. Another drawback of their approach is that by using human intuition as a metric, they're promoting association rules that satisfy pre-existing notions about human behavior (e.g. if someone buys milk, they'll *probably* get eggs too), however these types of rules are usually regarded as common knowledge, whereas the beauty of association rule mining is in its ability to surface association rules that - while true - seem unintuitive, and therefore are less likely to be known by the management of such organizations.

2.4.6 Association Rules from Minimum Spanning Trees

(Valle et al. 2018) proposed a novel methodology to study the structure and behavior of consumer market baskets from the topology of a minimum spanning tree which represented the interdependencies between products, and use this information to complement the association rule generation process. The input to their proposed methodology was a correlation matrix between the set of all one-hot encoded purchase vectors such that each vector denoted the presence or non-presence of each product from the dataset in that vector. The dataset used for the MST construction was a list of 1,046,804 transactions containing a set of 3,240 unique products from a large supermarket chain branch in Santiago, Chile. When building this correlation matrix, the authors opted to use the Pearson's Coefficient (**Pearson 1895**) - which is equivalent to the coefficient ϕ for binary data (**Ernest C and El-Sanhurry 1991**) - over the traditionally used Jaccard distance to compute the similarity between the binary product vectors, as the former provides both a positive and negative association between products. Additionally, they used the distance function $d_{ij} = \sqrt{2(1 - \phi_{ij})}$ to transform the correlation matrix into a distance measurement (i.e. the weight of the edges)⁶. The authors constructed a MST for 220 product subcategories, and noted that there was a significant level of grouping between product sub-categories that belonged to the same parent category. To remove edges from the MST that were not statistically significant, the authors used the mutual information (**Cover and Thomas 2006**) measure $\sum_{x,y} \log_2 \frac{r(x,y)}{p(x)q(y)}$ between product subcategories p and q , and were able to prune 14 edges, all of which were connected to a terminal node, therefore effectively pruning 14 vertices from the MST too. To identify the most influential regions of the MST, the authors defined an influence zone of distances that were in the 10th percentile. To generate meaningful association rules, for each MST product i , the authors ran a search for the set of all association rules R_i such that $P_i \rightarrow P_j (i \neq j)$. Then from the resulting set of rules, they searched for rules that obeyed $P_i \rightarrow P_m$ where m a product node connected to the product i in the minimum spanning tree. For both resulting sets of rules for each product, the mean of their lift scores were observed, and the authors determined that the rules that were reinforced by the MST had a higher mean, and that a majority of these rules had a lift score above the 90th percentile.

To identify the clusters each of the products should be identified under, the authors constructed a hierarchical tree using the average linkage clustering method, and by using an unspecified cut distance, they were able to produce 17 taxonomic groups (i.e. clusters). Cross-referencing their results with the actual parent categories of the products, they were able to conclude that the MST did indeed categorize the product

⁶ ϕ_{ij} is the correlation score between products at indexes i and j on the correlation matrix.

sub-categories into clusters with a reasonable degree of accuracy. The authors then compared their MST to another methodology, namely the structured association map (SAM) (**Kim 2017**), using the Jaccard distance as a measure of similarity, and were able to generate interesting 2x2 rules (i.e. $\{A, B\} \rightarrow \{C, D\}$), all with lift scores above 1.0, with one rule even having a lift score of 106.46. They concluded that while both approaches provided different information, they both visually identify the strongest relationships between the products, and provide useful information to reduce the search space for association rules.

Critical Analysis

The authors' approach seems to be novel, thorough and well structured. Their methodology successfully employed the use of minimum spanning trees to complement the association rule generation process with sound results. One caveat of their approach is that they only used the MST to generate single-element rules (i.e. $\{A\} \rightarrow \{B\}$, where the antecedent and consequent contain only one element each). Using the distance score in conjunction with the importance function they defined (i.e. $\sum_{k \in K_u} \frac{1}{w_{uk}}$), they could have defined a system to produce multi-element rules (i.e. where either/both the antecedent and the consequent have more than one element) While single-element rules are easily understandable and tend to have high lift values when extracted from the MST, multi-element rules would provide an additional layer of insight as to how a range of products (perhaps a cluster) relate to another.

2.4.7 Summary

In conclusion, (**Agrawal, Imieliński, et al. 1993**) introduced a formal system for association rules, and a method to generate them from a transactional database, which was further improved when (**Agrawal and Srikant 1994**) introduced the Apriori Algorithm. Instrumental to the success of this algorithm is its ability to prune a bulk of the rules such that their support scores need not be checked. (**Pennsylvania 2020**) defines the equation for calculating the number of possible rules for an itemset d as:

$$\text{number of rules} = \sum_{k=1}^{d-1} \left(\binom{d}{k} \times \sum_{j=1}^{d-k} \binom{d-k}{j} \right)$$

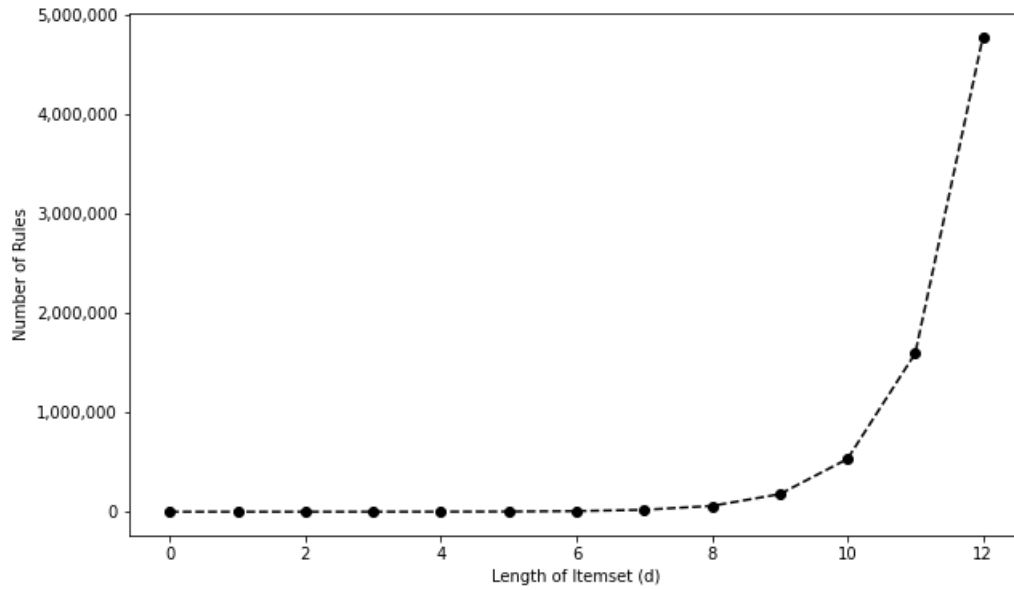


Figure 2.4: Number of Association Rules for an Itemset

We have plotted Figure 2.4 to illustrate the exponential growth of rules given an itemset's length d . This exponential growth reinforces the need for the rule pruning techniques introduced in (Agrawal, Imieliński, et al. 1993) to be able to complete the computations within a reasonable time frame, and will therefore be incorporated into our methodology. However, while these papers only based the interestingness of an association rule on objective measures such as the support, confidence and lift scores of these rules, (Zekic-Susac and Has 2015) proposed a methodology where subjective human input was used to validate the interestingness of these rules. A drawback of the above methods, however, is the large number of rules produced. (Zhong et al. 2015) proposed a solution to the relatively slow computation time that the Prim's algorithm and Kruskal's algorithm offer, where the Kruskal's algorithm was optimized using K-Means, leading to a significant performance increase as illustrated in Figure 2.3. The methodology proposed in this paper was a framework, where Kruskal's Algorithm could be substituted with any MST algorithm, such as Prim's Algorithm. (Dongen 1969) introduced a novel way to identify and isolate dense regions within a graph, and we have used their algorithm to cluster our own graphs. (Valle et al. 2018) introduced a methodology to extract high value association rules from a minimum spanning tree, used to complement the rules produced by the Apriori algorithm. A caveat of this approach, however, is that it can only produce rules such that the antecedent and consequent are

sets with one element each. This paper has been the primary motivation for our work, and therefore we have incorporated into our work several techniques that the authors used and/or introduced.

As a note, (**Brin et al. 1997**) defined another metric to assess association rules - *conviction* - now commonly referred to as *lift*. The lift of an association rule $i_k \rightarrow i_j$ is the rise that i_k gives to the confidence of the rule. The formula for lift is:

$$\text{lift}(i_k \rightarrow i_j) = \frac{\text{confidence}(i_k \rightarrow i_j)}{\text{support}(i_j)}$$

All the research conducted above has served as the inspiration for this project.

Chapter 3

The CGRG Algorithm

In this section, we introduce the main contribution of this paper: the Clustered-Graph Rule Generation (CGRG) algorithm. The CGRG algorithm derives association rules from a clustered minimum spanning tree. This chapter will focus on the workings of the algorithm.

3.1 Data Processing

Given an itemset $I = \{I_1, I_2, \dots, I_m\}$ and a set of transactions $T = \{T_1, T_2, \dots, T_n\}$ such that $T_i \subseteq I$, every transaction t_i will be transformed into a binary purchase vector, as described in Section 2.1.1. An $m \times m$ correlation matrix will then be computed using the Pearson's Correlation Coefficient from the set of binary purchase vectors, composed of the correlation every item has against every other item. A graph $G = (V, E)$ will be constructed from this correlation matrix, such that the vertices $V = I$, and every edge will be the correlation value between the two items it connects. A minimum spanning tree is a sub-graph composed of the *shortest* path connecting all vertices (i.e. the lowest sum of weights), and therefore to do so from our graph, the MST would only capture strongly negative and weakly positive relationships only, whereas we want to capture the strongest relationships between products. Therefore to extract a MST with the strongest associations, the values in the correlation matrix must first be transformed before a graph is constructed from them.

3.2 Distance Function

As mentioned in Section 2.1.1, the Pearson's Correlation Coefficient is equivalent to the Phi Coefficient (ϕ) for binary variables, as is the case for our binary purchase vectors. Given ϕ_{ij} for items I_i and I_j in the correlation matrix, (Valle et al. 2018) used the distance function

$$\phi_{ij} = \sqrt{2(1 - \phi_{ij})}$$

to transform their correlation matrix. Given that we are using the Pearson's Correlation Coefficient that gives us a correlation score in the interval $[-1,1]$, this equation is not suitable for us as it discards the strongly negative associations by outputting a larger weight (e.g. a correlation score of -1 would be transformed to 2) which would not be captured in the MST. Therefore, we modify the equation to be

$$\phi_{ij} = \sqrt{2(1 - |\phi_{ij}|)}$$

allowing us to capture both positive and negative associations alike. Figure 3.2 illustrates the effect of our distance function, where the stronger the correlation of the input, the lower the output. Given that our initial correlation values were bound to the interval $[-1,1]$, the output of the distance function is similarly bound to the interval $[0, \sqrt{2}]$.

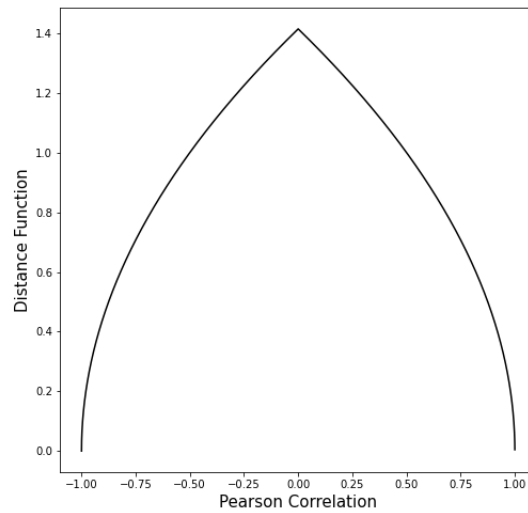


Figure 3.1: The effect of the distance function $\sqrt{2(1 - |x|)}$

Once the correlation matrix has been transformed via this function, the graph $G = (V, E)$ can be constructed. Using Kruskal's algorithm, the minimum spanning tree can then be constructed from the graph G .

3.3 Clustering and Rule Generation

3.3.1 Markov Clustering

Once the MST has been constructed, it can then be clustered using the Markov Clustering (MCL) Algorithm. Multiple cluster configurations will be generated using the algorithm with varying inflation scores to identify the most modular configuration¹, which will then be used to segment the MST.

3.3.2 Itemset Generation

For every cluster Cl_i identified by the MCL algorithm, all proper subsets cl such that $cl \subseteq Cl_i$ are generated. The set of proper subsets are stored against the key i , which denotes the index of cluster Cl_i , effectively assigning each cluster its proper subsets. Listing 3.1 is the pseudo-code for this operation.

```

1 given CLUSTERS = { $Cl_1, Cl_2, \dots, Cl_n$ }
2 define itemsets_by_cluster as {}
3 for  $Cl_i$  in CLUSTERS
4   to itemsets_by_cluster add ({all  $cl$  if  $cl \subseteq Cl_i$  at index  $i$ })

```

Listing 3.1: Cluster Itemset Generation

3.3.3 Bi-Cluster Rule Generation

Bi-cluster rules are those where the antecedent and the consequent originate from distinct and separate clusters. All possible bi-cluster rules are generated such that for any two given clusters Cl_k and Cl_j :

$$cl_k \rightarrow cl_j; \quad cl_k \subset Cl_k, \quad cl_j \subset Cl_j$$

Listing 3.2 presents the pseudo-code for the bi-cluster rule generation. All bi-cluster combinations are generated and stored as a pair of indices (i.e. (i, j) for clusters Cl_i and Cl_j). For every cluster pair generated, every configuration itemsets associated with each cluster (calculated in Listing 3.1) is added to the ruleset such that a rule exists for every itemset c_k associated with cluster C_k and every itemset c_j associated with cluster C_j .

¹Where the connectedness between dense clusters is minimal

```

1 given CLUSTERS = {Cl1, Cl2, ..., Cln}
2 given itemsets_by_cluster = {...} // already populated
3 define rules as ∅
4 define combs as ∅
5 to combs add all nC2 combinations from {1, 2, ..., n}
6
7 for comb in combs:
8     define antecedent_itemsets as (itemsets_by_cluster at (c at index 1)) // first index
      is 1
9     define consequent_itemsets as (itemsets_by_cluster at (c at index 2))
10    for antecedent in antecedent_itemsets:
11        for consequent_item in consequent:
12            to rules add (antecedent → consequent)
13            to rules add (consequent → antecedent)

```

Listing 3.2: Bi-Cluster Rule Generation

3.3.4 Intra-Cluster Rule Generation

Intra-cluster rules are those where itemsets in both the antecedent and consequent originate from the same cluster. This can be represented as:

$$cl_{k1} \rightarrow cl_{k2}; \quad cl_{k1} \subseteq Cl_k, cl_{k2} \subseteq Cl_k, cl_{k1} \cap cl_{k2} = \emptyset$$

```

1 given CLUSTERS = {Cl1, Cl2, ..., Cln}
2 given itemsets_by_cluster = {...} // already populated
3 define rules as ∅
4 for i in itemsets_by_cluster
5     define itemsets as (itemsets_by_cluster at index i) // itemsets at ith cluster.
6     define combs = ∅
7     to combs add all pC2 combinations from itemsets // For all p elements in itemsets
8
9     for comb in combs
10        define antecedent as (comb at index 1) // first index is 1
11        define consequent as (comb at index 2)
12        to rules add (antecedent → consequent)
13        to rules add (consequent → antecedent)

```

Listing 3.3: Intra-Cluster Rule Generation

Listing 3.3 is the pseudo-code for the intra-cluster rule generation. A rule is generated from every configuration of two subsets from the subsets associated with a given cluster.

3.3.5 Rule Pruning

```

1 given rules = {...}           // already populated
2 sort rules ascending by antecedent // sort by number of items in antecedent
3 define min_support as float    // user-specified value
4 define min_confidence as float // user-specified value
5 define valid_rules as {}
6 define below_threshold as {}
7 for r in rules
8     antecedent = (r at index 1) // first index is 1
9     consequent = (r at index 2)
10    define is_above_threshold = True
11    // check if support lookup can be skipped
12    for itemset in below_threshold
13        if itemset  $\subset$  r
14            is_above_threshold = false
15            break
16    if is_above_threshold
17        // calculate all supports
18        define support_antecedent as float
19        define support_consequent as float
20        define support_r as float
21        define confidence as (support_r  $\div$  support_antecedent)
22        define lift as (confidence  $\div$  support_consequent)
23        if support_antecedent < min_support
24            to below_threshold add support_antecedent
25            next loop // move to next rule in for loop
26        if support_consequent < min_support
27            to below_threshold add support_consequent
28            next loop
29        if confidence < min_confidence:
30            next loop
31        // If all constraints met, add rule
32        to valid_rules add r

```

Listing 3.4: Rule Pruning

Listing 3.4 presents the pseudo-code for rule pruning, employing the use of the *Apriori Principle* described in Section 2.4.3, which states that *the support of a set is - at most - equal to the support of its subsets*. We first sort the rules in ascending order by the number of items in the antecedent of each rule. When iterating through the rules, if the support of either the antecedent or consequent is found to be below the user specified support constraint, it is added `below_threshold` - the set of itemsets found to be below our constraint. For every subsequent iteration, if it is found that any set from `below_threshold` is a subset of the current rule, we can discard the rule and avoid having to calculate its support as we know it will be below our support constraint. Our final rules are those that remain after pruning.

Figure 3.2 illustrates the complete flow for the CGRG algorithm.

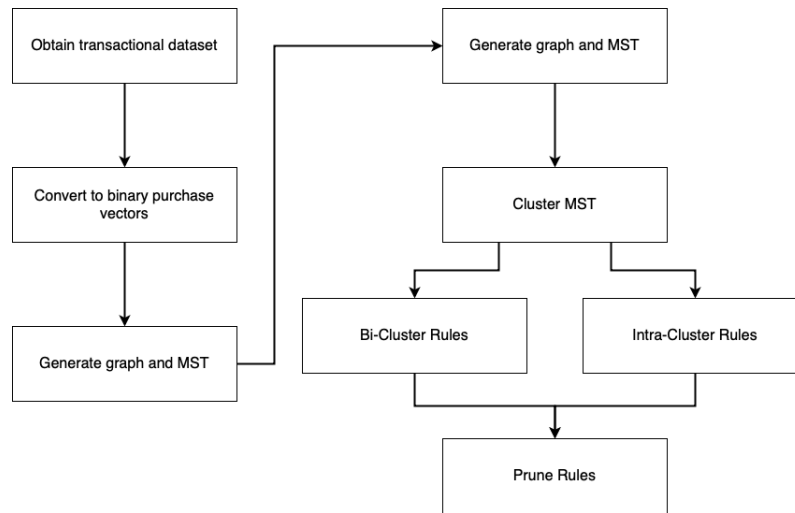


Figure 3.2: CGRG algorithm

Chapter 4

Experiments and Analysis

4.1 Environment

All the code for this algorithm was written in Python and Rust. Python was used to read and sanitize the initial dataset, and Rust was used to generate the binary purchase vectors. We opted to use Rust instead of Python for this task because the generation of this vectors has a time complexity of $O(N^2)$ at worst, and therefore may take an order of magnitude longer to run on a slower language such as Python. Python was used for the rest of the tasks, which included the graph generation and clustering, as well as the itemset generation and rule pruning. The following external Python libraries were used to aid development:

- `pandas`: Data manipulation.
- `numpy`: Data manipulation.
- `matplotlib`: Plotting library.
- `seaborn`: Plotting library.
- `networkx`: Graph generation and plotting.
- `markov_clustering`: Markov Clustering Algorithm.

4.2 CGRG and Apriori Algorithm

We used both the CGRG and the Apriori Algorithm to generate rules for our dataset, with the support constraint at 0.1% and the confidence constraint at 25%. Given these constraints, the Apriori algorithm generated 1,222 rules, and the CGRG generated 123 bi-cluster rules as well as 40 intra-cluster rules, totalling 163 rules.

Apriori Rules

We present the first 5 rules generated by the Apriori Algorithm, ranked by highest support.

```
{chewing gum and candy} → {cigarettes}
support: 0.0726 | confidence: 0.2986 | lift: 1.0985
{cigarettes} → {chewing gum and candy}
support: 0.0726 | confidence: 0.2671 | lift: 1.0985
{water} → {chewing gum and candy}
support: 0.0473 | confidence: 0.3052 | lift: 1.2554
{filters} → {lubricant}
support: 0.0468 | confidence: 0.9381 | lift: 2.6850
{chocolates} → {chewing gum and candy}
support: 0.0435 | confidence: 0.3117 | lift: 1.2820
```

CGRG

Similarly, we present the first 5 rules generated by the CGRG, ranked by highest support. The type of rule has also been annotated (i.e. bi-cluster or intra-cluster).

```
{chewing gum and candy} → {cigarettes}
support: 0.0726 | confidence: 0.2986 | lift: 1.0985 | type: bi-cluster
{cigarettes} → {chewing gum and candy}
support: 0.0726 | confidence: 0.2671 | lift: 1.0985 | type: bi-cluster
{water} → {chewing gum and candy}
support: 0.0473 | confidence: 0.3052 | lift: 1.2554 | type: intra-cluster
{filters} → {lubricant}
support: 0.0468 | confidence: 0.9381 | lift: 2.6850 | type: intra-cluster
{chocolates} → {chewing gum and candy}
support: 0.0435 | confidence: 0.3117 | lift: 1.2820 | type: bi-cluster
```

Analysis

We observe that there is a 100% overlap between the top five rules generated by the Apriori algorithm and the CGRG. The 100% overlap stands true for up until the first 13 rules for both algorithms.

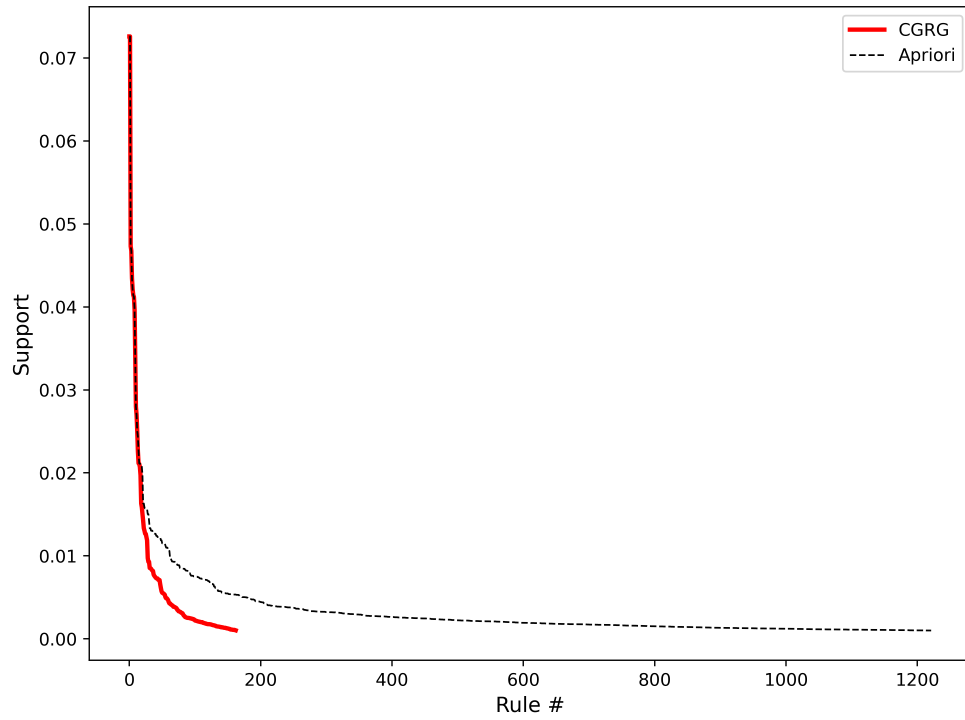


Figure 4.1: Ranked supports for both the CGRG and Apriori Algorithm

Figure 4.1 illustrates the support values for the x^{th} rule for both the CGRG and Apriori when they are sorted by highest support score to lowest. We can infer from this figure that the CGRG captures the strongest rules present in the Apriori ruleset, which leads us to another conclusion: *describe rule here*. In other words, given an itemset $I = i_1, i_2, \dots, i_m$ and clusters A and B , rules which follow:

$$i_k \rightarrow i_j$$

$$i_k \subset A, \quad (i_j \subset B \mid i_j \subset A)$$

are more likely to have a higher support score than rules whose antecedent and/or consequent are composed of items from multiple clusters.

References

- Abdelnabi, Omar Khaled Abdelaziz (2018). *Minimum Spanning Tree*. URL: <https://www.hackerearth.com/practice/algorithms/graphs/minimum-spanning-tree/tutorial/>.
- Agrawal, Rakesh, Tomasz Imieliński, et al. (1993). “Mining Association Rules between Sets of Items in Large Databases”. In: *Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data*. Association for Computing Machinery, pp. 207–216. ISBN: 0897915925. DOI: 10.1145/170035.170072. URL: <https://doi.org/10.1145/170035.170072>.
- Agrawal, Rakesh and Ramakrishnan Srikant (1994). “Fast Algorithms for Mining Association Rules”. In: *Proceedings of the 20th International Conference on Very Large Databases*, pp. 487–489.
- Brin, Sergey et al. (June 1997). “Dynamic Itemset Counting and Implication Rules for Market Basket Data”. In: *SIGMOD Rec.* 26.2, pp. 255–264. ISSN: 0163-5808. DOI: 10.1145/253262.253325.
- Cover, Thomas M and Joy A Thomas (2006). *Elements of information theory*.
- Dijkstra, E. W. (1959). “A note on two problems in connexion with graphs”. In: *Numerische Mathematik* 1. ISSN: 1. DOI: 10.1007/BF01386390.
- Dongen, Stijn Marinus van (Sept. 1969). “Graph Clustering by Flow Simulation”. Dutch. Dissertation. Universiteit Utrecht. Chap. 1, p. 5. URL: <http://www.library.uu.nl/digiarchief/dip/diss/1895620/full.pdf>.
- Ernest C Jr, Davenport and Nader A. El-Sanhury (1991). “Phi/Phimax: Review and Synthesis”. In: *Educational and Psychological Measurement* 51.4, pp. 821–828. DOI: 10.1177/001316449105100403.
- Han, Jiawei et al. (May 2000). “Mining Frequent Patterns without Candidate Generation”. In: vol. 29. 2. New York, NY, USA: Association for Computing Machinery, pp. 1–12. DOI: 10.1145/335191.335372. URL: <https://doi.org/10.1145/335191.335372>.
- Jarník, Vojtěch (1930). “O jistém problému minimálním”. In: *Práce Moravské Přírodovědecké Společnosti*, pp. 57–63.
- Kaggle (2020). *Sales data for a chain of Brazilian stores*. Kaggle. URL: <https://www.kaggle.com/marcio486/sales-data-for-a-chain-of-brazilian-stores>.
- Kim, Jun Woo (2017). “Construction and evaluation of structured association map for visual exploration of association rules”. In: *Expert Systems with Applications* 74. DOI: 10.1016/j.eswa.2017.01.007.
- Kruskal Jr, Joseph Bernard (1956). “On the Shortest Spanning Subtree of a Graph and the Traveling Salesman Problem”. In: *Proceedings of the American Mathematical Society* 7, pp. 48–50. DOI: 10.1090/S0002-9939-1956-0078686-7.

- Markov, A.A. (2006). “Extension of the law of large numbers to quantities, depending on each other (1906). Reprint.” rus. In: *Journal Électronique d’Histoire des Probabilités et de la Statistique [electronic only]* 2.1b, Article 10, 12. URL: <http://eudml.org/doc/128778>.
- Pearson, Karl (1895). “Note on Regression and Inheritance in the Case of Two Parents”. In: *Proceedings of the Royal Society of London* 58, pp. 240–242. ISSN: 03701662.
- Pennsylvania, Junita College (2020). *Generating Association Rules*. Junita College Pennsylvania. URL: <http://faculty.juniata.edu/rhodes/ml/assocRules.html>.
- Prim, Robert C. (1957). “Shortest Connection Networks and Some Generalizations”. In: *Bell System Technical Journal* 6 (6), pp. 1389–1401. DOI: 10.1002/j.1538-7305.1957.tb01515.x.
- Valle, Mauricio A. et al. (May 2018). “Market basket analysis: Complementing Association Rules with Minimum Spanning Trees”. In: *Expert Systems with Applications* 97, pp. 146–162. DOI: 10.1016/j.eswa.2017.12.028.
- Zekic-Susac, Marijana and Adela Has (Oct. 2015). “Discovering market basket patterns using hierarchical association rules”. In: *Croatian Operational Research Review* 6, pp. 475–487. DOI: 10.17535/crorr.2015.0036.
- Zhong, Caiming et al. (2015). “A fast minimum spanning tree algorithm based on K-means”. In: *Information Sciences* 295, pp. 1–17. ISSN: 0020-0255. DOI: <https://doi.org/10.1016/j.ins.2014.10.012>. URL: <http://www.sciencedirect.com/science/article/pii/S0020025514009943>.