Ultra-Fast Streaming Camera Platform for ICU Applications

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Abstract: This paper explores the applicability of chemical reaction optimization in association rule mining. We apply CRO on transactional database. Our algorithm generates N number of rules from the given database. The proposed algorithm is tested on real-life data from friendshop mall, Addis Ababa, Ethiopia. From the results, we find it to be the best alternative to the existing popular algorithm like apriori algorithm and the FP-growth algorithm.

Keywords: CRO, Association rule mining, Apriori, FP-growth, Chemical Reaction Optimizations.

I. INTRODUCTION

One of the Market basket analysis is association rule mining. In association rule mining, we analyze the purchasing habit of the customer. This analysis is processed by discovering association among the different items placed in the shopping basket of the customer. The analysis is about to find frequently purchase items together. The process of chemical reaction is used in Chemical Reaction Optimization (CRO) [7]. This recent metaheuristic is applied to solve many combinatorial problems successfully. In many problems, CRO outperforms many existing metaheuristics in most of the test cases. We propose an algorithm using CRO to solve association rule mining. The propose CRO approach is tested on books dataset and different algorithms, namely the Apriori algorithm and FP-growth algorithm.

II. RELATED WORK

To infer knowledge from the database or big data, we require data mining [1, 2, 3]. Using the customer’s market basket business analysis is possible. This market basket of the customer helps in future business predictions. One of the uses of data mining on these type of data is association rule discovering. Association rule mining is one of the methods in an unsupervised system known as pattern recognition. This is a method of searching undiscovered rules in the database. Discovery of huge rules may sometimes give negative potential because of lack of proper analysis.

Use of an evolutionary algorithm for association rule mining is first done by Sag-gar et al.[4]. He uses a genetic algorithm(GA) to optimize the rule generated by the Apriori algorithm. Waiswa and Baryamureeba[5], mine the association rules based on GA method. For this, they used the Pareto-based multi-objective evolutionary algorithm. The concept of a fuzzy association rule is used by Kaya and Alhajj [2]. To extract semi optimal rules they proposed multi-objective. The use of GA for extrac-tion of the rule having a negative attribute is proposed by Anandhavalli et al. [8]. Cluster-based multi-objective GA is present by Hadian et al.[9]. Some of the researchers also tried Particle swarm optimization(PSO) for extracting association rules[6]. Kuo et al.[10] is among the first researcher to use PSO for association rules mining. The concept of weighted particle swarm optimization is used by Gupta[11].Asadi et al.[12] use PSO to derive the threshold value for a priory algorithm. Nandhini et al.[13] use PSO and domain ontology for extraction of the association rule.

III. ASSOCIATION RULE MINING USING CRO

The algorithm starts with the initialization of CRO parameters PopSize, KE-loss Rate, MoleColl, buffer, InitialKE, α, β. Set of solutions(Association Rules) are also generated at the beginning which is present as a set of molecule represented as M. In the next different elementary section of CRO is applied. We will discuss them one by one. Finally, our algorithm gives the best rules. We have to execute the algorithm for N number of times to get N different rules. Now we will discuss the algorithm, initial population, and operators of CRO.

3.1. CRO Algorithm

\[ M \leftarrow \text{set of molecules} \]
\[ AR \leftarrow \text{association rules} \]
\[ \text{Begin} \]
\[ \text{Initialize PopSize, KE-loss Rate, MoleColl, buffer, InitialKE, } \alpha \text{ and } \beta \text{ in the initial stage.} \]
\[ M \leftarrow \text{GenMole(PopSize)} \]
\[ \text{for }\ M_1 \leftarrow \text{do} \]
\[ \text{calculate PE for each molecule and set InitialKE for each molecule} \]
\[ \text{Initialize value for KE, NumHit, MinPE, MinHit and Minstruct} \]
\[ \text{end for} \]
\[ AR \leftarrow \text{assign random molecule from M} \]
\[ \text{while (PE of molecule remain constant for successive iteration)} \]
\[ \text{generate a random number } b \in [0,1] \]
\[ \text{if } b > \text{MoleColl} \]
\[ \text{mi} \leftarrow \text{select a molecule randomly from M} \]
\[ \text{if (number of hits - minimum hit number) > } \alpha \]
\[ \text{Apply decomposition(mi)} \]
\[ \text{else} \]
\[ \text{Apply On-wall-Ineffective-Collision(mi)} \]
\[ \text{endif} \]
\[ \text{else} \]
\[ \text{mi, m2} \leftarrow \text{select two molecule randomly from M} \]
\[ \text{if KE} \leq \beta \]
\[ \text{Synthesis(mi, m2)} \]
\[ \text{else} \]
\[ \text{Inter-Molecular} \]
\[ \text{End} \]
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Ineffective Collision ($m_1, m_2$) 
endif
update AR 
endif
end

3.2. Molecule

The function GenMole(NumSize) in the algorithm is responsible for initial population or molecules. These molecules represent association rules. Two approaches are available to represent association rules. The first approach represents a set of rules in a single molecule called as Pittsburgh approach, and another approach is the Michigan approach, where a single molecule represents a separate rule. Here we followed the Michigan approach. We represent each molecule by a vector. The size of the vector is equal to $l$ where $l$ equals to number of the item. The entries in the vector will be anyone from $\{0,1,2\}$. The $i$th entry in the molecule $w$ will follow the following rules.

$$ W[i]= \begin{cases} 
0 & \text{if item } i \text{ is not present in molecule } w \text{ representing rule } \\
1 & \text{if item } i \text{ is present in the antecedent part of rule in molecule } w \\
2 & \text{if the item } i \text{ is present in the consequent part of rule in molecule } w 
\end{cases} $$

For example let, as we have 5 items set as $\{I_1, I_3, I_3, I_4, I_5\}$ and one rules like $I_1I_4 \Rightarrow I_2I_5$, then the molecule representing this rule is represented in figure 1.

Figure 1: Molecule representing a single rule

3.3. Potential Energy

The potential energy will decide the potential of each molecule in CRO. It is like fitness function in GA. We use the fitness function proposed by Sarath et al. [6]. They justify the use of the following fitness function

$$ \text{Fitness} = \text{support}(A \rightarrow B) \ast \text{confidence}(A \rightarrow B) \quad (1) $$

where $A \rightarrow B$ are association rule.

The author uses this because he wants to maximize. In CRO implementation it became minimization problem, so we have to represent PE as

$$ \text{PE}=1- \text{support}(A \rightarrow B) \ast \text{confidence}(A \rightarrow B) \quad (2) $$

where $A \rightarrow B$ are association rule.

3.4. On-Wall Ineffective Collision

This operator of CRO is like the mutation operator of the genetic algorithm. In the randomly selected molecule, the value of 1or 2 is replaced with 0. The reason behind the construction of this operator is inspired by a property of support i.e. $\forall A, B \subseteq I \text{ Sup-port}(A) \supseteq \text{Support}(A, B)$.

3.5. Decomposition

This process generates two new molecules from a single molecule. The reason behind it is to increase the search space. The decomposition operator for the association rules mining is designed as fol-low. The source molecule is divided into two from a ran-domly selected point and the vacant space in the newly produce molecule is filled up with any of the value from $\{0, 1, 2\}$.

3.6. Synthesis Operator

The operator combines two molecules into one molecule with a solution. It decides a point, from the first molecule first portion is copied to the new molecule and rest from the second molecule.

3.7. Inter-Molecular Ineffective Collision Operator

This operator produces new two molecules from the old two molecules. It is something similar to the crossover operator of GA.

IV. EXPERIMENTAL RESULTS

In order to implement the CRO based association algorithm, we use Matlab version R2017a. The experiments are conducted on an HP computer with the windows10 operating system. The architecture of the machine is Intel Core-i7 processor, 2.4 GHz, and 4 GB memory. Different CRO parameter used in our implementation is present in table I.

<table>
<thead>
<tr>
<th>(M Number of Molecule)</th>
<th>KELoss Rate</th>
<th>MolecColl</th>
<th>buffer</th>
<th>InitialKE</th>
<th>$\alpha$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>0.2</td>
<td>0.2</td>
<td>0</td>
<td>1000</td>
<td>500</td>
<td>1</td>
</tr>
</tbody>
</table>

Table I: CRO Parameter For Association Rule Mining

Apriori algorithm and FP-Growth algorithm are used for result comparisons. The books dataset taken from XLMINER tool (www.solver.com/xlminer-data-mining) containing 11 items and 2000 transactions purchased by customers is used for implementation.

The rule generated by our algorithm is presented in table number II The corresponding potential energy is also represented in the last column.
The main aim is to extract alternative to existing traditional methods. This algorithm can be used as a better approach gives a better result in terms of efficiency. By analyzing these tables, it is visible that many rules from Apriori and FP-growth are present in our CRO based algorithm. It indicates that this CRO based association rule mining algorithm can be successfully used as alternatives to this two algorithms.

<table>
<thead>
<tr>
<th>Sl No</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Support(%)</td>
<td>0.26</td>
<td>0.13</td>
<td>0.11</td>
<td>0.2</td>
<td>0.17</td>
<td>0.12</td>
<td>0.16</td>
<td>0.17</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>Confidence(%)</td>
<td>0.61</td>
<td>0.76</td>
<td>0.57</td>
<td>0.71</td>
<td>0.67</td>
<td>0.81</td>
<td>0.82</td>
<td>0.69</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>Potential Energy</td>
<td>0.85</td>
<td>0.91</td>
<td>0.94</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
<td>0.9</td>
<td>0.87</td>
<td>0.89</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Table II: Association Rules Generated By CRO Algorithm

Table number III and IV represents the rules generated by Apriori algorithm and FP-Growth algorithm on the same book dataset.

<table>
<thead>
<tr>
<th>SlNo</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Support(%)</td>
<td>0.13</td>
<td>0.15</td>
<td>0.15</td>
<td>0.12</td>
<td>0.13</td>
<td>0.15</td>
<td>0.15</td>
<td>0.12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Confidence(%)</td>
<td>0.78</td>
<td>0.78</td>
<td>0.78</td>
<td>0.78</td>
<td>0.76</td>
<td>0.79</td>
<td>0.78</td>
<td>0.81</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table III: Association Rules Generated By Apriori Algorithm

REFERENCES


