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On Parallelization of the NIS-Apriori Algorithm for Data Mining

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Abstract

We have been developing the \textit{getRNIA} software tool for data mining under uncertain information. The \textit{getRNIA} software tool is powered by the NIS-Apriori algorithm, which is a variation of the well-known Apriori algorithm. This paper considers the parallelization of the NIS-Apriori algorithm, and implements a part of this algorithm based on the Apache-Spark environment. We especially apply the implemented software to two data sets, the Mammographic data set and the Mushroom data set in order to show the property of the parallelization. Even though this parallelization was not so effective for the Mammographic data set, it was much more effective for the Mushroom data set.

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1. Introduction

Rough set theory, proposed by Pawlak, gives us the mathematical framework for table data analysis\textsuperscript{12,13,14}. This theory is applied to tables for mining rules, reading a tendency and a pattern, etc.\textsuperscript{7,13,14}. In our study, we proposed the framework \textit{Rough Non-deterministic Information Analysis (RNIA)}, and push forward a study of the data mining technique in tables with non-deterministic information. We call such tables \textit{Non-deterministic Information Systems (NISs)}\textsuperscript{15,16,18}.

In rough set theory, we usually handle tables with deterministic information, which we call \textit{Deterministic Information Systems (DISs)}. \textit{NIS} and \textit{Incomplete Information Systems} were proposed for dealing with information incompleteness in \textit{DIS}\textsuperscript{8,9,10,11}. Lipski employed the modal logic, and proved the logical properties in question-answering\textsuperscript{9,10}. Orłowska investigated the certainty and the possibility in \textit{NIS}\textsuperscript{11}. We follow this robust framework, and we are developing the algorithms and the software tools in \textit{RNIA}.

The \textit{Apriori} algorithm is known well as the representative algorithm for data mining\textsuperscript{1,2}. This algorithm deals with the \textit{item} sets, which we call \textit{transaction data}. For example, transaction data is automatically generated by using POS systems. However, if we identify an item with a descriptor \textit{[attribute,attribute, value]} in \textit{DIS}, we can similarly consider

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the Apriori algorithm in DIS. We adjusted this Apriori algorithm in DIS to the NIS-Apriori algorithm in NIS. This is the core algorithm for our getRNIA system\(^{17,19,20}\).

In this paper, we consider the parallelization of the NIS-Apriori algorithm for handling large scale data, and implement a part of this algorithm. Based on the experiment, the effectiveness of the parallelization was confirmed, especially for the Mushroom data set\(^5\). This paper is organized as follows: Section 2 recalls the rules in RNIA, and Section 3 reviews the Apriori algorithm and the NIS-Apriori algorithm as well as the getRNIA software tool. Section 4 investigates the parallelization of the NIS-Apriori Algorithm, and implements a part of this algorithm based on the Apache-Spark environment\(^4\). Finally, Section 5 concludes this paper.

### 2. Rules in Rough Non-deterministic Information Analysis (RNIA)

This section briefly surveys the framework of RNIA. A Deterministic Information System DIS \(\psi\) is a quadruplet below:\(^{13,14}\)

\[
\psi = (OB,AT,\{VAL_A \mid A \in AT\}, f), \quad f : OB \times AT \rightarrow \bigcup_{A \in AT} VAL_A.
\]

where \(OB\) is a finite set whose elements are called objects, \(AT\) is a finite set whose elements are called attributes, \(VAL_A\) is a finite set whose elements are called attribute values and \(f\) is a mapping. We usually consider a table instead of this quadruplet \(\psi\). DIS \(\psi_1\) in Table 1 is an exemplary deterministic information system, and we see that the object \(x_1\) means some implications, like \([\text{Color}, \text{red}] \Rightarrow [\text{Weight}, \text{light}]\) and \([\text{Color}, \text{red}] \land [\text{Size}, \text{small}] \Rightarrow [\text{Weight}, \text{light}]\).

| Objects \(x\) | Color | Size | Weight |
|--------------|-------|------|--------|
| \(x_1\)     | red   | small| light  |
| \(x_2\)     | blue  | small| light  |
| \(x_3\)     | red   | small| heavy  |
| \(x_4\)     | blue  | large| heavy  |

Table 1. An exemplary DIS \(\psi_1\).

Let us consider each implication \(\tau\) below,

\[
\tau : \land_{A \in CON}[A, val_A] \Rightarrow [Dec, val], \quad (val_A \in VAL_A, val \in VAL_{Dec}),
\]

\(CON \subseteq AT\) : (a set of) condition attributes, \(Dec \in AT\) : the decision attribute.\(^2\)

We say \(\tau\) is a rule (or a candidate of a rule) in \(\psi\), if \(\tau\) satisfies a constraint in \(\psi\). We say \(\tau\) is supported by \(x \in OB\) in \(\psi\), if \(f(x,A) = val_A\) for every \(A \in CON\) and \(f(x,Dec) = val\) hold. For specifying the object \(x\), we may employ the notation \(\tau^x\). The most familiar constraint is defined by the following\(^{14}\), and we also employ this constraint for two threshold values \(\alpha\) and \(\beta\) (0 < \(\alpha\), \(\beta\) ≤ 1.0).

\[
support(\tau^x) = \frac{\text{OBJ}(\tau)}{|OB|} \geq \alpha, \quad accuracy(\tau^x) = \frac{\text{OBJ}(\tau)}{|OBJ(\land_{A \in CON}[A, val_A])|} \geq \beta.
\]

Here, OBJ(\(\cdot\)) means a set of objects supporting formula \(\cdot\).\(^3\)

NIS \(\Phi\) is also a quadruplet below\(^{11,13,14}\)

\[
\Phi = (OB,AT,\{VAL_A \mid A \in AT\}, g), \quad g : OB \times AT \rightarrow P(\bigcup_{A \in AT} VAL_A) \quad \text{(a power set)}.
\]

Every set \(g(x,A)\) is interpreted as that there is an actual value in \(g(x,A)\) but this value is not known\(^{11,13,14}\). By using NIS, it is possible to handle information incompleteness in DIS. Especially, if the actual value is not known at all, \(g(x,A)\) is equal to \(VAL_A\). This corresponds to the missing value\(^6\). We usually consider a table instead of this quadruplet \(\Phi\). Table 2 is an exemplary NIS \(\Phi_2\).

Now, we introduce the derived DIS from NIS. Since each \(VAL_A\) \((A \in AT)\) is finite, we can generate one \(\psi\) by replacing each non-deterministic information \(g(x,A)\) with an element \(v \in g(x,A)\). We named such \(\psi\) a derived DIS from NIS, and define the following:

\[
DD(\Phi) = \{\psi \mid \psi \text{ is a derived DIS from NIS } \Phi\}.
\]

\(\Phi\) is a derived DIS from NIS \(\Phi\).
In $\Phi_2$, there are 256 ($=2^8$) derived DISs, and DIS $\psi_1$ is a derived DIS from $\Phi_2$. Based on the interpretation of non-deterministic information, we see an actual DIS $\psi_{\text{actual}}$ exists in 256 derived DISs. We consider the following two types of rules with modal concepts.

(Certain rule) An implication $\tau$ is a certain rule, if there is $\tau^i$ such that $\text{support}(\tau^i) \geq \alpha$ and $\text{accuracy}(\tau^i) \geq \beta$ in each $\psi \in DD(\Phi)$.

(Possible rule) An implication $\tau$ is a possible rule, if there is $\tau^i$ such that $\text{support}(\tau^i) \geq \alpha$ and $\text{accuracy}(\tau^i) \geq \beta$ in at least one $\psi \in DD(\Phi)$.

**Remark 1.** In DIS $\psi$, $\text{support}(\tau^i) = \text{support}(\tau^j)$ and $\text{accuracy}(\tau^i) = \text{accuracy}(\tau^j)$ hold. So, we may identify $\tau^i$ with $\tau$. However, in NIS $\Phi$, we may have such case that $\tau^i$ satisfies the constraint, but $\tau^j$ does not satisfy the constraint. If there is at least one $\tau^i$ satisfying the constraint, we see this $\tau^i$ is the evidence for the rule $\tau$.

We have $DD(\Phi) = \{\psi\}$ as the special case, and two types of rules define the same rules in $\psi$. Therefore, these two types of rules are the natural extension from rules in DIS. However, we need to pay attention to the number $|DD(\Phi)|$. In the Mammographic data set $\Phi_{\text{Mammo}}^5$, $|DD(\Phi_{\text{Mammo}})|$ is more than 10 power 100.

### 3. Apriori Algorithm Adjusted to DIS, NIS-Apriori Algorithm, and the getRNIA Software

For adjusting the *Apriori* algorithm to DIS, we focus on descriptors and the structure of $\tau : \land_{\text{CON}}[A, val_A] \Rightarrow [\text{Dec}, \text{val}]$. In the first step, we examine rules with one descriptor in the condition part of $\tau$, i.e., rules in the form of $[A, val_A] \Rightarrow [\text{Dec}, \text{val}]$. In the second step, we examine rules with two descriptors, i.e., rules in the form of $([A, val_A] \land [B, val_B]) \Rightarrow [\text{Dec}, \text{val}]$. In the third step, we examine rules with three descriptors. Like this, we sequentially pick up any rule in the form of $\tau : \land_{\text{CON}}[A, val_A] \Rightarrow [\text{Dec}, \text{val}]$. In this process, we employ the following properties:

(The property on support) $\text{support}(\tau) \leq \alpha$ holds, if $\text{support}(\land_{\text{CON'}}[A, val_A]) \leq \alpha$ for at least one $\text{CON'} \subset \text{CON}$ or $\text{support}([\text{Dec}, \text{val}]) \leq \alpha$.

(The property on accuracy) $\text{accuracy}(\tau) \geq \beta$ may hold, even if $\text{accuracy}(\land_{\text{CON'}}[A, val_A]) \Rightarrow [\text{Dec}, \text{val}]) < \beta$ holds for every $\text{CON'} \subset \text{CON}$ ($\text{CON'} \neq \text{CON}$).

By employing these properties, we adjust each step in the *Apriori* algorithm to DIS.

**Step 1**
We generate $\text{CAN}_1$, $\text{CAN}_{\text{Dec}}$, and $\text{IMP}_1$ in the first step.

\[
\begin{align*}
\text{CAN}_1 &= \{[A, val_A] \mid \text{support}(A, val_A) \geq \alpha, A \in AT \setminus \{\text{Dec}\}\}, \\
\text{CAN}_{\text{Dec}} &= \{[\text{Dec}, \text{val}] \mid \text{support}([\text{Dec}, \text{val}]) \geq \alpha\}, \\
\text{IMP}_1 &= \{[A, val_A] \Rightarrow [\text{Dec}, \text{val}] \mid [A, val_A] \in \text{CAN}_1, [\text{Dec}, val] \in \text{CAN}_{\text{Dec}}\},
\end{align*}
\]

For each $\tau \in \text{IMP}_1$, we calculate $\text{support}(\tau)$ and $\text{accuracy}(\tau)$ for deciding whether $\tau$ is a rule or not. In this step, we recognize a set of rules in the form of $[A, val_A] \Rightarrow [\text{Dec}, \text{val}]$. We add this implication to $\text{RULE}_1$. For $\tau$ satisfying $\text{support}(\tau) \geq \alpha$ and $\text{accuracy}(\tau) < \beta$, we add this $\tau$ to $\text{REST}_1$.

**Step 2**
We generate $\text{IMP}_2$ in the second step. Because of the property on accuracy, we need to consider $\text{REST}_1$.

\[
\begin{align*}
\text{IMP}_2 &= \{[A, val_A] \land [A', val_{A'}] \Rightarrow [\text{Dec}, \text{val}] \mid \text{[A, val_A] \Rightarrow [Dec, val] \in REST}_1, [A', val_{A'}] \Rightarrow [\text{Dec}, \text{val}] \in \text{REST}_1\}.
\end{align*}
\]
For each \( \tau \in IMP_2 \), we calculate criterion values \( \text{support}(\tau) \) and \( \text{accuracy}(\tau) \) for deciding whether \( \tau \) is a rule or not. In this step, we recognize a set of rules in the form of \([A, val_A] \land [A', val_{A'}] \Rightarrow [Dec, val]\). We add this implication to \( RULE_2 \). For \( \tau \) satisfying \( \text{support}(\tau) \geq \alpha \) and \( \text{accuracy}(\tau) < \beta \), we similarly add this \( \tau \) to \( REST_2 \). We sequentially continue this procedure until \( IMP_n = \emptyset \). In each step, the properties on \( \text{support} \) and \( \text{accuracy} \) are effectively employed, and we recognize \( \cup_i RULE_i \) as a set of all rules.

In the \textit{Apriori} algorithm for the transaction data, the total search of the data set is employed frequently in order to calculate criterion values. In rough sets, we make use of the equivalence classes, and we always consider the equivalence class. Namely, we obtain a set \( \{ x \in OB \mid x \text{ supports } [A, val_A] \} \) for \([A, val_A] \) and a set \( \{ x \in OB \mid x \text{ supports } [Dec, val] \} \) for \([Dec, val] \) at the first step. By using the merging procedure\(^{20}\), we are managing the equivalence class \( M \) for each implication \( \tau \), and we are calculating criterion values of \( \tau (=\tau^*) (\forall x \in M) \). Since we are following rough set theory, we currently manage the equivalence classes, however we are also considering the total search of the data set instead of the equivalence classes.

Now, we cope with the \textit{NIS-Apriori} algorithm. For considering this algorithm, we defined the following.

\[
\begin{align*}
(1) \ & \min\text{support}(\tau^*) = \min_{\tau \in DD(\Phi)} \{ \text{support}(\tau^*) \text{ in } \psi \}, \\
(2) \ & \min\text{accuracy}(\tau^*) = \min_{\tau \in DD(\Phi)} \{ \text{accuracy}(\tau^*) \text{ in } \psi \}, \\
(3) \ & \max\text{support}(\tau^*) = \max_{\tau \in DD(\Phi)} \{ \text{support}(\tau^*) \text{ in } \psi \}, \\
(4) \ & \max\text{accuracy}(\tau^*) = \max_{\tau \in DD(\Phi)} \{ \text{accuracy}(\tau^*) \text{ in } \psi \}.
\end{align*}
\]

We proved that it is possible to calculate the above criterion values in the polynomial time, and there is at least one \( \psi_{\min} \in DD(\Phi) \) causing the point \((\min\text{support}(\tau^*), \min\text{accuracy}(\tau^*)) \). There is also at least one \( \psi_{\max} \in DD(\Phi) \) causing the point \((\max\text{support}(\tau^*), \max\text{accuracy}(\tau^*)) \). The details are in the references \(16 \) and \(18\). Based on these results, we obtained Figure 1 for each \( \tau^* \).

![Implication \( \tau^* \)](image)

**Fig. 1.** Each pairs \((\text{support}(\tau^*),\text{accuracy}(\tau^*)) \) in \( (\psi \in DD(\Phi)) \) belongs to the rectangle area. In \( DIS \), the minimum and the maximum points are the same, however they are different in \( NIS \).

We have the following by using Figure 1.

(1) \( \text{support}(\tau^*) \geq \alpha \) and \( \text{accuracy}(\tau^*) \geq \beta \) hold for each \( \psi \in DD(\Phi) \), if and only if \( \min\text{support}(\tau^*) \geq \alpha \) and \( \min\text{accuracy}(\tau^*) \geq \beta \).

(2) \( \text{support}(\tau^*) \geq \alpha \) and \( \text{accuracy}(\tau^*) \geq \beta \) hold for at least one \( \psi \in DD(\Phi) \), if and only if \( \max\text{support}(\tau^*) \geq \alpha \) and \( \max\text{accuracy}(\tau^*) \geq \beta \).

Namely, we can handle certain rules by comparing \( \min\text{support}(\tau^*) \) and \( \min\text{accuracy}(\tau^*) \) with threshold values \( \alpha \) and \( \beta \), respectively. We can similarly handle possible rules by comparing the point \( \max\text{support}(\tau^*) \) and \( \max\text{accuracy}(\tau^*) \) with threshold values \( \alpha \) and \( \beta \). We adjusted \textit{Apriori} algorithm in \( DIS \) to \( NIS \) by using the above properties. Since we can calculate criterion values in the polynomial time, the computational complexity of the \textit{NIS-Apriori} algorithm is about the twice of the \textit{Apriori} algorithm.
We opened a software getRNIA powered by the NIS-Apriori algorithm. In this web page, we can execute some demonstration files. In the Mammographic data set $\Phi_{\text{Mammo}}$, $|DD(\Phi_{\text{Mammo}})|$ is more than $10^{100}$, however we can easily obtained rules depending upon more than $10^{100}$ derived DISs.

4. Parallelization of the NIS-Apriori Algorithm and RNIA-Spark

This section reconsiders the parallelization of NIS-Apriori, and reports the current state of the implementation. The parallelization for data mining has been investigated by Agrawal. In the reference 3, some parallelization processes based on the transaction data sets were considered.

4.1. Parallelization of NIS-Apriori

As we have shown in Section 3, NIS-Apriori generates the following sets sequentially.

\[
\begin{align*}
\text{IMP}_1 &= \{[A, val_A] \Rightarrow [Dec, val] | [A, val_A] \in \text{CAN}_1, [Dec, val] \in \text{CAN}_{Dec} \}.
\text{IMP}_2 &= \{[A, val_A] \land [A', val_{A'}] \Rightarrow [Dec, val] | [A, val_A] \Rightarrow [Dec, val] \in \text{REST}_1 \}, \\
\text{IMP}_3 &= \{[A, val_A] \land [A', val_{A'}] \land [A'', val_{A''}] \Rightarrow [Dec, val] | [A, val_A] \Rightarrow [Dec, val] \in \text{REST}_1, \\
&\quad [A', val_{A'}] \land [A'', val_{A''}] \Rightarrow [Dec, val] \in \text{REST}_2, \\
&\quad [A', val_{A'}] \land [A'', val_{A''}] \Rightarrow [Dec, val] \in \text{REST}_2 \}.
\end{align*}
\]

(9)

For each implication $\tau \in \text{IMP}_k (k = 1, 2, \cdots)$, we apply the calculation specified in Figure 1, and obtain the certain and possible rules. Figure 2 indicates this procedure.

Fig. 2. The evaluation process of the implications by NIS-Apriori

We focused on this procedure, and considered the parallelization in Figure 3. In Figure 2, each implication $\tau_i$ is examined sequentially. In Figure 3, the list of implications are divided into four sub-lists, and each list is handled simultaneously. We implemented a software tool for the fixed number of the core processors, and newly revised this software tool so as to detect the number of the core processors automatically. The new software tool generates the sub-lists based on the number of the core processors, and assigns each procedure to each core processor. Even though this is more general software than the previous implementation, the implementation is restricted to the set $\text{IMP}_1$. As for the set $\text{IMP}_2$ and $\text{IMP}_3$, we are still in progress.

In the following, we know spark1p.py takes one core processor, and we see each task is executed sequentially. On the other hand, spark_multi.py takes four core processors, and we see each task is executed at the same time.

> pyspark ./rnia_spark/rnia_spark1p.py local data/mush3.pl
15/02/10 09:04:05 INFO Executor: Running task ID 1
15/02/10 09:04:08 INFO Executor: Running task ID 2
15/02/10 09:04:11 INFO Executor: Running task ID 3
15/02/10 09:04:13 INFO Executor: Running task ID 4
Fig. 3. The evaluation process of the implications for the quad-core processor.

```
> pyspark ../rnia_spark/rnia_spark_multi.py local data/mush3.p
15/02/10 09:07:09 INFO Executor: Running task ID 1
15/02/10 09:07:09 INFO Executor: Running task ID 2
15/02/10 09:07:09 INFO Executor: Running task ID 4
15/02/10 09:07:09 INFO Executor: Running task ID 3
```

### 4.2. Apache-Spark Environment

Spark is a MapReduce-like data-parallel computation engine open-sourced by UC Berkeley. The Spark Python API (PySpark) exposes the Spark programming model to Python. At a high level, every Spark application consists of a driver program that runs the user’s main function and executes various parallel operations on a cluster. We employ this environment for implementing the software tools for RNIA, and we call this framework RNIA-Spark. In RNIA-Spark, we distribute rule generation operations of different descriptors to a cluster which may consist of multiple processors.

The main abstraction Spark provides is a resilient distributed dataset (RDD), which is a collection of elements partitioned across the nodes of the cluster that can be operated on in parallel. In RNIA-Spark, we try to partition the whole rule generation task to separate rule generation tasks of different descriptors.

### 4.3. An Automated Detection of Core Processors

However in the previous version of RNIA-Spark, we hard-coded the number of processors for parallelized rule generations. In this paper we use Python’s multiprocessing module to check system specs, and optimize the parallel execution based on the number of cores.

Firstly, we need to import the multiprocessing module and call the cpu_count function to obtain the number of cores, and assign it to a variable NCore, which will be used in the main function later.

```python
# check number of cpus >python2.6
import multiprocessing
NCore = multiprocessing.cpu_count()
```

Then, we need to import SparkContext and define the main function, which accepts several arguments needed when we run RNIA-Spark from command line afterward. The first thing a Spark program must do is to create a SparkContext object, which tells Spark how to access a cluster. For example, the first parameter sys.argv[1] is a string specifying a Spark or Mesos cluster URL to connect to, or a special local[NCore] string to run in local mode.

The second parameter rnia_spark is the application name, which will be shown in the cluster web UI. The plCleaning here is the data cleaning function used to convert raw *.pl files or csv files to formatted data. The following ruleGeneration function is the core of RNIA-Spark, which applies NIS-Apriori algorithm on formatted data based on the settings we configured in the raw file. It returns a list of rules or an empty list if none of the rules satisfy. Finally, the dTCF2list function’s job is to convert the list of results to readable texts.
from pyspark import SparkContext
def ruleGeneration(argW, orDsp=None):
    ...
dctps=sc.parallelize(
        list(itertools.product(
            xrange(0,len(AT[D])),
            condition_indexes)),
        NCore)
    ...

if __name__ == "__main__":
    if len(sys.argv) < 3 or len(sys.argv)>4:
        print >> sys.stderr, "Usage: ./pyspark rnia_spark_multi.py <master> <file>"
        exit(-1)
    localCore="local[{NCore}]".format(NCore=NCore)
    sc = SparkContext(localCore, "rnia_spark")
    argWrapper=plCleaning(file_name)
    dataWrapper= ruleGeneration(argWrapper)
    rules=_dTCF2list(dataWrapper)

4.4. An Implementation and Experiments

To take full advantage of rnia_spark_multi.py, we need a computer of more than 4 cores or a cluster of more than 4 nodes. We obtain the following comparison result on an 8-core PC.

Firstly, we execute rnia_spark_multi.py on data Mammo.pl, which has 960 objects and 6 attributes per object. The Mammo.pl is the revised Mammographic data set\(^5\) as we have specified in Section 2. The result proves that the rnia_spark_multi version is not very efficient because the cost of parallel procedure itself is much more expensive than the efficiency it brings on such scale of data.

\[\text{Number of cores: 1} \quad \text{Data Cleaning time: 0.315397977829} \quad \text{Rule Generation time: 0.308684110641}\]

\[\text{Number of cores: 4} \quad \text{Data Cleaning time: 0.312597036362} \quad \text{Rule Generation time: 0.241578102112}\]

\[\text{Number of cores: 8} \quad \text{Data Cleaning time: 0.352070093155} \quad \text{Rule Generation time: 0.268180847168}\]

The following figure is the execution time (the difference between the finishing time and the starting time) of the duplicated Mushroom data set\(^5\) including descriptions of hypothetical samples corresponding to 23 species of gilled mushrooms. Every Mushroom data set has 8124 objects and 22 attributes per object which may contain non-deterministic attribute values. From top to bottom, the lines are the result of RNIA-Spark with single processor, result with 4 processors, and result with 8 processors. Obviously, RNIA-Spark on multiple processors become more efficient when the dataset grows bigger.

As for this parallelization, we can easily have the following.
(1) The parallelization will be effective, if \(IMP_1\) has the large number of implications.
(2) The parallelization may not be effective, if \(IMP_1\) has the small number of implications.
(3) Since \(IMP_1\) depends upon the threshold values \(\alpha\) and \(\beta\), the parallelization will be effective for \(\alpha\) and \(\beta\) with lower values. The parallelization may not be effective for \(\alpha\) and \(\beta\) with higher values.
(4) The rule generation from the Mushroom data set will correspond to the effective case, and the rule generation from the Mammo.pl data set will correspond to the ineffective case.
Fig. 4. Execution time for the Mushroom data set by the multiple core version of RNIA-Spark

5. Concluding Remarks

This paper briefly surveyed rough sets in DIS, rough sets in NIS, RNIA and rule generation. We implemented the web software getRNIA based on the NIS-Apriori algorithm, and opened it to the public.\textsuperscript{17,19,20} This is implemented in Python, and employs Google App Engine. We are now adding the parallelization functionality to the NIS-Apriori algorithm, especially the parallelization for the evaluation of the criterion values by using Apache-Spark environment. As Agrawal described,\textsuperscript{3} we need to consider the parallelization in other procedures. Even though our work is in progress, we think the parallelization of the algorithm will take the important role for analyzing big data.

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