A Technique to Association Rule Mining on Multiple Datasets

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***Abstract*— This research aims at studying the method for association rule mining on multiple datasets. Current with technology and information systems enabling agencies or organization has a data-storage system, but the problem is that those with a larger data set, which is difficult in the association rule mining, because it requires a computer with a high-performance to process, which was followed by a cost increase. How it can help solve this problem is to distribute data process according to multiple computers, then combined rules of each machine using Fact + + Reasoner for check conflicts of rules, and will therefore have powerful association rules similar to the method for association rule mining on one dataset. We thus propose a technique for association rule mining on multiple datasets.**

***Index Terms*—Association rule mining, Controlled language, Attempto Controlled English**

I. Introduction

Current, with the rapid development of technology allows agencies and organizations have adopted various technologies applied to the agency or the organization even more. These technologies make it possible to easily and systematically, but what follows is data that is stored large, which is difficult in association rule mining. As it required a computer with high-performance to processing and high cost, which the large organizations to have the financial resources to association rule mining from large data set. There is a technique to help fix this problem is to distribute the data set to be processed by multiple computers, by the computer, it does not require a high-performance to processing in association rule mining. However, it may have a conflict with the association rules in the process of combining association rules from each machine, and association rules from multiple datasets may be inefficient compared to the association rules from only data set. So in the process of combining association rules requires a technique to help fix the problems mentioned above.

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Step in the combine association rules from distributed data is essential as well, as association rules from multiple datasets must be close to the most powerful association rules from one datasets and association rules must be inconsistency. Examination of conflict in association rules is used Fact + + Reasoner [7] and need to write rules in the form of Attempto Controlled English (ACE) [2], which is a Controlled Natural Language (CNL) on the Protégé.

Researches related to association rule mining on multiple datasets have to appear very little. Probably, due to the association rule mining on multiple dataset that is difficult process of combined association rules from distributed data, association rules with efficient close to that of association rule mining from one datasets. The researchers appeared, there was an inefficient comparison clearly. [1, 3, 8]

From the above it can be seen that association rule mining relations from large dataset it is difficult, there is a need to distribute data processing according to multiple computers. Combining association rule from each of computers may be a problem in the conflict of association rules and the efficiency of association rules. We thus propose a technique to association rule mining on multiple datasets.

II. Background

A. Association Rule Mining

Association Rule Mining is a process that has been popular in the relationship between the data that is how most association rule mining in a variety of ways. In this paper, the algorithm Apriori [6] of the association rule mining.

TABLE 1
PURCHASE TRANSACTIONS OF ALL CUSTOMERS

Order	Milk	Water	Candy	Sausage
1	1	1	0	0
2	0	1	1	0
3	0	0	0	1
4	1	1	1	0
5	0	1	0	0

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Table 1 is show a purchase transaction of all customers and then fined the frequency pattern of purchases of customers in each piece, to find the relationship of each product which is shown in Table 2, after which it will be used with high frequency items set to generate association rules, which is in the form of IF condition Then result by the criteria used in the present are the following:

- Support is the frequency of the event occurring
- Confidence is the frequency of the incident with other events occurring together.

TABLE 2
THE FREQUENCY OF CUSTOMER PURCHASES.

	Milk	Water	Candy	Sausage
Milk	2*	2	1	0
Water	2	4*	2	0
Candy	1	1	2*	0
Sausage	0	0	0	1*

B. Attempto Controlled English

ACE is a controlled natural language that is based on first-order logic language, which combines the advantages of natural languages ˚ı ˛ formal language to want to make the writing language in the form of human and machine can understand, can be written in the form of simple English sentences [2], as shown by Figure 1 is an example of comparison between FOL, DL, OWL, UML, and ACE. ACE is a plugin of Protégé editor, in this research association rules are written in the form of ACE because will lead association rules to check conflicts with Fact++ Reasoner in Protégé editor. Table 3 shows an example of converting association rules in the form of ACE.

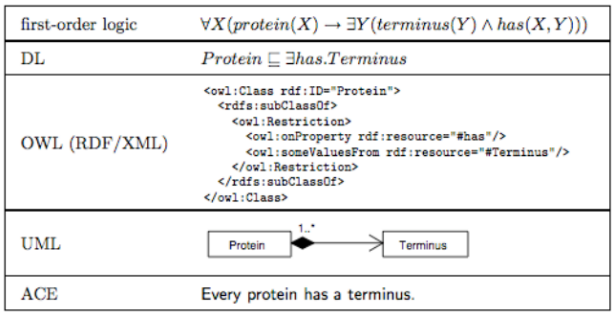


Figure 1 Example of comparison between FOL, DL, OWL, UML, and ACE

TABLE 3
EXAMPLE OF CONVERTING ASSOCIATION RULES IN THE FORM OF ACE

Original association rules	Association rules in ACE
{CLASS=crew} => {SEX=male}	If X is a **crew** then X is a **male**.
{CLASS=crew, AGE=adult} => {SEX=male}	If X is a **crew** and X is an **adult** then X is a **male**.
{CLASS=crew, AGE=adult, SURVIVED=no} => {SEX=male}	If X is a **crew** and X is an **adult** and X is a n: **not-survivor** then X is a **male**.

C. FaCT++ Reasoner

FaCT + + is reasoner was developed from FaCT algorithm using C + + language development, which is based on Description Logics (DL), to be used for checking the inconsistency of Ontology [7], for example following:

Every man is a human.
John is a man.
John is not a human.

For example, it can be seen that the conflict in the sentence "John is not a human", because two sentences have previously said that "John is a human" and could not use sentences in an example to created ontology. In this research, association rule mining from distribute data, may be association rules is a conflict, so it need FaCT++ Reasoner to checking the conflict of the association rules from multiple datasets

III. METHODOLOGY

This research proposed a technique for association rule mining on multiple datasets, the data is divided according to multiple computers to help in the association rule mining, replace association rule mining from large dataset, which require a computer with high-performance to process. But in the process of combined association rules from multiple datasets is difficult, because to the association rules with performance close to the association rule mining from large dataset and association rules that may conflict.

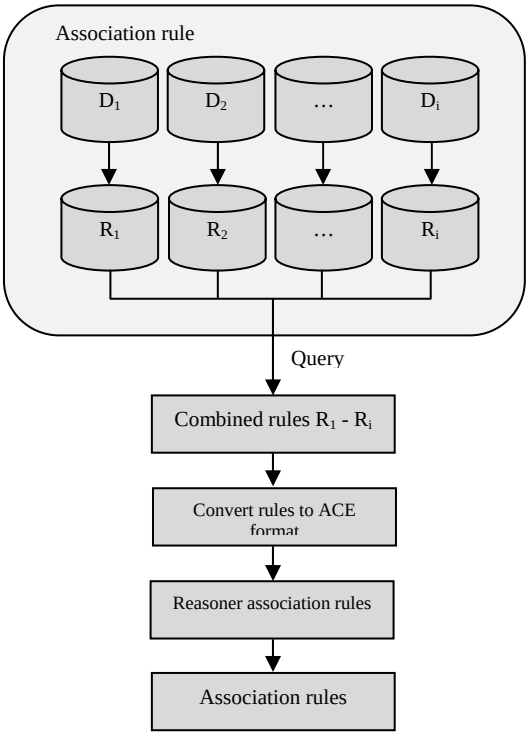


Figure 2 Conceptual framework of the research

R_1	R_2	R_3
{CLASS=third} => {AGE=adult}		
{CLASS=crew} => {SEX=male}	{CLASS=crew} => {SEX=male}	{CLASS=crew} => {SEX=male}
{CLASS=crew} => {AGE=adult}	{CLASS=crew} => {AGE=adult}	{CLASS=crew} => {AGE=adult}

R
{CLASS=crew} => {SEX=male}
{CLASS=crew} => {AGE=adult}

Figure 3 Example combined association rules

Figure 1 shows conceptual framework of the research. First, association rule mining from multiple datasets by $D_1, D_2, \ldots, D_t$ with $t = 1, 2, \ldots, n$. Second, combined association rules from first step by $R = R_1 \cap R_2 \cap \ldots \cap R_t$ with $t = 1, 2, \ldots, n$ which is shown in figure 3. Third, converting association rules in the form of ACE. Forth, checking the conflict of the association rules with FaCT++ Reasoner. Finally, the association rules from multiple datasets with similar efficient to the association rules from one dataset, this can be checked from the ontology created from Protégé editor.

IV. Experiment Result

This research experimented to compare the results from the association rule mining on multiple datasets and the association rule mining on one dataset used Breast-cancer dataset from the UCI Machine Learning Repository. Breast-cancer dataset has 10 attributes and 286 data instances, figure 4 is an example of Breast-cancer dataset are 5 instants.

The experiment will divided breast-cancer dataset for association rule mining to three datasets, which use minimum support for association rule mining at 0.3 and 0.5. Table 4 show comparative results of association rule mining on multiple dataset and association rule mining on one dataset with minimum support 0.3, it can be seen that the association rules from multiple dataset missing a lot, and when considering ontology Figure 5 shows that association rules from multiple dataset and association rules from one dataset are clearly different. Table 6 show comparative results of association rule mining on multiple dataset and association rule mining on one dataset with minimum support 0.5, it can be seen that there are some association rules from multiple dataset still missing, and when considering Ontology of Figure 6 shows that association rules from multiple dataset effectively close association rules from one dataset.

Association rule mining with minimum support 0.3 and 0.5, table 8 show association rule mining from multiple dataset with minimum support 0.5 it provides the number of rules closely to association rule mining from one dataset more than minimum support 0.3. Association rule mining from multiple dataset there is a missing, can be certain association rules of table 5 and table 7 to fill in some missing association rules.

age	menopause	tumor-size	inv-nodes	node-caps	deg-malig	breast	breast-quad	irradiat	Class
40-49	premeno	15-19	0-2	yes	3	right	left_up	no	recurrence-events
50-59	ge40	15-19	0-2	no	1	right	central	no	no-recurrence-events
50-59	ge40	35-39	0-2	no	2	left	left_low	no	recurrence-events
40-49	premeno	35-39	0-2	yes	3	right	left_low	yes	no-recurrence-events
40-49	premeno	30-34	3-5	yes	2	left	right_up	no	recurrence-events

Figure 4 Example of Breast-cancer dataset

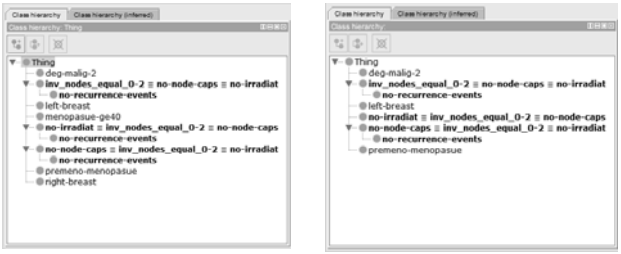
TABLE 4
COMPARATIVE RESULTS OF ASSOCIATION RULE MINING ON MULTIPLE DATASET AND ASSOCIATION RULE MINING ON ONE DATASET WITH MINIMUM SUPPORT 0.3

Original association rules	Combined association rules
if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast then X is a n:no-node-caps.	if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast then X is a n:no-node-caps.
if X is a n:no-node-caps and X is a n:left-breast then X is a n:inv_nodes_equal_0-2.	if X is a n:no-node-caps and X is a n:left-breast then X is a n:inv_nodes_equal_0-2.
if X is a n:premeno-menopasue and X is a n:inv_nodes_equal_0-2 then X is a n:no-node-caps.	if X is a n:premeno-menopasue and X is a n:inv_nodes_equal_0-2 then X is a n:no-node-caps.
if X is a n:premeno-menopasue and X is a n:no-node-caps then X is a n:inv_nodes_equal_0-2.	if X is a n:premeno-menopasue and X is a n:no-node-caps then X is a n:inv_nodes_equal_0-2.
if X is a n:left-breast and X is a n:no-irradiat then X is a n:no-node-caps.	if X is a n:left-breast and X is a n:no-irradiat then X is a n:no-node-caps.
if X is a n:no-node-caps and X is a n:left-breast then X is a n:no-irradiat.	if X is a n:no-node-caps and X is a n:left-breast then X is a n:no-irradiat.
if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast then X is a n:no-irradiat.	if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast then X is a n:no-irradiat.
if X is a n:left-breast and X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.	if X is a n:left-breast and X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.
if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast and X is a n:no-irradiat then X is a n:no-node-caps.	if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast and X is a n:no-irradiat then X is a n:no-node-caps.
if X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps and X is a n:left-breast then X is a n:no-irradiat.	if X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps and X is a n:left-breast then X is a n:no-irradiat.
if X is a n:no-node-caps and X is a n:left-breast and X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.	if X is a n:no-node-caps and X is a n:left-breast and X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.
if X is a n:premeno-menopasue and X is a n:no-irradiat then X is a n:no-node-caps.	if X is a n:premeno-menopasue and X is a n:no-irradiat then X is a n:no-node-caps.
if X is a n:premeno-menopasue and X is a n:no-node-caps then X is a n:no-irradiat.	if X is a n:premeno-menopasue and X is a n:no-node-caps then X is a n:no-irradiat.
if X is a n:premeno-menopasue and X is a n:inv_nodes_equal_0-2 then X is a n:no-irradiat.	
if X is a n:premeno-menopasue and X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.	
if X is a n:inv_nodes_equal_0-2 and X is a n:deg-malig-2 then X is a n:no-node-caps.	if X is a n:inv_nodes_equal_0-2 and X is a n:deg-malig-2 then X is a n:no-node-caps.
if X is a n:no-node-caps and X is a n:deg-malig-2 then X is a n:inv_nodes_equal_0-2.	if X is a n:no-node-caps and X is a n:deg-malig-2 then X is a n:inv_nodes_equal_0-2.
if X is a n:left-breast and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.	if X is a n:left-breast and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.
if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast then X is a n:no-recurrence-events.	
if X is a n:menopasue-ge40 and X is a n:inv_nodes_equal_0-2 then X is a n:no-node-caps.	
if X is a n:menopasue-ge40 and X is a n:no-node-caps then X is a n:inv_nodes_equal_0-2.	
if X is a n:inv_nodes_equal_0-2 and X is a n:right-breast then X is a n:no-node-caps.	
if X is a n:no-node-caps and X is a n:right-breast then X is a n:inv_nodes_equal_0-2.	
if X is a n:left-breast and X is a n:no-recurrence-events then X is a n:no-node-caps.	
if X is a n:premeno-menopasue and X is a n:inv_nodes_equal_0-2 and X is a n:no-irradiat then X is a n:no-node-caps.	
if X is a n:premeno-menopasue and X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps then X is a n:no-irradiat.	
if X is a n:premeno-menopasue and X is a n:no-node-caps and X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.	
if X is a n:left-breast and X is a n:no-recurrence-events then X is a n:no-irradiat.	
if X is a n:inv_nodes_equal_0-2 and X is a n:left-breast and X is a n:no-recurrence-events then X is a n:no-node-caps.	
if X is a n:no-node-caps and X is a n:left-breast and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.	

if X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps and X is a n:left-breast then X is a n:no-recurrence-events.	
if X is a n:menopasue-ge40 and X is a n:no-irradiat then X is a n:no-node-caps.	
if X is a n:menopasue-ge40 and X is a n:no-node-caps then X is a n:no-irradiat.	
if X is a n:premeno-menopasue and X is a n:no-recurrence-events then X is a n:no-node-caps.	
if X is a n:deg-malig-2 and X is a n:no-irradiat then X is a n:no-node-caps.	if X is a n:deg-malig-2 and X is a n:no-irradiat then X is a n:no-node-caps.
if X is a n:no-node-caps and X is a n:deg-malig-2 then X is a n:no-irradiat.	if X is a n:no-node-caps and X is a n:deg-malig-2 then X is a n:no-irradiat.
if X is a n:right-breast and X is a n:no-irradiat then X is a n:no-node-caps.	
if X is a n:no-node-caps and X is a n:right-breast then X is a n:no-irradiat.	

TABLE 5
ENTAILMENT FROM REASONER ASSOCIATION RULES WITH MINIMUM SUPPORT 0.3

Entailment	ACE If-then
Every inv_nodes_equal_0-2 is a no-irradiat that is a no-node-caps .	If X is a n:inv_nodes_equal_0-2 and X is a n:no-irradiat then X is a n:no-node-caps .
Every no-irradiat is an inv_nodes_equal_0-2 that is a no-node-caps .	If X is a n:no-irradiat and X is a n:inv_nodes_equal_0-2 then X is a n:no-node-caps .
Every no-node-caps is an inv_nodes_equal_0-2 that is a no-irradiat .	If X is a n:no-node-caps and X is a n:inv_nodes_equal_0-2 then X is a n:no-irradiat .



(a) (b)

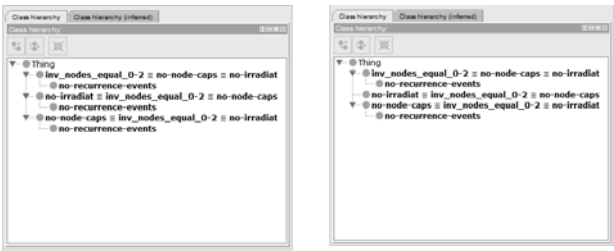
Figure 5 Ontology from association rule mining on one dataset (a) and association rule mining on multiple dataset (b) with minimum support 0.3

TABLE 6
COMPARATIVE RESULTS OF ASSOCIATION RULE MINING ON MULTIPLE DATASET AND ASSOCIATION RULE MINING ON ONE DATASET WITH MINIMUM SUPPORT 0.5

Original association rules	Combined association rules
if X is a n:inv_nodes_equal_0-2 then X is a n:no-node-caps.	if X is a n:inv_nodes_equal_0-2 then X is a n:no-node-caps.
if X is a n:no-node-caps then X is a n:inv_nodes_equal_0-2.	if X is a n:no-node-caps then X is a n:inv_nodes_equal_0-2.
if X is a n:no-irradiat then X is a n:no-node-caps.	if X is a n:no-irradiat then X is a n:no-node-caps.
if X is a n:no-node-caps then X is a n:no-irradiat.	if X is a n:no-node-caps then X is a n:no-irradiat.
if X is a n:inv_nodes_equal_0-2 then X is a n:no-irradiat.	
if X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.	if X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.
if X is a n:inv_nodes_equal_0-2 and X is a n:no-irradiat then X is a n:no-node-caps.	if X is a n:inv_nodes_equal_0-2 and X is a n:no-irradiat then X is a n:no-node-caps.
if X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps then X is a n:no-irradiat.	if X is a n:no-node-caps then X is a n:no-irradiat.
if X is a n:no-node-caps and X is a n:no-irradiat then X is a n:inv_nodes_equal_0-2.	if X is a n:no-irradiat and X is a n:inv_nodes_equal_0-2.
if X is a n:no-recurrence-events then X is a n:no-node-caps.	if X is a n:no-recurrence-events then X is a n:no-node-caps.
if X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.	if X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.
if X is a n:no-recurrence-events then X is a n:no-irradiat.	
if X is a n:inv_nodes_equal_0-2 and X is a n:no-recurrence-events then X is a n:no-node-caps.	if X is a n:inv_nodes_equal_0-2 and X is a n:no-recurrence-events then X is a n:no-node-caps.
if X is a n:no-node-caps and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.	if X is a n:no-node-caps and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.
if X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:no-node-caps.	if X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:no-node-caps.
if X is a n:no-node-caps and X is a n:no-recurrence-events then X is a n:no-irradiat.	if X is a n:no-node-caps and X is a n:no-recurrence-events then X is a n:no-irradiat.
if X is a n:no-node-caps and X is a n:no-irradiat then X is a n:no-recurrence-events.	
if X is a n:inv_nodes_equal_0-2 and X is a n:no-recurrence-events then X is a n:no-irradiat.	if X is a n:inv_nodes_equal_0-2 and X is a n:no-recurrence-events then X is a n:no-irradiat.
if X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.	if X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.
if X is a n:inv_nodes_equal_0-2 and X is a n:no-irradiat then X is a n:no-recurrence-events.	
if X is a n:inv_nodes_equal_0-2 and X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:no-node-caps.	if X is a n:inv_nodes_equal_0-2 and X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:no-node-caps.
if X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps and X is a n:no-recurrence-events then X is a n:no-irradiat.	if X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps and X is a n:no-recurrence-events then X is a n:no-irradiat.
if X is a n:no-node-caps and X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.	if X is a n:no-node-caps and X is a n:no-irradiat and X is a n:no-recurrence-events then X is a n:inv_nodes_equal_0-2.
if X is a n:inv_nodes_equal_0-2 and X is a n:no-node-caps and X is a n:no-irradiat then X is a n:no-recurrence-events.	

TABLE 7
ENTAILMENT FROM REASONER ASSOCIATION RULES WITH MINIMUM SUPPORT 0.5

Entailment	ACE If-then
Every no-recurrence-events is a no-irradiat .	If X is a n:no-recurrence-events then X is a n:no-irradiat .
Every inv_nodes_equal_0-2 is a no-irradiat that is a no-node-caps .	If X is a n: inv_nodes_equal_0-2 and X is a n: no-irradiat then X is a n:no-node-caps .
Every no-irradiat is an inv_nodes_equal_0-2 that is a no-node-caps .	If X is a n:no-irradiat and X is a n:inv_nodes_equal_0-2 then X is a n:no-node-caps .
Every no-node-caps is an inv_nodes_equal_0-2 that is a no-irradiat .	If X is a n:no-node-caps and X is a n:inv_nodes_equal_0-2 then X is a n:no-irradiat .



(a) (b)

Figure 6 Ontology from association rule mining on one dataset (a) and association rule mining on multiple dataset (b) with minimum support 0.5

TABLE 8
COMPERATIVE RESULTS OF NUMBER OF RULES FROM ONE DATASET AND NUMBER OF RULES FROM MULTIPLE DATASET

Minimum support	Number of rules from one dataset	Number of rules from multiple dataset
0.3	65	37
0.5	24	19

V. Conclusion

Association rule mining from large dataset, need a computer with high-performance to process and high cost. There is a technique to help fix this problem is to distribute datasets to be processed by multiple computers. The process combined association rules from distribute datasets take the same association rules and checking the conflict of the association rules.

From such experiments can be seen that association rule mining from multiple dataset with minimum support that many have a closely efficient the association rule mining from one dataset. This consider from ontology and inconsistency association rules, but association rule mining from multiple dataset there is a missing, can be result of reasoned process to fill missing association rules.

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