Multi-Agent Joint Learning from Argumentation

Junyi Xu(✉), Li Yao, Le Li, and Jinyang Li

Science and Technology on Information Systems Engineering Laboratory,
National University of Defense Technology, Changsha, China
xujunyi0923@163.com

Abstract. Joint learning from argumentation is the idea that groups of agents with different individual knowledge take part in argumentation to communicate with each other to improve their learning ability. This paper focuses on association rule, and presents MALA, a model for argumentation based multi-agent joint learning which integrates ideas from machine learning, data mining and argumentation. We introduce the argumentation model Arena as a communication platform with which the agents can communicate their individual knowledge mined from their own datasets. We experimentally show that MALA can get a shared and agreed knowledge base and improve the performance of association rule mining.

Keywords: Argumentation · Data mining · Association rule · Multi-agent learning

1 Introduction

With the rapid development of data mining and knowledge discovery technology, people can get potential knowledge in large amount of data through data mining techniques. However, the knowledge gained by mining is too lengthy and jumbled, so it is difficult for users to filter and apply the knowledge in problem solving. As an important branch of data mining, association rule mining also has this bottleneck in practical application. In order to solve this problem, some researchers have integrated argumentation theory in artificial intelligence with data mining technology to improve the quality of data mining [1,2].

As the experience knowledge mined by individual Agent is incomplete and maybe defective, thus Multi-Agent Joint Learning or agent mining [12] can optimize the experience knowledge to obtain high-quality experience rules for groups to share. From the perspective of joint learning, this paper attempts to apply argumentation theory to distributed association rule mining problem using the idea of "joint learning from argumentation" and proposes an argumentation based multi-agent learning approach MALA. Our experiments show that: argumentation-based joint learning method can effectively achieve reasonable knowledge assessment and optimization in association rule mining and enhance the quality of data mining.

L. Cao et al. (Eds.): ADMI 2013, LNAI 8316, pp. 14–25, 2014.
DOI: 10.1007/978-3-642-55192-5_2,

The paper is organized as follows. Section 2 provides a quick overview of related work. Section 3 formally proposes the new idea of "joint learning from argumentation". Next, Sect. 4 presents MALA-Arena, a model of multi-agent joint learning from argumentation using Arena. After that, Sect. 5 introduces a dialectic analysis model Arena which is used for multi-agent argumentation in MALA. Finally, Sect. 6 presents an experimental evaluation of our model. The paper closes with conclusions.

2 Related Works

Recent years, a number of different approaches have been proposed to integrate argumentation and machine learning. Governatori and Stranieri investigate the feasibility of KDD in order to facilitate the discovery of defeasible rules for legal decision making [3]. In particular they argue in favor of Defeasible Logic as an appropriate formal system in which the extracted principles should be encoded in the context of obtaining defeasible rules by means of induction-based techniques.

The idea that argumentation might be useful for machine learning was discussed in [4], since argumentation could provide a sound formalization for both expressing and reasoning with uncertain and incomplete information. Since the possible hypotheses induced from data could be considered an argument, and then by defining a proper attack and defeat relation, a sound hypotheses can be found.

Ontan and Plaza in [5] research concept learning, and put forward a multi-Agent inductive learning framework A-MAIL, which integrates inductive learning, case-based reasoning and argumentation theory. In this framework, Multi-Agent Inductive Learning consists of three stages: individual induction; argumentation process; and belief revision. The proposed method is different from ours. In A-MAIL, each Agent just use argumentation based inductive learning to revise their own knowledge and multi-Agent system do not form a shared knowledge base. Moreover, A-MAIL focus-es on inductive learning while MALA focuses on association rules.

Maya proposes argumentation from experience in [6], and combines argumentation theory with data mining techniques. Agent gets association rules as their arguments in the library of their own experience through data mining. PADUA argumentation model is designed to achieve two party argumentation processes and resolve uncertainties classification problems. Later, PISA model is designed in [7] in order to solve the multi-classification problem. However, PISA has complicated strategy and complex argumentation process, so that the model does not have general applicability. Subsequently, the concept of collaborative group of Agents is proposed for arguing from experience in [8].

In order to enhance the versatility of PISA, Maya simplifies the speech acts and removes a complex strategy in argumentation in [9]. The improved model can be used to solve the following problem in classification: multi-agent classification, ordinal classification and imbalance classification. Although the simplified model improves the versatility, its classification accuracy is decreased.

In this paper, Multi-Agent joint learning from the argumentation model MALA is different from PISA model. PISA model focuses on classification problem and its goal is to improve the classification accuracy through multi-Agent argumentation, while the purpose of MALA is to realize knowledge sharing in distributed data mining. Argumentation in PISA is driven by the target of classification while MALA is driven by association rule.

3 Joint Learning from Argumentation

As guided by the "Knowledge spiral" model, this paper will apply argumentation theory to distributed association rule mining issues and propose a new method of "joint learning from argumentation". This section briefly describes the principle of the method.

3.1 A Knowledge Spiral Mode

Nonaka designed a knowledge spiral model (see Fig. 1) in knowledge management area [10]. The knowledge spiral shows how organizations extract shared explicit knowledge from individual tacit knowledge. Organizations develop tools and models to accumulate and share knowledge from individuals. The knowledge spiral is a continuous activity of knowledge flow, extraction, and sharing by individuals, groups, and organizations. Knowledge spiral starts at the individual level and moves up to the organizational level through expanding communities of interaction. Nonaka argues that an organization has to promote a facilitating context in which the organizational knowledge-creation process can easily take place. Learning jointly from argumentation can achieve the organizational knowledge-creation process.

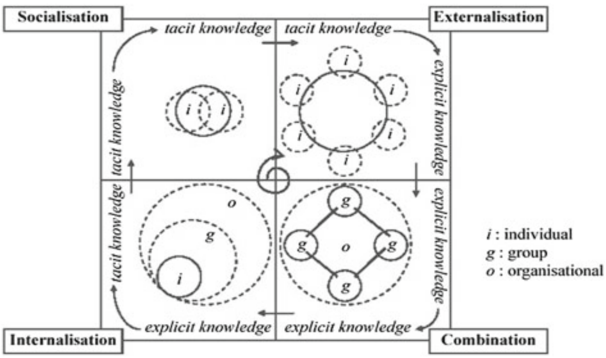

Fig. 1. The knowledge spiral model [10]

From the knowledge spiral model we can find: Individuals with the same task in an organization can obtain group knowledge with consensus through mutual communication. These common knowledge as explicit knowledge will further enhance the individuals' ability to solve new tasks. Then new individual knowledge will be exchanged again to form higher quality consensus knowledge, so as to achieve further knowledge sharing and application. Knowledge spiral model indicates the mutual transformation of individual knowledge and group knowledge, explicit knowledge and tacit knowledge, as well as spiral development process of knowledge evolvement.

3.2 An Approach to Joint Learning from Argumentation

In Multi-agent system, the local knowledge of single Agent is limited; as a result their problem-solving ability is limited. In order to effectively organize and optimize knowledge of multi-agent system to enhance the overall capacity of multi-Agent system, we need to optimize and share individual knowledge. However, individual Agent has different knowledge, and such knowledge is likely tacit, which led to difficulties in knowledge extraction and sharing.

In response to the problem, this paper proposes the idea of joint learning from argumentation (Multi-Agent Learning jointly from Argumentation, MALA) guided by "Knowledge spiral" model. MALA method divides the learning process into three stages: the individual association rule mining, multi-agent argumentation and the group knowledge extraction, as shown in Fig. 2.

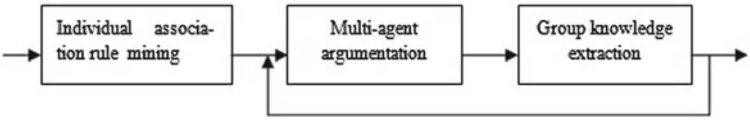

Fig. 2. Learning process in MALA

In the stage of individual association rule mining, each Agent first perform the ex-tended association rule mining in local experience dataset, and form the local experience Knowledge Base in the form of Experience Argument Schema (EAS) [11]. Through data mining technology, we can find the potential knowledge of individuals and realize externalization of tacit Knowledge in individual Agent, and use EAS to represent experience knowledge.

In the stage of Multi-agent argumentation, we use argumentation techniques to achieve mutual learning between Agents. For the same case, Agent uses EAS as the main form of the argument on argumentation platform to express their views and to communicate and compare their local experience knowledge with the other Agents. Through argumentation, experience knowledge of high quality with consensus can be formed. So argumentation model can provide a platform for Multi-Agent System to communicate and discuss individual experience knowledge. Agents can analysis and discuss a specific topic to reach the consensus.

In the stage of Knowledge extraction, the outcome of argumentation is clearly represented to form the shared explicit knowledge, and stored in the shared global knowledge base. In the following argumentation, each Agent will use shared know-ledge and local experience knowledge to argue.

The method of "joint learning from argumentation" can effectively merge the local experience knowledge of individual Agent: Individual Agent can realize the function of individual knowledge externalization by association rule mining; through the process of multi-Agent argumentation, individual Agents with different knowledge can interact and communicate with each other so as to reach consensus, and realize the transformation of individual knowledge into organizational knowledge; Ultimately, the shared knowledge of multi-Agent System further guide individuals of following problem solving and continue accumulation and refinement to form the spiral evolution process.

4 Realizing MALA Using ARENA

According to the above approach of joint learning from argumentation, we design a model of multi-agent joint Learning from Argumentation using Arena, called MALA-Arena.

In MALA-Arena, multi-agent system first performs association rule mining on distributed datasets and individual Agents form their independent local knowledge bases. Given a set of Agent $A = \{A_1, \ldots, A_m\}$, acquisition of Agents local knowledge is built on the basis of association rule mining. Each Agent A_i has a separate example dataset $D = \{d_1, \ldots, d_n\}$. In order to achieve a unified knowledge form, each Agent A_i uses the same association rule mining algorithm in each example dataset, and takes the support and confidence measure to assess the pros and cons of association rules. By association rule mining, each Agent forms their local knowledge base EAS. Agent's local knowledge base can be expressed as a set of Experience Argument Schema (EAS) $EAS = \{eas_1, \ldots, eas_n\}$.

There are inconsistencies between datasets D_i of each Agent which result in inconsistent knowledge in each Agents local knowledge bases EAS_i. In order to effectively integrate the inconsistent knowledge, we can use the method of multi-Agent argumentation. On this basis, we design a multi-agent argumentation model Arena, which transforms the multi-party argumentation process into two-party argumentation processes to achieve assessment and screening of association rules. To a specific topic t_i, Agent can use their own Experience Argument Schema (EAS) on the Arena to construct arguments and attack relations to argue with other Agents. After the end of argumentation, the main argument of winner becomes the valuable knowledge k_i.

For the valuable knowledge k_i get from the current argumentation, multi-agent system needs feedback. According to the correct classification result of current case t_i, system will determine whether the valuable knowledge is consistent with the correct result. If the result is consistent, the valuable knowledge k_i will be stored in the global knowledge base K; Otherwise, Multi-Agent

System will discard the knowledge. Through a large number of training cases, Multi-Agent System can accumulate a focused set of association rules by using "learning from argumentation" and eventually form a shared global knowledge base $K = \{k_1, \ldots, k_n\}$.

The main process of MALA-Arena is as follows:

1. Agent A_i gets local knowledge base EAS_i by association rules mining on his own dataset D_i. Knowledge in local knowledge base is in the form of Experience Argument Schema (EAS);
2. For a specific input case t , each Agent uses their own EAS to generate argument eas_i in the current argumentation on Arena;
3. After the end of current argumentation, multi-agent system can get a valuable rule k;
4. Feedback process: to determine whether the current case t can be correctly classified by the valuable rule k according to the known result of classification;
5. If correctly classified, the valuable rule k will be stored in the global knowledge base K as a multi-agent shared knowledge; if classification is not correct, it means this rule is flawed, not to join the global knowledge base;
6. Repeat the learning process 2–5, and the shared knowledge in the global knowledge base K continue to accumulate, eventually converge to a stable state.

The brief algorithm of MALA-Arena is as follows:

```
Algorithm  MainControl of  MALA-Arena
Input: Training Set T
For each(Ai)do
EASi = Associasion_Rule_Mining(Di);
While (ti in T) do // there are still other input data
k = Arena(ti, EAS) //argumentation in Arena
{ Broadcast ti;
  Get_Participants (Qp); // getting participants from queue of
  Agents
  Initial (grid of dialectical analysis trees);
  For each participant Pi do
    Propose_Argument (Pi, easi);
    Change the speak token;
  End for
  If Pi == silence then
    select next participant Pi+1;
  end if
  If only Pi == active then
    Pi == winner;
    Return (k);
  End if
} // The argument game is over
```

```
bool i = Verify(k, ti);
if i == true then
  Add_To_Knowledge_Base(k);
else if i == false then
//do nothing
End if
End while
K = Get_Knowledge_Base();
Return (K);
Output: Knowledge base K
```

5 Argumentation Model Arena

Arena is a dialectic analysis model for multiparty argument games (more details in [11]). In Arena, we designed four roles: Referee, Master, Challenger and Spectator. In Arena, all the arguments between the Master and the Challenger are about the association rules. The whole process of argumentation is stored in the grid of dialectic analysis trees.

In Arena, the Referee doesn't participate in argumentation but manages the argumentation process according to the dialogue rules of Arena. And there can be only one Master and one Challenger to take part in the argumentation, while other participants are not allowed to speak when they are just Spectator.

The Referee is a neutral agent which manages a variety of tasks to facilitate multi-party dialogues from experience. It has following responsibilities: Starting a dialogue; Identifying the roles of Master, Challenger, and Spectator along with the change of the game situation; Monitoring the dialogue; Maintaining the dialectic analysis tree to reflect the moves made by the masters or the challengers; Terminating the dialogue once a termination condition is satisfied; Announcing the games winner, his opinion and the valuable experience rule.

Participant Agents can produce arguments in form of Experience Argument Schema EAS from local knowledge base. Suppose that x represents the case under discussion. EAS is defined as follows: Conclusion: $w(x)$; Premises: $l_1(x), l_2(x), \ldots, l_n(x)$; Confidence: c; Conditions: $u_1(x), u_2(x), \ldots, u_s(x); \neg v_1(x), \neg v_2(x), \ldots, \neg v_t(x)$; Exceptions: $e_1, \ldots, e_k$. Such argument schema for experience can be read as follows: In my experience, if anything x doesnt belong to $\{e_1, \ldots, e_k\}$, with features $u_1, u_2, \ldots, u_s$ and not with features $v_1, v_2, \ldots, v_t$, then x with features $l_1, l_2, \ldots, l_n$, are Ws (or have feature W) with probability c.

In Arena, all the participating agents will play a role of Master, Challenger and Spectator. During an argumentation, the participating agents need to compete for Master or Challenger continually with his own set of EASs. Once Master and Challenger are identified, the agents can use one of the six speech acts, which collectively form the basic building blocks for constructing Master-Challenger dialogues in Arena.

In Arena, there are also six speech acts in Arena: ProposeOpinion, Distinguish, Counter Rule, BeInapplicable, BeAnException, and Defeated. These speech acts fall under three basic types: stating a position, attacking a position and conceding defeated, as follows (Table 1):

Table 1. Speech acts in Arena

Type	Speech acts	Content
Stating position	ProposeOpinion	Proposing the opinion about the case under discussion according to a new EAS with highest confidence from his local knowledge
Attacking position	Distinguish	Addition of new premise(s) to a previously proposed EAS, so the confidence of the new rule is lower than the original one
	CounterRule	Using a new EAS with higher confidence to attack the conclusion or the confidence of the adversarys EAS
	BeInapplicable	Stating that the EAS of the adversarys argument is inapplicable to this case in his own knowledge
	BeAnException	Stating that the case under consideration is an exception of the EAS in his own knowledge
Conceding defeated	Defeated	Stating that the player concedes defeated

At the beginning of the argumentation, the Referee broadcast the discussion topic, and the first agent who proposes its opinion about the current topic becomes the Master of Arena. All the other participants whose option is different from the Master can challenge the Master and form the queue of challengers, and the first participant in the queue is selected to be the Challenger of Arena. All the other participant agents except Master and Challenger are Spectator of Arena.

Noted that during the argumentation the Spectator can apply for Master or Challenger at any moment, and the Referee just put its argument in the application queue. Since the defeated argument of the old Master cant be used to apply for Master again, the old Master may produce another argument for the instance under discussion, and uses this new argument to apply for Master once more. In addition the defeated Challenger has no chance to challenge the same Master again.

If the Master is defeated by the Challenger, this Challenger will become the new Master, and he can propose his opinion about the current topic from his own knowledge base. All the other participants decide whether or not to challenge this new option. Otherwise, if the Challenger is defeated, the next participant in the queue is selected to be the Challenger, and the argumentation between

Master and Challenger continues. If the Master can defeat all the challengers, the Master wins the argumentation and the Masters association rule will be considered a valuable rule.

There is a termination condition: the queue of Challenger is empty or Master is empty. When Master isn't empty, the Match has a winner. Otherwise, the Match is tie. Since the number of the arguments produced by a participant is finite and the defeated arguments cant be allowed to use repeatedly, the termination of the game is thus guaranteed (Fig. 3).

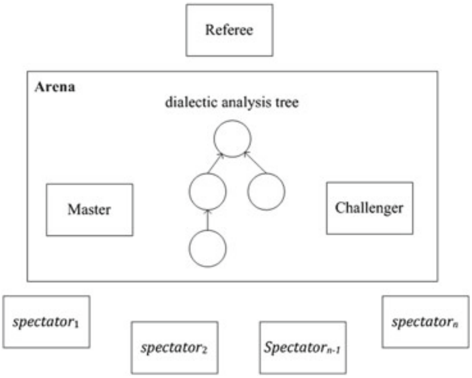

Fig. 3. The basic structure of Arena model

6 Experiments

In order to empirically evaluate MALA-Arena we use three machine learning data-sets: nursery, scale and Tie-Tac-Toe from the UCI Machine Learning Repository[1]. The nursery dataset contains 12960 examples belonging to 5 different classes. The scale dataset contains 625 examples belonging to 3 different classes. The Tie-Tac-Toe dataset contains 958 examples belonging to 2 different classes. In the experiment, we use 4 Agents to take part in MALA-Arena. And all records of each datasets are divided into four parts equally, which belongs to four Agents respectively. We use Agent1, Agent2, Agent3 and Agent4 to represent these agents. Each Agent produces his association rules in the form of EAS with the confidence level to 50 % and the support level to 1 % using Apriori-TFP data mining Algorithm [13].

To evaluate MALA-Arena, we used 10 fold cross validation (TCV) test on each dataset. In an experimental run, we use the training set to form the sharing knowledge base, which will be evaluated using the test set. For each dataset, we report the average results for each group of TCV test.

We compared the results of MALA-Arena with respect to the result of centralizing all the examples and performing centralized association rule mining algorithm TFPC [14]. Thus, the difference between the results of TFPC

[1] UCI machine learning repository: http://archive.ics.uci.edu/ml/datasets.

and agents using MALA-Arena with Apriori-TFP should provide a measure of the benefits of MALA-Arena, whereas comparing with centralized association rule mining algorithm gives a measure of the quality of MALA-Arena outcome. Table 2 shows a row for each of the data sets we used in our evaluation. Performance is measured using accuracy in classification. Analyzing the results in Table 2 we can see that accuracy of MALA-Arena is more than 80 %, while TFPC is below 70 %. MALA-Arena can greatly increase the accuracy over the TFPC algorithm in three datasets. This shows that MALA-Arena successfully integrates argumentation and association rule mining, and allows agents to learn highly accurate knowledge without requiring the centralization of all data.

Moreover, from Table 3 we can see that the number of valuable rules generated by MALA-Arena is much smaller than the number of association rules mined by individual Agents from their own example bases. The average number of rules in knowledge base generated by MALA-Arena is almost lower than 100, while there are thousands of rules of each Agent in nursery and Tie-Tac-Toe datasets. So MALA-Arena can be a filter to control the size of knowledge from association rule mining and increase the quality of knowledge base.

Table 2. Accuracy of MALA-Arena and TFPC in different datasets

Accuracy	Nursery (%)	Scale (%)	Tie-Tac-Toe (%)
MALA-Arena	94	81.1	86.2
TFPC	63.53	65.26	60.96

Table 3. Number of association rules (ARs) of different knowledge bases in different datasets

Number of ARs	Agent1	Agent2	Agent3	Agent4	MALA-Arena
Nursery	1769	1802	1765	1781	79.5
Scale	318	297	280	295	102.7
Tie-Tac-Toe	9238	9590	9346	9396	70.3

In summary, we can conclude that MALA-Arena successfully achieves multi-agent joint learning from argumentation, since performance is outstanding from the TFPC approach. Moreover, this is achieved extract a small size of knowledge from individual Agents to get a high accuracy. Additionally, on average, the number of rules of MALA-Arena is much lower than that of individual Agents, which is interesting since it could be used to improve the quality of data mining, by distributing the task among several agents, later arguing about their local knowledge and finally forming a focused sharing knowledge base.

7 Conclusion

In this paper, we have proposed the theory of joint learning from argumentation which provides a new way to evaluate and share the knowledge mined from different databases and demonstrates a fact that a combined analytical and inductive machine learning method could overcome the pitfalls in each separate approach.

This paper has presented MALA, an approach to Multi-Agent Learning jointly from Argumentation. The key idea is that argumentation can be used as a formal learning framework to exchange and discuss the local knowledge learnt by agents using association rule mining. In our experiments, we designed and realized MALA-Arena. Multi-agent joint learning from argumentation is performed by three processes: individual association rule mining, multi-agent argumentation and know-ledge extraction. The results of experiments reveal MALA-Arena has an effective capability in learning from argumentation and the final sharing knowledge from MALA-Arena can perform well. Finally, our approach is focused on association rule mining, and future work aims at other data mining methods to integrate in the model for joint learning from argumentation.

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