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Layered MIML Structure Used in Complicated System

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Abstract. In this paper, we presented an improved learning frame based on MIML structure, which is combined with feedback mechanism. In real-world, there are many problems mentioned in complicated systems, traditional multi-instance multi-label structure would only consider the initial and fianl state, when facing with much more complicated system, the lack of middle decision layer affect the whole capability of system. The new proposed structure-MD-MIML frame will help us to solve these task more easily by layered MIML with reward machanism. Finally, we use RoboCup Simulation 2D as platform to verify our frame and algorithms, the result shows the frame presented is valid and well-performed.

Keywords: Multi-instance learning, Multi-label learning, Multi-instance Multi-label learning

1. Introduction

Machine learning[1] bases on the research of how computer enhances the performance of system automatically by accumulating the experience, which involve Artificial Intelligence, Probability Statistic, computational complexity, philosophy, psychics, genetics and neurophysiology, etc. With the rapid development of the application in machine learning, it becomes more mature and wide in recent 20 years. Especially in computer-assisted medical diagnoses, biologic informatics, computational finance, net security and so forth. Machine learning is a forceful tool for various researches during the steps such as observation, hypothesis, validation and conclusion[2].

Instance is a main form when machine learning focus on experience data, an instance describes the character of an object, e.g. a vector of color denotes one picture. Traditional machine learning would be divided into both supervised learning and unsupervised learning by the training instance labeled or not: supervised learning, with the labeled training instance, aiming at inducing the conception of label from training sample, then predicting the label of unseen instance exactly; while, unsupervised learning means to discover the inside structure of instance without the labeled one. The extensive usage of machine learning makes it various when facing at actual problems, some of which neither belong to supervised learning, nor unsupervised learning. Considering the fuzzy extent of the label for training instance, we separate machine learning simply into these structures besides supervised and unsupervised learning: Semi-supervised learning, Multi-instance learning, Multi-label learning, Reinforcement learning, Active learning[7,20].

2. Related Work

As mentioned before, when solving problems by machine learning algorithms, normally we extract feratures of this object first, by using a feature vector describes the object, later on, we reach the instance. After associating it and the label of this object, we get an example[3].

2.1. Traditional Supervised Learning

In this learning, every training instance owns only one label, the mission of learning is to associate each single instance with single label. Obviously, let X denote the instance space (or feature space) and Y denote

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of class labels. Then the task is to learn a function f: X→Y from a given data set {(x_1, y_1), (x_2, y_2), …, (x_m, y_m)}, where $x_i \in X$ is an instance and $y_i \in Y$ the known label of x_i. Figure 1 shows the traditional supervised learning[3,4,5]. (single-instance single-label learning).

2.2. Multi-instance Learning

Although the formation above works well in some small scale problems, many actual situations refer to a number of instances and the same labels simultaneously. Dietterich et al.[6] came up with multi-instance learning when they were investigating the problem of drug activity prediction. In multi-instance learning, the training set is composed of many bags each contains many instances. A bag is positively labeled if it contains at least one positive instance; otherwise it is labeled as a negative bag. The task is to learning some concept from the training set for correctly labeling unseen bags[3,4,5,6].

Fig 1. Traditional Supervised Learning

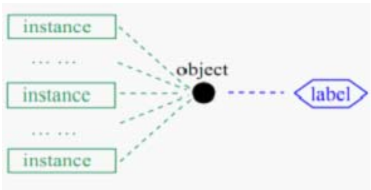

Fig 2. Multi-instance Learning

Formally, the task of MIL is to learn a function fMIL:2^X→{-1,+1} from a given data set {(X_1,y_1), (X_2,y_2) ,…,(X_m,y_m)}, where $X_i \in X$ is a set of instances {$x_1^{(i)}$,$x_2^{(i)}$,…,$x_{ni}^{(i)}$}, $x_j^{(i)} \in X$ (j=1,2…,ni), $y_i \in$ {-1+1} is the label of X_i[4]. Multi-instance problem extensively exist in real-world application[9], but this uniqueness problems have not been particularly distinguished until Dietterich et al.[6,7,8]. Nowadays, multi-instance learning techniques have been successfully applied to diverse applications including scene classification[7,8]. Musky problem is one of the application of multi-instance learning[6]. By the same research, Maron[10] used this algorithm into other multi-instance problems, like stock choose in finance investment fields.Ruffo[11] achieved data mining by MIL; Antrews[12], Huang[13], Yang[14], Zhang[15], respectively applied MIL in imagine retrieve; Chevaleyre[16] also researched Mutagenesis problems by MIL. All these applications and researches point out that the MIL works significatively truly in unseen promiscuous problems with multi-instance features[17].

2.3. Multi-label Learning

Multi-labeled learning[18] studies the problem where a real-world object described by one instance is associated with a number of class labels[4]. For instance, in text categorization, each document may belong to several predefined topics, like government and health(Mc Callum 1999;Schapire&Singer 2000); in functional genomics, each gene may be associated with a set of functional classes, such as metabolism, transcription and protein synthesis(Elis-seeff&Weston 2002); in scene classification, each scene image may belong to several semantic classes, such as beach and urban(Boutell et al.2004). When solving these multi-label learning problems, each example (a real-world object) in the training set is represented by a single instance associated with a set of labels, and the task is to output a label set whose size is unknown a priori for the unseen example[9].

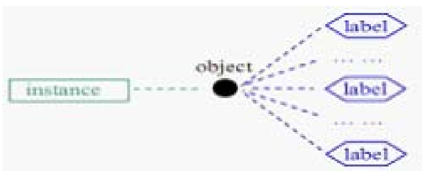

Fig 3.Multi-label Learning

Formally the task of MLL is to learn a function f_{MLL}: $X \rightarrow 2^y$ from a given data set $\{(x_1,Y_1),(x_2,Y_2),\ldots,(x_m,Y_m)\}$, where $xi \in X$ is an instance and $Yi \in Y$ is a set of labels, $\{y_1^{(i)},y_2^{(i)},\ldots,y_{li}^{(i)}\}$, $y_k^{(i)} \in Y$ (k=1,2…,li). Figure 3 shows the structure of multi-label learning[3,4].

It is substantially shown that multi-label learning deals with ambiguous objects, especially which have different semantic meanings simultaneously if they are viewed differently. Previous approaches to multi-label learning mainly include decomposing the task into multiple independent binary classification problems each for a class(Joachims1998; Yang1999), considering the ranking quality among labels (Schapire & Singer2000; Crammer& Singer 2002; Elisseeff &Weston 2002; Zhang &Zhou 2006) and exploring the class correlation (McCallum1999; Ueda & Saito 2003; Ghamrawi & McCallum 2005; Yu, Yu, & Tresp2005; Zhu et al. 2005; Liu, Jin. & Yang2006)[9].

2.4. Multi-instance Multi-label Learning

In real-world, each object always dose not own only semantic meaning,but something multi-meanings. Figure 4 gives a picture which denotes 'elephant', on the contrary, we can also regard it as 'lion', 'grass', even 'tropic', 'Africa', which are semantic meanings concluded from the picture. Because of these multi-semantic meanings, it is not explicit to express a picture with multi-semantic meanings as an only single learning structure. Zhou[3] indicated that in order to solve these multi-vocal problems, first finding the 'proper' meaning from the 'might be' ones, then ensuring the 'exist' meaning by context-sensitive conditions. In a word, this measure just considers a proper label set as a corresponding set of instances. Zhou[3] proposed Multi-label Multi-instance learning which based on explicit sets of instances and labels[3,4,5].

The task of MIML is to learn a function f_{MIML}:$2^X \rightarrow 2^Y$ from a data set $\{(X_1,Y_1),(X_2,Y_2),\ldots,(X_m,Y_m)\}$, in which $X_i \in x$ denote a set of instances $\{x_{i1},x_{i2},\ldots,x_{ni}\}$, $x_{ij} \in x$, (j=1,2,ni), where $Y_i \in Y$ is a set of proper labels $\{y_{i1},y_{i2},\ldots,y_{ili}\}$, $y_{ik} \in Y$(k=1,2,…,li), meanwhile, ni means the number of instances in X_i, li means the number of labels in Y_i. Figure 5 shows the structure of MIML[3,4,5].

Fig 4. Picture with various meaning

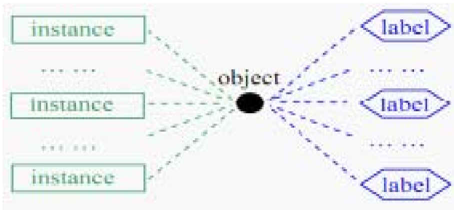

Fig 5. MIML

Zhou presented D-MIMLSVM learning based on regularization because of the degeneration process in MIMLBOOST or MIMLSVM, which may lose information[3,4]. The regularization method utilizes the loss between labels and the predictions on the bags as well as on the constituent instances, meanwhile, it considers the relatedness between the labels associated to the same examples. The general loss function V for MIML setting below [3,4]:

$$v(\{X_i\}_{i=1}^m,\{Y_i\}_{i=1}^m,f)=\frac{1}{mT}\sum_{i=1}^{m}\sum_{t=1}^{T}(1-y_{it}f_t(X_i))+\frac{\lambda}{mT}\sum_{i=1}^{m}\sum_{t=1}^{T}l(f_t(X_i),\max_{j=1,2,\ldots n_i} f_t(x_{ij})) \tag{1}$$

Here, the first part considers the loss between the bag X_i 's label and its corresponding predictions $f(X_i)$, the second part considers the loss between $f(X_i)$ and the prediction of X_i 's constituent instances. By using the idea of [3,4], then the regularized framework for MIML in Eq.2 below:

$$\min_{f\in H}\frac{1}{T}\sum_{t=1}^{T}\|f_t\|_H^2+\mu\left\|\frac{\sum_{t=1}^{T}f_t}{T}\right\|+\gamma V(\{X_i\}_{i=1}^m,\{Y_i\}_{i=1}^m,f) \tag{2}$$

Where the γ is a regularization parameter that balance the model complexity and the empirical risk, and the μ is a parameter to trade off the discrepancy and commonness among the labels[3,4].

3. MD-MIML With Reward Frame

Focusing on the solutions of MIML algorithms, each improved algorithms mentioned before are all aimed to solve ambiguity of input space or outputs space, i.e. imagine retrieve and text retrieve. Recently, application in distance metric from MIML data and gene expression pattern annotation have been researched much. Each learning method is based on actual problems of huge input and output space. While, these learning algorithms only focus on established instances and labels, and there is no mid-labels between them. In complicated systems, we find the relation between instances and labels are quite changeful, by which means an instance can be a label for next cycle of MIML structure. To solve the various situations concretely, we proposed an improved learning frame with several known MIML structures. By the combining design, each cycle of MIML has an evaluating system, which is focus on improving the whole learning frame, which is as shown below in Figure 6.

In Figure 6, it is a simple frame of MD-MIML with reward. With this design, we use feedback mechanism to measure the initial multi-instance multi-label learning. By evaluating, some changes make sense in the next cycle of multi-instance multi-label learning. It helps much in complicated system in order to use the last labels to improve the whole system. In MD-MIMLSVM with reward learning,

we use MIML learning algorithm based on regularization strategy mentioned, D-MIMLSVM[3,4,5], The steps of new algorithm listed below:

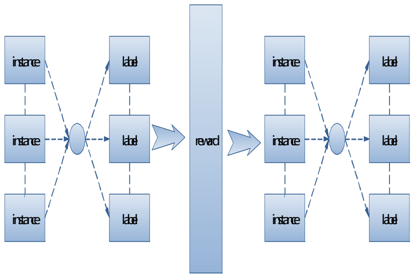

Fig 6. MD-MIMLSVM with Reward

- Step 1: Initial the first group of instances and labels.
- Step 2: Use the D-MIMLSVM to give the proper label for each instance.
- Step 3: Give the judgement fo Step 2,and tailor the mapping of each instance-labels to assessing by system reward structure.
- Step 4: Make sure the next cycle's intsnace by foregoing labels, a new MIML frame is made up of these new pairs of instances and labels.
- Step 5: Use the method mentioned in Step 2,and assess the new mapping of new instances and labels.
- Step 6: Back to Step 3 until it matches the demand of the system.

4. Application Of New Learning Frame

We use RoboCup 2D as the platform to verify the MD-MIMLSVM with reward. RoboCup 2D is a sort of simulation for football game used in computer between each team designed by people. This 2D simulation is under Linux environment with platform server developed by RoboCup committee. In this game, each team has 11 players in the field, and the field absolutely accords to the real game scene. Being a dynamic environment in the match, each client controls only one agent which means one player and all his behaviors are included, the goal of each team is consistent, which should be done by all agents, so in Robocup, we consider it as a multiple agent system[19].

In RoboCup, the track of that ball will be determined by the situation of player who holds it, and the situation of his teammate who is ready to catch the ball, meanwhile, the strength and angle used to the ball will also make sense. Partially, some players that hold ball will not choose to pass ball because it is more available for him to dribble. Therefore, which situation would be safer or more dangerous for these players? When a player holding ball falls into the more dangerous situation,what would be the best choice? All these problems introduce to our new algorithms,which use multi-instance multi-label ideas to judge the dangerous parameters for players first, then training the best action according all these dangerous parameters.

Fig 7. RoboCup 2D simulation

First in RoboCup, we training the players for a function fMIML: $2^X \rightarrow 2^Y$ by data set $\{(X_1,Y_1), (X_2,Y_2), \ldots, (X_m,Y_m)\}$, in which the X denotes the players while Y denotes the dangerous zone parameters which determined from 0.0 to 1.0, and 1.0 means razor-edge. In fact, each player point to a proper dangerous parameter, as Figure 8 shows the dangerous parameter for red player 5, the value is almost closes to 1.0, while for green player 4 or 8, the dangerous parameter is almost 0.0. The reason for dangerous parameter is that the distance between the player and self-goalie, the number of opponent player nearby, the number of teammate nearby, etc. We quantitate the interrelated factors to predict each label(dangerous parameters) for instances(players) using D-MIMLSVM ideology under the direction of Figure 8.

After the prediction of dangerous parameter, we can check the instance-label pair by empirical analysis, as mentioned above, the dangerous parameter lies on several essences, i.e. the number of teammates or opponent players, the distance between the player and self-goalie, etc. Assuming the effective practice, the experiential function of instance-label will be decided as below:

$$f_i(x) = \tau \sum_{\gamma} \left\| \varepsilon \sum_{m} l_o - \delta(\gamma \sum_{n} l_s + \lambda l_g) \right\|_{\gamma=0}^{R} \tag{3}$$

in which, the l0 denotes the distance between player i and opponent players, ls denotes to the distance between the player i and teammate, lg denotes to the distance between player i and self-goalie, and m, n denote to the number of teammates and opponent players corresponding to reasonable radius by r; meanwhile the τ, ε, δ, γ, λ denote to discounted parameters.

Considering the difference between label from MIML and Eq.3, we should readjust the label using the idea of Qsim[21], in this method, we get the difference of label first, marked as △fi , the last labeled dangerous parameter will be determined as:

$$f_L = \frac{\Delta f_i}{f_i(x) + f(x)} f_i(x) \bullet f(x) \tag{4}$$

Using Eq.3 and 4 to estimate the instance-label pair, and modifying some potential error might comes from the first round of MIML. Then use the predetermined labels as the instances for the second round of MIML.In RoboCup, after getting the dangerous parameters, each player should take actions in order to assure the situation in the field available for self-side, so in the second round of MIML,we would like to get the dangerous parameter-action pair, whatever action will be chosen, we can conclude to passing, dribbling, and running; each action will get the proper angle, strength, etc. With the introduction above, finally we get the instructional action for each player.

5. Expriment

We use TiJi as the experiment team to verify the algorithm useful. To materialize the contrast, we set a team which use the D-MIMLSVM (aims at learning the player-action pair independently) learning called TiJi_D, while another team called TiJi_MD which uses the learning frame mentioned above(MD-MIMLSVM with reward).

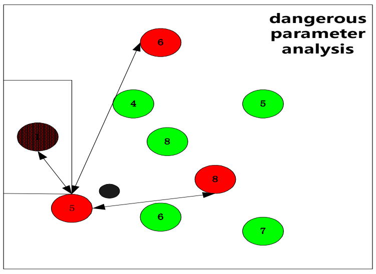

Fig 8. Analyse the dangerous parameter

Table 1 score between each team

Game	Conclusion the score		
	TiJi_MD&TiJi	TiJi_D&TiJi	TiJi_MD&TiJi_D
5th	4:0	3:1	3:2
15th	4:1	3:3	5:2
25th	6:1	5:1	6:1
35th	7:3	4:2	5:1
45th	5:3	1:0	2:2

First in order to conclude the matches among each team, and weaken the error by random match, we choose the score every other 10 games from the 5th game, as Table 1 below. Deriving to the matches above, we conclude the average rate of error for each player of TiJi_MD, TiJi_D and TiJi team, just as Figure 9.In the end, we use the three teams(TiJi_MD, TiJi_D, TiJi) match against UvA team(world champion in 2002&2003), conclude the rate of controlling ball for each team as Figure 10.

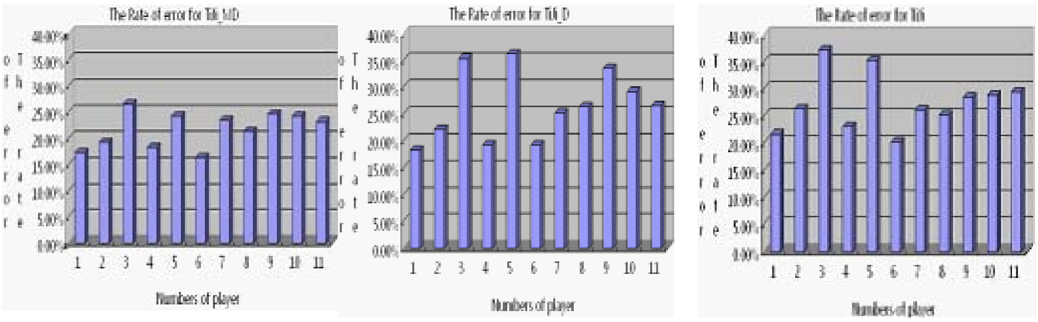

Fig 9. Conclude the rate of error for each team.

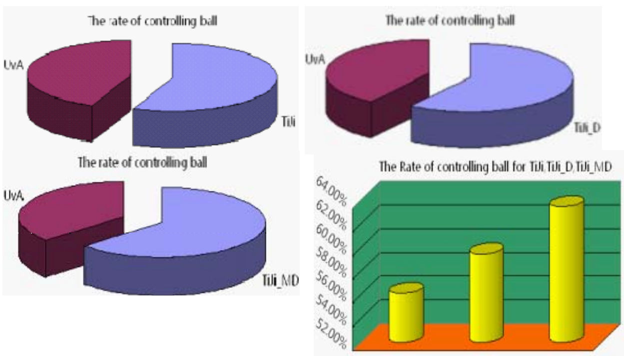

Fig 10. the rate of controlling ball for each team

According to the result of examination above, we discover the team using new frame played better than any other teams. Although we did not use the academic illation, the proposal of MD-MIML with reward solved the complicated problem at a certain extent, and improved the new team of RoboCup.

6. Conclusion

The MD-MIML frame presented in the paper figured out some huge systems with complicated decision. Its satisfying performance proved the availability of new algorithm. This proposal decomposed complicated system into several problems like multi-instance multi-label frame, using the reward of each structure to integrate the whole problem easily and conveniently. The examples in section 5 proved its efficiency, and the platform give us the new aspect domain to apply MIML thought. In further research, we will prove this frame using theoretic discursion and improve MIML frame convincingly, meanwhile, it is necessary to prove this new investigated frame universal for mostly complicated systems. What's more, the improvement of MIML algorithm will attract many researchers, next step we will also focus on the advanced algorithms in this domain.

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