MULTIPLE INSTANCE LEARNING TECHNIQUES FOR MULTIMEDIA DATA MINING AND THEIR APPLICATIONS

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Abstract
Instance Learning (MIL) is schemed as a reformation of supervised learning for problems with insufficient knowledge about labels of training examples. In supervised learning, every single training instance is assigned with a detached or real-valued label. In multi-instance learning, the training set includes labeled bags that consist of unlabeled instances, and the job is to predict the labels of undiscovered bags. This paper exhibits different multiple-instance learning based approaches to deal with mining unstructured data such as text and imagery. Initially, it introduces the evolution of multi-instance learning. Then, growth on the study of learnability, learning algorithms and applications. In particular, this paper addresses a unified view to look into multiple instance learning algorithms.

Index Terms – Bag, Instance, Label, Multi-Instance Learning, Instance, Multimedia Data, Multimedia Data Mining

I. INTRODUCTION

The phrase multi-instance learning was discovered by Dietterich et al. [1] when they were analyzing the problem of drug activity prediction. In multi-instance learning, the training set comprise of numerous bags, each contains various instances. The labels are only attached to bags of instances. In the binary case, a bag is labeled positive if at least one instance in that bag is positive, and the bag is labeled negative if all the instances in it are negative. Although the labels of the training bags are aware, however, the labels of the instances in the bags are undefined. The aim is to construct a learner to learn some concept from the training set for correctly classifying undiscovered bags as shown in Fig.1.

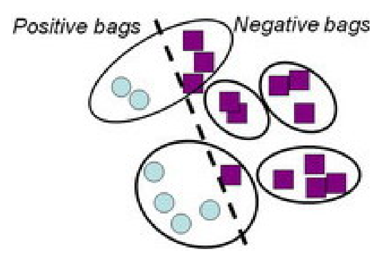

Figure 1. The concept behind multiple instances learning

Multi-instance learning has been found useful in several fields such as image categorization [2][3], image retrieval [4] , text categorization [5][6].

II. MIL APPLICATIONS

This section outlines the applications of MIL techniques, in addition to drug activity prediction, text categorization, image retrieval and classification.

A. Drug Activity

The first application of multiple-instance learning was to drug activity prediction. In the activity prediction application, one objective is to predict whether a candidate drug molecule will bind strongly to a target protein known to be involved in some disease state. Typically, one has examples of molecules that bind well to the target protein and also of molecules that do not bind well. Much as in a lock and key, shape is the most important factor in determining whether a drug molecule and the target protein will bind. However, drug molecules are flexible, so they can adopt a wide range of shapes. A positive example does not convey what shape the molecule took in order to bind – only that one of the shapes that the molecule can take was the right one. However, a negative example means that none of the shapes that the molecule can achieve was the right key.

B. Image set Classification

Image categorization is one of the most successful applications of multi-instance learning. Images are viewed as bags, each of which contains a number of instances corresponding to regions obtained from image segmentation. The standard MIL problem assumes that a bag is labeled positive if at least one of its instances is positive; otherwise, the bag is negative.

C. Text Classification

For text classification, documents are represented as bags and instances correspond to short passages (e.g., paragraphs) in the documents. A document is considered positive if at least one part of the document is related to the subject.

D. Classification of dementia in brain MRI

Multiple instance learning (MIL) method is used in an application for the detection of Alzheimer's disease (AD) and its prodromal stage mild cognitive impairment (MCI) [12].

E. Content-Based Image Retrieval

Content-Based Image Retrieval is another domain where the MIL representation has been used. In this domain, the task is to find images that contain objects of interest, such as tigers, in a database of images.

F. Object Tracking

Tracking generic objects has remained very challenging. Object tracking has many practical applications (e.g. surveillance, HCI) and has long been studied in computer vision. To implement such a tracker, an MIL algorithm is required.

III. METHODS

Many multi-instance learning methods have been developed during the past decade.

A. Diverse Density (DD)

The main idea of DD[7] approach is to find a concept point in the feature space that are close to at least one instance from every positive bag and meanwhile far away from instances in negative bags. The optimal concept point is defined as the one with the maximum diversity density, which is a measure of how many different positive bags have instances near the point, and how far the negative instances are away from that point.

B. Expectation-Maximization version of Diverse Density (EM-DD)

EM-DD [8] starts with an initial guess of the concept point *t* (which can be obtained using original DD algorithm), and then repeatedly performs the following two steps: in E-step, the current hypothesis of concept *t* is used to pick the most likely instance from each bag given a generative model; in M-step, a new concept *t'* is estimated by maximizing a transformed DD defined on the instances selected in the E-step using the gradient search. Then, the old concept *t* is replaced by the new concept *t'* and the two steps are repeated until the algorithm converges. This EM-DD algorithm implements a "hard" version of EM, since only one instance per bag is used for estimating the hypothesis. It can be also regarded as a special case of the K-means clustering algorithm, where only one cluster is considered. By removing the noise-or (or a "softmax") part in the original DD algorithm, EM-DD turns a multi-instance problem into a single-instance one, and thus greatly reduces the complexity of the optimization function and the computational time.

C. MI-Winnow

MI-Winnow [9] which combines the multiple instance problem with Winnow. This approach uses the training data to filter the instances from the positive bags to determine which ones are most likely to be truly positive since those are the instances that produce best results

D. MILES (Multiple-Instance Learning via Embedded instance Selection)

MILES [10] maps each bag into a feature space defined by the instances in the training bags via an instance similarity measure. This feature mapping often provides a large number of redundant or irrelevant features. Hence, 1-norm SVM is applied to select important features as well as construct classifiers simultaneously.

E. Mi-SVM and MI-SVM

Two maximum margin multiple-instance learning methods, mi-SVM and MISVM, based on support vector machines have been proposed in [11], mi-SVM for instance-level classification and MI-SVM for bag-level classification. The mi SVM explicitly treats the instance labels in positive bags as unobserved hidden variables subject to constraints defined by their bag labels. In comparison, the MI-SVM aims to maximize the bag margin, which is defined as the margin of the most positive instance in case of positive bags, or the margin of the least negative instance in case of negative bags.

F. MIGraph and miGraph

The MIGraph [13] method explicitly maps every bag to an undirected graph and uses a new graph kernel to distinguish the positive and negative bags. The miGraph method implicitly constructs graphs by deriving affinity matrices and defines an efficient graph kernel considering the clique information.

G. MIForests: Multiple-Instance Learning with Randomized Trees

MIForests [14] defines the labels of instances inside positive bags as random variables and use a deterministic-annealing style procedure in order to find the true but hidden labels of the samples.

IV. Experiments

The above MIL approaches are evaluated on the standard data sets namely MUSK1, MUSK2, TREC9 data and Corel image data. Table 1 shows the performance comparison of the MIL approaches.

Table 1. Classification Accuracy (%) on benchmark tasks

Algorithm	**Musk 1**	**Musk 2**	**Text Categorization**	**Corel Images**
MIGraph	90	90.0	-	85.1
miGraph	88.9	90.3		86.8
MISVM	77.9	84.3	93.9	74.7
miSVM	87.4	83.6	93.5	82
DD	88.0	84.0	-	81.5
EM-DD	84.8	84.9	85.8	78.3

V. CONCLUSIONS

In this paper, we study several popular MIL methods for multimedia data analysis and their applications. Experiments conducted were able to obtain very good results across a variety of data sets. Some MIL algorithms are consistently superior to their supervised counterparts. Its continued success however depends on the significance and popularity of the applications where MIL stands out as the primary choice.

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