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Neighborhood rough sets based multi-label classification for automatic image annotation

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ABSTRACT

Automatic image annotation is concerned with the task of assigning one or more semantic concepts to a given image. It is a typical multi-label classification problem. This paper presents a novel multi-label classification framework MLNRS based on neighborhood rough sets for automatic image annotation which considers the uncertainty of the mapping from visual feature space to semantic concepts space. Given a new instances, its neighbors in the training set are firstly identified. After that, based on the concept of upper and lower approximations of neighborhood rough sets, all possible labels of the given instance are found. Then, based on the statistical information gained from the label sets of the neighbors, maximum a posteriori (MAP) principle is utilized to determine the label set for the given instance. Experiments completed for three different image datasets show that MLNRS achieves more promising performance in comparison with to some well-known multi-label learning algorithms.

1. Introduction

Nowadays, we are faced with a plethora of images. As the images databases grow in size and number, a large body of research has been carried out to explore effective and efficient image retrieval (IR) approaches. In general, IR research pursuits can be categorized into three main areas [1]. In the first area, we are concerned with traditional text based image retrieval (TBIR) where the images are annotated manually by human. However, manual image annotation is time-consuming and expensive. Then the research focuses on the content-based image retrieval (CBIR) [2], where images are retrieved based on content features such as color, shape and texture. However, recent research has shown that there is a significant semantic gap between low-level content features and high-level semantic concepts. To bridge the semantic gap, the IR research has been shifted to semantic-level approaches [3,4], where the images are annotated with semantic labels based on the automatic image annotation (AIA) technology and then can be retrieved by keywords similar to TBIR.

With much effort devoted to semantic-level image retrieval, automatic image annotation has started drawing more attention [5–10]. Previous main approaches towards automatic image annotation modeled the learning problem as machine translation [5,6], correlations learning tasks [7,8]. In addition, some other researches regarded the automatic image annotation as multi-label classification problem [9,10] for the reason that an image could be related to more than one semantic concept simultaneously. However, the previously mentioned methods suffer from some limitations. First, most of these approaches

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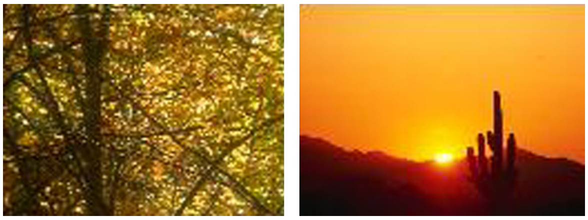

Fig. 1. Examples of multi-label images.

are based on a strong assumption that the visual similarity guarantees semantic similarity which is in conflict with the semantic gap. In fact, two images with the similar visual contents may correspond to quite different semantic concepts. Taking Fig. 1 for example, an autumn scene and a sunset scene may share some warm, bright colors. Therefore there is confusion between the two scenes in the feature space when the color features are used. Second, they ignore the impact from the limited quantity of the training instances which leads to inexact distribution of each class during the process of classification. For these reasons, there exists some uncertainty in the mapping of visual feature space to semantic concepts space.

Rough sets form a vehicle to deal with the ambiguous, vague, and uncertain knowledge. In order to reduce the bias between visual similarity and semantic similarity, we propose a multi-label classification framework based on the neighborhood rough sets, named MLNRS. By introducing the concept of upper and lower approximations of neighborhood rough set model, the framework can find all the possibly related labels of the given instance and then confirm the final labels according to the information of the neighborhood of the given instance. Empirical results using three image annotation data sets suggest that the proposed approach can improve the performance and reduce the training time compared with other standard multi-label algorithms.

The rest of this paper is organized as follow. Sections 2 and 3 provide background material on multi-label classification and neighborhood rough sets respectively. Section 4 introduces the proposed approach. Section 5 contains experimental results obtained by applying our algorithms and other multi-label learning algorithms to multi-labeled scene classification. Finally Section 6 concludes this work and points to future research direction.

2. Multi-label classification

Multi-label classification [11] is a supervised learning problem that an instance may be associated with multiple labels. This is different from the traditional single-label classification tasks [12]. In single-label classification tasks, an instance is only associated with one label and the classes are mutually exclusive by definition. Let Γ be the domain of the instances to be classified, Y be a finite set of labels and H be the set of the classifiers for $X \to Y$. The goal of the single-label classification task is to find the classifier $h \in H$ for each given instance $x \in X$ by maximizing the probability of $h(x) = y$, i.e. $y = \arg\max_i P(y_i|x)$. While in multi-label classification tasks, the base classes are non-mutually exclusive and may overlap in the selected feature space. As before, let X be the domain of the examples to be classified and L be the finite set of labels. Now let Y be a set of binary vectors, each of length $|L|$. Each vector $y \in Y$ indicates membership in the base classes in $L(1 = \text{member}, 0 = \text{non-member})$. H is the set of classifiers for $X \to Y$. The goal of the multi-label classification task is to output a classifier $h \in H$ which optimizes the specific evaluation metric (e.g., Hamming loss) for $h(x) = y$.

2.1. Learning algorithms

Multi-label classification algorithms can be categorized into 2 different groups [11]: (i) problem transformation methods and (ii) algorithms adaptation methods. The first group includes methods that are algorithm independent. They transform the multi-label problem into one or more single-label problems. The representative transformation method include binary relevance method (BR) [9,13,14], binary pairwise classification approach (PW) [15] and label combination or label power-set method (LC) [16,17]. BR transforms a multi-label problem into multiple binary problems. Each binary model is trained to predict one label; Classifier Chain (CC) [18] is a BR-based methods which can overcome the label-independent defect while maintaining the acceptable computational complexity of BR. PW can also be used to address multi-label problem, where a binary model is trained for each pair of labels; LC transforms a multi-label problem into a single-label problem by treating all label sets as atomic labels. The second group includes methods that extend specific learning algorithms in order to handle multi-label data directly. Well-known approaches include Adaboost [19], decision trees [20], and lazy methods [21–24]. Adaboost.MH and Adaboost.MR [19] are two extensions of Adaboost for multi-label classification. Comité et al. [20] extended the alternating decision tree learning algorithm for multi-label classification. ML-*k*NN [21] is an adaptation of the *k*NN lazy learning algorithm for multi-label data. In ML-*k*NN, in order to assign a set of label to an instance, a decision is made separately for each label by taking into account the number of neighbors containing the label to be assigned. ML-*k*NN fails to take into account the dependency between labels, while DML*k*NN [22] considers the dependencies between classes. In order to decide whether a particular label should be included among the unseen instance's labels, DML*k*NN takes into