Incremental Attribute Learning based on KNN

Ting Wang, Sheng-Uei Guan and Zhihong Wang

Abstract—**Incremental Attribute Learning (IAL) has been treated as an applicable approach for solving high-dimensional classification problems, and it has been successfully applied in many other predictive algorithms, like Neural Networks (NN), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO). So far, it is not employed for K Nearest Neighbor (KNN), another very popular algorithm in pattern classification. Therefore, in this paper IAL is attempted to be used with KNN. Experiments based on some benchmarks showed that such an approach can works very fast and the results are also acceptable.**

***Index Terms*—Incremental Attribute Learning, KNN, Pattern Classification, Discriminative Ability**

I. Introduction

In machine learning, high-dimensional problems will cause dimensional disasters that may cause systems halt in computing. To solve these problems, some dimensional reduction strategies like feature selection and feature extraction have been presented [1, 2]. However, these methods are invalid when the problem has a large number of features and all the features are crucial with similar importance in the problem simultaneously. Thus feature reduction is not the ultimate technique for coping with high dimensional problems.

One useful strategy for solving high-dimensional problems is “divide-and-conquer”, where a complex problem is firstly separated into some smaller modules by features. These modules will be integrated after they have been tackled independently. A representative of such methods is Incremental Attribute Learning (IAL), which incrementally trains pattern features in one or more size. It has been shown as an applicable approach for solving machine learning problems in regression and classification using Genetic Algorithms (GA) [3, 4], Neural Networks (NN) [5, 6], Support Vector Machines (SVM) [7], Particle Swarm Optimization (PSO) [8], Decision Tree [9], and so on. These previous studies also have shown that IAL can exhibit better performance than conventional methods which prefer to train all pattern features in one batch. For example, based on machine learning repository from University of California, Irvine (UCI)[10], Guan and his colleagues employed IAL to solve some classification and regression problems by neural networks. Almost all their results were better than those derived from conventional methods [4, 11], where the classification errors of IAL using neural network in the datasets of Diabetes, Thyroid and Glass were reduced by 8.2%, 14.6% and 12.6%, respectively [12]. This illustrated that IAL is not a pure algorithm in the training of machine learning, but a predictive strategy which can be implemented by different algorithms for pattern recognition and classification.

However, as a very important pattern classification method, K Nearest Neighbor (KNN) has not been tried for IAL so far, although many other predictive approaches have been widely used in IAL. Therefore, it is necessary for us to attempt KNN in IAL. In the other aspect, because IAL incrementally imports features into systems, it is necessary to know which feature should be introduced in an earlier step. Thus feature ordering should be implemented as an independent preprocess apart from conventional preprocessing tasks like feature selection and feature extraction [13]. Usually, feature ordering relies on feature's discriminative ability. Therefore, when KNN is applied on IAL, the most important thing in feature's preprocessing is to calculate features' discriminative abilities for training sequence.

In this paper, IAL using KNN will be presented, including the feature preprocessing like feature ordering and training. In section 2, a brief introduction of KNN will be given; in section 3, IAL and its preprocessing will be introduced; in the fourth section, the model of KNN for IAL will be presented; then the experiments using benchmarks will be shown in the next section; conclusions will be drawn in the last section.

II. IAL and its Preprocessing

A. IAL

IAL is a “divide-and-conquer” machine learning strategy which gradually trains input features one after another. There are two main objectives for implementing such a novel approach. One is to solve easy problems at the early stage of the process. Due to the fact that each feature has a different ability in classification for different output, IAL aims to, firstly, solve easy pattern recognition problems by using several corresponding features and, secondly, leave difficult problems to the next round using some other different features. The other objective is to avoid dimensional disasters. The “divide-and-conquer” character of IAL has the capability to reduce the complexity of computing as not all features will be imported for calculation at the same time. Such a process is effective to avoid the curse of

Manuscript received January 8, 2018; revised February 10, 2018. This work was supported in part by the China Jiangsu Provincial Department of Science and Technology under Grant BC2016006.

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ISBN: 978-988-14048-8-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

dimensionality in computing where the problem has a high-dimensional feature space. Therefore, as a new approach, IAL not only can cope with problems which can be solved by existing methods, but also applicable for problems which have newly imported features or problems whose number of features is large. Generally, IAL focuses on the input aspect, while the output aspect is concentrated by another similar incremental approach called Hierarchical Incremental Class Learning (HICL) [14-17], which is not a research topic in this study.

A number of experiments and studies have shown that IAL often exhibits better performance than other conventional machine learning techniques that train data in one batch. Based on the datasets of Machine Learning Repository from University of California at Irvine (UCI), Guan et al. employed IAL to solve several classification and regression problems by NN [5, 6, 11, 12, 18-23], PSO [8] and GA [4, 24]. Almost all of their results using IAL were better than those derived from traditional methods. Specifically, based on Incremental Learning in terms of Input Attributes (ILIA) [5] and Incremental neural network Training with an Increasing input Dimension (ITID) [6], two effective algorithms were developed on the basis of IAL, and as a result, classification errors obtained by incremental neural networks for input feature learning of Diabetes, Thyroid and Glass datasets reduced by 8.2%, 14.6% and 12.6%, respectively [6, 18]. Furthermore, based on OIGA, the testing error rates derived by incremental genetic algorithms of Yeast, Glass and Wine declined by 25.9%, 19.4% and 10.8% [3], respectively, in classification. Further, Ang et al. proposed interference-less networks in his paper. He divided features into several groups without interference in the same group. Such an approach led to more acceptable results from the experiments [23].

Moreover, Chao et al. used a decision tree to implement IAL, and presented Intelligent, Incremental and Interactive Learning (i+Learning) and i+Learning regarding attributes (i+LRA) in their paper [9]. These algorithms were employed to run in 16 different datasets supplied by UCI. The results indicated that the algorithms based on IAL performed better than ITI in 14 of the 16 datasets. Furthermore, Agrawal and Bala presented an incremental Bayesian classification approach for multivariate normal distribution data. In their experiments, features are imported one by one into Bayesian classifier. Their experimental results also demonstrates that feature-based incremental Bayesian classifier is computationally efficient over batch Bayesian classifier in terms of time, although both of the results derived by these two methods are equivalent [25]. In addition, successful research on incremental SVM extended IAL to a wider application field [7]. All of these previous IAL studies showed that IAL can indeed improve the performance of pattern recognition. These studies denoted that different feature ordering can exhibit different pattern recognition results and feature ordering is gradually recognized as a formal preprocessing step of IAL.

Recently, IAL has been employed into real-world application. Kankuekul et al. developed a new online incremental zero-shot learning method based on self-organizing and incremental neural networks (SOINN) for applications in robotics and mobile communications. Comparing the conventional method with their proposed approach, this novel approach can learn new attributes and update existing attributes in an online incremental manner in a more effective way [26]. Moreover, Kawewong, A. and O. Hasegawa presented a new approach called Attribute Transferring based on SOINN (AT-SOINN) for learning and classifying object's attribute in an online incremental manner. Comparing with some state-of-the-art methods, AT-SOINN performs a fast attribute learning, transferring and classification while at the same time retaining the high accuracy of attribute classification [27].

IAL is definitely can be implemented based on a number of intelligent predictive methods. The achievements of IAL contribute to the characteristics of this novel machine learning strategy. Compared with other machine learning strategies for pattern recognition, some of these characteristics are similar to the existing methodologies while others are not. For example, there is another well-known “divide-and-conquer” strategy called Incremental Learning (IL), which concentrates on the number increase with respect to training samples [28]. Nevertheless, IAL is different. It focuses on an increase in the number of features. In addition, IAL utilizes features one by one, or group by group, which is different from conventional machine learning techniques that always train data in one batch. Last but not least, apart from feature reduction in preprocessing, IAL has another unique data preparation process called feature ordering that is required for almost all problems solved by IAL.

B. Preprocessing of IAL

Preprocessing is a very important stage for every machine learning algorithm. It can enhance the performance, reduce the problem scales and increase the accuracy. Usually, feature selection and feature extraction are conventional approaches for pattern classification. However, in IAL, features are gradually imported into the training systems, so that the preprocessing of IAL is not the same as conventional algorithms. Apart from feature selection and extraction, feature ordering is also necessary for IAL's feature preprocessing. It will determine which feature should be introduced into training in the first place and which one should be imported later.

In previous studies, features ordering have been researched in many different ways. Features are sorted based on wrappers [6] or filter approaches. In the aspects of filter approaches, statistical correlations[29], entropy[30], Fisher's Linear Discriminant[31] and some other integrated approaches[32-34] are employed for the feature ranking, and features are sorted before it is imported into the training systems. Experimental results shown that these preprocessing approaches for feature ordering can effectively obtain better performance for pattern classification problems. In previous studies ,these algorithms are employed for Neural Networks. Therefore, such a method is used for KNN. Whether it is still feasible for KNN will be verified in this research.

ISBN: 978-988-14048-8-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

III. KNN BASED ON IAL

A. KNN

K Nearest Neighbors (KNN) algorithm is a non-parametric method used for classification, where the input consists of the k closest training examples in the feature space, and the output in classification is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (*k* is a positive integer, typically small). If $k = 1$, then the object is simply assigned to the class of that single nearest neighbor. KNN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The KNN algorithm is among the simplest of all machine learning algorithms.

B. KNN with IAL

IAL preprocessing for KNN is not special but the same as it is used for other pattern classification algorithms, like NN or GA. Therefore, feature preprocessing methods used for other classification problems also can be employed for KNN. This includes feature selection, feature extraction and feature ordering. Moreover, once the training sequence is obtained, KNN will be applied on different dimensions, and maybe different labels will be given to each pattern in different dimensions. The first majority label of the pattern will be regarded as the final result of the classification. This algorithm is named as KNNIAL. Main steps of KNNIAL algorithm has been shown below.

Algorithms of KNNIAL

Step 1. Data Normalization.

Step 2. Feature Ordering is derived from some criteria.

Step 3. Data Transformation according to the ordering.

Step 4. Dataset is divided into training and testing sets.

Step 5. The 1st feature is imported. Select the 1st pattern in testing set, seek the k nearest neighbors of this pattern in training set, mark the 1st pattern with the class label whose quantity is the largest in k patterns.

Step 6. After all patterns are tested with feature 1, all patterns obtain it temporary label derived from feature 1.

Step 7. Continue this operation, until the last pattern in last feature, then all patterns will get a series of labels derived from different features, respectively.

Step 8. Label the pattern with the first majority according to all labels derived from different features.

IV. BENCHMARKS

The proposed KNN with ordered IAL method were tested on three benchmarks from UCI machine learning datasets[10]. They are Diabetes, Cancer, and Thyroid. All of these three datasets are classification problems. In these experiments, all the patterns were randomly divided into two groups: training set (50%), and testing set (50%). Especially, the training data were firstly used to rank features based on Accumulative Discriminability(AD) [32] in the first place as a preprocessing task while KNNIAL was employed for classification according to this feature ordering in the following step. Furthermore, to compare with approaches without using IAL, conventional approaches where features are imported into KNN in one batch are also employed for the comparison. Error rate and the variance of the error rates were employed to evaluate the performance of pattern classification. Especially, the variance is also the symbol for the stability of proposed approach. The following subsections present the details of different experiments using different datasets.

A. Diabetes

Diabetes is a two-category classification problem which has 8 continuous input features that are used to diagnose whether a Pima Indian has diabetes or not. There are 768 patterns in this dataset, 65% of which belong to class 1 (no diabetes), 35% class 2 (diabetes). Table I shows the results in comparison with classification using KNNIAL based on AD feature ordering and the conventional method which has no feature ordering. According to the results, KNNIAL obtained the lowest error rate (23.96%) when the k=5. Moreover, the variance of KNNIAL is 0.0004075, which is much lower than that of conventional KNN, which is 0.0005499. Thus using KNNIAL can obtain a better and more stable result in Diabetes.

B. Cancer

Cancer is a classification problem including 9 continuous inputs, 2 outputs, and 699 patterns, which is used to diagnose breast cancer. 66% of the patterns belong to class 1 (benign) and 34% of them belong to class 2 (malign). Table II shows Cancer's experimental results. By comparison, based on the feature ordering derived from AD, KNNIAL in this test obtained better results when k=5 and k=7, where the classification error rate is 1.15%. Although conventional KNN also obtained a 1.15% in error rate when k=3, but the variance of KNNIAL is 0.0000303 and that of conventional KNN is 0.0000521, which showed that KNNIAL is more stable than the conventional method.

C. Thyroid

Thyroid diagnoses whether a patient's thyroid has over-function, normal function, or under-function based on patient query data and patient examination data. This classification problem has 21 inputs features, 3 outputs, and 7200 patterns, where class 1, 2 and 3 have 2.3%, 5.1% and 92.6% of all the patterns, respectively. Table III presents the classification results of Thyroid dataset, where the KNN based on IAL was using the feature ordering derived from AD. Compared with the error rate of conventional KNN, KNNIAL exhibited better performance, where the lowest error rate of the former is 6.22% (k=3 and k=5) and that of the latter is 3.28% (k=1 and k=3), and the variance of the former is 0.0000141 and that of the latter is 0.0000027. Such a result shows that KNNIAL is much better than conventional KNN.

TABLE I
RESULTS OF DIABETES

	Feature Ordering	Classification Error
KNNIAL (AD)	2-6-7-8-5-4-1-3	28.65%(k=1) 25.00%(k=3) **23.96%(k=5)** 25.52%(k=7) **VAR: 0.0004075**
KNN Conventional method		30.21%(k=1) 25.52%(k=3) 25.52%(k=5) 25.52%(k=7) VAR: 0.0005499

TABLE II
RESULTS OF CANCER

	Feature Ordering	Classification Error
KNNIAL (AD)	3-2-6-7-5-1-8-4-9	1.72%(k=1) 2.30%(k=3) **1.15%(k=5)** **1.15%(k=7)** **VAR: 0.0000303**
KNN Conventional method		2.87%(k=1) **1.15%(k=3)** 1.72%(k=5) 1.72%(k=7) VAR: 0.0000521

TABLE III
RESULTS OF THYROID

	Feature Ordering	Classification Error
KNNIAL (AD)	21-18-19-15-20-17-13-7-12-5-4-8-3-9-16-6-14-1-11-10-2	**3.28% (k=1)** **3.28% (k=3)** 3.50% (k=5) 3.61% (k=7) **VAR: 0.0000027**
KNN Conventional method		7.00%(k=1) 6.22%(k=3) 6.22%(k=5) 6.33%(k=7) VAR: 0.0000141

V. CONCLUSIONS AND FUTURE WORK

In this paper, KNN based on IAL is presented for pattern classification. Different from conventional KNN which imports features in one batch, KNNIAL introduces features one by one according to the feature ordering based on some preprocessing feature ranking method. Experimental results using UCI benchmarks show that KNNIAL based on AD feature ordering can not only obtain lower classification error rates with different datasets, but also exhibit more stable performance than the conventional KNN. The reason why KNNIAL performs better than conventional KNN is that features with greater Discriminability are reused again and again in KNNIAL, where their weights in IAL is heavier than those with small Discriminability. In addition, KNN works faster than some other predictive methods, like Neural Networks or Genetic Algorithms. Therefore, KNNIAL is an efficient approach for fast solutions of pattern classification.

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ISBN: 978-988-14048-8-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)