Modeling Human Activity Recognition by Dimensionality Reduction Approach

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Abstract

Human activity recognition (HAR) is a very hot research topic in computer vision nowadays. Recently, numerous application (HAR) systems and approaches have been proposed. The prediction in human mobility using big data however still remains a challenge to the classification problem. This is mainly due to the huge variations, such as growing information amount and high dimensionality of data, the difficulty in modeling the precise relationship between the large number of feature variables, and the class variable. In such cases, it is highly desirable to reduce the information to a small number of dimensions in order to improve the accuracy and effectiveness of the classification process. Nevertheless, the performance of (HAR) is not high enough yet. This paper aims at improving the performance of human mobility modeling and mining by employing dimension reduction based on statistical techniques. The developed method has been applied on a new and publicly available human activities dataset. The obtained results are effectively interpreted, and the efficacy of the suggested method over the well-known methods is discussed.

Keywords: Dimension Reduction, Classification, Human Activity Recognition.

1. Introduction

With the rapid aging of the population, a reflection emerged around the technology providing practical solutions to the needs of the elderly, for home care, with enhanced safety and improved quality of life. Shares of recognition-based technologies arouse more interest because of their effectiveness. The tracking behavior and, specifically, the person's ability to perform everyday activities are important to detect the entry into dependence of the person and detect risky situations.

Human activity recognition generally comprises a step of extracting primitives and a classification step. The extraction of primitives is to identify distinctive characteristics while being robust to noise. In the classification stage, we are interested in the possibility of identifying the actions using machine learning methods, taking into account the variability that a class action may be exposed, especially if performed by different subjects and different kind of size and speed and different way.

Classification, one of the popular human activity recognition, has been applied in many areas of human decision-making. A number of methods and algorithms have been developed for human activity recognition problems, including statistical models, decision and regression trees, rules, connectionist networks, probabilistic networks. Supervised classification forms the core of what has been recently called the data mining. The methods originated in statistics in the early nineteenth century, under the Moniker discriminant analysis. The applications of supervised classification in real life are very vast, like human activity recognition, automatic speech recognition, face detection, signature recognition, customer discovery, spam detection, systems biology etc.

Nevertheless, in the last decades, the interest in the dimensionality of many classification problems has increased. Much of human activity recognition problems have provided results of high dimensionality, along with a substantially growing trend. One of the major current challenges concerning many classical classification algorithms is, dealing with large high dimensional data. At this stage, some of the increase in dimensionality, where the number of variables or features (p) and the number of samples (n) are greater, can affect the performance of classification algorithms. Examples of datasets include text data, speech data and digital images often have thousands of features and hundreds of thousands or millions of objects. This makes it difficult or even impossible to apply supervised classification methods (e.g., logistic regression, discriminant analysis).

A general framework is therefore suggested for the structural (HAR) problem that can be formulated for dimension reduction and class prediction. This framework will be applied on a new and publicly available human activities dataset, and the obtained results will be interpreted and discussed.

2. Background

Among the branches of computer sciences, human activity recognition, artificial intelligence, and data mining are the branches which are related to each other and to statistics and mathematics. Their goal is to allow computers to perform tasks involving learning or reacting to data.

2.1. Human activity recognition

Computer vision is an exciting topic of research to develop the computer systems analysis and interpretation the visual capabilities of a scene close contents to those of human vision. One of the major objectives in computer vision is to recognize and understand human mobility, in order particularly to define the classification of human activities.

2.2. Dimension Reduction

The problem of dimensionality reduction can be defined by assuming that we have dataset represented in a $n \times p$ matrix 'y' consisting of n datavectors $y_{i_{(i \in \{1,2,\ldots,n\})}}$ with dimensionality 'p'. Assume further that this dataset has intrinsic dimensionality 'k' (where$k < p$, and often $k \ll p$). Here, in mathematical terms, intrinsic dimensionality means that the points in dataset 'y' are lying on or near a manifold with dimensionality 'k' that is embedded in the p-dimensional space. Dimensionality reduction techniques transform dataset 'y' with dimensionality 'p' into a new dataset 'x' with dimensionality

'k', while retaining the geometry of the data as much as possible. In general, neither the geometry of the data manifold, nor the intrinsic dimensionality 'k' of the dataset 'y' are known. Therefore, dimensionality reduction is an attention-demanding problem that can only be solved by assuming certain properties of the data (such as its intrinsic dimensionality).

2.2.1. Dimension Reduction based Sliced Inverse Regression (SIR)

A parametric regression model describes the relationship between a dependent variable $y \in \mathbb{R}$ and a predictor $x \in \mathbb{R}^p (p \gg 1)$ with $\mathbb{E}(x) = \mu$ and $\mathbb{V}(x) = \Sigma$ of the form:

$$y = f_\theta(x) + \varepsilon,$$

Where 'f_θ' belongs to a family of functions parameterized by 'θ' (vector parameters real) and 'ε' is a random error term. In this type of model, the ultimate goal is to estimate the parameter 'θ'.

The parametric estimation techniques (methods of maximum likelihood and least squares for example) are efficacies when the family 'f_θ' is correctly specified. However, in many applications, highlighting a suitable parametric model is not simple. Also, when a parametric model is not available, the nonparametric regression techniques appear as an alternative, providing the desired flexibility in modeling. In that case, the above mentioned relation is transformed into:

$$y = f(x) + \varepsilon \ ,$$

Functional regression is based on a local smoothing that utilizes the properties of continuity and differentiability of the regression function 'f'. The quality of the local smoothing at a point, therefore, depends on the presence of sufficient data in the vicinity of this point. When the variable is univariate ($p = 1$), we can mention among others the method cores or smooth splines. However, when the dimension of 'x' becomes large, the number of observations required for the local smoothing grows exponentially with dimension. So unless you have a huge sample size, these nonparametric methods are no longer appropriate due to the low number of points in the region of interest.

To overcome this problem known as the "curse of dimensionality" some methods for dimension reduction suppose that 'x' can be replaced by a vector of dimension 'k', strictly less than 'p', without losing information on the conditional distribution of 'y' at given 'x'. The corresponding model assumes dependency between the predictors, and the response variable is described by linear combinations of predictors.

2.3. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis or (LDA) method is a statistical discriminative way. Let the probability that an element with measurement vector 'y' belongs to group 'g' is $P(g_i|y)$.

We consider the set of distributions $\{P(g_1|y), P(g_2|y), \ldots, P(g_N|y)\}$ which are multivariate normal distributions $N(\mu_i, \Sigma_i)$ with the common variance:

$$\Sigma_1 = \Sigma_2 \ = \ \ldots = \ \Sigma_N = \Sigma \ ,$$

Each element is classified into the group 'g_i' where the posterior probability $P(g_i|y)$ that it is a member of that group, given its value of y, is the largest. (LDA) applies Bayes formula to evaluate $P(g_i|y)$ using $P(y|g_i)$ and the prior probability $P(g_i)$. This posterior probability is calculated using Baye's rule as: $\mathrm{p}(g_i|\mathrm{y}) = \frac{\mathrm{p}(y|ig_i)\mathrm{p}_i}{\sum_{k=0}^{N}\mathrm{p}(y|g_j)\mathrm{p}_k}$, Where '$p_k$' is the prior probability that a case is a member of group 'k'.

3. Methods

A general framework is suggested for the structural (HAR) problem that can be formulated for dimension reduction and class prediction. Under this framework, our procedure consists of two basic steps (Fig 1): the first step is dimension reduction, in which data are reduced from higher p-dimensional vectors space to a lower k -dimensional factor space. The second step is the construction of learned model for human activity prediction, in which response classes are predicted using a class prediction method on the extracted factors.

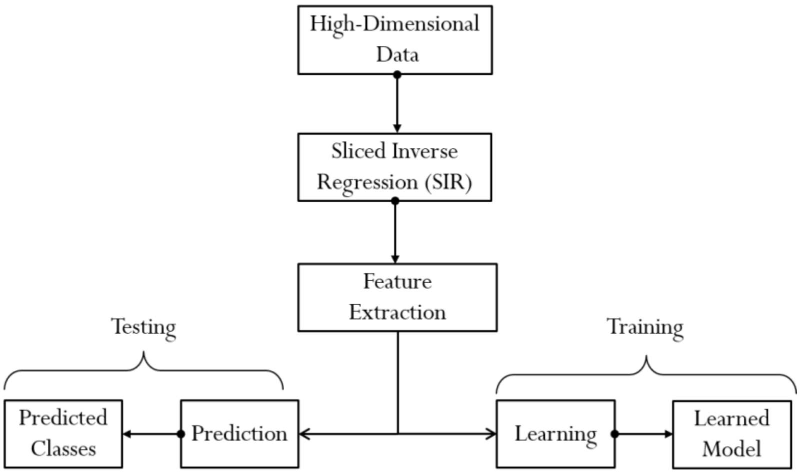

Fig 1: A dimensionality reduction framework (HAR)

3.1. Dataset and Preprocessing

The established algorithms are applied to a publicly available dataset 'Human Activity Recognition Using Smartphones Data Set'. HAR-database built from the recordings of 30 subjects performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors. The dataset contains 561 attributes with 10299 instances. The experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed six different activities (walking, walking upstairs, walking downstairs, sitting, standing, laying) wearing a smartphone (Samsung Galaxy S II) on the waist.

3.2. Feature Extraction

Although the procedure described here can handle a large number of attributes, it may still be too large for practical use. While, the model assessment procedure requires fitting the data many times, it is very time-consuming process due to cross-validation and re-randomization. In addition, a considerable percentage of attributes do not show differential expression between the groups and only a subset of attributes is worthy of interest. A dimension reduction is performed in this study, for function extraction by sliced inverse regression (SIR).

3.3. Class Prediction

The high dimension of 'p' is then reduced to a lower dimension 'k' after dimension reduction. The original data matrix is constructed by a matrix of factors ($n \times k$, where $k < n$), constructed by (SIR), as described in the previous section. Once the k-factors are composed, prediction of the response classes using linear discriminate analysis is taken into consideration.

4. Results and Discussion

The interest of dimension reduction by considering applications for the class prediction of HAR-data has been illustrated. We compare the results produced by our procedure with the performance of the direct classification approach.

4.1. Application to HAR-Dataset

After data preprocessing, the proposed performance evaluation procedure on the HAR-dataset is applied. We choose 8000 instances randomly to train model and the 2299 remainder instances are used to test the model. Table 1 gives the estimates of common factors 'k' after the dimensionality reduction and the classification accuracy performances.

Dataset	p	Reduction model	k	Classification model	Classification accuracy %
HAR	561	SIR	**61**	SIR-LDA	98,49
			26		93.46
			15		92.35
	561	PCA	**61**	PCA-LDA	98,04
			26		92.89
			15		92.22
	561	Pristine	**561**	LDA	98.31

Table 1- p: number of selected variables; k: estimated number of factors.

4.2. Discussion

In this paper, the possibility of dimensionality reduction by employing dimension reduction based on sliced Inverse regression (SIR) to solve the course of dimensionality problem arising in the context of big data is explored, and its performance in class prediction framework for human activity recognition using LDA is evaluated. A priori, LDA can handle a large number of variables. However, as many other multivariate methods it is challenging due to large computational time and risk of over-fitting. Therefore, dimensionality reduction for many variables so as to reduce the large computational time has been used.

Table 1 represents the results obtained by applying the three models; SIR-LDA, PCA-LDA and LDA on the experimental dataset. Concerning dimensionality reduction task, three different criteria to estimate the number of common factor have been defined. The first criterion is the higher eigenvalue to one which provides us 61 common factor, the cumulative variance equal to 80% as the second criterion, which produces 26 common factor. After dimensionality reduction the results of class prediction show that, for $k = 61$ the best accuracy is obtained by SIR-LDA model 98.49 %, which is followed by

PCA-LDA model 98.04 %. For $k = 26$ the highest accuracy is obtained from SIR-LDA model, and then PCA-LDA model with values 93.46 %, 92.89 % respectively.

In the case of third criterion, the number of common factors from the best classification accuracy is evaluated which provides a near classification accuracy of second criterion (93.46%) and the respective 'k' is lower than 26. The results demonstrate that the achieved accuracy is comparable with the other two criteria, furnishing k=15. For the excellent classification accuracy, SIR-LDA model 92.35% is obtained, which is pursued by PCA-LDA model with 92.22% accuracy. It is evident that the number of common factors are equal to quarter of the first criterion, and about half of reduction has been accomplished in comparison with the second criterion, inferring the efficacy of the proposed framework. The descending order of the number of common factors can be described as following:

$$\boldsymbol{k_{SIR-LDA} < k_{PCA-LDA} \ll P_{LDA}}$$

5. Conclusion

This paper reports an efficient dimension reduction approach for the class prediction related to the human activity recognition. The proposed algorithm performs dimensionality reduction with two processes, i.e. the SIR-based dimensionality reduction and the PCA-based dimensionality, and the obtained results are compared, interpreted, and discussed. The principle advantage of this approach is that the number of features can be remarkably reduced from p=561 to k=15 for HAR-dataset, with a fine classification accuracy (92.35%). In addition, the suggested method is capable of addressing some crucial dimensionality reduction issues as well. The application of the proposed method on the experimental dataset results in the achievement of the best performance for dimensionality reduction (in terms of least time consumption and CPU-expenditure). It is also emphasized that the suggested method appears to be more effective than the well-known methods of its kind, and it may possibly be generalized on different types of machine learning with the reduced data.

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