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Analysis of Speech Signal with Linear and Quadratic Discriminant Analysis: A Fundamental Approach

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Abstract: ***Mapping of information using pattern classifiers has become more popular now days, even though without a obvious agreement on what classifiers need to be utilized or even just how benefits must be screened. This paper states that by comparative analyses how information maps in multiple class situation which provides the information concerned on neural representation. Speech signal generated from wireless devices may have noise. Noise must be separated from signal. In order to separate noise from speech signal Linear and quadratic discriminant analysis can be used. Logistic regression can be also be used in order to get accurate signal on receiver end since it will calculate the probability.***

Keywords: Linear Discriminant Analysis, Quadratic Discriminant Analysis, Information Mapping, logistic regression.

1. Introduction

1.1 Overview

This paper focuses on the basic components related to this thesis. It includes Linear and Quadratic Discriminant Analysis followed by logistic regression applied on Speech signal in order to separate noise/clusters and essential information.

1.2 Linear Discriminant Analysis

Discriminant Analysis (DA), a multivariate statistical technique is commonly used to build a Predictive / descriptive model of group discrimination based on observed predictor Variables and to classify each observation into one of the groups. Linear Discriminant Analysis used in statistics, pattern recognition and machine learning to find linear combination of features which characterizes or separate two or more class of objects or events. It takes only few parameters and provide accurate estimate

1.3 Quadratic Discriminant Analysis

Quadratic Discriminant Analysis is closely related to linear Discriminant analysis where it is assumed that the measurement from each class are normally distributed .Unlike LDA however, in QDA there is no assumption that the covariance of each of the classes is identical.

1.4 Logistic Regression

It is a type of regression analysis used for predicting the outcome of a categorical dependent variable (a dependent variable that can take on a limited number of values, whose magnitudes are not meaningful but whose ordering of magnitudes may or may not be meaningful) based on one or more predictor variables. That is, it is used in estimating empirical values of the parameters in a qualitative response model.

2. Review of Literature

The Author aim in [1], Laplacian interaction of Linear Discriminant Analysis and a modeling approach using continuous mixture density HMMs is studied experimentally. The largest improvements in speech recognition accuracy could be obtained when the classes for the LDA transform were defined to be sub-phone units. On a 12,000-word German recognition task with small overlap between training and test vocabulary a reduction in error rate by one fifth was achieved compared to the case without LDA. On the development set of the DARPA RM1 task the error rate was reduced by one third. For the DARPA speaker-dependent no grammar case, the error rate averaged over 12 speakers was 9.9%. This was achieved with a recognizer employing LDA and a set of only 47 Viterbi-trained context independent phonemes.

Aamir Khan (et .al) in [2], worked in a biometric identity system using Principal Component Analysis and Linear Discriminant Analysis with K-Nearest Neighbor and has implemented such system in real-time using signal wave. Embedded biometric systems must be robust with the emergence of fourth generation communication devices and advancement in security systems. This report reveals the realization of such technologies which demands reliable and error-free biometric identity verification system. Due to Eigen-decomposition in high dimensional image space and degeneration of scattering matrices in small size sample, high dimensional patterns are not restricted. It has been shown that dimensionality reduction, Generalization, and maximizing the margins are controlled by minimizing weight vectors. As a result good patterns obtained by multimodal biometric system.

The Author, K. Ducinskas (et .al) aim in [3], the problem of classification of the realization of the stationary univariate Gaussian random field into one of two populations with different means and different factorized covariance matrices is considered. Unknown means and the covariance matrices of the feature vector components are estimated from spatially correlated training samples using the maximum likelihood

approach and assuming spatial correlations to be known. In this paper a set of numerical calculations for the spherical spatial correlation function is performed and two different spatial sampling designs are compared.

The Author, Maja Pohar (et .al), aim in [4], Using linear Discriminant analysis and logistic regression categorical outcome variables are analysed. While both are appropriate for the development of linear classification, linear Discriminant analysis makes more assumptions around the underlying facts. Hence, it is assumed that logistic regression is the more flexible and more robust method in case of violations of these assumptions. The performance of the methods is studied by simulations. Results shows that linear discriminant and logistic regression are closely related whenever the normality assumptions are not too badly violated and set some guidelines for recognizing these situations. Inappropriateness of LDA in all other cases has been discussed.

The Author, Hakan Erdogan Proposed in [5], Feature extraction is a necessary initiative in speech recognition applications. Additionally to static features extracted from every frame of speech information, it is good to use dynamic features (called ¢ and ¢¢ coefficients) that use information from neighboring frames. In this paper, regularization of LDA and Heteroscedastic LDA transforms has been performed using two methods: (1) Using statistical priors for the transform in MAP formulation (2) Using structural constraints on the transform. As prior, transform is used that computes static coefficients. The second strategy advises utilizing completely new coefficients intended for static, first difference and second difference operators are compared to get the standard ones in order to improve performance. enhancement has become attained with this experiment in comparison with MFCC characteristics. Additionally, good results attained in certain AURORA2 assessments in comparison with LDA+MLLT characteristics.

The Authors, Jing-HaoXue (et .al) Proposition in [6], Comparison of Discriminative and generative classifiers is an endless matter. As an important handout to this topic, based on their empirical and theoretical comparisons between the naive Bayes classifier and linear logistic regression, Ref. [6] assert that there exist two distinct method of performance between the discriminative and generative classifiers with regard to the training data set size. Simulation and empirical studies suggest that, as a complement of their work, however, counsel the existence of the two distinct schemes might not be so reliable. Additionally, for datasets in real world, so far there is no theoretically correct, general yardstick for choosing between the discriminative and the generative approaches to classification of an observation x into a class y; the choice depends on the relative confidence we have in the correctness of the specification of either probability {(y|x) or p (x,y) } for the data. Besides, it has been suggested that pairing of either LDA assuming a common diagonal covariance matrix (LDA-_) or the naive Bayes classifier and linear logistic regression may not be perfect, and hence it may not be authentic for any claim that was derived from the comparison between LDA-_ or the naive Bayes classifier and linear logistic regression to be generalized to all generative and discriminative classifiers.

The Authors, Mark A. Kon (et .al) aim in [7], This paper is an introduction for the non-expert to the theory of artificial neural networks as embodied in current versions of feed forward neural networks. There is a lot of neural network theory which is not mentioned here, including the large body of work on natural neural nets (i.e., the theory of neural networks in animals). For some excellent foundational work on this topic, see [G1, G2]. We also include very recent work [KP] regarding what we consider to be the next important step in the theory of neural networks and their complexity, namely informational complexity theory for neural nets.

The Authors, Francisco Pereira (et .al)Proposition in [8], Mapping of information using pattern classifiers has become more popular now a days, even though without a obvious agreement on what classifiers need to be utilized or even just how benefits must be screened. This paper states that by comparative analyses how information maps in multiple class situation which provides the information concerned on neural representation.

The Authors, Valentin Todorov (et .al) aimed in [9], the problem of the non-robustness of the classical estimates in the setting of the quadratic and linear discriminant analysis has been addressed by many authors: Todorov (et.al). To get excessive dysfunction these kinds of techniques provide excessive dysfunction point estimators associated with location and covariance matrices just like Minimum volume ellipsoid, Minimum covariance determinant a. many authors use also one step re-weighting after the high breakdown point estimation in order to obtain increased efficiency. Woodruff and Rockeinstead described to use iteration as by, since this is the preferred way of getting efficiency with high breakdown. Furthermore it has been experimented with the pairwise classes of algorithms proposed by Maronna and Zamar which were not used up to now in the context of discriminant analysis. The techniques for powerful linear Discriminant research are generally compared on a pair of genuine data sets and over a large no. of simulation.

According to Brett Y. Smolenskiin [10] Speech that is corrupted by an meddlesome speaker, but contains segments that are still usable for applications such as speaker identification or speech recognition, is referred to as "usable" speech. The situation where there exists more than one person talking at the same time is referred to as co-channel speech. Unfortunately, currently available usable speech measures only detect about 75% of the total available usable speech with about 25% false alarms. To improve on this performance, optimal Bayesian classification is being used. Since these usable speech measures were gaussian distributed, quadratic discriminant functions were obtained for the optimal Bayesian classifier. Using this approach results obtained as 10% improvement in the total percentage of hits over the Adjacent Pitch Period Comparison (APPC) measured, and a 10% decrease in the total percentage of false alarms. This amounts to a 39% decrease in detection error.

3. Problem Identification:

In above review it has been identified that there no way to classify noise from particular speech signal. Principal component analysis is being used but it does not show exact classification.
If there is large no. data set then in case of LDA it does not show exact classification among data items.
On the other hand quadratic discriminant analysis overcome the problem if signal is of long range i.e. RF signal.

4. Proposed Methodology

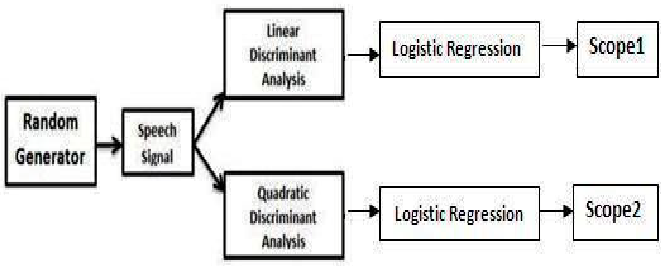
It has been identified that LDA can be used for speech signal but it will classify the data in two classes.

Quadratic Discriminant Analysis classify the data item in more than two classes but if there is large no. of data items then it is also not possible to classify the data item in multiclass for that purpose Logistic regression is being used it find the probability of which data item exactly belong to which class.

4.1 Methodology and Procedure:

When signal is generated by random generator (i.e. wireless devices) then in order to distinguish between clusters and noise from that signal following methodology has been applied:

Linear Discriminant Analysis which shows the separation between noise and signal with linear boundary, it is efficient but not applicable for RF signal or a signal which has high frequency range.



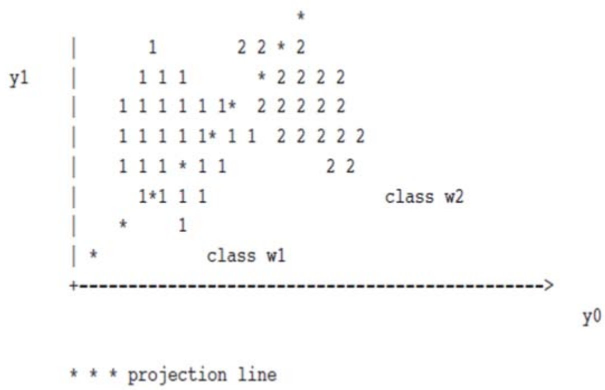
LDA seeks to reduce dimensionality while preserving as much of the class discriminatory information as possible. Assume we have a set of D-dimensional samples $\{^{(1}, x^{(2}, \ldots x^{(N}\}$, $N1$ of which belong to class $\omega 1$, and $N2$ to class $\omega 2$. We seek to obtain a scalar y by projecting the samples x onto a line$y = w^T x$

Of all the possible lines we would like to select the one that maximizes the separability of the scalars. Quadratic Discriminant Analysis which can be applicable for signals have high frequency range that is RF Signals. Here the measurements of two classes are normally distributed. Quadratic Discriminant analysis is closely related to linear Discriminant analysis, where it is assumed that the measurements from each class are normally distributed. Unlike however, in there is no assumption that the covariance of each of the classes is identical. When the normality assumption is true, the best possible test for the hypothesis that a given measurement is from a given class is the likelihood ratio test. Suppose there are only two groups y{0,1} and mean of each class are defined by $\mu_{y=0}$ and $\mu_{y=1}$and the Covariance defined by $\Sigma_{y=0}$ and$\Sigma_{y=1}$ then likelihood formula is given by-

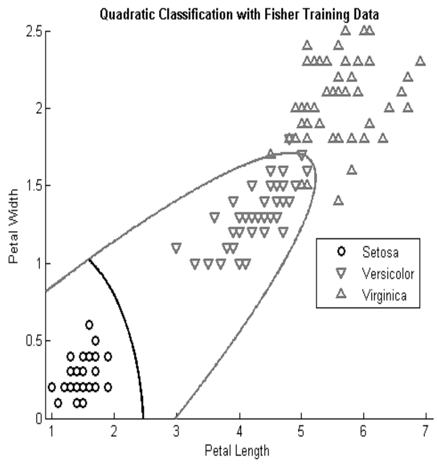
$$\frac{\sqrt{2\pi|\Sigma_{y=1}|}^{-1}\exp\left(-\frac{1}{2}(x-\mu_{y=1})^T\Sigma_{y=1}^{-1}(x-\mu_{y=1})\right)}{\sqrt{2\pi|\Sigma_{y=0}|}^{-1}\exp\left(-\frac{1}{2}(x-\mu_{y=0})^T\Sigma_{y=0}^{-1}(x-\mu_{y=0})\right)} < t$$

5. Results

5.1 After Linear Discriminant Analysis graph will be obtained as follows:



5.2 After Quadratic Discriminant Analysis graph will obtained as follows:



6. Conclusion

The main aim of this paper is use Linear and quadratic discriminant analysis in order to distinguish between noise and accurate signal in the form of two classes so that when signal is generated by wireless device and when it will be received by receiver before receiving signal should be noise free. Another most important benefit is that signal can also be classified by using these approaches.

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