Speaker Recognition in non-linear signal processing and pattern recognition.

Rune A. Heick, Rasmus S. Reimer & Nicolai Glud

Aarhus University, Department of Engineering

Abstract

The Content of this paper seeks to present the knowledge gained throughout the non-linear signal processing and pattern recognition course from Aarhus University, department of engineering. The paper is split into multiple sections explaining the data used in the paper, the methods used to treat the data and the methods used for categorising the data.

I. Introduction

The idea behind the project is to recognise the speaker using the methods and categorisers learned in the course pattern recognition and machine learning (TINONS). The voices of all authors was recorded and imported to matlab. The features from the data was extracted in matlab using the Mel-frequency cepstral coefficient(Hereafter MFCC) method from the voicebox toolbox. The MFCC's are used as features for the classifiers that are tested in this paper.

II. Data Gathering

How did we get data?

III. Feature Extraction

Introtext to MFCC

Math

How we use it

Intermediate result

IV. Features

Size and number of features and stuff.

V. Dimensionality Reduction

e.g. finding projection vectors, choosing number of components, applications.

I. PCA

Introtext

Math

How we use it or why we don't use it

Intermediate result

II. Fisher

Introtext

Math

How we use it or why we don't use it

Intermediate result

VI. Classifiers

Classifiers were first know from the world of linear regression. The classifiers found in this section are featured in the non-linear signal processing and pattern recognition course. The section seeks to explain the basis of each of the classifiers along with how we have used them in our project. Intermediate results can be found in the section about the classifiers while the comparison between classifiers can be found in the Results section.

I. Linear Classifier

> "e.g. cost/error function, decision boundary and training method"

The goal of linear classification is to take an input vector with multiple x values and assign it to one of multiple classes K. This can be done with one or more linear decision boundaries. The first way to classify is called the one-vs-one linear classifier. This works for 2 classes as seen in figure 1. If multiple clusters of x belonging to more than 2 classes are present we get ambiguous regions as one class might appear to be two different classes. An example of this can be seen in figure 2.

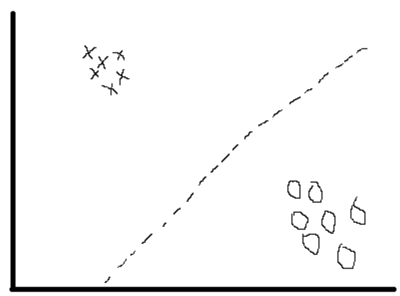

Figure 1: *One-vs-one linear classifier for 2 classes*

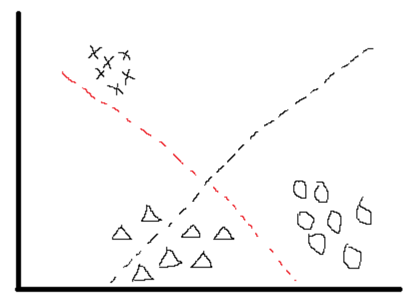

Figure 2: *One-vs-one linear classifier for 3 classes*

Another way to classify the 3 classes seen in figure 2 could be to utilise 1-of-k classification. This can be seen in figure 3. The 1-of-k classifier has no ambiguity in this case.

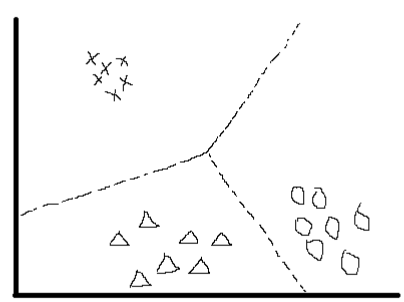

Figure 3: *1-of-k linear classifier for 3 classes*

In math terms the one-vs-one can be written as:

$$y(\mathbf{x}) = \tilde{\mathbf{w}}^T \tilde{\mathbf{x}} \tag{1}$$

This is prone to ambiguity for more than 2 classes. We know that the ambiguity issue can be avoid by using the form:

$$y_k(\mathbf{x}) = \mathbf{w}_k^T \mathbf{x} + \omega_{k0} \tag{2}$$

and choosing the value of x to be a part of class k if $y_k(\mathbf{x}) > y_m(\mathbf{x})$ for all $m \neq k$. This leads to decision boundaries corresponding to the 1-of-k classifier.

How we use it

Intermediate result

II. Probability Classifier

e.g. maximum likelihood, training/testing and generative vs. discriminative models.

Introtext

Math

How we use it or why we don't use it

Intermediate result

III. Artificial Neural Network Classifier

e.g. graphical network model, training method, model flexibility (expressive power)

Introtext

Math

How we use it or why we don't use it

Intermediate result

IV. EM Classifier

e.g. training method, cost functions, model order selection, initialisation of parameters.

Introtext

Math

How we use it or why we don't use it

Intermediate result

V. Sequential Models

Markov model and Hidden Markov Model.
e.g. meaning of parameters, left-to-right model, outline of training/testing method.

Introtext

Math

How we use it or why we don’t use it

Intermediate result

VI. Support Vector Machines

e.g. decision function, support vectors, soft margins, kernel trick.

Introtext

Math

How we use it or why we don’t use it

Intermediate result

VII. Results

Compare all the methods in a table in order to show the performance.

VIII. Discussion

I. Subsection One

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II. Subsection Two

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IX. Conclusion

References

[Figueredo and Wolf, 2009] Figueredo, A. J. and Wolf, P. S. A. (2009). Assortative pairing and life history strategy - a cross-cultural study. *Human Nature*, 20:317–330.