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Sensitivity analysis of fuzzy Goldman typical testors

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Abstract

In the framework of supervised classification problems, the estimation of feature relevance and the search of all discriminating sub-descriptions of objects have great practical significance. Solving this problem in real situations is not always an easy task, because of the computational cost. The problems due to the size of matrix representation of objects, the computational complexity of algorithms, the non-standard object descriptions like mixed incomplete, which appear very frequently in Soft Sciences, and also the presence of fuzzy characteristics in the class descriptions or in the similarity measure used in the modeling of the problem in question have a big influence on the computational cost. Here, real valued similarity measures between feature values will be considered. Fuzzy Goldman typical testors are useful for estimating feature relevance and for searching all discriminate sub-descriptions of objects, but the computational complexity of algorithms to compute all Fuzzy Goldman typical testors is too high. Modifications of the training matrix very frequently appear in real world problems. Any modification to the training matrix can change the set of all Fuzzy Goldman typical testors, so this set must be computed again after each modification. This paper analyzes one of the sensitivity problems in Pattern Recognition: how does the set of all Fuzzy Goldman typical testors change after modifications of the training matrix. Four theorems about the behavior of the set of all Fuzzy Goldman typical testors are proposed and proved. An alternative method for calculating all Fuzzy Goldman typical testors of the modified matrix, more efficient than any traditional testor finding algorithm, is proposed. The new method's complexity is analyzed and some experimental results are shown.

Keywords: Pattern recognition; Combinatorial problems; Fuzzy Goldman typical testor; Feature relevance; Logical combinatorial approach

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1. Introduction

Fuzzy Goldman typical testors are used for feature weighting and feature selection in the framework of fuzzy supervised classification problems [11]. In this work, we present a new method to compute Fuzzy Goldman typical testors [4] when there are some changes in data. The key problem is what to do if some training data is modified, the simplest way is to recalculate all Fuzzy Goldman typical testors from the modified training data, but it may be too expensive. Here, we present a more sophisticated method which uses information about the specific modification and allows to adjust the set of all Fuzzy Goldman typical testors. This new method has lower complexity than the option of recalculating it from the modified data.

In the following sections we introduce some preliminary concepts; explain Fuzzy Goldman typical testors, how they can be used for feature weighting and feature selection, and how they can be calculated; expose the sensitivity theorems which assure the correctness of the proposed method; describe the new method and its complexity; show some experimental results; and give our conclusions.

2. Preliminary concepts

Let Ω be a set of objects. following [11], a *description* $I(O) \in M_1 \times \cdots \times M_n$ (initial representation space—IRS) is defined for every object $O \in \Omega$. This description is represented by an m-tuple $(x_1(O)/\mu_{\tilde{R}}(x_1),\ldots,x_n(O)/\mu_{\tilde{R}}(x_n))$ of the values of n features of the fuzzy set $\tilde{R}=\{x_1/\mu_{\tilde{R}}(x_1),\ldots, x_n/\mu_{\tilde{R}}(x_n)\}$, where $\mu_{\tilde{R}}(x_i) \in L$ (a totally ordered set) could represent the confidence degree assigned to the feature x_i, for $i=1,\ldots,n$ (for example, an equipment, used to measure some feature, can only have an accuracy of 90%) with $x_i(O) \in M_i$, the set of admissible values of the feature x_i.

A *mixed incomplete description of an object* is understood to be a description in terms of nominal, ordinal and/or numerical values simultaneously. Each M_i may include a special symbol: "*", that represents the absence of a value for the feature x_i in the description of an object (missing data). Therefore, the object descriptions could be given in the form of quantitative and qualitative features simultaneously with missing data; this is the meaning of *mixed incomplete*. Hence, over IRS no algebraic or topologic structure is assumed. Also no algebraic or logical operations or any distance (metric) are defined a priori.

Analogously, a *sub-description* $I|_{\tilde{T}}(O)$ of O in terms of a fuzzy subset $\tilde{T}$ of $\tilde{R}$ is a p-tuple $(x_{i_1}(O)/\mu_{\tilde{T}}(x_{i_1}),\ldots,x_{i_p}(O)/\mu_{\tilde{T}}(x_{i_p}))$, if $\tilde{T}$ has p features $i_1,\ldots,1_p$. There are problems in practice where the confidence of the feature x_i is not maximal.

Without loss of generality, we assume that the feature set R and any subset of R are crisp sets, then $M=\{I(O_1),\ldots,I(O_m)\} \subseteq M_1 \times \cdots \times M_n$. In order to simplify the notation we assume that $I(O)=O$. Also, M denotes the set of object descriptions in a matrix representation.

Let $C_i : M_i x M_i \to [0,1]$ be a real valued dissimilarity comparison criterion for the feature x_i, $i=1,\ldots,n$, such that $C_i(x_i(O),x_i(O))=0$ and $C_i(x_i(O_1),x_i(O_2))>0$ iff $x_i(O_1) \neq x_i(O_2)$, where greater values indicate greater dissimilarity.

A supervised fuzzy classification framework is assumed [12,15]. In Ω, and also in M, there are r fuzzy object classes $\tilde{K}_1,\ldots,\tilde{K}_r$, such that each object description of M has associated a class