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Optimization Using Practical Swarm Optimization on the Medical Application Problem

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ABSTRACT

The digital image has become one of the most important contributions in the current iconographic scene. Its speed up growth in the different contexts of graphic and audio-visual production has prompted several changes of great significance and has eased the development of an increasing digital community. In our work we will focus on classification tasks. A classifier is any system capable of predicting the class to be assigned to a grouped data set, which we call a pattern. Each pattern is defined by the values of its "attributes". The process by which a classifier can predict said class can be based on information that is provided a priori (rules introduced by an expert) but, in the field of Artificial Intelligence, research is usually focused on systems that are capable of learning the relationship between attributes and classes on their own. Refer to a simple example, data from a patient's medical history could constitute a pattern; its attributes would include information identified by labels (sex, nationality), or by numerical data (age, weight, values of medical tests indicators). In this example, the diagnosis of the patient in relation to a disease could be abstracted as a classification problem: the class would be binary if you have the disease (yes or no). Other problems that could be defined are their degree of propensity for a specific disease. In either case, the "class" that the system predicts is usually defined as an element within a predefined set of labels. When the classifier has a set of model patterns, for which it knows the associated class, supervised inductive learning models can be applied. In these, the known data set (learning patterns) is analyzed to generate a classification model. Having carried out this task, the classifier *should be able to generalize the available information to predict the class that corresponds to any other data pattern presented to it. The reason why the classifier can make this prediction is due to the correct representation of the correlations that exist between the attributes and the class associated with each pattern.*

KEY WORDS

Classification, Digital Image, Optimization, Pattern Reorganization, Prediction.

INTRODUCTION

A specific type of classifier is one that is based on the nearest neighbour rule. This classifier is considered “lazy because the input data is not pre-processed in any way. All patterns known to the classifier are kept; when the classifier must predict the class to be associated with an unknown pattern, it is simply assigned the class of the closest known pattern. This closeness is defined in terms of a proximity function (normally, a distance function) that must be previously defined. An effortless way of representing a classifier of this type consists in assuming a problem in which there are two numerical attributes. In this case, the attribute space will be a section of the plane. Over this space you can simply use the Euclidean distance to measure the proximity between the patterns. It is seen that each known pattern defines around it a region in which it is responsible for attributing the value of the class; the union of these regions constitutes the attribute space. The calculation of distances between patterns is an expensive process; for this reason, in these cases an attempt is made to use data selection methods to reduce the computational cost of the classification process. Once the data selection is done, the classifier retains a much smaller amount of information and consequently the classification process is accelerated. The information that is retained is a set of prototype. There are several ways to generate these sets of prototypes: some systems limit themselves to choosing some of the patterns as prototypes (Prototype Selection); others choose the prototypes without the need for them to match known patterns (Prototype Replacement). Both problems can be addressed using metaheuristic search algorithms, such as Evolutionary Algorithms or the so-called Swarm Intelligence Algorithms. The advantage of such an approach is that the algorithm behaves robustly and efficiently in a wide set of domains. One of these latter algorithms is called Particle Swarm Optimization (PSO). The PSO algorithm is widely used for solving optimization problems and has become popular thanks to its speed of convergence and the simplicity of its implementation. However, it is not yet used consistently in classification problems.

The PSO algorithm could be used directly in classification problems. To do this, we would first have to transform the classification problem into an optimization problem, by means of an adequate coding of the solutions in the particles of the swarm. However, this way of solving the problem has significant drawbacks: The size of the search space grows proportionally to the number of prototypes to be obtained. In PSO, the dimension of the particles is fixed and the same for all of them, so that there is no flexibility for the algorithm to choose by itself the most appropriate values for the classification problem that you want to solve. There is a problem of symmetries in coding: a particle would be a set of prototypes in a certain order. However, all the permutations of that order correspond to a single solution to the problem. This type of situation is known to impair the performance of any search metaheuristic. Consequently, the aims for this Doctoral Thesis can be seen from two points of view: The quality of said algorithm will be measured in terms of:

- A good result in terms of generalizability, that is, the application of the algorithm to unknown patterns (prediction). This measure is the basic objective of any classification system.
- A reduced set of prototypes in the solution. In this way, the prediction can be made with minimal computational cost.

- Computational cost of affordable training. The calculation of distances to prototypes is a computationally intensive process, and an inductive type system has to perform this process repeatedly, over a number of iterations and for a population of individuals. Therefore, attention should be paid to this aspect.
- Applicability to diverse data sets, including data sets with noisy patterns.

Review of Literature

Rules based on prototypes, which take the form of clauses of logic about about similarity, expressed in terms of a function of proximity (may or may not be a mathematical distance), between the attributes of the patterns and those of a set of examples whose class I know each other and that serves as a reference. They are usually also called ¯ Classifiers by Similarity . In particular they belong to this class It is the classifiers that use the rule of the nearest prototype:

If pi = argmin P (δ(P atronj, pk ∈P)), then Class (Patronj) =Class (pi) .Among them I can cite IBK (Aha etal., 1991), or also well K* (Cleary and Trigg, 1995). I could also include in this category certain classifiers based on networks of neurons or Networks of Radial Base Function Neurons (RBFNN, (Powell, 1987).

Rules based on fuzzy logic, analogous to the first, but ex- in clauses that analyze the membership of attributes to fuzzy sets whose inference rules come from the field of Fuzzy Logic. Common in this field are approximations of evolutionary type, such as the one proposed in (Ishibuchi etal., 1999), where individual sets of rules are evolved or (Shi etal., 1999), in which encodes a whole fuzzy classification system by means of a Genetic algorithm.

Different types of rule can express relationships of different complexity between attributes. On an “attribute space” defined by the number of attributes, the patterns of the same class would form region as whose imaginary separation would be given by the “decision boundary”. In (Duch and Grudzinski, 2001) the different types of rules are analyzed in function of the type of decision boundary that they are capable of generating. In funtion of the boundary type (for example, if they are linear), you can define equivalence classes between rule types. The way to evaluate the usefulness of a classification system is multiple.

A detailed study of the characteristics, advantages and ways of using these tables in (Fawcett, 2004). The use of techniques is also attracting growing interest. Multi objective to add the evaluation measures previously cited. That is, they are considered learning objectives, independently, the classification success rate, complexity of the system, solution, computational cost, and other specifics of the algorithm used to the classification. To a large extent the success of the field comes from the development recent evolutionary multi-objective optimization algorithms. You can consider (Jin, 2006) and (Jin, 2007) for a reviews.

In (Devroye et al., 1996) you can consult the statistical analysis of the sifter with K neighbour. Its strength lies in the convergence test of the classification error under limit conditions: it is shown that, when the number of available patterns converges to infinity, the 1-NN algorithm coverge to an error no worse than twice the Bayesian error, which is considered the lower limit achievable. Similarly, when K neighbour are used, approximates the Bayesian error, for a certain value of K that grows as a function of the number of patterns available.

The statistical analysis of these classifiers considers that they allow us to consider the probability that a pattern v belongs to a given class C (p (C | x)). It is determined that said probability is proportional to the number of Class C patterns among the K closest neighbour. Consequently, the decision rule must assign to pattern x the most numerous classes among those K neighbours. The relationship of this classifier with methods of Classical classification in (D. Michie and DJ Spiegel halter, 1994). The concept of proximity or similarity requires the definition of a measure over the attribute space of the patterns. It is common to use the Euclidean distance, but there are also other options (Atkeson et al., 1997), as the weighted Euclidean distance, Minkowski distance, etc. selection of the appropriate proximity measure for a problem can be determined by so that the classifier performs well.

From a performance point of view, the task of classifying a pattern is a costly process, since it requires calculating the distance to all known patterns. Although there are procurements that avoid performing the full distance comparision as (Arya and Mount, 1993), remains a factor of inefficiency.

There are numerous methods of this type, which I can group into two following groups, in which I follow the denomination that is usedin (Kuncheva and Bezdek, 1998): methods of selection of instances or prototypes (Instance Selection or Prototype Selection) and replacement methods term of prototypes (Prototype Replacement).

There are methods that seek a more systematic approach to the problem, through the use of geometric approximations such as those described in (Godfried T. Toussaint and Poulsen, 1984). These techniques consist of generate graphs that establish a neighbourhood relationship based on the distance between the patterns. Once one of these graphs has been generated, the set of prototypes is obtained from the original set eliminating all those patterns whose neighbours on the graph are all of the same class.

Research Methodology

The planned of two-stage hybrid data mining process. In the first stage, we adopted the statistical pre-processing method. It will delete the negligible features to minimize uncertainty in the next step of data mining. In the second process, we proposed the data mining strategy focusing on the PSO norm, which was called discrete PSO. In this study, we tested our proposed DPSO algorithm using the set of Wisconsin breast results. There were 9 attributes and 1 order variable for the data collection. We replaced the missing data with the values that most commonly occur in this feature. The meaning of 9 attributes, aside from the order variable, is between 1 and 10 and the higher value is a rarer tumor condition, like data presented in table 1. The data set comprises 698 points, and 461 have been diagnosed as benign (order= 2) and 238 (Order = 4) to be metastatic. We also split the training data set that comprises 459 patient information and validation data set comprising 240 patient records randomly from the initial data set.

Table 1: Date set Variable

Feature Date Varible		**Simplified domain express**
Lump Viscosity	1-10	Z1
Cell Size Uniformities	1-10	Z2
Cell Shape Uniformities	1-10	Z3
Fringe Cohesion	1-10	Z4
Singhle Decidua Cell Size	1-10	Z5
Basic Core	1-10	Z6
Mild Chormatin	1-10	Z7
Regular Core	1-10	Z8
Mitospore	1-10	Z9
Ordar	2,4	Z10
	2: Benign, 4: Metastatic	

Table 2: Encoding form

No. of feature Variable	Variable 1	>or=or<	....	Variable m	>or=or<	Threshold

Table 3: The example of encoding

2	1	3	4	5	1	2

The data collection is used to learn about breast cancer and then to offer the law of judgments. The test data set was not used to build the output verification process. The hybrid solution's flow diagram is seen in Table 2 and 3.

Result and Discussion

PSO owes its origins to bird entertainment in a group flock. Any portion hurried in this technique with a pace matched to its partner's flying memory and experience. The impartial function values of a particle are calculated by a fitness value. PSO is a genetic algorithm process, analogous to the neural networks in which an arbitrary population of solutions initializes a complex structure. In PSO, a random velocity is often assigned to create an atom, in addition to any latent key. In the problem space each particle moves along its co-ordinates, relating to a superlative key. In addition, the fitness benefit for the supplemental treatment is often taken into consideration. This fitness attribute is best. The location of these strategies is known to be the highest. In our optimistic process, we used a personalized version of PSO to implement a revolutionary technique. Here we've assigned the estimation of the weight factor after the option of robustness with a view to increasing the likelihood of selecting the right particle.

CONCLUSION AND FUTURE WORK

The diagnosis of PSO breast cancer was a tedious operation. Different study in the area of breast cancer diagnosis was conducted via the PSO algorithm. In this study we presented a professional object recognition and monitoring dependent on motion. We also improved a distinctive technique by implementing an optimization algorithm to monitor the appropriate entity throughout the image processing phase. We also established a specific way to select the threshold value needed for the entity to be identified from the video using the optimization algorithm. Furthermore, a point-based algorithm was suggested. In this, point labels or nodes are allocated to 12 separate areas of the breast that monitor movement events reliably by calculating dissimilarity. In order to show the efficacy of the system proposed, we correlated the specificity and the recall benefit with F-measurement of the method proposed with the current method for object identification and monitoring. According to the output review, the suggested approach has a higher F-measurement value relative to other approaches. Computing costs and time are further minimized since the algorithm is linearly complex. For a single object frame diameter and utilizing 25 model detector features, the average time to process is 102 ms. If the model detector uses only 10 features, the total is decreased to 26 ms as the algorithm operates quickly enough to enable realistic usage. With the aid of parallelism, real time application may be made feasible. A development of this work will be the extraction of human structural features utilizing multi-resolution approaches including the transformation of the contour let. The device suggested functions sequentially, using the effects of object identification as feedback as monitoring. However, monitoring may be used for identification purposes. The strongest way to avoiding the survivor with breast cancer is to recognize it early by testing your breast for differences in form or scale. Data mining and statistical analysis is one of the simplest ways to seek a huge volume of valuable data in amounts of enormous quantities. The proposed PSO algorithm scheme can be applied in different fields of solving classification problems. In general terms, we can suggest the application of the perspective for every problem in which the coding of individuals it should consider the same solution to all permutations of a series of partial solutions. In this sense, one could think of developing a generalization of the Prototype Swarm to a Generalized Particle Swarm framework for solving problems with these characteristics.

In Section above we propose some works aimed at generalizing the principles that have been included in the proposed algorithms. On the other hand, there is the possibility of improving the Prototype Swarm algorithms, some of which we point out in this Section. Neighbourhood definition is not generated explicitly. Although it is not desirable to use the calculation algorithm of the Voronoi graph, there are algorithms such as some versions Growing Neural Gas Network, in which the prototypes that are candidates for having said neighbourhood relationship are explicitly identified. To do this, for each pattern it is determined which is the closest prototype, and also the second prototype in order of proximity. These two prototypes share a boundary that is found somewhere between the pattern and the second neighbour.

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