A Computational Intelligence Approach for Ranking Risk Factors in Preterm Birth

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Abstract - **The aim of this paper is to propose a filter, based on a multi-objective evolutionary algorithm, for attributes' ranking in the context of a data mining task. The behavior of this filter is analyzed for the problem of ranking risk factors in preterm birth. The results obtained by applying the proposed evolutionary approach are compared with rankings obtained by applying some classical attributes selection methods and a logistic regression procedure. The influence of the ranking on a supervised classification (based on a radial basis function neural network) is also analyzed and the results suggest that the evolutionary approach provides a good quality ranking.**

I. INTRODUCTION

Identifying and ranking risk factors are important tasks in medical data analysis. They are usually approached by applying statistical tools to databases containing information about an investigated pathology. In most situations the data, containing information about the presence/absence of some symptoms (factors), belong to two classes (one corresponding to the case when a given illness was present and another one when the illness was absent) and the task is be to identify the factors with a significant influence on the presence/absence of that illness.

Such a task is equivalent to the problem of selecting, starting from a training data set, the relevant attributes for a supervised classification process. The classification performance significantly depends on the attributes' relevance, while their number influences the computational costs. Therefore, attributes' selection is a key step in any data mining process.

Besides the statistical methods, also computational intelligence techniques, particularly neural networks and evolutionary algorithms, have been successfully applied in attribute selection tasks [1-4].

The aim of this paper is to present an evolutionary approach in attribute ranking based on interpreting the problem as a multiobjective optimization one. This evolutionary approach of ranking the attributes is applied for a case study in obstetrics whose aim is to identify maternal risk factors for spontaneous preterm birth. The paper is organized as follows. Section two overviews some recent works related with the use of computational intelligence techniques in the design of filters for attributes' selection. The formulation of the problem of the attributes' ranking as a multiobjective optimization problem is given in the third section, where the evolutionary approach is also presented. The results obtained by applying the proposed technique in the case of ranking the risk factors in preterm birth are presented in discussed in section four. The last section concludes the work.

II. RISK FACTORS RANKING AND ATTRIBUTE SELECTION

In a medical decision system, the problem of predicting the presence of a suspected pathology (based on a set of existing associated factors) can be formulated as a classification task. Thus, identifying the risk factors means in fact selecting the most relevant attributes with respect to the classification task.

In choosing the appropriate method for selecting the attributes two important elements should be considered: (i) the measure of their relevance to the classification task; (ii) the way the attributes' space is explored.

For evaluating the relevance of a subset of attributes to the classification process, there are two main approaches [5]: the filter method and the wrapper method.

The filter method is based on estimating some relevance measures using only the initial data and their labels (in the case of supervised classification). The natural approach is to use just enough attributes to divide up the instance space in a way that separates all the training instances [5]. The relevant attributes should be chosen by ranking all of them with respect to the classification task. The main difficulty here is identifying the appropriate relevance measures.

The wrapper approach is characterized by the fact that selection is made based on the behavior of the classifier on the analyzed subset of attributes. This means that, in order to evaluate an attribute subset, the classifier is trained for this subset and its performance on a validation set is used to assess the relevance of the subset. This way, the selection is tuned to the classifier learning scheme, thus the wrapper approach usually leads to better results than the filter approach, but the computational cost is significantly higher.

The second important element in the process of attribute selection is the exploration of the space of all possible attributes subsets. As the exhaustive exploration of this space is usually not applicable, the classical approach is to apply a greedy strategy either in a forward manner (starting from the empty set of attributes and adding the most promising one at each step) or in a backward manner (starting from the entire set of attributes and removing the least promising one at each step). However, such a greedy strategy usually leads to a local optimum. In order to eliminate this drawback, there were proposed searching strategies based on evolutionary algorithms [1-4].

Reference [2] presents the use of a genetic algorithm to simultaneously find a proper subset of examples and attributes in a wrapper approach based on the nearest neighbor classification. The selection in the genetic algorithms favors configurations with a small classification error and a small number of examples and attributes. These three optimization criteria are linearly combined in a single criterion by using some user specified parameters.

Yang and Honavar proposed another wrapper-based approach, which uses a genetic algorithm in order to explore the attribute space [3]. The selector is based on a neural network and uses as relevance measures the generalization accuracy of the neural network classifier (to be maximized) and the classification cost (to be minimized). These criteria are combined by dividing the first one to the second one.

The approaches in [1] and [4] are also based on combining a wrapper method with an evolutionary algorithm, so the evaluation of each attribute subset entails training and validating a classifier (which already are quite computationally expensive) and using evolutionary algorithms to explore the space (which amplify this computational cost even more, as all elements of the population have to be evaluated at each generation).

Taking all these into account, we decided to combine a filter approach for measuring attribute relevance with an evolutionary algorithm for exploring the attribute subsets' space.

III. A Multiobjective Evolutionary Optimization Approach for Attribute Selection

In the absence of a universally accepted relevance measure, different criteria should be simultaneously used in order to deal with the attribute selection/ranking problem. Thus this problem can be naturally cast as a multiobjective optimization, i.e. find the subset(s) which simultaneously optimize different criteria.

Both attribute selection and attribute ranking are related with the problem of assigning weights to attributes. After each attribute received a weight proportional with its relevance to the classification task, selection consists just in using a threshold to separate the relevant attributes from irrelevant ones while ranking consists in decreasingly sorting the list of attributes based on their weights. When the weights are binary values, the attribute weighting is reduced to the attribute selection. In the following we describe a method to find, in an evolutionary manner, the appropriate weights for the attributes.

A. Measures of Attributes Relevance

The measures to be used should be selected depending on the method for attribute selection. When wrapper methods are used, the measures are particularly represented by the classification accuracy on the training set or the generalization measured on a validation set.

In the case of filter methods, the measures are more related to the intrinsic properties of data, e.g. compactness of classes, separation between classes, correlation between attributes and classes labels. Since these measures are used in our approach, they will be described in the following.

Let us consider a set of N labeled data: $\{x_i^r; i=\overline{1,N}\}$, where $r \in \{1,...,k\}$ is the class label and each x_i^r is a vector with n numerical components, each component being related to an attribute value. We also consider that each class C_r contains n_r data.

The intraclass distance is a measure which reflects the density of data within a class and can be defined as the average of the distances between data and the center of their corresponding classes:

$$D_1 = \frac{1}{N}\sum_{r=1}^{k}\sum_{i=1}^{n_r} d(x_i^r, m_r) \tag{1}$$

where $m_r = (\sum_{i=1}^{n_r} x_i^r)/n_r$ denotes the center of class C_r and $d(\cdot,\cdot)$ is the standard Euclidean distance.

The separability between classes is measured through the interclass separation which is defined as the average distance between the centers of all classes and the center of the entire data set:

$$D_2 = \frac{1}{N}\sum_{r=1}^{k} n_r d(m_r, m) \tag{2}$$

where $m = (\sum_{r=1}^{k} n_r m_r)/N$.

The smaller the intraclass distance and the larger the interclass distance are, the easier is to classify the data, meaning that the involved attributes are relevant to the classification.

In order to evaluate the attribute subsets, each subset should be described by a vector of weights: $(w_1,...,w_n)$, where $w_i \in [0,1]$ could be interpreted as the relevance of attribute *i*. If the weights have binary values, then a value of one for the weight w_i means that the attribute *i* is selected; similarly, a zero value means the attribute *i* is ignored. In order to include the attributes weights into the intra- and inter-classes distances, the Euclidean distance involved in (1) and (2) should be replaced with:

$$d_w(x,y) = \sqrt{\sum_{i=1}^{n} w_i^2 (x_i - y_i)^2} \tag{3}$$

This is the only modification needed in order to work with weighted attributes and it is appropriate both in the case of binary and in the case of continuous weights.

As is illustrated in [4] the pair of measures (D_1, D_2) does not always work well as a class separability measure, thus a complementary measure was also proposed: the attribute class correlation measure [4], which is based on the idea that the correlation between the changes in the attributes values and the differences of class labels should be taken into account when ranking the importance of attributes. In the case of weighted attributes the correlation measure presented in [4] can be extended as follows:

$$C_w = \left(\sum_{i=1}^{n} w_i C(i)\right) / \left(\sum_{i=1}^{n} w_i\right)$$

$$C(i) = \frac{\sum_{j_1 \neq j_2} | x_{j_1}(i) - x_{j_2}(i) | \varphi(x_{j_1}, x_{j_2})}{n(n-1)/2} \quad (4)$$

where $x_j(i)$ denotes the component *i* of data *j* and $\varphi(x, y)$ is 1 if *x* and *y* belong to different classes and it is -0.05 if they belong to the same class.

The weights vector which minimizes the intra-class distance (1) and maximizes the inter-classes distance (2), and the attribute class correlation measure (4) will give us the relevance of each attribute with respect to the classification task. Unfortunately, an ideal weight vector optimizing all three measures usually does not exist. In such a situation, trade-off solutions should be used instead.

In order to solve such a multi-objective optimization problem, there are at least two approaches: (i) combining all criteria in a single one; or (ii) estimating a set of trade-off solutions (the so-called Pareto optimal solutions).

Most approaches in attribute selection combine the measures in one optimization criterion arriving to a single-objective optimization problem. When linear combinations of criteria are used (as in [2] and [4]) another problem arises: that of choosing appropriate values for the coefficients involved in the linear combination. Different sets of coefficient values lead to different solutions. The influence of these coefficients on the solution is clearly illustrated in [4] suggesting that the choice of these coefficients is a critical element.

Instead of combining all criteria in one objective function, an alternative would be to solve the multi-objective optimization problem directly by using the classical Pareto dominance concept. A solution vector w_1 dominates another vector w_2 if it is better than w_2 with respect to all criteria. On the other hand, a vector is considered to be non-dominated if there is no other vector which dominates it. By applying a Pareto-type multi-objective optimization algorithm, the result is a set of reciprocally non-dominated vectors. Such an approach is proposed in [1], where a multi-objective genetic algorithm is used in combination with a decision-tree based wrapper method. The criteria to be minimized were the classification error and the size of the decision tree.

The advantage of obtaining an entire set of solutions is that we can combine the rankings provided by all solutions in order to obtain a more reliable ranking.

B. The Evolutionary Approach

Evolutionary algorithms are stochastic searching methods which iteratively transform a population of candidate solutions by applying nature inspired operators: recombination, mutation and selection. They proved to be effective in approximating the set of Pareto optimal solutions corresponding to multi-objective optimization problems and are currently applied in solving different problems from science and engineering [6].

In the approach we propose, the population consists of a set of weight vectors randomly initialized in $[0,1]^n$. At each generation, a new population is generated by applying recombination and mutation. The population of survivors is constructed through a selection operator based on the dominance relation between the vectors containing values of the three evaluation measures (D_1, D_2, C). From the large plethora of multi-objective evolutionary algorithms, the variant we chose was NSGA-II (Nondominated Sorting Genetic Algorithm) [7]. It is based on specific polynomial recombination and mutation operators, and a selection operator which uses the concept of non-dominance ranking and that of crowding. By applying this algorithm to a population of *m* weight vectors one usually obtains, after some hundreds of generations, a set of *m* reciprocally nondominated solutions. Each one contains the weights of *n* attributes and can be considered a solution of the optimization problem. Based on these *m* weight vectors one can obtain *m* rankings of the attributes, which are not necessarily distinct. The final ranking is calculated as the average of all these rankings.

The approach we propose is different from that presented in [1] with respect to three elements: the attribute selection method which is of filter type instead of wrapper type; the criteria to be optimized, which are three instead of two; the evolutionary algorithm.

IV. A Case Study: Ranking the Risk Factors of Preterm Birth

Full-term births are between 37 and 42 gestational weeks-long, while those happening before are considered to be pre-term. Although, at present, infants born after 20 weeks of gestation can survive, they frequently suffer from lifelong and severely debilitating handicaps. Moreover, the care of these preterm neonates entails higher costs. In conclusion, preventing preterm birth and prolonging gestation (when clinically appropriate) is not only an important medical issue, but also a public health and a healthcare managing problem.

Identifying the risk factors associated with spontaneous preterm labour has been concentrating substantial research efforts, as this would allow developing models for risk prediction [8-11]. Being able to select individuals at risk would give the doctors time for close monitoring and intervention.

A. The Set of Data

The data for this study were provided by the University Hospital of Obstetrics-Gynaecology „Dr. Dumitru Popescu" from Timisoara which also contributed the medical analysis of the attributes' relevance. The data consisted of perinatal information collected from the paper-based medical records of patients who received perinatal care in the Hospital during Jan-Dec 2006.

The analyzed set of data consisted of 177 records containing information concerning mothers and their children. This set of data was obtained by a preliminary preprocessing consisting in eliminating the records with missing values and the attributes which were obviously irrelevant from the point of view of predicting preterm birth risk (e.g. personal ID) or those which were highly correlated (e.g. from weight, height and body mass index only the last one was kept). The number of attributes retained after the preliminary preprocessing is 22 (including the attribute containing the class label: full-term birth and preterm birth). The list of all attributes is presented in Table 1.

B. Experimental Design and Comparative Ranking Results

In order to apply the ranking approach presented in Section 3, the data were numerically coded and normalized such that all values were between 0 and 1. The class labels (full-term and preterm birth) were assigned based on the gestational age (births before 37 weeks were considered to be preterm). Thus the gestational age was highly and directly correlated with the class label and was expected to have a high relevance.

TABLE 1.
LIST OF ALL ATTRIBUTES

Code	Attribute	Code	Attribute
A1	Maternal age	A12	Weight gain during pregnancy
A2	Body Mass Index	A13	*Fundus uterus* – height
A3	Smoking	A14	Gestational age
A4	Parity	A15	Type of birth – vaginal/CSection
A5	No. Pregnancies	A16	Child sex
A6	Hemoglobin level	A17	Child head perimeter
A7	Low/high red cell count	A18	Child weight
A8	Glucose level	A19	Child length
A9	Systolic BP	A20	Apgar score
A10	Diastolic BP	A21	Live/still birth
A11	Abdominal perimeter	A22	*Full-term / Preterm (class label)*

In order to analyze the behavior of the evolutionary ranking of attributes, we used two sets of data: (i) the first set contained all attributes, including the gestational age at birth moment; (ii) the second set contained only attributes which were recorded before the birth moment (which could play a role as predicting factors of preterm birth).

The first data set was used in order to validate the ranking method, while the second one was used to identify the relevant attributes which could ensure a low classification error.

The comparative analysis was based on the following methods:

M1: a filter type ranking of attributes based on the informational gain (IG) [5];
M2: a filter type ranking of attributes based on the symmetrical uncertainty (SU) [5];
M3: a ranking based on the coefficients obtained by logistic regression (LR); in this case, the higher was the absolute value of a regression coefficient, the higher was considered the corresponding attribute's relevance;
M4: a ranking method based on the evolutionary multi-objective approach (EMOA) described in Section III B.

For the first three methods, the corresponding functions from the public domain data mining tool Weka [12] were used (with their implicit parameters).

For the evolutionary variant, the tests were conducted based on a Java program implemented starting from the C-code of the original NSGA-II [13]. The parameters of the evolutionary algorithm were set as follows: 80 elements in population; 750 generations; a recombination probability of 0.9; and mutation probability equal to $1/n$ (n being the number of attributes). A run of this algorithm gave us a set of 80 weights vectors, all of them being reciprocally non-dominated with respect to the three measures described in Section III A. That meant that none of the vectors was better than any other one with respect to all criteria. Thus the final ranking had to take into account all the results. In order to combine all of them, we first ranked the attributes based on each solution, and using these rankings we computed the averaged rank. The final ranking was based on these averages.

The results obtained for the first set of data (with 21 attributes) are presented in Table 2, which contains the attributes listed in decreasing order of relevance estimated from the set of data. For the evolutionary method, besides the sorted list of attributes, the averaged values of ranks and their corresponding standard deviations are also presented.

All rankings listed in Table 2 have in the first position the attribute corresponding to the gestational age, which is in accordance with the way the classes were constructed (based on the gestational age). Moreover, in the first positions are placed mostly the attributes related to the child (A17, A18, A19, A21), which seems to be a natural ranking. This test on the first set of data gave a first validation for the ranking methods, including the evolutionary one.

The results obtained for the second set of data (containing only 14 attributes, those which were recorded before the birth) are presented in Table 3. Again, all four methods placed the same attribute in the first position (A13 – fundus uterus height). Moreover, the first two filters generated identical rankings, which can be explained by their similar approaches. The variability of the ranks assigned by the methods based on logistic regression and on the evolutionary approach can be explained by the low predictive power of the attributes with respect to the analyzed set of data (excepting the first attributes).

TABLE 2.
ATTRIBUTE RANKING BY DIFFERENT METHODS (21 ATTRIBUTES)

Rank	M1 (IG)	M2 (SU)	M3 (LR)	M4 (EMOA)	
				Attribute	Average rank (stdev)
1	A14	A14	A14	A14	2.9(1.9)
2	A18	A18	A18	A21	3.7(3.5)
3	A19	A19	A19	A17	3.8(2.5)
4	A17	A17	A17	A18	5.7 (3.5)
5	A13	A21	A21	A19	5.9 (3.5)
6	A21	A13	A13	A20	8.1 (4.2)
7	A15	A15	A20	A13	8.1 (4.7)
8	A16	A3	A11	A11	10 (4.4)
9	A3	A16	A12	A4	10.2 (4.3)
10	A7	A7	A15	A12	11.6 (5.3)
11	A6	A6	A16	A1	12.2 (3.5)
12	A2	A2	A3	A5	12.4 (4.9)
13	A4	A4	A1	A2	13.3 (3.7)
14	A5	A5	A2	A9	14.41 (3.6)
15	A12	A12	A4	A15	14.43 (4.9)
16	A20	A20	A10	A10	14.44 (4.3)
17	A1	A1	A9	A3	15.21 (5.7)
18	A9	A9	A6	A8	15.27 (4.1)
19	A8	A8	A7	A7	15.4 (5.7)
20	A11	A11	A8	A6	15.7 (3.9)
21	A10	A10	A5	A16	17.6 (3.9)

C. Using the Attributes Ranking in a Classification Process

Obtaining a ranking can be helpful in selecting those attributes which lead to a low error classification ratio and allow developing an effective predictive model. Without a prior ranking, almost 2^n subsets should be tested in the case of n attributes. Based on a ranking, the number of subsets to be tested depends linearly on the number of attributes. A common strategy is the backward selection of attributes which consists in starting with the entire set of attributes and removing them successively in a decreasing order of their rank (i.e. the increasing order of their relevance).

We applied this strategy to validate the ranking obtained by the evolutionary approach. In order to classify the data, we used a radial basis function neural network classifier implemented in Weka.

This implementation uses a k-means clustering algorithm to estimate the centers corresponding to the hidden neurons and a simple training algorithm to estimate the weights corresponding to the output neurons. The implicit value of two hidden neurons was used since our aim was not tuning the neural network, but comparing the influence of the ranking on the classifier performance. The classification ratio was computed by applying a 10-fold cross validation technique.

TABLE 3.
ATTRIBUTE RANKING BY DIFFERENT METHODS (14 ATTRIBUTES)

Rank	M1 (IG)	M2 (SU)	M3 (LR)	M4 (EMOA)	
				Attribute	Average rank (stdev)
1	A13	A13	A13	A13	4.1 (2.7)
2	A16	A16	A12	A12	5.8 (2.9)
3	A3	A3	A10	A9	6.4 (3.6)
4	A6	A6	A4	A11	6.4 (4.0)
5	A7	A7	A2	A4	6.6 (4.4)
6	A5	A5	A6	A10	6.9 (3.9)
7	A4	A4	A7	A5	7.5 (4.1)
8	A2	A2	A9	A2	7.97 (4)
9	A11	A11	A16	A7	7.98 (3.1)
10	A1	A1	A8	A6	8.1 (4)
11	A12	A12	A3	A3	8.4 (3.5)
12	A8	A8	A11	A1	8.6 (4.1)
13	A10	A10	A1	A8	9.5 (3.8)
14	A9	A9	A5	A16	10.2 (2.7)

In Table 4, the correct classification ratios for the subsets generated by using the rankings obtained with the four analyzed methods are presented. The first column contains the ranks from Table 3. The selected attributes depend on the ranking, i.e. if the first four attributes were selected, that would mean: A13, A16, A3, A6 in the case of methods M1 and M2; A13, A12, A10, A4 in the case of the method based on logistic regression; and A13, A12, A9, A11 in the case of the evolutionary approach.

TABLE 4.
CLASSIFICATION RESULTS FOR SUBSETS OF ATTRIBUTES SELECTED BASED ON DIFFERENT RANKINGS

Ranks of selected attributes	Correct classification ratio (%)		
	M1(IG), M2(SU)	M3 (LR)	M4 (EMOA)
1-14	77.96	77.96	77.96
1-13	78.53	78.53	79.09
1-12	76.27	76.83	77.40
1-11	76.27	77.4	78.53
1-10	78.53	79.09	80.79
1-9	78.53	78.53	80.79
1-8	79.09	80.79	80.22
1-7	79.66	80.22	80.79
1-6	77.96	79.66	81.92
1-5	76.83	81.35	81.92
1-4	78.53	*82.48*	*83.05*
1-3	76.83	81.35	82.48
1-2	*80.79*	81.92	81.92
1	79.09	79.09	79.09

The best classification performance was obtained by retaining the first four attributes in the order given by the evolutionary approach. These attributes were: A13 (*fundus uterus* – height), A12 (weight gain during pregnancy), A9 (systolic BP), A11 (abdominal perimeter). The results are plausible for the set of data we used since they contain values measured close to the birth moment.

The slightly higher values of the correct classification ratio when the attributes were selected based on the ranking obtained by using the proposed approach suggest that this could be a valuable candidate in identifying the relevant attributes.

V. Conclusions and Further Work

Predicting risk factors in the context of a medical decision process is similar with identifying relevant attributes with respect to a supervised classification task. Both problems are equivalent to the problem of estimating the attributes weights which optimize some criteria computed based on a training data set. Thus we arrived to a multi-objective optimization problem which we tried to solve by applying a state of the art evolutionary algorithm, NSGA-II [7].

The results we obtained for a set of obstetrical data illustrate the fact that the technique we propose is competitive (from the point of view of the results it generates) with respect to some classical techniques like filters based on the informational gain and symmetrical uncertainty or the logistic regression.

However, some issues concerning the proposed approach should be further addressed: (i) improving the scalability in order to apply the technique for large sets of data; (ii) extending the set of criteria in order to obtain more reliable ranking results; (iii) test the behavior of the approach for extended lists of potential risk factors, including medication of mother during the pregnancy or just before it.

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