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AN IMPLEMENTATION OF ARTIFICIAL ADVISOR FOR DYNAMIC CLASSIFICATION OF OBJECTS

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ABSTRACT: The paper presents an original method of dynamic classification of objects from a new domain which lacks an expert knowledge. The method relies on analysis of attributes of objects being classified and their general quality Q, which is a combination of particular object's attributes. The method uses a test of normality as a basis for computing the reliability factor of the classification (*rfc*), which indicates whether the classification and the model of quality Q are reliable. There is no need to collect data about all objects before the classification starts and possibly the best objects ale selected dynamically (on-the- fly) while data concerning consecutive objects are gathered. The method is implemented as a software tool called Artificial Classification Adviser (ACA). Moreover, the paper presents a case study, where the best candidates for firefighting mobile robot operators are selected.

1. INTRODUCTION

The need for information is constantly growing, along with advances in science and technology. As a result, data describing different types of objects reach enormous sizes and require a lot of time and resources to be processed. However, raw values of an object's attributes are often useless. The usefulness of an object for a given purpose, which may be calculated and denoted as its quality Q (a quality function combining values of multiple attributes; a quality of the engine to be used in a race car, for example) is thus more important. The quality may be the basis for selection of the best (or good enough) objects among the many available.

Procedures of selection, when based on an expert knowledge about the quality of objects, are well known and widely discussed [2, 4, 5, 15]. Many methods, algorithms and tools have been already developed for this purpose [12, 13, 14]. Moreover, there are many reliable methods for evaluating classifiers for known objects [4, 5]. Actually, solutions to the problem may be divided into two categories, as follows:

1) Predictive and descriptive models of the quality of an object already exist, and can be used directly for a reliable selection of objects.

2) The expert knowledge concerning quality is contained in examples, which can be used to build a reliable classifier and perform the selection of objects.

Examples of such methods of selection/classification are: decision trees [9, 10], decision rules [8], etc. [2, 7, 11, 15]. Unfortunately these methods are useless when it is not known how to measure Q of objects because they come from a new domain, and furthermore when the selection should be fast and dynamic, what means that the objects must be selected before the data set has been collected in full.

In [6] an original method of selection of objects from a new domain which lacks an expert knowledge is presented. The core of the method s software Artificial Classification Adviser (ACA), which allows for making the selection more reliable and minimizing the number of selection errors. This software tool is useful for testing and verifying models proposed by an Expert Candidate (EC), thus a person who decides about the selection but is not an expert. An additional advantage is that the selection/classification of the best (or at least good enough) objects may be performed on-the-fly, without the need to collect all the data firstly. This way, the total cost of the process is greatly reduced.

In the paper the ACA and a representative example of its application is given. The next chapter presents the problem of selection without an expert knowledge. Main assumptions of the dynamic classification are presented in chapter 3. Chapter 4 presents software architecture of the Artificial Classification Adviser (ACA). Case study, where operators of a firefighting mobile robot are selected is presented in chapter 5. The paper ends with conclusions.

2. MOTIVATION

Suppose a problem of urgent selection of best objects belonging to a new domain has appeared. For example, it should be selected best versions of weapons or robots, which are endowed with absolutely new features, so that a decision which of these objects should be passed to production could be undertaken properly. Since the domain is new, there are neither any examples of how to do the selection correctly nor any experts who can advise it. Moreover, there are no examples of good and bad objects which could be used to build a classifier. In such a case he who undertakes the task of classification of objects or creating the model is only an expert candidate (EC). His knowledge refines while collecting data concerning objects. As long as models of quality Q (predictive and/or descriptive) are unknown, the results of selection/classification are uncertain and subjective. Thus, the main task is to create a correct or at least the best reliable models (predictive and descriptive) of the Q, as fast as possible. The task requires solving problems resulting from the lack of knowledge concerning characteristics of objects. Particularly it concerns:

1) Identification of the uncorrelated attributes which a good object should have and the way they should be measured.
2) How the attributes should be combined to create the measure of quality Q?
3) What are the threshold values of Q for considering an object as good?

Another problem is a quality of the set of objects which is used as a basis. The model should be created on the basis of data which are considered a representative sample of the population. Uncertain characteristics of objects make it difficult to assess the quality of the sample (whether or not the objects represent all classes of the population). Moreover, the data usually come from real experiments, thus may contain errors, inaccuracies and gaps, disturbing the process of model creation.

Also, the case of urgent selection of the best/good enough objects as fast as possible is related to the problem presented above. An EC may be a head-hunter willing to find the best candidates before his competitors and before the skills test ends. In such case, the best, possible to obtain result of the skills test is unknown. In fact, the skills test may be too hard to reach the maximum result. The EC must decide to start the selection as soon as he is convinced that the best candidates had already finished the skills test.

Summarizing, there is a need for a method of measuring dependability of models, thus the reliability of the classification itself. This would be especially useful in case of processing objects with initially unknown characteristics and also if the dynamic classification is required.

3. DYNAMIC CLASSIFICATION

In [6] a method of dynamic classi cation, where there isno need to collect a complete set of data before the selection starts is introduced. It is assumed that the data may come from a new domain (objects have unknown characteristics) what means that expert knowledge is not available. The classi cation is performed by a person who is an Expert Candidate (EC). His decisions are supported by so called Arti cial Classi cation Adviser (ACA). While using the ACA objective knowledge of the EC also improves. The method of dynamic classification/selection is based on the following assumptions:

1) The quality (a non-measurable Q) is estimated on the basis of attributes of an object coming from a skills test (ST).
2) Normal distribution for each of the attributes over a set of the objects is expected.
3) The input stream of data consists of results of the skills test concerning consecutive objects. The data are collected and analysed on-the-fly. Meanwhile, the EC's knowledge improves during the process.
4) The resulting values may be imprecise (incomplete, ambiguous, conflicting), because real life data are expected.
5) The distribution of Q is normal for large enough group of analysed objects.

The algorithm of the classification is shown on Fig. 1. Firstly, an EC defines initial set of presumptions, including the predictive model of Q. Some parameters of the skills test (ST) may also be de ned optionally, especially the way the given attributes are going to be measured. An EC defines the model and parameters using his own intuition, as there is lack general of knowledge about the characteristics of objects which are to be classified. Thus, these presumptions are more or less accurate. Next, the data coming from the ST are analysed using the ACA for fulfilment of assumptions defined above, especially (2) and (5).

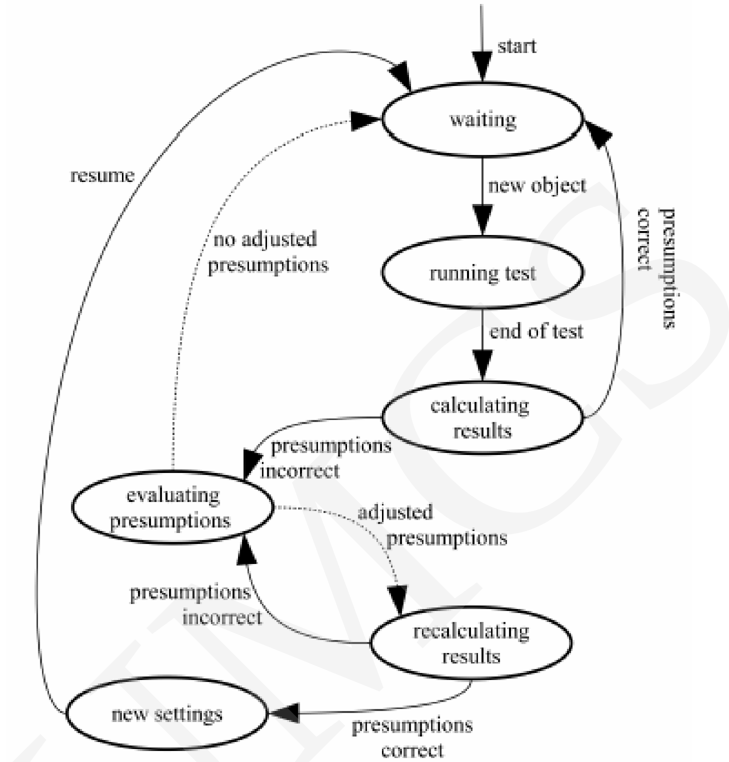

Figure 1 The collaboration of EC, ACA and the skills test: ACA's activities drawn as solid lines, EC's as dashed lines

The likelihood of compliance with the normal distribution is computed using the Lilliefors test for normality [1]. Next the result is transformed using a characteristic function (rough set theory) for making the result more appropriate for the classification. The final result is called reliability factor for the classification (*rfc*). The *rfc* is computed for the particular attributes *(rfc_A)* and also for the quality Q *(rfc_Q)*. For making the change in the distribution more meaningful, the rfc_A/rfc_Q is computed after collecting a few (e.g. five) consecutive results coming from the skills test. Moreover, for the most reliable classification, a few consecutive rfc_A/rfc_Q values should be taken into account instead of a single value. The EC decides how many *rfc* values must reach a given threshold and how high is the threshold for getting a "stable" *rfc* (Fig. 2).

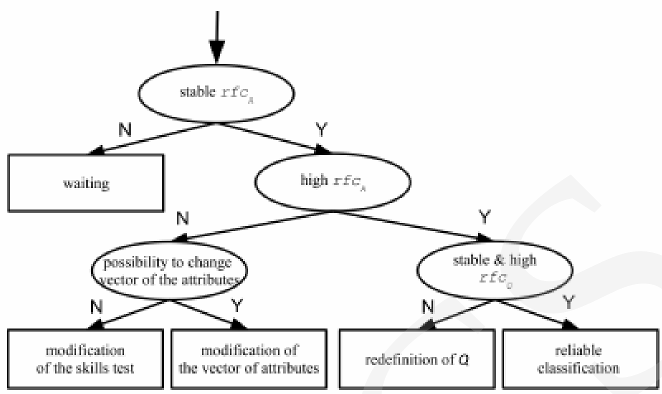

Figure 2 Decision tree for the EC

A cautious EC may use high threshold (e.g. 1.0) and high count (e.g. 7 consecutive *rfc* values), while a self-con dent one may use lower threshold (e.g. 0.5) and lower count (e.g. 3). The detailed description of computing the *rfc* is presented in [6].

Using the returned information (rfc_A *and* rfc_Q) as a basis, an EC takes his decisions with respect to the scheme shown on Fig. 2. As more and more data are collected, the model of the data refines and an EC's knowledge increases. The model is verified on-the-fly and it can be modified at any moment of the classification.

4. SOFTWARE DYNAMIC CLASSIFIER ARCHITECTURE

The ACA was developed using Java technology, it was designed to process on-the-fly data coming from some form of a skills test, thus a continuous input stream (or a file) of data of unknown length is expected. It is assumed that the data are initially processed and complete, incomplete data e.g. coming from an interrupted skills test are dropped before streaming to the ACA. The ACA graphical user interface uses standard Java swing libraries, it presents all useful statistical data concerning current set of data, such as the number of objects, minimum and maximum value of each attribute, likelihood of compliance with the normal distribution, kurtosis, skewness and current rfc_A/rfc_Q. Thus an EC has all the useful information at hand.

The ACA allows for analysis of the distribution or historical data in graphical form. The distribution diagram simply shows a histogram of the chosen column of data, compared to the ideal normal distribution curve computed for the same average and standard deviation values. The historical diagram shows how the *rfc* value changed during the process of gathering the data (Fig. 3, 4, 5). The horizontal axis represents the number of objects and the vertical axis the rfc_A or rfc_Q.

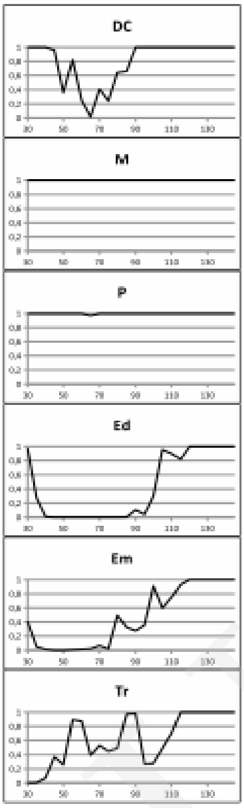

Figure 3 Changes of the rfc_{CA} for all the attributes over time, measured after every 5 tested candidates, starting from 30

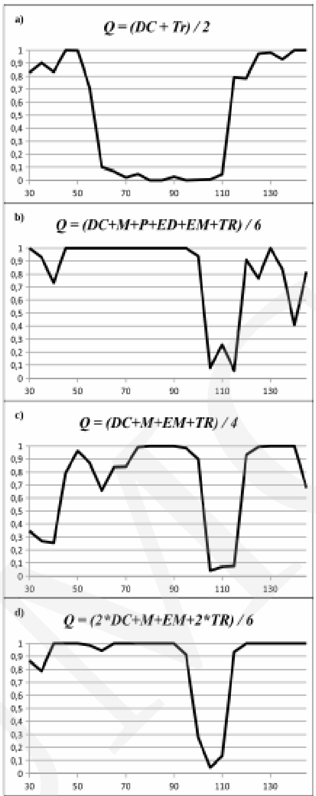

Figure 4 Values of rfc for different models of Q proposed by an EC

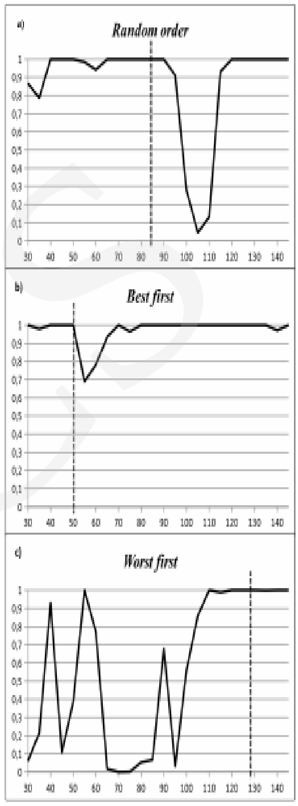

Figure 5 alues of *rfc* for the best Q and different data orders

5. CASE STUDY - FIREFIGHTING ROBOT OPERATORS

For the evaluation, we propose a problem of selecting operators of mobile, remotely controlled firefighting robot (mobot). As the use of mobile robots in fire-squads is a new idea [3], there are virtually no experts in this domain. The ACA will be used for selecting the best operators from many applicants. Such person should have attributes of both a good fireman and agile mobot operator. If we assume that there is no squad of firefighting mobot operators, there are no knowledge concerning this domain, no set of examples suitable for building a model, neither an expert in this domain. Thus the intuition of an EC may be assisted with the information coming from the ACA.

For the evaluation a real data coming from a skills test are used. The data was gathered during a research conducted in our Department, where students played the roles of mobile robot operator candidate. A software virtual mobot simulator was used for this purpose. The operator's task was to detect as many as possible changes in an environment, which had a form of a closed room filled with objects (e.g. spheres, cones, lamps, wardrobes, chairs). Operators were not aware when and where the scene as changing (e.g. colour, position, presence of objects). The virtual mobot was able to move in one of eight directions and take photos on demand. Results of the research, along with the description of the virtual mobile robot simulator used as a skills test, are fully described in [6]. During the skills test, the following attributes were measured and analysed:

- DC - *perceptivity*, computed on the basis of the number of correctly detected changes;
- M - *efficiency*, computed on the basis of inverse of the number of moves;
- P - *frugality*, computed on the basis of inverse of the total number of pictures taken by a camera;
- Ed - *perfection*, computed on the basis of inverse of the number of incorrectly reported changes (detection errors);
- Em - *carefulness*, computed on the basis of inverse of the number of incorrect moves (e.g. hits in a wall, broken objects);
- Tr - *swiftness*, computed on the basis of inverse of the reaction time (how long a change was detected after it was applied to the scene).

Results of the skills test are scaled to t the <0, 1> range, where 1 always corresponds to the best value. The scaling takes place due to different ranges of attributes (e.g. range of the DC is <0, 100>, while range of the Ed and Em is <0, 4>). If an EC wants to emphasize the impact of a particular attribute on the Q, weight could be used. This way or another, the resulting Q should always t the <0, 1> range.

A person performing the selection (EC) first of all must be sure whether the skills test results are reliable. With respect to the assumptions presented in chapter 3, the EC should check whether the distribution of the data is close to normal. For this purpose, the rfcA of all attributes must be analysed (Fig. 3). Fortunately, all attributes may be included in the Q, because their distribution gets close to normal along with more and more incoming data. It must be denoted that these diagrams (Fig. 3) were generated on a basis of the complete set of candidates. In contrast, an EC uses data which was collected up to a given moment of time, must analyse them on-the-fly and also make decisions concerning the classification, without waiting for completion of the skills test for all candidates. Next, the EC, with the help of his intuition, has to deny the initial model of the quality of a candidate (Q). He may assume that a fireman-operator has to be quick (high Tr) and perceptive (high DC). Thus the initial model (additive) of Q may be de ned as a sum of the chosen attributes (Fig. 4a):

$$Q = (DC + Tr)/2 \qquad (1)$$

After about 70 candidates the rfc_A drops down and the model is considered as unstable, thus the EC extends the additive model using all available attributes (Fig. 4b):

$$Q = (DC + M + P + ED + EM + TR)/6 \qquad (2)$$

The improved model is also unstable, thus the EC proposes a new one using four chosen attributes (Fig. 4c):

$$Q = (DC + M + EM + TR)/4 \tag{3}$$

Eventually, supplementing the model with weights gives proper result - stable and reliable model of Q (Fig. 4d):

$$Q = (2 \cdot DC + M + EM + 2 \cdot TR)/6 \tag{4}$$

It is worth mentioning that the procedure presented above may be performed dynamically, as more and more data are collected by the ACA during the skills test. This way, possibly the best firefighting mobot operators are chosen before the skills test ends. The diagram shown on Fig. 5a presents the final stage of the skills test after finishing by all of the candidates (identical to Fig. 4d). This is the case of one of n = 145! possible combinations of the order of incoming data, where good and bad candidates are randomly mixed. If the EC wants to finish the selection as soon as possible, he won't have to wait for the results of the skills test for all the candidates (there was 145 candidates in our case, and average time required to finish the skills test by a single candidate was 4320 seconds). The EC may start the selection as soon as the rfc_A/rfc_Q reaches stable levels. In the presented case, the EC assumed that the model becomes stable if 5 consecutive *rfc* values reached at least 0.95. In the random case (Fig. 5a) this took place after finishing the skills test of the 85th candidate (shown as a dotted line on the diagram). This way, the whole process may be speeded up by about 70 hours (60 candidates would be dropped).

For the comparison, two different extreme cases were also analysed[1] :

- The best first (Fig. 5b) - the best candidates finish the skills test earlier (like in real life, when the best prepared candidates are the fastest in carrying out the test tasks).
- The worst first (Fig. 5c) - the worst candidates finish the skills test earlier (also like in real life, when unprepared candidates give up after hearing the tasks to be done).

Results of the analysis are presented in Table 1 and Fig. 5. Assuming that the EC must select 10 the best candidates, the table is supplemented with the average Q in the chosen group.

Table 1Results of the dynamic classification for three different orders of incoming data

Data order	Stable model after candidate #	Time saving	Average Q in the chosen group
Random	85	70h	0.823
The best first	50	114h	0.797
The worst first	130	18h	0.767

[1] The data was sorted using the DC (perceptivity) as a key, because it was the priority of the skills test.

In comparison to the results of static selection done after finishing all 145 skills tests (Table 2) we find that a reliable selection may be performed on-the-fly, if values of *rfc* become stable.

Table 2 Results of the static classification for the whole group of candidates

	Tested	Total time of the skills tests	Average Q in the chosen group
Selection after finishing all skills tests	145	17h	0.832

Average Q for the whole group of candidates reached 0.652, thus the average Q for the chosen group is high enough to prove that the selection is correct while significantly reducing the time of the classification.

6. CONCLUSIONS

The paper presents briefly a methodology for dynamic classification of objects of unknown characteristics which was introduced in [6]. The methodology was implemented in software as the Artificial Classification Adviser. The ACA, in connection with a skills test, allows for the following:

- Verification of correctness of the skills test.
- Dynamic testing and evaluating of predictive models of Q proposed by an EC, and possibility to pick the most reliable one.
- Dynamic creation of descriptive models of objects, including the quality (Q).
- On-the-fly selection of possibly good/the best objects, with given reliability, during the skills test.
- Refinement of the knowledge of an EC, concerning the objects being classified.

Reliability of the classification is evaluated on the basis of main assumptions (Chapter 3), especially compliance of the distribution of attributes with normal distribution. The method proved to be useful, if there is lack of knowledge concerning objects being classified and there are no classic methods of evaluation of the proposed models. In such case, as there are no experts in the domain, intuition is used instead of the knowledge. The ACA assists an EC in his decisions, allows for minimizing the number of classification errors.

The ACA is especially useful in the two following cases: there is no knowledge concerning objects which are to be classified or there is already selected group of objects (possibly by an expert), but the classification rules are unknown. In the former case, an EC choses a group of possibly the best objects, due to his rational decisions supported with the statistical analysis. As the *rfc* reaches high enough and stable level, an EC may classify objects with a given reliability. This way, thanks to the help of ACA, the number of classification errors is minimized. The latter case corresponds to the process of training/learning of an EC. If there is already a group of chosen objects, it may be compared with an EC's decisions to evaluate his knowledge, with the help of ACA.

The case study presented in the paper demonstrates the use of ACA for selecting humans for a firefighting mobot operator, but the same method could be applies for different purposes, e.g. selecting the best pilots, students, medicals, especially working in a new domain. Moreover, the method is also useful for selecting non-human objects like manufactured goods, food products, insurance policies and so on.

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