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Intelligent classification of rock masses

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Abstract

In this work classifying methods are examined from the view of Artificial Intelligence.
Special reference is made to a pre-existing method of classifying rock masses (Bieniawski's classification method) and two typical attempts to use Artificial Intelligence tools are referred:
a) Transference of the methodology procedure in an expert system's shell, and
b) Training of a neural network with sets of inputs - results in order to map the outer performance of the methodology.

For an extension, machine learning is proposed as a tool for derivation of new classification methods taylored to specific systems. Fuzzy logic, self - adjustable neural networks and dynamic interaction among the input parameters of a system (instead of using net values) are among the new techniques.

Key-Words: Classification, Clustering, Artificial Intelligence, Expert Systems, Neural Networks, Fuzzy Logic.

1. Introduction

A definition of Intelligence is "The ability of recognizing similarities and dissimilarities". In other words : "The ability of grouping".

Given a number of objects or individuals each of which is described by a set of numerical measures, a classification scheme can group the objects into a number of classes such that objects similar in some respect belong to the same class.

Grouping methods can be :
declarative (the intergroup boundaries are predefined by examples. If conflicting examples exist, some criterion refines declaratively the proper group selection).
procedural (the experience has formed a predefined procedure that can be applied step by step to every new independent classification question. We have to do with a "classification method").
dynamic (there is not predefined experience but general laws and every classification question affects the rest. We have to do with a "clustering method").

Grouping methods have been invented in diverse sciences and different group cases.

Declarative methods seem more scientific but procedural ones are indispensable to some knowledge areas. Indeed, their existence is usually releiving, in case of unclear measurements, difficulty of correlating the measurements or absence of "natural scaling".

Finally, dynamic grouping (clustering) has its origin in statistics and, as such, it required strict mathematical manipulation. However, robust numerical algorithms, programed for the fast computers of nowadays, have already proved that they can replace efficiently the older analytical methods. Clustering methods are *tools for producing knowledge* in the context that, though they are not knowledge based algorithms, their results may offer ideas towards the derivation of new declarative classification methodologies.

A recent application of artificial intelligence tools to a classification in the engineering area concerns Rock Mass classification.

A pre-existing Rock Mass classification method, introduced by Bieniawski many years ago, is indeed declarative and uses five input parameters (P1, P2, P3, P4, P5 classification criteria) according to the following table (after [1]):

(P1) Strength of intact rock

Uniaxial Compr. Strength(MPa)	>200	100-200	50-100	25-50	10-1
Point load strength $I_{s(50)}$	>8	4-8	2-4	1-2	Too low
Rating	15	12	7	4	2-0

(P2) Drill core quality

	90-100%	75-90%	50-75%	25-50%	<25 %
Rating	20	17	13	8	3

(P3) Joint Spacing

	>3m	1-3 m	0.3 - 1m	0.05-0.3m	<0.05m
Rating	30	25	20	10	5

(P4) Joint condition

	Very rough surfaces No separation	Slightly rough surfaces Separation < 1mm	Slightly rough surfaces Separation < 1mm	Slickensided or Gouge 5mm thick or Joints open 1-5 mm	Gouge >5mm
Rating	25	20	12	6	0

(P5) Water conditions

	Completely dry	Completely dry	Moist-only interstitial water	Water under moderate pressure	Severe water problems
Rating	10	10	7	4	0

Bieniawski's index (**R**ock **M**ass **R**ating) is the Sum of the 5 previous ratings.

Rock Mass Rating was based on rock mass paradigms from the South Africa area. Since the first appearance of the method, it has been applied with success in a lot of projects over the world, in order to deduce the rock mass classes and , consequently, to give estimations about rock properties, by use of the five prementioned standard criteria as inputs.

Rock Mass Rating values correspond, by definition, to the following class values and their attached interpretations :

RMR (Sum)	100 -81	80- 61	60 - 41	40 - 21	<20
Class	**I**(Very good)	**II** (Good)	**III** (Fair rock)	**IV** (Poor)	**V** (Very poor)

2. A knowledge module for Rock classification advice.

Anthony Butler [2], at Waterloo University, took advantage of the facilities an expert system's shell provides and developed a module, named "CLASSEX", which can be used for Bieniawski's classification.

Such a module is not , of course, strictly declarative and crisply mathematical as the application of the above table boundaries are. On the contrary, an expert system is "model driven" and allows commenting, consulting, checking and correcting input values, even proposing manipulation methods for every special rock case. In general, the expert system "CLASSEX" simulates the overall procedure a meeting with a real expert could be.

3. A neural network that simulates Bieniawski's classification performance.

The outer performance of some existing classification methology, such as Bieniawski's rock mass classsification method, can be mapped on a neural network of the "mapping networks" type, such as the "back propagation" one .

A neural network of this kind creates a "model-free" connection of the input parameters (in this paradigm, the input parameters are data values of the 5 criteria : strength of intact rock, drill core quality, joint spacing, joint condition, groundwater conditions) with the output parameters (Rock Mass Rating datum value) after an iterative procedure which feedforwards through the network all the available inputs ("data driven" method) and adjusts the interconnection coefficients (weights) in a way that the desirable outputs result.

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Additional intermediate nodes and an intervening non-linear transformation is appropriate for the "back- propagation" type of neural network, as explained in various sources [3] , [4].

The input values, scaled to [0,1], in order to achieve logistic equivalence in the computations, become the "content" of the input neurons (nodes) of the network. The interconnection coefficients (weights) to every next node level are adjusted in such a way that the linear combination of neuronal quantities and weights, after passing through some non-linear transformation (e.g. a sigmoidal function that outputs to [0,1] and that is why the scaling of output data is also usual) gives at the output level the desirable output results. A feed-forward step is always followed by adjustment of the weights through back propagation of the resulting *error*. The error is the difference of the real output value from the desired output result. A network with weights adjusted in such a way can output good class value predictions to new input parameter question sets.

The authors used 20 data cases (each containing the 5 known input parameters together with the desired output Rock Mass Rating) placed in the 20 records of a file, which formed the "training set". A "back propagation program" developed by them [4] was used to "train" iteratively the network. After applying a number of times the iterative procedure of adjusting the weights, good weight values for a 5-3-1 "back propagation" network were obtained.

Satisfactory answers to new classification questions resulted by use of the final weights [5].

4. Other "Intelligent classification" proposals

To think about creating new classification methods (Creation of knowledge), new ideas can pop up from the results of the classic clustering techniques [6].

However, nowadays, there are a lot of AI tools that can help towards this scope, as well :

a) Recursive partitioning, ID3 and other induction tools [7].

b) Self- adjustable neural networks [3], [4] .

c) Other numerical representations of parameter correlation schemes such as the matrix presented in Hudson's monography [8].

The matrix refers especially to rock mechanics systems but its use may be generalized.

In this matrix, the critical parameters for the given engineering circumstances are posed in the diagonal places. These parameters are candidate criteria for the classification (e.g. Uniaxial Compressive

Strength, Joint orientation, Ground water conditions, In situ stress e.t.c.).

Numerical values estimating the interaction among critical parameters fill the rest cells of the matrix as following : The influences of every diagonal term on the rest diagonal terms fill the row cells of this term and the influences of the rest diagonal terms on the mentioned term fill its column cells. The overall intensity of a parameter i , when i is considered being a cause, is the sum **Ci** of all its row terms. Its overall intensity, when i is considered being an effect, is the sum **Ei** of all its column terms.

P1		I_{13}		
	P2	I_{23}		
I_{31}	I_{32}	**P3**	I_{34}	I_{35}
		I_{43}	**P4**	
		I_{53}		**P5**

$\Sigma I_{3i} = \mathbf{C_3}$ $\Sigma I_{j3} = \mathbf{E_3}$

In the previous figure only Bieniawski's parameters have been placed at the diagonal positions of an interaction matrix, in order to define an index as a function of these parameters. The simplest function is their sum, which corresponds to Bieniawski's index:

$$\text{Rock Mass Rating} = \sum_{i=1}^{5} Pi$$

If we want to estimate the most significant parameters and use them for the development of *a special rock classification index for the project at hand* (a perspective like this was preseen by J. Hudson in one of his earlier works [9]), we can choose the parameters with the bigger sum <C+E> among the complete list of the candidate parameters. Then, each parameter, before entering the proposed sum will be pre-multiplied by a number proportional to the magnitude of its <C+E> value.

5. Application of the fuzzy logic.

Fuzzy logic, though belonging to machine learning techniques, can not guide by itself towards the derivation of some independent

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classification methodology. It functions as a complement to every procedural (or declarative) methodology.

For example, Bieniawski's classification can become "fuzzy" if the fuzzy aggregation procedure proposed by Zadeh [10] for multi-criteria decision modelling is applied. Instead of using the net criterion values, the rock mass can be grouped or said to belong to each class with a different degree of belief, derived by expert judgement. For engineering purposes, the degrees of belief can be the membership grades that are obtained by scaling from some central value (normally the middle value of each class) [11]. Assuming that the various criteria are of equal importance, the fuzzy set of decision alternatives may be defined as the union of the intersection set $D = \bigcup_{classes} [\bigcap_{criteria} C]$,

the elements of which have membership values deriving from the correspondent fuzzy operations :

$$\mu_D = \max_{class} (\min_{criterion} \mu_c) \text{ values}$$

An example classification follows:

Standard Bieniawski's method

Criteria	Value	Rating
Uniaxial compressive strength (MPa)	150	12
Drill core quality (%)	70	13
Joint spacing (m)	0.5	20
Joint condition	Slightly rough surfaces Separation <1mm	20
Groundwater	Water under moderate pressure	4
		69

(Corrections due to joint orientation not applied).

"Fuzzified Bieniawski's classification"

Criteria	Degrees of belief (membership values) of belonging to each class : I	II	III	IV	V
Uniaxial compr. strength (MPa)	0.65	0.75	0.58	0.50	0.40
Drill core quality (%)	0.70	0.80	0.70	0.55	0.40
Joint spacing (m)	0.80	0.90	0.55	0.25	0.05
Joint condition	0.40	0.80	0.70	0.30	0.10
Groundwater	0.05	0.30	0.60	0.80	0.70
Min value of each class	**0.05**	**0.30**	**0.55**	**0.25**	**0.05**
Max value among min values of all classes				**0.55**	

The declarative method results a total score of "69", which addresses to class II, "good rock".

However, "fuzzy classification" is particularly affected by the most extreme membership values of the different criteria and its results are more conservative (class III, "fair rock").

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