RULE EXTRACTION FROM SUPPORT VECTOR MACHINES APPLIED TO THE CONSTRUCTION OF A GEOMECHANICAL QUALITY INDEX

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Abstract. Given the non-existence of a standard quality index for ornamental slate, granite and marble blocks, classical classification methods such as Bieniawski's RMR and Barton's Q are typically used, very much unquestioningly and indiscriminately. These methods, however, were originally designed for a different purpose, namely, to identify and solve stability problems in underground excavations.

These classical methods, furthermore, rely on pre-established parametric formulas that do not necessarily coincide in terms of criteria with rock quality experts. In fact, the fit between both perspectives has never been properly evaluated.

In this talk we propose a quality index for ornamental rock constructed by using machine learning techniques to model the quality grade allocation procedure as applied by the expert. This quality index is composed of a set of logical rules consisting of mathematical inequalities in relevant geomechanical quality variables.

Given their predictive capacity in classification and regression problems, we chose to use support vector machines (SVMs) to implement expert criteria learning. Nonetheless, the fact that the SVMs have the drawback of being difficult to interpret complicates the process of extracting the quality rules used by an expert. To overcome this drawback, we used classification and regression trees (CARTs) trained using SVM output.

In a comparison using real data, the proposed method produced results that represented a considerable improvement over the classical methods.

Being aware of the logical rules applied by the expert in order to determine the quality of ornamental rock means that variables of relevance to quality can be identified. Furthermore, preference mechanisms of which the expert may not be aware are brought to light and so can be ratified or corrected. The ultimate outcome is an improvement in the quality evaluation process and greater coherence in the quality index.