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Machine Learning Algorithms for Rock Cutting Slopes Stability Condition Identification

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Abstract

Transportation systems play a fundamental role in nowadays society. Indeed, every developed or countries undergoing development have invested and keep investing to build a safe and functional transportation network. The main concern nowadays, particularly for developed countries that already have a very complete network, is to keep it operational under all conditions. However, due to the network extension and increased budget constraints, such task is difficult to accomplish. In the framework of transportations networks, particularly for railway, slopes are perhaps the element for which their failure can have a strongest impact at several levels. Although there are some models and systems to detect slope failures, most of them were developed for natural slopes, presenting some constrains when applied to engineered (human-made) slopes. They have limited applicability as most of the existing systems were developed based on particular case studies or using small databases. Moreover, another aspect that can limit its applicability is related with the information used to feed them, such as data taken from complex tests or from expensive monitoring systems.
Aiming to overcome this drawback, we took advantage of the high flexible learning capabilities of Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), which have been used in the past to model complex nonlinear mappings. Both data mining algorithms were applied in the development of a classification tool able to identify the stability condition of a rock cutting slope, keeping in mind the use of information usually collected during routine inspections activities (visual information) to feed them. For that, two different strategies were followed: nominal classification and regression. Moreover, to overcome the problem of imbalanced data, three training sampling approaches were explored: no resampling, SMOTE and Oversampling. The achieved results are present and discussed, comparing the performance of both algorithms (ANN and SVM) according to each modeling strategy as well as the effect of the sampling approaches.

Keywords: Rock cutting slopes; Stability condition; Soft computing; Artificial neural networks; Support vector machines.

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1. Introduction

The existence of a set of tools capable of helping decision makers to take the best decisions is a key point for a good optimization of the available budgets of any company.
In the framework of transportations networks, in particular for a railway, slopes are perhaps the element for which their failure can have the strongest impact at several levels. Therefore, it urges the necessity to find an accurate way to identify potential problems before they result in failures.

Although there are some models and systems to detect slope failures, most of them were developed for natural slopes, presenting some constraints when applied to engineered (human-made) slopes. They have limited applicability as most of the existing systems were developed based on particular case studies or using small databases. Furthermore, another aspect that can limit its applicability is related with the information required to feed them, such as data taken from complex tests or from expensive monitoring systems. Some approaches found in the literature for slope failure detection are identified below.

Pourkhosravani and Kalantari (2011) summarize the current methods for slope stability evaluation, which were grouped into Limit Equilibrium (LE) methods, Numerical Analysis methods, Artificial Neural Networks and Limit Analysis methods. There are also approaches based on finite elements methods (Suchomel et al., 2010), reliability analysis (Husein Malkawi et al., 2000), as well as some methods making use of data mining (DM) algorithms (Cheng and Hoang, 2014; Ahangar-Asr et al., 2010; Yao et al., 2008). More recently, a new flexible statistical system was proposed by Pinheiro et al. (2015), based on the assessment of different factors that affect the behavior of a given slope. By weighting the different factors, a final indicator of the slope stability condition is calculated.

In summary, most of the approaches so far proposed share the main limitations, which are related with its applicability domain or dependency on information that is difficult to obtain. Indeed, the prediction of whether a slope will fail or not is a multi-variable problem characterized by a high dimensionality.

Aiming to overcome these drawbacks, we took advantage of the learning capabilities of flexible data mining algorithms, in particular the Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs). These data mining algorithms were used to fit a large database of rock cutting slopes in order to predict the stability condition of a given slope according to a pre-defined classification scale based on four levels (classes). One of the underlying premises of this work is to identify the real stability condition of a given slope based on information that can be easily obtained through visual routine inspections. For that, more than sixty variables related with data collected during routine inspections as well as geometric, geological and geographic data were used to feed the models. This type of visual information is sufficient from the point of view of the network management, allowing the identification of critical zones for which more detailed information can then be obtained in order to perform more detailed stability analysis, which is out of the scope of this study.

2. Data characterization

In this work we propose a model for stability condition (EHC, Earthwork Hazard Category, adapted from Power et al. (2016)) identification, of rock cutting slopes using soft computing tools.

The EHC system comprises 4 classes (“A”, “B”, “C” and “D”) where “A” represents a good stability condition and “D” a bad stability condition. In other words, the expected probability of failure is higher for class “D” and lower for class “A”. To fit the models for EHC prediction, a database was compiled containing information collected during routine inspections and complemented with geometric, geological and geographic data of each slope. The database was gathered by Network Rail workers and is concerned with the railway network of the UK. For each slope a class of the EHC system was defined by the Network Rail Engineers based on their experience/algorithm (Power et al., 2016), which will be assumed as a proxy for the real stability condition of the slope for the year 2015.

Fig. 1 depicts the distribution of the 5945 records by each EHC class (Power et al., 2016). From its analysis, it is possible to observe an asymmetric distribution (imbalanced data). Indeed, more than 86% of the rock cutting slopes are classified as “A” and less than 1% belongs to class “D”. Although this type of asymmetric distribution, where most of the slopes present a low probability of failure (class “A”), is normal and desirable from the safety point of view and slope network management, it can represent an important challenge for data mining models learning, as detailed in next section.

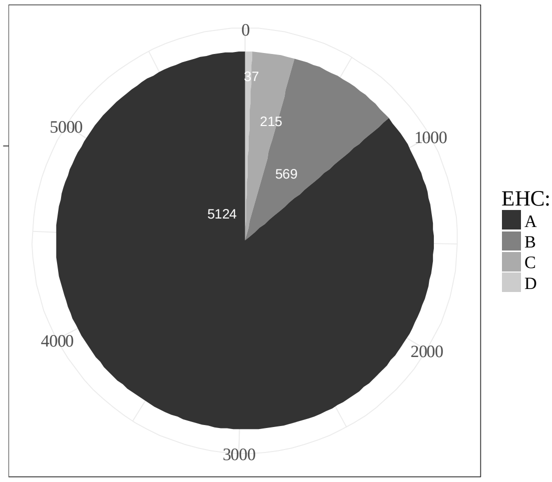


Fig. 1 Rock cutting slopes data distribution by EHC classes

3. Modelling

In this work we applied two of the most flexible data mining algorithms, namely ANNs and SVMs, to model EHC prediction of rock cutting slopes. These two algorithms had already been successful applied in different knowledge domains (Liao et al., 2012) including in civil engineering (Tinoco et al., 2014a,b). There are also some examples of ANN and SVM applications in slope stability analysis, such as the works published by Yao et al., (2008) and Cheng et al., (2012).

ANNs try to simulate basic aspects of the human brain (Kenig et al., 2001). The information is processed using iteration among several neurons. This technique is capable of modeling complex non-linear mappings and is robust in exploration of data with noise. In this study we adopt the multilayer perceptron that contains only feedforward connections, with one hidden layer containing H processing units. Because the network's performance is sensitive to H (a trade-off between fitting accuracy and generalisation capability), we adopt a grid search of {0; 2; 4; 6; 8} during the learning phase to find the best H value. The neural function of the hidden nodes was set to the popular logistic function $1 / (1 + e^{-x})$.

Concerning to SVMs, they were initially proposed for classification tasks (Cortes and Vapnik, 1995) and later adapted to regression tasks after the introduction of the ε-insensitive loss function (Smola and Scholkopf, 2004). The main purpose of the SVM is to transform input data into a high-dimensional feature space using non-linear mapping. The SVM then finds the best linear separating hyperplane, related to a set of support vector points, in the feature space. This transformation depends on a kernel function. In this work the popular Gaussian kernel was adopted. In this context, its performance is affected by three parameters: γ, the parameter of the kernel; C, a penalty parameter; and ε (only for regression), the width of an ε-insensitive zone (Safarzadegan Gilan et al., 2012). The heuristics proposed by Cherkassky and Ma (2004) were used to define the first two parameter values, C=3 (for a standardized output) and $\varepsilon = \hat{\sigma}/\sqrt{N}$, where $\hat{\sigma} = 1.5/N \cdot \sum_{i=1}^{N}(y_i - \hat{y}_i)^2$, y_i is the measured value, $\hat{y}_i$ is the value predicted by a 3-nearest neighbour algorithm and N is the number of examples. A grid search of {1; 3; 7; 9} was adopted to optimize the kernel parameter γ.

As a first attempt, we approach EHC prediction of rock cutting slopes following a nominal classification strategy. Then, aiming to improve the models performance, the problem was also addressed following a regression strategy, adopting a regression scale where “A” = 1, “B” = 2, “C” = 4, “D” = 10, which was that leading to the best performance. Moreover, in order to minimize the effect of the imbalanced data as shown in Fig. 1, two resample approaches were applied over the training data before fitting the models, namely Oversampling (Ling and Li, 1998) and SMOTE (Chawla et al., 2002). When approaching imbalanced classification tasks, where there is at least one target class label with a smaller number of training samples when compared with other target class labels, the simple use of a data mining training algorithm will lead to datadriven models with better prediction accuracies for the majority classes and worst classification accuracies for the minority classes. Thus, techniques that adjust the training data in order to balance the output class labels, such as Oversampling and SMOTE, are commonly used with imbalanced datasets. In particular, Oversampling is a simple technique that randomly adds samples (with repetition) of the minority classes to the training data, such that the final training set is balanced. SMOTE is a more sophisticated technique that creates "new data" by looking at nearest neighbours to establish a neighbourhood and then sampling from within that neighbourhood. It operates on the assumptions that the original data is similar because of proximity. More recently, Torgo et al. (2015) adapted the SMOTE method for regression tasks.

All experiments were conducted using the R statistical environment (Team, 2009) and supported through the rminer package (Cortez, 2010), which facilitates the implementation of ANNs and SVMs algorithms, as well as different validation approaches such as cross-validation.

For models assessment and comparison, three metrics were calculated: recall, precision and F1-score. The recall measures the ratio of how many cases of a certain class were properly captured by the model. In other words, the recall of a certain class is given by TruePositives/(TruePositives+FalseNegatives). On the other hand, the precision measures the correctness of the model when it predicts a certain class. More specifically, the precision of a certain class is given by TruePositives/(TruePositives + FalsePositives). The F1-score was also calculated, which represents a trade-off between the recall and precision of a class. The F1-score corresponds to the harmonic mean of precision and recall. For all four metrics, the higher the value, the better are the predictions, and their values can range from 0% to 100%. The generalization capacity of the models was accessed through a 5-fold cross-validation approach under 20 runs (Hastie et al., 2009). This means that each modeling setup is trained 5×20=100 times. Also, the four prediction metrics are always computed on test unseen data (as provided by the 5-fold validation procedure).

4. Results and Discussion

As described above, for EHC prediction of rock cutting slopes we applied two different data mining algorithms (ANN and SVM) under two distinct modeling strategies: nominal classification and regression. Moreover, in order to overcome the problem of unbalanced data, three training sampling approaches were explored: Normal (no resampling), OVERed (Oversampling) and SMOTEd (SMOTE). In case of regression, we compared two sampling approaches: Normal (no resampling) and SMOTEd (SMOTE for regression). We note that the different sampling approaches were applied only to training data, used to fit the data-driven models, and the test data (as provided by the 5-fold procedure) was kept without any change.

Table 1 summarizes recall, precision and F1-score of all fitted models for EHC prediction of rock slopes, according to a nominal classification and regression strategies as well as using SMOTE and Oversampling approaches.

Table 1. Metrics in EHC prediction of rock cutting slopes (best values in bold).

Model		Approach	Recall				Precision				F1-score			
			A	B	C	D	A	B	C	D	A	B	C	D
Classification	ANN	Normal	96.23	52.95	20.40	3.65	94.66	49.06	39.22	13.71	**95.44**	50.93	26.84	5.77
		SMOTEd	88.10	67.60	36.58	17.30	98.50	38.36	26.14	10.89	93.01	48.95	30.49	**13.37**
		OVERed	90.20	67.96	39.58	**12.84**	98.01	41.27	33.47	12.70	93.95	**51.35**	36.27	12.77
	SVM	Normal	97.39	39.79	6.44	0.41	91.63	48.57	42.95	18.75	94.42	43.74	11.20	0.80
		SMOTEd	85.53	82.64	2.07	1.49	97.27	33.03	34.36	17.19	91.01	47.25	3.90	2.74
		OVERed	**99.78**	7.14	0.00	0.00	86.95	**62.83**	NA	0.00	92.92	12.82	NA	NA
Regression	ANN	Normal	93.70	48.30	41.77	3.38	95.01	41.38	40.19	30.49	94.35	44.57	**40.96**	6.09
		SMOTEd	85.90	68.37	**45.84**	4.32	98.07	33.85	32.95	**35.56**	91.62	45.28	38.34	7.70
	SVM	Normal	96.32	49.83	0.30	0.00	92.56	46.33	**54.17**	NA	94.40	48.02	0.60	NA
		SMOTEd	77.13	**93.15**	11.12	0.00	**99.40**	27.61	48.33	NA	86.86	42.59	18.08	NA

For a better analysis and models performance visualization, Fig. 2 compares recall, precision and F1-score metrics of all models in EHC prediction following a nominal classification strategy. From its analysis we can observed that all models present a high performance in class "A" identification of rock cutting slopes (F1-score higher than 91%). However, for class "C" and particularly for class "D", the models have difficulties in predicting these classes correctly. Indeed, and using F1-score as reference, the best performance in identification of slopes of class "D" is lower than 14% which was achieved by the ANN algorithm after balancing the database through the SMOTE approach.

Analyzing the influence of the SMOTE and Oversampling approaches, we can observe a slight increase of model performance for classes "C" and "D" prediction. In other words, by using a training sampling approach we can improve models performance, particularly for the minority classes.

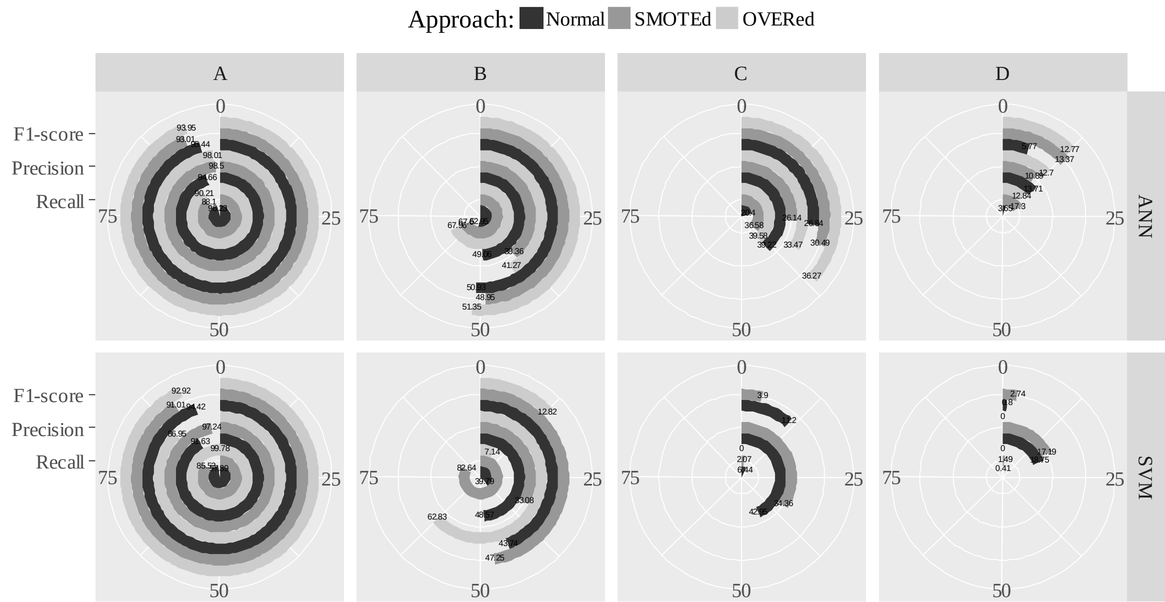


Fig. 2 Models comparison based on recall, precision and F1-score, according to a nominal classification strategy in EHC prediction of rock slopes.

Fig. 3 compares model performance based on recall, precision and F1-score metrics following a regression strategy. Also here, a high performance was achieved for classes "A" and "B" identification of rock slopes, but a very low response is observed for class "D". When following a regression strategy, the application of a balancing approach, i.e., SMOTE sampling, had almost no effect on the model's performance.

Fig.4 shows the relation between observed and predicted EHC values according to the best fits, following a nominal classification (Fig. 4a) and regression (Fig. 4b) strategies. From its analysis, we can observe that rock slopes of class "A" are almost correctly identified. Also for class "B" a promising performance is observed, with an F1-score around 70%, namely following a nominal classification strategy. However, for class "C" and particularly for class "D", for which the expected probability of failure is higher, models evidence difficulties in identifying these classes accurately. From Fig. 4a analysis, only around 12% of rock cutting slopes classified as "D" were correctly identified, which represents a low performance. According to a regression strategy, the performance in class "D" prediction is still lower (see Fig. 4b). Overall, the methodology applied for EHC prediction of rock cutting slopes needs future development in order to overcome this gap.

5. Conclusions

As a conclusion, an attempt to predict Earthwork Hazard Classification (EHC) of rock cutting slopes through the application of data mining techniques was presented. Although the achieved overall performance has fallen short of what was expected, the high performance observed for class "A" and "B", open good expectations for further developments aiming models performance improvement, particularly for class "D" (minority class) prediction.

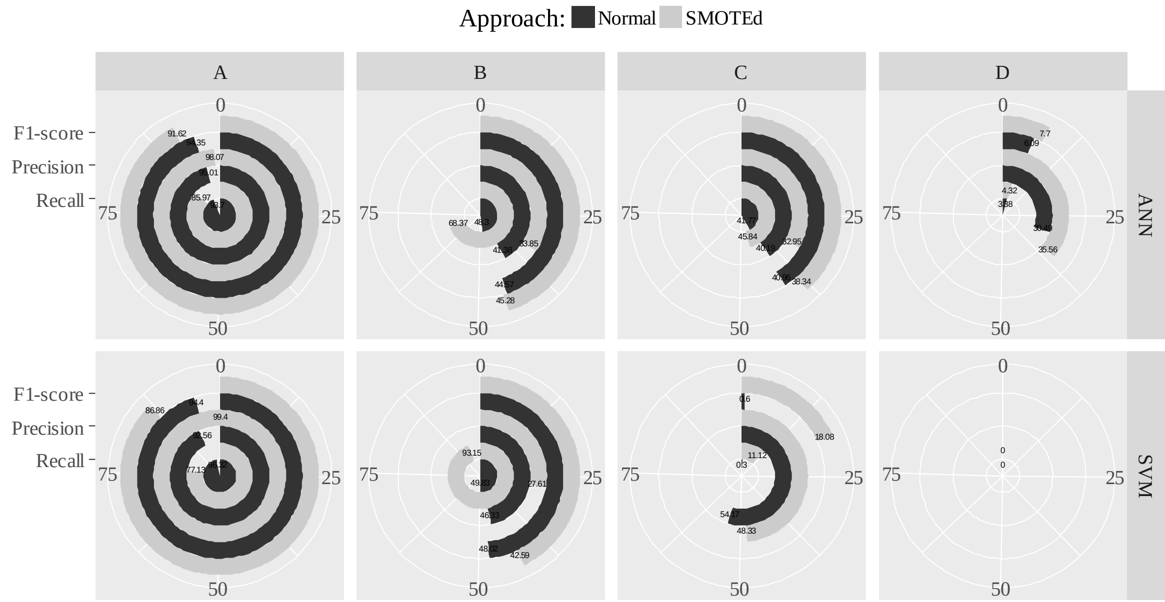
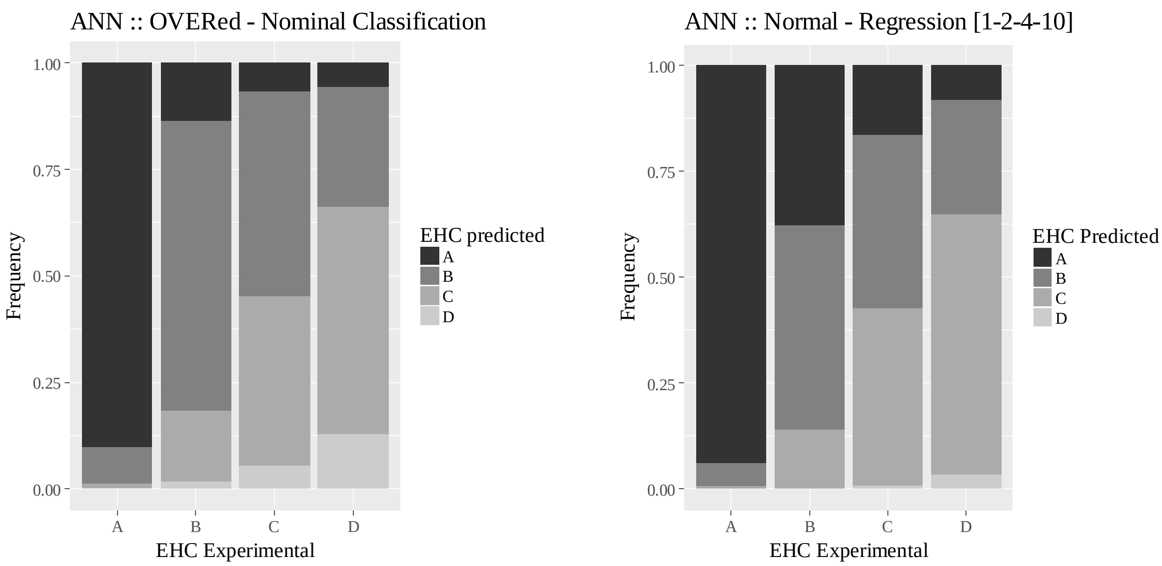


Fig. 3 Models comparison based on recall, precision and F1-score, according to a regression strategy in EHC prediction of rock cutting slopes.

Moreover, and considering the overall performance of all models, we would like to stress that soft computing algorithms, particularly ANNs, can be seen as a tool with some potential to identify stability condition of engineered slopes. Also the use of a balancing approach, such as SMOTE or Oversampling, can help to increase models performance. Thus, considering the high number of variables taken as models inputs, as a further developments we intend to reduce the number of variables trough the application of some feature selection methodologies (e.g. through the application of genetic algorithms). This will allow reducing models complexity and eventually improving its performance.



a) b)

Fig. 4 ANN models performance comparison in EHC prediction of rock cutting slopes according to (adapted from Tinoco et all, 2017): a) nominal classification strategy following a OVERed approach; b) regression strategy with no resampling.

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