

Report on my own edx project

FUNG CHE HEI

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1. Introduction

1.1 Background

There are many valuable minerals and geological materials in the Earth that are stored in the form of some kinds of ores, lode, vein and reef. Mining is the human activities to extract those of them. Although mining activity seems interesting for human to discover different kinds of minerals in the Earth, it is a dangerous activities because a hazard of seismic bumps would occurs in many underground mines. Inaccurate prediction and detection would cause great damage to human life.

Therefore a good seismic hazard assessment is important and required for mining activities. With the aid of machine learning technologies, some research including clustering [1] and artificial neural networks [2] are used for prediction of seismic tremors in the past years.

1.2 Aim

Our main aim is:

- to forecast the high energy seismic bumps (higher than 10^4 J) in mine

With predicting the possibility of the occurrence of hazardous situation, appropriate risk assement and supervision service can be made. For example, reducing the risk of rockburst by the use of distressing shooting method and withdrawing workers from the threatened area.

1.3 Data set Information

The data set used is called “seismic-bumps Data Set” which is downloaded from UCI Machine Learning Repository. <https://archive.ics.uci.edu/ml/datasets/seismic-bumps#>

Here we read the downloaded data set and call it ‘seismic’.

```
seismic <- as.data.frame(read_csv("data/seismic_bumps.csv"))
```

An overview on the seismic-bumps Data Set

```
nrow(seismic)
```

```
## [1] 2584
```

```
ncol(seismic)
```

```
## [1] 20
```

```
head(seismic)
```

```
##   id seismic seismoacoustic shift genergy gpuls genergy gdpuls ghazard nbumps
## 1  1      a              a     N   15180   48    -72    -72      a      0
## 2  2      a              a     N   14720   33    -70    -79      a      1
## 3  3      a              a     N    8050   30    -81    -78      a      0
## 4  4      a              a     N   28820  171    -23     40      a      1
## 5  5      a              a     N   12640   57    -63    -52      a      0
## 6  6      a              a     W   63760  195    -73    -65      a      0
##   nbumps2 nbumps3 nbumps4 nbumps5 nbumps6 nbumps7 nbumps89 energy maxenergy
## 1      0      0      0      0      0      0      0      0      0
## 2      0      1      0      0      0      0      0    2000    2000
## 3      0      0      0      0      0      0      0      0      0
## 4      0      1      0      0      0      0      0    3000    3000
## 5      0      0      0      0      0      0      0      0      0
## 6      0      0      0      0      0      0      0      0      0
##   class
## 1     0
## 2     0
## 3     0
## 4     0
## 5     0
## 6     0
```

After having a quick look on the data set, there are 2584 rows (observations) and 20 columns (attributes). Each observation contains a summary statement about seismic activity in the rock mass within one shift (8 hours) which will be described in section 1.4, to predict ‘hazardous’ (positive class with value = 1) and ‘non-hazardous’ (negative class with value = 0) states. If ‘hazardous’ is predicted, it is possibly that seismic bump with an energy higher than 10^4 J would occur in the next shift.

Here note the there is unbalanced distribution of positive and negative class. Among 2584 observations, only 170 of them are positive class.

```
sum(seismic$class == 1)
```

```
## [1] 170
```

1.4 Arributes Information

- 1. seismic: result of shift seismic hazard assessment in the mine working obtained by the seismic method (a - lack of hazard, b - low hazard, c - high hazard, d - danger state);
- 2. seismoacoustic: result of shift seismic hazard assessment in the mine working obtained by the seismoacoustic method;
- 3. shift: information about type of a shift (W - coal-getting, N -preparation shift);

- 4. genenergy: seismic energy recorded within previous shift by the most active geophone (GMax) out of geophones monitoring the longwall;
- 5. gpuls: a number of pulses recorded within previous shift by GMax;
- 6. gdenergy: a deviation of energy recorded within previous shift by GMax from average energy recorded during eight previous shifts;
- 7. gdpuls: a deviation of a number of pulses recorded within previous shift by GMax from average number of pulses recorded during eight previous shifts;
- 8. ghazard: result of shift seismic hazard assessment in the mine working obtained by the seismoacoustic method based on registration coming from GMax only;
- 9. nbumps: the number of seismic bumps recorded within previous shift;
- 10. nbumps2: the number of seismic bumps (in energy range $[10^2, 10^3)$) registered within previous shift;
- 11. nbumps3: the number of seismic bumps (in energy range $[10^3, 10^4)$) registered within previous shift;
- 12. nbumps4: the number of seismic bumps (in energy range $[10^4, 10^5)$) registered within previous shift;
- 13. nbumps5: the number of seismic bumps (in energy range $[10^5, 10^6)$) registered within the last shift;
- 14. nbumps6: the number of seismic bumps (in energy range $[10^6, 10^7)$) registered within previous shift;
- 15. nbumps7: the number of seismic bumps (in energy range $[10^7, 10^8)$) registered within previous shift;
- 16. nbumps89: the number of seismic bumps (in energy range $[10^8, 10^{10})$) registered within previous shift;
- 17. energy: total energy of seismic bumps registered within previous shift;
- 18. maxenergy: the maximum energy of the seismic bumps registered within previous shift;
- 19. class: the decision attribute - '1' means that high energy seismic bump occurred in the next shift ('hazardous state'), '0' means that no high energy seismic bumps occurred in the next shift ('non-hazardous state').

1.5 Variables Information

There are totally 18 input variables (attributes) and 1 binary output variable (class) in the data set. The below table summarize some information of the variables.

Table 1: Variable Summary Table

variable	Cardinality	Filled	Nulls	Total	Uniqueness
class	2	2584	0	2584	0.0
energy	242	2584	0	2584	0.1
gdenergy	334	2584	0	2584	0.1
gdpuls	292	2584	0	2584	0.1
genenergy	2212	2584	0	2584	0.9

variable	Cardinality	Filled	Nulls	Total	Uniqueness
ghazard	3	2584	0	2584	0.0
gpuls	1128	2584	0	2584	0.4
id	2584	2584	0	2584	1.0
maxenergy	33	2584	0	2584	0.0
nbumps	10	2584	0	2584	0.0
nbumps2	7	2584	0	2584	0.0
nbumps3	7	2584	0	2584	0.0
nbumps4	4	2584	0	2584	0.0
nbumps5	2	2584	0	2584	0.0
nbumps6	1	2584	0	2584	0.0
nbumps7	1	2584	0	2584	0.0
nbumps89	1	2584	0	2584	0.0
seismic	2	2584	0	2584	0.0
seismoacoustic	3	2584	0	2584	0.0
shift	2	2584	0	2584	0.0

Although ‘maxenergy’ and ‘nbumps’ are numeric data representing the magnitude of energy and number of bumps respectively, they have a relatively small cardinality which result in zero Uniqueness (defined by the ratio of Cardinality to Total). Therefore they are classified into catagorical variables. For those variables with uniqueness greater than zero are then classified as numeric variables. Below is the table that summarizing the variable type of class and each attributes.

Table 2: Variable Type

Variable	Type
class	binary
energy	numeric
gdenergy	numeric
gdpuls	numeric
genergy	numeric
ghazard	catagorical
gpuls	numeric
maxenergy	catagorical
nbumps	catagorical
nbumps2	catagorical
nbumps3	catagorical
nbumps4	catagorical
nbumps5	catagorical
nbumps6	catagorical
nbumps7	catagorical
nbumps89	catagorical
seismic	catagorical
seismoacoustic	catagorical
shift	catagorical

1.6 Key Steps

2. Data Analysis

2.1 Data Cleaning

2.2 Data Exploration and Visualization

2.3 Modeling Approach

3. Results and Discussion

4. Conclusion and Future Work

4.1 Limitation

More and more advanced seismic and seismoacoustic monitoring systems allow a better understanding rock mass processes and definition of seismic hazard prediction methods. Accuracy of so far created methods is however far from perfect. Complexity of seismic processes and big disproportion between the number of low-energy seismic events and the number of high-energy phenomena (e.g. $> 10^4$ J) causes the statistical techniques to be insufficient to predict seismic hazard. Therefore, it is essential to search for new opportunities of better hazard prediction, also using machine learning methods. Unbalanced distribution of positive ('hazardous state') and negative ('non-hazardous state') examples is a serious problem in seismic hazard prediction. Currently used methods are still insufficient to achieve good sensitivity and specificity of predictions.

Acknowledgement

Marek Sikora^{1,2} (marek.sikora '@' polsl.pl), Lukasz Wrobel^{1} (lukasz.wrobel '@' polsl.pl) (1) Institute of Computer Science, Silesian University of Technology, 44-100 Gliwice, Poland (2) Institute of Innovative Technologies EMAG, 40-189 Katowice, Poland

Reference

- 1. Lesniak A., Isakow Z.: Space-time clustering of seismic events and hazard assessment in the Zabrze-Bielszowice coal mine, Poland. *Int. Journal of Rock Mechanics and Mining Sciences*, 46(5), 2009, 918-928
- 2. Kabiesz, J.: Effect of the form of data on the quality of mine tremors hazard forecasting using neural networks. *Geotechnical and Geological Engineering*, 24(5), 2005, 1131-1147
- 3.