# An Overview of Data Mining and Process Mining Applications in Underground Mining

*Edyta BRZYCHCZY*[1)]

[1)] Ph.D., DSc.; AGH University of Science and Technology, Cracow, Poland

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## Abstract

*The underground mining process can be analysed with a data-oriented or process-oriented approach. The first of them is popular and wide known as data mining while the second is still not often used in the conditions of the mining companies. The aim of this paper is an overview of data mining and process mining applications in an underground mining domain and an investigation of the most popular analytic techniques used in the defined analytic perspectives ("Diagnostics and machinery", "Geomechanics", "Hazards", "Mine planning and safety"). In the paper two research questions are formulated: RQ1: What are the most popular data mining/process mining tasks in the analysis of the underground mining process? and RQ2: What are the most popular data mining/process mining techniques applied in the multi-perspective analysis of the underground mining process? In the paper sixty--two published articles regarding to data mining tasks and analytic techniques in the mentioned domain have been analysed. The results show that predominatingly predictive tasks were formulated with regard to the analysed phenomena, with strong overrepresentation of classification task. The most frequent data mining algorithms is comprised of the following: artificial neural networks, decision trees, rule induction and regression. Only a few applications of process mining in analysis of the underground mining process have been found – they were briefly described in the paper.*

*Keywords: data mining, process mining, analysis, mining process, underground mining*

**Introduction**

The Industry 4.0 concept has a strong impact on the analytic activities of companies, which are willing to implement various solutions being an inherent part of modern smart factories. Nowadays, companies all over the world and across industries actively recognize and implement 4.0. solutions i.e. intelligent sensors, mobile devices or IoT platforms. Therefore, as result very fast growth of data gathered in organisations that need processing can be observed. These data are a potential source of new, useful knowledge for the decision-making process, that should be discovered. The knowledge discovery process in data can be supported by IT systems of different types (i.e. databases, analytic software, and cloud computing) and the data analytics domain. That is why big data and advanced analytics are the key features of today's companies.

The mining industry is also strongly involved in the implementation on Industry 4.0. solutions and the development of analytic competences. The analytics of the mining process should take into account the specific conditions of the mining process realisation as well as the nature of the mining process itself. The mining process, especially underground, is a complex system of people and machinery activities carried out in changeable working conditions. The occurrence of natural hazards, climate conditions as well as deposit geology have great impact on mining process performance.

The underground mining process can be analysed with the data-oriented or the process-oriented approach. The data-oriented approach is called data mining (DM) and is comprised of various tasks, algorithms and techniques that are very popular and wide known whilst the process-oriented approach is still not widely used in mining process analytics. This rather new research discipline is called process mining (PM) and enables modelling, diagnostics and the enhancement of the business processes using event data from IT systems supporting and monitoring the process execution.

The aim of the paper is an overview of data mining and process mining applications in an underground mining domain and investigation of the most popular analytic techniques used in the defined analytic perspectives. In the paper the following research questions are formulated:

RQ1: What are the most popular DM/PM tasks in the analysis of the mining process?

RQ2: What are the most popular DM/PM techniques applied in the multi-perspective analysis of the underground mining process?

These questions will be answered with an overview of data mining and process mining applications in the multi-perspective analysis of the underground mining process.

The paper's structure is as follows. In Section 2 the main analytic approaches are characterised. An overview of the DM and PM application in mining process analytics is presented in Section 3. Section 4 concludes the paper and provides the answers to the formulated research questions.

**The main analytics approaches**

In a modern business analytic two main approaches can be distinguished:

1. data-oriented analytics,
2. process-oriented analytics.

Data-oriented analytics offers new capabilities of knowledge discovery from data with the use of classic and advanced algorithms of data science (namely data mining - DM). The

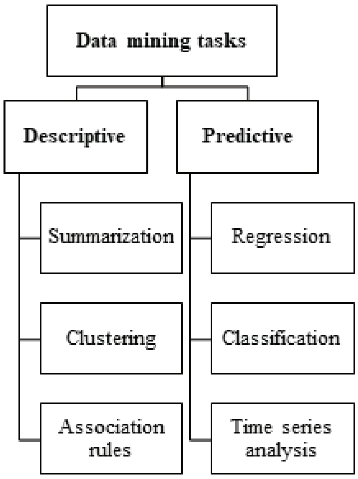


Fig. 1. Main tasks of DM
Rys. 1. Główne zadania DM

main tasks of data mining can be divided into descriptive and predictive tasks (Fig.1).

The main descriptive tasks include: summarization, clustering and association rules. Summarization enables the characterization of the dataset with the use of statistics and visualization techniques. Clustering is used for the segmentation of observations from a dataset into groups based on similarities among the selected attributes. Association rules (often used in a basket analysis) indicate the patterns in a dataset between the observations in a form of simple or complex rules. The mentioned tasks concentrate on a description and grouping or pattern findings in an available dataset.

Predictive tasks include regression, classification and time series analysis. The main distinctive feature from the descriptive tasks is that the obtained models built on the available dataset can be used for prediction. Regression enables the finding of a function describing the dependency between the selected variables (mainly of the numerical type). Classification is used for building the model describing rules for data mapping into predefined classes or groups (mainly of the categorical type). Time series analysis regards to analysis of variable values changes in the time.

Data-oriented algorithms are mainly a part of the machine learning domain and in dependency on the analytic tasks various techniques are used (Table 1).

In general, machine learning can be divided into supervised and unsupervised learning. The distinction is based on the necessity of target variable indication (in supervised learning a target variable should be indicated). From this point of view, in descriptive tasks unsupervised learning is used, while in predictive tasks supervised techniques are applied.

The data mining approach is nowadays wide known and used in the analytic community, however very fast growth of process-oriented analytics cannot be disregarded (Fig.2).

The number of papers on process mining in the Scopus database has tripled in the last 8 years.

Process-oriented analytics offers new capabilities of knowledge discovery about process execution from event logs with the use of process mining techniques. Process mining (PM) is a relatively new analytic discipline and is characterized as a bridge between data and process science (van der Aalst 2016).

The main tasks that could be proceed with process mining techniques include (van der Aalst 2016): the discovery of process models, conformance checking and enhancement. Their characteristics are presented in Table 2.

The basic data structure for process mining – namely event log – includes: case id, the timestamp of an event and an event name. These data can be extended with other contextual information related to resources, costs etc. The process models built on the top of the event log can be expressed in a form of dependency graphs, Petri nets or BPMN models. Process models enable conformance checking and in-depth process analysis in time, resource or case perspectives.

The presented approaches establish a complementary source of potentially new and useful knowledge in an organization for process improvement and optimization of the economic or production results. In the next sections an overview of their applications in the multi-perspective analysis of the underground mining process is presented.

**An overview of the data mining and process mining applications in underground mining process analytics**

***Data Mining applications***

An overview of data mining applications in the underground mining process analysis has been based on 62 papers searched with use of the Science Direct, Scopus, IEEE Explore and Google Scholar databases (examples of used terms: “analysis+mining+process+underground”, “prediction+underground+mine”, “data+analysis+longwall”, “machine+learning+longwall”).

In the paper, for the purpose of a more detailed description of data mining applications in underground mining process analytics, the following perspectives have been introduced: “Diagnostic and machinery”, “Geomechanics”, (other) “Hazards” and “Mine planning and safety”.

The distributions of the papers in terms of publication year and defined analytic perspective are presented in Fig.3 and Fig. 4.

Most of the analysed papers have been published in the last 5 years. The distribution of the papers in relation to de-

Tab. 1. Example techniques used in DM tasks. Source: based on (Larose and Larose 2014)
Tab. 1. Przykładowe techniki wykorzystywane w zadaniach DM

| Data mining task | Example techniques |
|---|---|
| summarization | statistical analysis, histograms, plots |
| clustering | K-means, Kohonen, k-NN |
| association rules | A priori, FP Growth |
| regression | linear regression, neural networks, |
| classification | decision trees, neural networks, support vector machine (SVM), Bayes classifiers |
| time series analysis | ARMA, ARIMA, models ARCH models, HMM models, trend estimation, decomposition, spectral analysis |

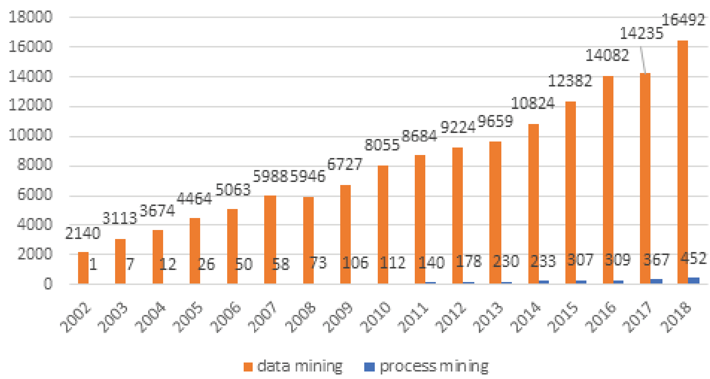


Fig. 2. The number of papers in the Scopus database (query for “data mining” or “process mining” in the title, abstract or keywords).
Rys. 2. Liczba artykułów w bazie Scopus (zapytanie dla “data mining” lub “process mining” w tytule, streszczeniu czy słowach kluczowych).

fined analytics perspectives is rather regular. In the “Diagnostic and machinery” and “Mine planning and safety” perspectives 15 papers were analysed per group, while in the “Geomechanics” and “Hazards” 16 papers were analysed per group.

In most publications, concerning the analysed phenomena, predictive tasks were formulated, with strong overrepresentation of the classification task (Fig.5).

The distribution of data mining tasks in various analytic perspectives of the mining process is presented in Table 3.

Except for the classification task, as popular data mining tasks regression and rule induction can be found. The multitask label introduced in the table indicates the presence of predictive and descriptive tasks in the published papers.

In the mentioned data mining tasks various techniques have been applied. A detailed overview with regard to the defined analytic perspectives is presented in the following part of the paper.

In the first analytic perspective – “Diagnostic and machinery” - the analysed papers have been related to strictly diagnostic problems (8) i.e. belt conveyor diagnostic, as well as machinery performance and its prediction (7), i.e. longwall powered support capacity. The applied data mining techniques in this perspective are presented in Table 4.

As it can be clearly observed the most popular techniques are artificial neural networks (8) and time series analysis (4).

ANN are also popular (6 findings) in papers included in the “Geomechanics” perspective (Table 5).

This collection is extended with decision trees algorithms (4 papers). Tree classifiers used in the analysed sample are comprised of some simple algorithms as i.e. CART as well as more sophisticated i.e. boosted trees.

It is worth of mentioning that the “Geomechanics” perspective contains papers related to: rock mechanics (2 papers), rock mass characteristic (2), seismic (9) and subsidence (3). Analysing the papers in the scientific databases it can be observed that the prediction of seismic events in underground mines is very often the subject of research.

Other “Hazards” perspective collects papers related to natural hazards (except seismic), namely: methane (7 papers), rock burst (5) coal combustion (2), gas and rock outburst (1) and roof fall (1).

The data mining techniques used in the “Hazards” analytic perspective are presented in Table 6.

In the analysed papers the most often mentioned DM techniques were ANN (5 papers), decision trees (5) and regression (5). Simple CART algorithms as well as the more advanced XGBoost were used. In the regression task simple models and logistic regression have been applied.

The last analytic perspective “Mine planning and safety” comprises of papers from a wide scope of issues related to mine planning i.e. equipment selection, production costs, coal

Tab. 2. PM tasks. Source: based on (van der Aalst 2016; Augusto et al. 2019; Carmona et al. 2018)
Tab. 2. Zadania PM

| Process mining task | Description | Example algorithms |
|---|---|---|
| Process model discovery | create a model without using any a-priori information on top of the event log | Alpha Miner<br>Heuristic miner<br>Inductive miner<br>Fuzzy miner |
| Conformance checking | an existing process model is compared with an event log in order to detect and locate deviations between the process model and the real process execution | casual footprints matrix<br>rule checking<br>token replay<br>alignments |
| Enhancement | The extension of the analysis or improvement of the process by the use of the additional information recorded in the event log i.e. involved resources or adding other perspectives to the process model (i.e. organizational, time or case perspective) | performance analysis<br>data-aware heuristic miner<br>social networks |

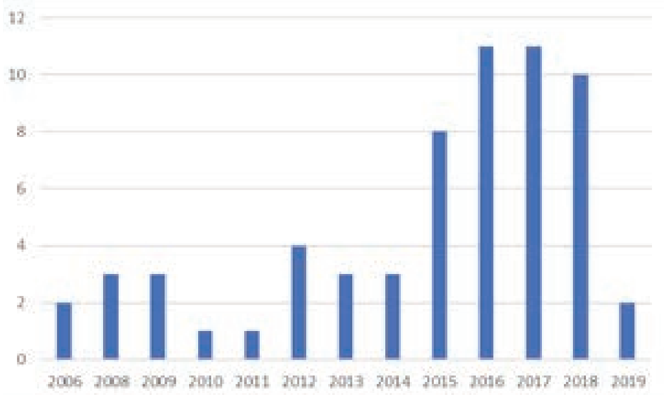


Fig. 3. Papers – year of publication distribution
Rys. 3. Artykuły – rozkład wg roku publikacji

prices (9 papers) and safety, mainly related to the analysis of occupational accidents (6). The main data mining techniques applied in this analytic perspective are presented in Table 7.

In the table, it can be observed that the most popular techniques are regression models (6 papers) and decision trees algorithms (4). The variety of the used techniques results from the specificity of the analysed issue. In some cases several techniques have been applied i.e. (Krzemień, A. et. al. 2015).

A holistic view of the DM techniques application in various analytic perspectives of the underground mining process is presented in Fig. 6.

A strong presence of "black-box" techniques can be found in "Diagnostic and machinery" and "Geomechanics" perspectives, where complex phenomena are analysed, very often without full available context information.

The presentation of the most popular DM techniques in the analyzed papers is shown in Figure 7.

The most popular DM techniques applied in the analytics of the mining process are: artificial neural networks, regression, tree models and rule induction.

An analysis of the mining process can be also supported with soft computing techniques. An example of their overview is presented in (Jang and Topal, 2014).

***Process Mining applications***

Papers with process mining applications in the underground mining process analysis have been searched with the use of the Science Direct, IEEE Explore, Scopus and Google Scholar databases. Due to the characteristic word play – "process mining" and "mining process", the following search terms have been used: "event+logs+process+underground", "event+logs+longwall+mining", "event+logs+ underground+process+analysis".

The results of searching in the mentioned databases are presented in Table 8.

Process mining applications in underground mining are rare and only several papers focus on this type of analytics of a mining process.

The first paper (Brzychczy and Trzcionkowska 2017) focuses on the analysis of mechanized roof support operations in underground mines. In the paper all three PM tasks can be found. Log Explorer, Mine Petri Net with Inductive Miner as well as Replay A Log on Petri Net for Performance/Conformance Analysis, plug-ins were used. In the paper (Brzychczy and Trzcionkowska 2019) a general idea of the underground mining process analysis based on sensor data and the creation of suitable event logs for process mining purposes are presented. Available data from

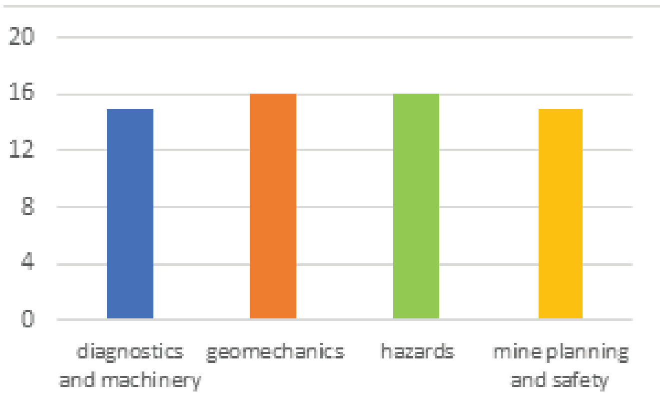


Fig. 4. Number of papers in the defined analytic perspectives
Rys. 4. Liczba artykułów w zdefiniowanych perspektywach analitycznych

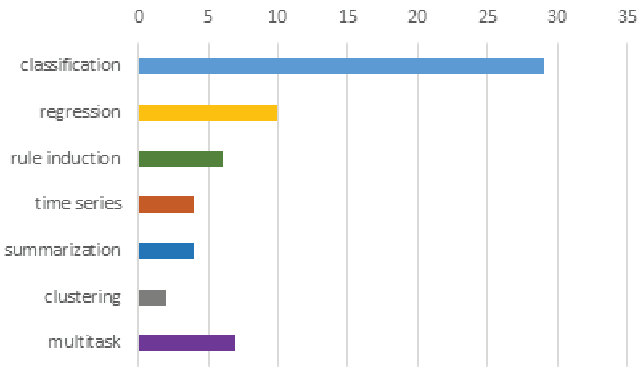


Fig. 5. Distribution of DM tasks in the analysed papers
Rys. 5. Zadania DM w analizowanych artykułach

Tab. 3. DM tasks by defined mining process analytic perspectives
Tab. 3. Zadania DM w zdefiniowanych perspektywach analitycznych procesu wydobywczego

| **Perspective** | **classification** | **regression** | **rule induction** | **time series** | **summarization** | **clustering** | **multitask** | **number of papers** |
|---|---|---|---|---|---|---|---|---|
| Diagnostics and machinery | 8 | 1 | 3 | 1 | 1 | - | 1 | 15 |
| Geomechanics | 9 | 1 | 1 | 2 | - | 1 | 2 | 16 |
| Hazards | 9 | 3 | 1 | 1 | - | 1 | 1 | 16 |
| Mine planning and safety | 3 | 5 | 1 | - | 3 | - | 3 | 15 |
| Total | 29 | 10 | 6 | 4 | 4 | 2 | 7 | 62 |

longwall monitoring systems are on a low-level of abstraction, that its direct analysis with process mining tools is pointless. Data in its existing form requires preprocessing with the use of supervised and unsupervised data mining techniques. These aspects were extended in papers (Brzychczy and Trzcionkowska 2018; Trzcionkowska and Brzychczy 2018).

The paper (He et al. 2019) presents process mining application to the emergency rescue processes analysis of fatal gas explosion accidents in China. In the paper process model discovery as well as other PM tasks were presented. Among others the following PM techniques were applied: Mine Petri Net with Inductive Miner, Check Conformance using ETConformance, Dotted charts and Social Networks Analysis.

The main reasons for a little number of PM applications in mining process analysis are: a lack of process mining tools awareness in the mining community and, what is more important, a lack of suitable event logs for process modelling and analysis. However, an observation of process mining discipline development as well as the interest of mining companies in advanced analytics of their processes entitles the

Tab. 4. DM techniques in the "Diagnostics and machinery" analytic perspective
Tab. 4. Techniki DM w perspektywie analitycznej „Diagnostyka i maszyny"

| Author(s) | TSA | BM | ANN | DT | RI | REG | CLS | kNN | SVM | STAT |
|---|---|---|---|---|---|---|---|---|---|---|
| Deb, D., Kumar, A. and Rosha, R.P.S. (2006) | | | ● | | | | | | | |
| Bongers D.R. and Gurgenci H. (2008) | | | ● | | | | | | | ● |
| Chatterjee, S. and Bandopadhyay, S. (2012) | | | ● | | | | | | | |
| Al-Chalabi, H. et al. (2014) | | | ● | | | | | | | |
| Michalak, M., Sikora, B. and Sobczyk, J. (2015) | ● | | | | ● | ● | | | | |
| Moczulski, W. et al. (2016) | | ● | ● | ● | | | | | | |
| Michalak, M., Sikora, B. and Sobczyk J. (2016) | | | | | ● | | | | | |
| Trzcionkowska A. and Brzychczy E. (2016) | | | | | ● | | | | | |
| Verma, A.K., Kishore, K. and Chatterjee, S. (2016) | | | ● | | | | | | | |
| Kesek, M. (2017) | | | | | | ● | | | | |
| Kucharczyk, D., Wyłomańska, A. and Zimroz, R. (2017) | ● | | | | | ● | | | | |
| Hargrave, Ch., James, C. and Ralston, J. (2017) | ● | | | | | | | | | |
| Kashnikov, A., Levin, L. (2017) | | | ● | | | | | | | |
| Wodecki, J., Stefaniak, P., Polak, M. and Zimroz R. (2018) | ● | | | | | | ● | | | |
| Jedliński, Ł. and Gajewski, J. (2019) | | | ● | | | | | ● | | |

TSA - time series analysis, BM – Bayesian models, ANN – artificial neural network, DT – decision tree models, RI – rule induction, REG – regression, CLS – clustering, kNN – k-nearest neighbour, SVM – support vector machine, STAT– probability distributions, multivariate analysis

Tab. 5. DM techniques in the "Geomechanics" analytic perspective
Tab.5. Techniki DM w perspektywie analitycznej „Geomechanika"

| Author(s) | TSA | BM | ANN | DT | RI | REG | CLS | kNN | SVM |
|---|---|---|---|---|---|---|---|---|---|
| Leśniak, A. and Isakow, Z. (2009) | | | | | | | ● | | |
| Sikora, M. and Wróbel (2010) | | | | | ● | | | | |
| Li, P., Tan, Z., Yan, L. and Deng, K. (2011) | | | | | | | | | ● |
| Kabiesz, et al. (2013) | | | | ● | ● | | | | |
| Lee, S. and Park, I (2013) | | | | ● | | | | | |
| Zhou, J. et al. (2013) | | | | | | | | | ● |
| Jakubowski, J. and Tajduś, A. (2014) | | | ● | ● | | | | | |
| Iannacone J.P. et al. (2015) | ● | | | | | | | | |
| Jamróz, D. and Niedoba, T. (2015) | | | ● | | | | | | |
| Boullé, M. (2016) | | ● | | | | | | | |
| Kurach, K. and Pawlowski, K. (2016) | | | ● | | | | | | |
| Hussain, S. et al. (2016) | | | ● | | | ● | | | |
| Polak, M. et al. (2016) | ● | | | | | | ● | | |
| Janusz, A. et al. (2017) | | | | ● | | ● | | | ● |
| Mahdevari, S., Shahriar, K., Sharifzadeh, M. and Tannant, D. D. (2017) | | | ● | | | | | | |
| Huang, L. et al. (2018) | | | ● | | | | | | |

Tab. 6. DM techniques in the "Hazards" analytic perspective
Tab. 6. Techniki DM w perspektywie analitycznej „Zagrożenia"

| **Author(s)** | **TSA** | **BM** | **ANN** | **DT** | **RI** | **REG** | **CLS** | **kNN** | **SVM** | **STAT** |
|---|---|---|---|---|---|---|---|---|---|---|
| Borowski, M. and Szlązak, N. (2006) | | | ● | | | | | | | |
| Özgen Karacan, C. (2008) | | | ● | | | | | | | |
| Krauze, E., (2009) | | | | | | | ● | | | |
| Sikora, M. and Sikora, B (2012) | ● | | | | ● | | | ● | | |
| Özgen Karacan, C. and Goodman, G.V.R. (2012) | | | | ● | | | | | | |
| Grzegorowski, M. and Stawicki, S. (2015) | | | | | | | | | | ● |
| He, M. et al. (2015) | | | ● | | | ● | | | ● | |
| Manowska, A. (2015) | | | | | | ● | | | | |
| Wojtecki, Ł. and Konicek, P. (2016) | | | | | | ● | | | | |
| Javadi, M., Saeedi G. and Shahriar, K. (2017) | | ● | | | | | | | | |
| Ribeiro e Sousa, L. et al. (2017) | | ● | ● | ● | | | | ● | ● | |
| Li, N. and Jimenez, R. (2018) | | | | | | ● | | | | |
| Lei, Ch. et al. (2018) | | | ● | ● | | ● | | | | |
| Bodlak, M., Kudełko J. and Zibrow, A. (2018) | | | | ● | | | | | | |
| Kozielski, M., Matyszok, P., Sikora, M. and Wróbel Ł. (2018) | | | | | ● | | | | | |
| Lei, Ch. et al. (2019) | | | | ● | | | | | ● | |

Tab. 7. DM techniques in the "Mine planning and safety" analytic perspective
Tab. 7. Techniki DM w perspektywie analitycznej „Projektowanie kopalń i bezpieczeństwo"

| **Author(s)** | **TSA** | **BM** | **ANN** | **DT** | **RI** | **REG** | **CLS** | **kNN** | **SVM** | **STAT** |
|---|---|---|---|---|---|---|---|---|---|---|
| Gawlik, L. (2008) | | | | | | ● | | | | |
| Sari, M. et al. (2009) | | | | | | | | | | ● |
| Cheng, J. and Yang, S. (2012) | | | | | | | | | ● | |
| Gernand, J.M. (2014) | | | | ● | | | | | | |
| Kopacz, M. (2015) | | | | | | | | | | ● |
| Krzemień, A. et. al. (2015) | ● | | ● | | | ● | | | | |
| Niedoba, T. and Ranosz, R. (2016) | | | | | | ● | | | | |
| Snopkowski, R., Napieraj, A. and Sukiennik, M. (2016) | | | | | | | | | | ● |
| Brzychczy, E., Kęsek, M., Napieraj, A. and Magda R. (2017) | | | | ● | ● | | | | | |
| Jonek-Kowalska, I. and Turek, M. (2017) | | | | | | ● | | | | |
| Fuksa, D. et al. (2017) | | | | | | ● | | | | |
| Duany, A. A., Lilford, E. and Topal E. (2018) | | | | ● | | | | | | |
| Sanmiquel L. et al. (2018) | | | | | ● | | | | | |
| Wyganowska, M. (2018) | | | | | | ● | | | | |
| Qiao, W. et al. (2018) | | | | ● | ● | | | | | |

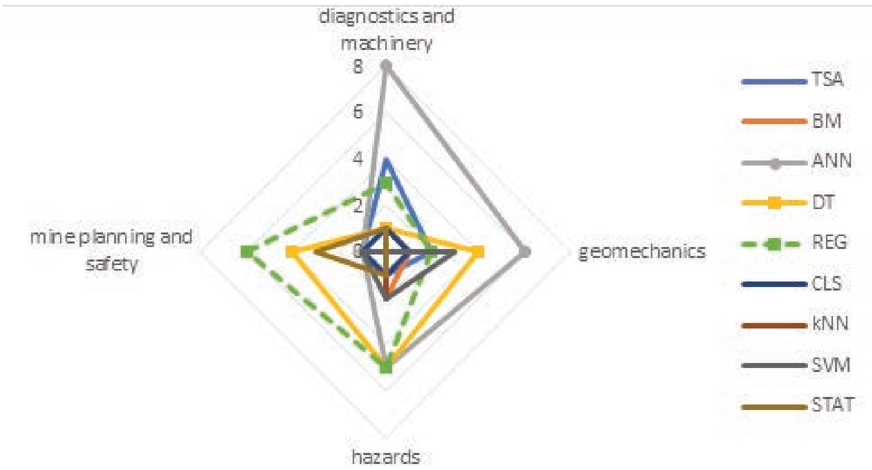


Fig. 6. The DM techniques applied in the analysed papers and defined perspectives
Rys. 6. Techniki DM zastosowane w analizowanych artykułach w ujęciu zdefiniowanych perspektyw

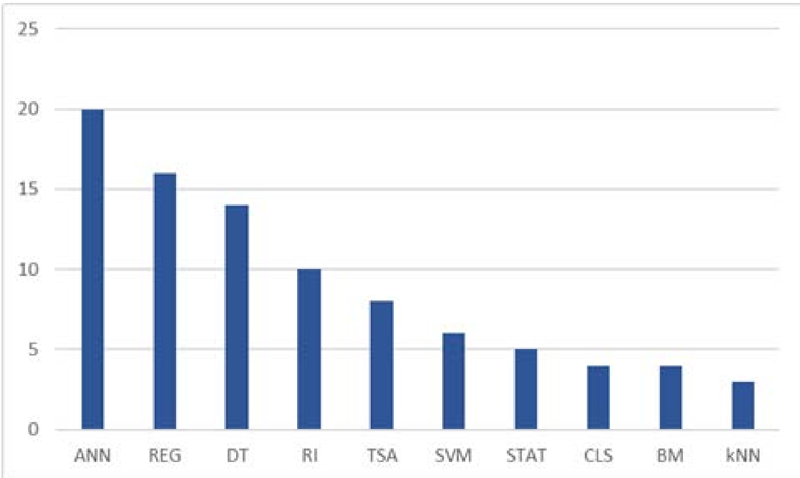


Fig. 7. The DM techniques applied in the analysed papers
Rys. 7. Techniki DM wykorzystane w analizowanych artykułach

Tab. 8. The results of searching PM applications in underground mining process analysis. Source: own searching – date 10.04.2019, * - only used in Google Scholar for result limitation
Tab. 8. Wyniki poszukiwania zastosowań PM w analizie podziemnego procesu wydobywczego

| Searched terms | Science Direct results (hints) | IEEE Explore results (hints) | Scopus results (hints) | Google Scholar app. results (hints) since 2015 |
|---|---|---|---|---|
| event logs process underground (mining*) | 5 (1) | 2 (0) | 9 (2) | 16 400 (5 in first 100 results) |
| event logs longwall mining | 1 (0) | 19 (0) | 5 (2) | 899 (3) |
| event logs underground (mining*) process analysis | 2 (0) | 1 (0) | 6 (2) | 16 700 (5) |

author to state that the number of these applications in the mining domain will increase in the next years.

**Conclusions**

An analysis of the gathered papers regarding data mining and process mining applications in the underground mining domain enabled to formulate the following conclusions and answers for the research questions:

- DM techniques are widely used for mining process analysis, mainly in the predictive kind of DM tasks, with strong overrepresentation of classification task (RQ1),
- the most popular DM techniques in the underground mining process analysis include: artificial neural networks, tree models, rule induction and regression (RQ2).

The different sophistication degree of used techniques can be found - from simple models (CART tree, linear regression, naïve Bayesian) to more complex (XGboost, Random Forrest, multi regression or Bayesian fuzzy models). The interest in various techniques is rather comparable in defined analytics perspectives with an exception of economics related papers (in the mine planning and safety perspective), where the over presence of regression models can be observed.

Due to small presence of process mining applications in the underground mining process analysis, only general conclusions can be drawn. Process mining is still not discovered by the mining community. However, several found papers have shown, that it can become a new potentially useful analytics in mining companies aiming in process improvement and efficiency increasing.

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## *Przegląd zastosowań technik drążenia danych i procesów w górnictwie podziemnym*

*Celem artykułu jest przegląd zastosowań eksploracji danych (data mining) i procesów (process mining) w analizie procesu wydobywczego w kopalniach podziemnych oraz identyfikacja najpopularniejszych technik analizy danych w tym zakresie. W artykule sformułowano dwa pytania badawcze: P1: Jakie są najpopularniejsze zadania eksploracji danych/eksploracji procesów w analizie procesu wydobywczego w kopalniach podziemnych? oraz P2: Jakie są najpopularniejsze techniki eksploracji danych/eksploracji procesów stosowane w wielowymiarowej analizie procesu wydobywczego w kopalniach podziemnych? W artykule przeanalizowano sześćdziesiąt dwie opublikowane prace dotyczące eksploracji danych w ujęciu zdefiniowanych perspektyw analitycznych ("Diagnostyka i maszyny", "Geomechanika", "Zagrożenia", "Projektowanie kopalń i bezpieczeństwo"). Wyniki pokazują, że w odniesieniu do analizowanych zjawisk formułowano głównie zadania predykcyjne, z silną nadreprezentacją zadania klasyfikacji. Do najczęściej wykorzystywanych technik eksploracji danych należą: sztuczne sieci neuronowe, drzewa decyzyjne, indukcja reguł i regresja. Eksploracja procesów w analizie procesu wydobywczego w kopalniach podziemnych została opisana tylko w kilku artykułach, które pokrótce omówiono.*



*Słowa kluczowe: eksploracja danych, eksploracja procesów, analiza, proces wydobywczy, górnictwo podziemne*