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Improving the Discovery of Technological Opportunities Using Patent Classification Based on Explainable Neural Networks

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Abstract:

Purpose: *The paper aims to present an approach supporting the improvement of technological opportunities discovery using patent classification based on explainable neural networks.*
Design/Methodology/Approach: *Empirical research was conducted applying a dataset containing U.S. patent documents. Firstly, this dataset was checked for the correctness of the saved patent data to be further analyzed. Then, a custom Bidirectional Encoder Representations from Transformers (BERT) Neural Network was developed and trained. Finally, the Local Interpretable Model-agnostic Explanations (LIME) method was applied for interpreting the results achieved with the BERT classifier.*
Findings: *The studied classifier achieved high quality (precision of 80.6%), allowing correct classification of the technologies described in the patents. Such neural classifiers are easy to use in practice and highly versatile; however, there is an insufficient trust of managers in the decisions suggested by that black-box method. The proposed new approach may help overcome the lack of trust of the users of neural models towards the technological opportunities suggested by them.*
Practical Implications: *Various patent databases are often used to discover innovative solutions, as well as economic and technological opportunities, because they contain vast resources of prosperous and extensive information recorded in patent documentation. Such analyzes are critical to businesses and public organizations as they help them make decisions about carrying out strategic investment projects. The presented approach, which supports the improvement of automated processes of technological opportunities discovery, may increase confidence in the results obtained using neural classifiers.*
Originality/Value: *Earlier studies focused mainly on using more effective classifiers and better learning algorithms. Progress in this type of research did not help solve the problem of the lack of reliable justification for individual decisions indicated by machine learning models. In this study, a proposal for an approach enables the discovery of technological opportunities using patent classification based on explainable neural networks.*

Keywords: *Patent analysis, artificial neural networks, BERT, explainable classification.*
JEL codes: *C63, O14, O32, O33.*
Paper Type: *Research Paper.*

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1. Introduction

In the contemporary economy, there is a continually growing demand for innovative technologies, the complexity of the global technology trade market and the increasing need to solve technology management problems in the short and long terms (Winkowski, 2020). Global technology competition is mainly about discovering technology opportunities and getting ahead of competitors in their use (Yoon *et al.*, 2015), which enables the effective development of unique entrepreneurial and technological competencies synergistically linked to several other parameters such as e.g. competitiveness, technological effectiveness, innovativeness and human capital asset (Chursin and Strenalyuk, 2018).

Much literature is related to technology opportunities recognition, its importance for creating new ideas, innovations and practical business results from R&D activities (Lee, Kim, and Shin, 2017). The analysis and classification of patents are useful tools to assist in carrying out analyzes and discovering technology opportunities. The results of effective patent data analysis can inspire the development of technological innovations, enable monitoring of technological development trends and support wise knowledge management towards introducing competitive innovations (Liu *et al.*, 2020).

Due to the rapidly growing number of patents and the complexity of the technologies presented in them, there is a gradual abandonment of manual content browsing and more and more attempts to use computer programs for this purpose appear. This type of activity motivation is a negative consequence for enterprises and public organizations in the absence of proper knowledge of technological novelties. Performing an automated analysis and the correct classification of patents help to find a core technology opportunity and may bring specific economic benefits for business. Automated analysis and classification of patents are facilitated since one of the essential patent document features is their high degree of structuring (Curran and Leker, 2011).

Automated patent analyzes are often supported by data mining and machine learning tools, enabling efficient and systematic technology opportunity analyzes (Lee, Kang, and Shin, 2015). These tools can help create business ideas, generate and develop new technology solutions, converge existing technologies or find similar ones (Song, Kim, and Lee, 2017). A substantial justification for implementing modern and effective technology opportunity discovery mechanisms based on the results of data classification from publicly available patent databases is that there is much more of such data compared to commercial databases, which are more structured and accessible in an easier way. There is, therefore, a clear justification for the need to develop approaches and methods to support the improvement of technological opportunities discovery by patent classification based on modern data analysis methods. When introduced, these improvement mechanisms should be tailored to the organizations' specific needs that carry out the classification and discovery of technological opportunities. The approach supporting the discovery of opportunities from technology portfolios, which are customized to a company target, may, e.g., be based on the application of patent classification as well as collaborative filtering in those portfolios where patents are represented in accordance with International Patent Classification (IPC) (Park and Yoon, 2017).

Considerable expectations are related to the possibilities of using Natural Language Processing (NLP) algorithms, techniques and tools to process, classify and statistically understand natural language-based data regarding key technologies described in patent databases. In particular, the use of modern classifiers may significantly reduce classification errors and contribute to the more effective discovery of technological opportunities as a result of improving the classification accuracy of patent data.

Hybrid approaches and many qualitative and quantitative methods are often used to discover innovative technological opportunities (Feng *et al.,* 2020). Text representation and class prediction, which are vital for patent classification, can be based, e.g. on the topic modeling technique, Latent Dirichlet Allocation (LDA) and Support Vector Machine (SVM) for automatic patent classification (Yun and Geum, 2020).

Among the modern classifiers that can be considered in this field are also those based on the single Bidirectional Encoder Representations from Transformers (BERT) Neural Network or on hierarchical patent classifier integrating two models, BERT (Devlin *et al.,* 2019) and Convolutional Neural Networks (CNN) (Lu and Ni, 2019). The usefulness of these neural networks applied in patent classification processes is limited by the inability to justify the results obtained and difficulty to trust them easily. Therefore, it is desirable to use not only effective neural classifiers but also methods of explaining the obtained results.

The paper's primary purpose is to present an approach supporting the improvement of technological opportunities discovery using patent classification based on explainable neural networks. Automatic classification of patents was implemented using the BERT neural network, and the interpretation of the results obtained with this classifier was carried out using the Local Interpretable Model-Agnostic Explanations (LIME) method (Ribeiro, Singh, and Guestrin, 2016; Ribeiro, 2016).

2. Research Methodology

Empirical research was conducted applying a dataset containing more than 200 000 patent documents saved in JavaScript Object Notation (JSON) format (Bourhis, Reutter, and Vrgoc, 2020). The patent dataset from the United States Patent and Trademark Office used in the calculation was saved in this format and made available by Li *et al.* (2017). At the subclass level, there are 637 categories. The analyzes were based on the IPC hierarchical classification system, which is the most popular and frequently used in the case of patent classification and identification of emerging technologies with machine learning, deep learning and various types of neural networks (Li *et al.*, 2018; Zhou *et al.*, 2021).

Due to computational limitations of available resources, the classification was performed on patent class level (130 categories – each subclass was transformed to class by removing the subclass indicator) on samples containing only one label assigned. For the network training, 220 000 samples (fulfilling the previous conditions) were selected randomly from the dataset over 2006-2014. For the training dataset, 4 000 random samples were chosen from patent data from 2015. The training and testing samples were built by combining the title and abstract (separated by '|' character) of the patent cropped to a maximum of 70 words. Before feeding to the network, the samples were tokenized with Bert WordPiece Tokenizer (Wu *et al.*, 2016).

Firstly, this dataset was checked for the correctness of the saved patent data to be further analyzed, after which custom BERT Neural Network was developed and trained. The implementation of neural networks was carried out using Keras-based deep learning models in Python, which is very popular among machine learners and communities of data scientists. Such a solution should allow proper classification of the technologies described in the patents as it is a useful machine learning tool that is well suited for solving text classification tasks and NLP problems (Sun *et al.*, 2019).

The implementation of BERT from Transformers library containing state-of-the-art NLP models was used (Wolf *et al.*, 2019). The model was pretrained on lower case English texts. To the pretrained BERT base, Flatten layer followed by the Dropout layer was added (0.1 of default dropout probability to avoid overfitting was set). Finally, the Dense classification layer with 130 neurons and Softmax activation (due to multiclass classification) were added. The huge advantage of using pretrained BERT is that it needs a small number of training epochs to fine-tune it to the desired task. The model was trained for one epoch with categorical cross-entropy loss on the training set on NVIDIA GeForce GTX 960M. Adam optimizer was used with learning rate 5e-5, and the Precision top 1 and the Recall top 5 were chosen for the classification performance metrics.

Finally, the LIME method was used for interpreting the results obtained with neural networks. To explain the model's classification for the single sample, LIME modified it multiple times and observed the impact of the changes on the classification probabilities (output of the model). Then, a simple interpretable linear model (such as linear regression) was trained on the set created from multiple perturbances of the sample (in the case of sentences - mostly by removing some words from the original sentence) and output probabilities of the original model. Thanks to this approach, LIME could locally approximate the BERT model and provide explanations of its predictions.

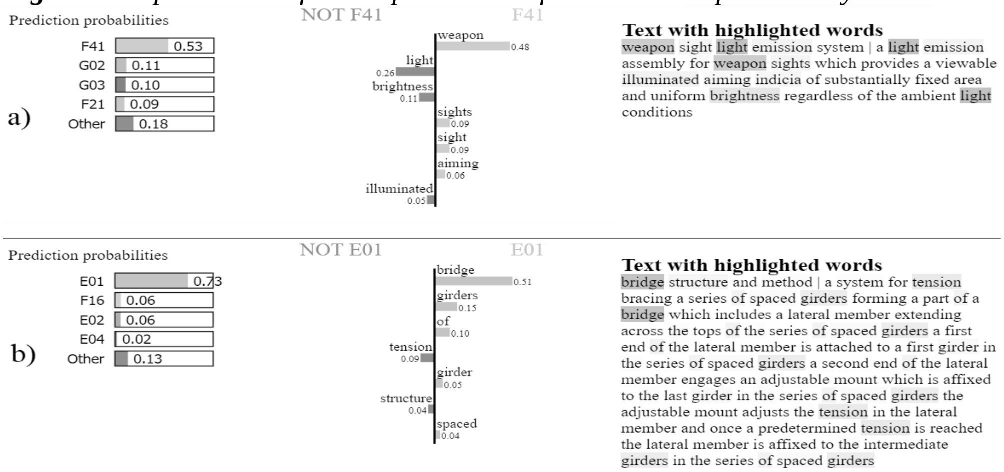
3. Results and Discussion

The training of the BERT model took more than 20 hours and yielded satisfactory classification results. The Recall top 5 metric achieved 95.8%, meaning that 3 832 out of 4 000 predictions for testing samples contained the correct predicted label as one of the top 5 classes. The Precision top 1 reached 80.6%, which signifies that the top predicted label was correct in 3 224 out of 4 000 predictions.

Various patent databases are often used to discover innovative solutions as well as economic and technological opportunities since they contain vast resources of extraordinarily varied and rich information recorded in patent documentation. Due to the difficulty of manually reviewing this type of files, machine learning methods such as Artificial Neural Network (ANN) are being developed, which can assist in finding technological opportunities as a result of patent data analysis. So far, there have been mainly studies related to the use of many supervised and unsupervised learning algorithms in this field. The results they generate are critical to businesses and public organizations as they help them make decisions about carrying out strategic investment projects. Neural networks are easy to use in practice and highly versatile; however, managers are often unwilling to follow the black-box method's decisions.

Therefore, the utilization of methods for ANN explanations opens new opportunities for building trust and safety of automated systems based on ANN. In Fig. 1, two example explanations are presented for correctly classified patents from the testing set. They give a fascinating insight into analyzed patents and show what difficulties the BERT model could face while classifying those samples. Additionally, the explanations improve understanding of the classification proposed by the network while searching for new technological opportunities.

Figure 1. *Explanations of BERT patent classification model provided by LIME*



Source: *Own study.*

The first example (a) shows the explanation of patent, which belongs to the 'Mechanical Engineering' section (F) and 'Weapons' class (F41). The network was not completely sure about assigning the patent to the F41 class as the abstract contains many words connected with optics. Therefore, words like 'light' or 'brightness' decreased the probability of the F41 class, and the G02 class ('Optics') is the second top prediction for this sample. In the second example (b), the network did not face problems with assigning the patent to the E01 class ('Construction of Roads', 'Railways' or 'Bridges') due to the use of nomenclature of bridge constructing field in the abstract and title of the patent.

4. Conclusions

Earlier studies focused mainly on reducing the difficulties associated with discovering technological opportunities using patent classification based on various neural networks through applying deep learning and improving learning methods towards obtaining more and more benefits resulting from the introduction of better classifiers and algorithms of supervised and unsupervised learning. Progress in this type of research did not help to solve the problem of the lack of reliable justification for individual decisions indicated by the ANN. In this paper, a proposal for an approach that enables explainable neural network patent classification is presented.

The conducted research contributes to the scientific literature on the discovery of technological opportunities using patent classification and makes the development of practical applications useful for business and public organizations. The authors proposed a new approach to help explain the results achieved with the use of selected ANN. The obtained findings may contribute to overcoming the lack of trust of the users of neural models in the achieved ANN results.

In the paper, the essential advantages and limitations of the proposed approach are discussed, and possible directions for further research development are indicated. For example, since the ANN classifier was not entirely accurate, there is still room to improve it. With the increased computational possibilities, experiments on the whole patent dataset can be conducted. The smaller dataset could introduce noise to the explanations, which, as a result, could partly focus on some insignificant features. Additionally, conducting experiments with subclasses of patent prediction would bring new value to the research in discovering technological opportunities.

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