Generation of Topical Educational Content by Estimation of the Number of Patents in the Digital Field

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***Abstract*—Analysis of trends in the development of emerging technologies based on patents is a well-recognized approach. An increase in the number of patents precedes the extensive spread of technological solutions and their incorporation in production and professional activities, making it possible to perform predictive analysis. The field of digital technology, which is changing most dynamically among production areas, was chosen as the object of study. The study develops an approach to the analysis of emerging technologies that are related to a given domain. Methods for obtaining quantitative parameters have been developed based on time series representing the number of patents per year. The concept of a parameter plane has been introduced. It includes the parameters of stable growth/decline and annual quantity of patents. A special feature of the approach is the calculation of parameters for the last observed segment of the stable dynamic behavior of the time series based on the developed algorithm. The work takes the Digital Marketing domain as an example and presents analysis of 296 keywords related to this concept. Based on time series constructed from the patent database for 2000-2021, the most promising technologies were identified. The application of the results for the generation of topical educational content in the Digital Marketing field is considered.**

Keywords—Time series; patent analysis; parameter plane; predictive analysis

I. Introduction

The timely choice of relevant development trajectories and the selection of the right keywords are involved in many applied issues of both scientific practice and private life. [1]. Questions arise about what skills one needs to learn in order not to waste time and to be sure that they will be in demand in the future, thus the knowledge of these skills may become a competitive advantage in the labor market. In production, especially in software engineering [2], it is important to plan which technologies to use so that the development of technologies does not overtake the process of assembling or creating a technological product. To remain competitive, high-tech companies must not only adapt to new technologies, but also stay abreast of technology trends. Furthermore, when a research team conducts research in a new domain, it needs to dive into the domain specifics and to identify current trends. For the above and other issues, it is important to have numerical estimates of prospects and the ability to quantitatively or qualitatively compare and select the necessary trends. Although there are many aspects in this area, it is proposed to focus on keywords when choosing technological development directions. This work focuses on the field of digital technologies, since the results can be easily interpreted both by the authors themselves and by a wide range of readers. However, it is assumed that the developed methodology can be expanded and quite easily transferred to other scientific areas that are related to technology.

Keywords are part of the metadata of scientific and technological text sources - articles, search queries [3] and patents. For the task at hand, it is proposed to use patents as a source of data. As it is known, the content of a patent contains a technical description of the invention in a fairly clear and complete manner and is intended to disclose the minimum content that makes the invention understandable and reproducible. Patent texts provide means for accessing one of the broadest open access resources for technical information.

Patents as a source for the analysis of promising technologies are quite recognized [4], and a significant number of studies have attracted attention to them. Patent analysis is a valuable approach for obtaining industry or technology information for forecasting based on both bibliometric data and patent information. For example, in study [5] the process of convergence of scientific knowledge to predict new technologies using a citation network and topology clustering is shown. Patent analysis includes several areas aimed to identify new technologies: analysis of bibliometric and patent metadata to determine the value of technologies [6], analysis and clustering of patent texts [7, 8], the use of supervised machine learning methods based on labeled samples [9], the use of deep learning methods [10]. Given the complexity of patent texts, bibliometric analysis is more common in research because it involves the analysis of structured data. However, metadata analysis cannot capture the detailed technical content of patents [11]. As shown in study [12], text mining enhances traditional methods based on bibliometric data in predicting technology change.

Thus, it has been established that patents are one of the best sources of information for selecting emerging technologies, although automatic analysis of text sources is associated with a lot of difficulties due to the combination of technical and legal languages and terms [13].

There are recent works that have been dedicated to the problem of identifying emerging technologies from patent texts. In study [14], approaches for identifying emerging technologies are tested on 1600 patents from four case studies; the proposed system made it possible to identify more than

4500 technology areas. In study [15], clusters of terms were analyzed and potentially promising directions for technology development were identified for various forecasting horizon lengths; the quantitative analysis carried out in the work showed that the system can successfully identify emerging and fading technologies. In study [16], the authors determine whether a new technology or innovation can succeed or fail, provided that the technology or innovation can be precisely defined in advance. It is also noted that there is information overload and the complexity of technological knowledge, which have a negative impact on the accuracy of patent search engines. Textual similarities of patents are discussed in study [17]. Machine learning methods are widely used [10, 18].

Patent analysis is used in many high-tech fields, such as automated driving [19], industrial engineering [20], tracking the evolution pathways of some nanogenerator technologies [21], and electric vehicle design [22].

There are attempts to use sources other than patents. Paper [23] outlines a scalable method for automatic bibliometric analysis by systematically extracting text from the arXiv repository. In study [1, 24], a service was developed that collects data from labor market vacancies. However, the past five years after the publication of the article [1] have shown that the forecasts obtained in 2017 were shown to be more accurate by data based on patents.

Despite the widespread and impressive results of using machine learning methods, it must be admitted that the most computationally feasible and well-interpreted results in the search for emerging technologies are based on linear trend analysis [25] and statistical methods [26], which allow to select technologies without involving an additional expert opinion. Therefore, further in this article statistical methods and linear approximation will be used. It is worth noting that it is necessary to take into account not only the number of patents, but also the dynamics of changes in their number. A growing number of patents can indicate development and growth of a technology.

It is important to have a quantitative indicator that allows one to compare technologies for the purpose of selecting emerging technologies. In study [27], which analyzed the Web of Science, it was stated that in an extensive literature review, the authors found a gap in methodological research, since there are no numerical metrics for new technologies. The presence of numerical indicators for new technologies will stimulate research, allow assessing the competitiveness of companies, allow assessing the technological competence of companies and individuals, and will also stimulate the education and institutions. The authors of study [27] formulated research objectives, two of which can be applied to the present study, namely, “What are the current research topics in the field of new technologies?”, “What is the direction of future research in the field of new technologies?” In the present article, the answer to the first question is left to the expert system, while the answer to the second lies in the aim of the article.

The purpose of the study is to develop numerical characteristics to perform estimated selection and evaluation of emerging technologies for the formation of topical educational content.

The contribution of this article is as follows:

1) Time series characterizing each keyword are considered. The time series represents the frequency of mentions of a keyword in the patent database per year. It is proposed to consider trends in technology development as trends in constructed time series.

2) For the time series characterizing the keyword, a definition of segments of stability has been introduced, specifically: stable growth, stable decline. It is proposed to consider stable growth in the final studied segment of the time series as a characteristic of the technology's prospects. The numerical estimate of technology prospects is based on the growth rate of the number of patents in the last stable segment.

3) Examples of calculations of the proposed characteristics for the Digital Marketing domain are considered. The possibilities of using the proposed solution for topical educational content creation are considered.

The further structure of the article is as follows – Section II is devoted to the context of the research - the creation of educational content based on topical technologies; Section III – presents data and models; Section IV – provides results obtained for the field of Digital Marketing; Section V contains a discussion of the results obtained; Section VI provides a conclusion to the work.

II. Background

The range of educational services is intensively expanding, creating conditions for the constant improvement of educational programs and individual learning paths. Thanks to the development and unification of information technologies and networks, new global scientific, technological, social, and humanitarian knowledge based on them becomes part of the modern worldview, quickly becoming available for teaching. The course of classical further mathematics and mathematical analysis has not undergone significant changes in 150 years, while applied disciplines are changing rapidly. In the authors' area of interest, for example, the use of cloud technologies has evolved from the audience's bewildered lack of understanding about the subject to, just 10 years later, an ordinary discipline for students with a set of practical exercises available to perform without need for specialized servers. Observations show that there is a tendency in the relationship in the chain science-technology-skill-process of learning a skill. Scientific knowledge accumulates, and as a result, a set of specialized terms is formed. Then this set of terms denoting new scientific knowledge or approaches moves to the technological level (which can be assessed by the volume of patents in accordance with the methodology of this article). Having reached a certain saturation of technologies, they are beginning to be implemented by companies, both leaders and innovation groups. This creates demand in the labor market for specialists with the necessary qualifications (corresponding to previously defined terms); accordingly, seeing the market need for appropriate specialists, educational institutions respond by introducing or changing disciplines in order to develop new in-demand skills in students (see Fig. 1). The figure shows that for each stage a corresponding measurable set has been found, the number of elements of which can be taken as a characteristic, while the calculation is proposed to be carried out on the basis of keywords.

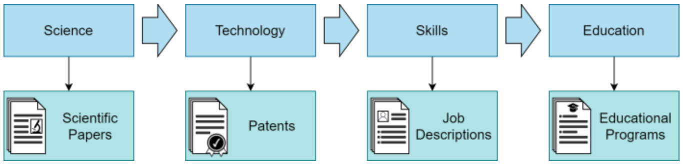


Fig. 1. The process of new educational programs development.

This process has different pace for different areas: the fastest changes occur in the IT sector, much slower in medicine, since it is necessary to go from a scientific hypothesis to an experimentally confirmed result and, ultimately, to the mass dissemination of technology. However, having now a database of articles and a database of patents, a modern technology development process can be retrospectively traced. Having observational data on past processes, one can make an assumption that the future technology demand can be predicted in advance based on predictive analysis methods (see Fig. 2).

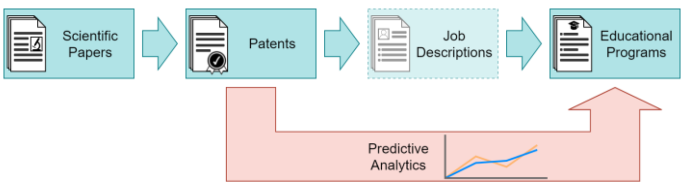


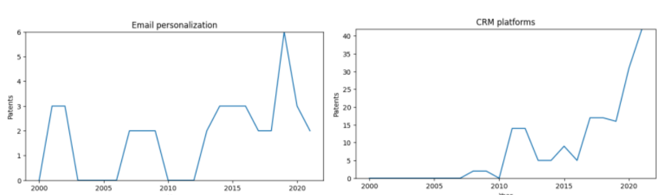
Fig. 2. The process of new educational programs development using predictive analysis methods.

It is proposed that, by observing trends in the increase in the number of patents (as an indicator of the past stage of converting scientific articles into patents), one can predict the demand for both the labor market and educational services.

III. Materials and Methods

The Espacenet service was chosen as the main data source for the research. The resolution for collecting quantity of matching documents was set to one year. The time range of data collection was defined as the time interval from 2000 to 2021 including the boundaries.

Data for each keyword is a time series, reflecting the dynamics of patent activity for the selected period. It is proposed to consider each keyword separately, that is, to consider separately each time series corresponding to the frequency of occurrence of the keyword in patents. Examples of the time series are shown in Fig. 3. By analyzing each of the time series, it is possible to determine whether it represents an emerging technology or not.



(a) (b)

Fig. 3. Examples of time series of patents per year for keywords (a) Email personalization; (b) CRM platforms.

As the literature review given in the introduction showed, patents are recognized as an indicator of technology development. High level of the number of patents per year shows the significance of the technology (keyword). For technologies with a low number of patents, one may decide that their consideration is premature. The main task is to search among technologies with an average number of patents (in the field under consideration) for promising ones according to the development forecast. In other words, it is important to predict the number of patents based on a short time series of the number of mentions of a given keyword in the patent database. The difficulty is that the time series is short, which is associated not only with database limitations, but also with the speed of technology change; 10-15 years is quite a long time for technologies in the digital sphere. The range of modeling methods for short time series is very limited; it is possible to determine only the general trend and build a regression model.

The life cycle of a technology development generally implies periods of development, stability and decay, at least theoretically. Many methods are based on this assumption, including the cumulative S-function [10]. But in practice one can also encounter other types of life cycle. A technology does not exist on its own; each technology includes other technologies and is itself part of larger technologies. Therefore, a technology can develop, then reach the stage of constant use, and then, under the influence of external conditions caused, for example, by the emergence of related technologies, it can again enter the development stage. This led to the rejection of hypothesis about the similarity of the dynamics of the number of patents to typical patterns of the technology development life cycle (growth, plateau, and decline). The dynamics of a time series can take any form. Since for a short-term (5-6 years) forecast of the prospects for the use and development of technologies the change in the years preceding the forecast is of importance, it is proposed to segment the dynamics of changes in the number of patents. Each of the segments is seen as a stability segment (stable growth, decline, or plateau), and the further estimate will be carried out based on the last segment.

Assumption: if a short time series of the number of patents that mention a keyword increases in the years preceding the forecast, then it can be assumed that this trend will continue in the future, therefore, the technology corresponding to the keyword is promising. Accordingly, if the time series in the years preceding the forecast shows a decline, then the forecast will also be characterized by a decline, and the technology can be considered obsolete.

Let's introduce the following definitions for formal numerical analysis purposes.

Definition 1. Let there be time series $X = \{x_1, ..., x_n, ..., x_N, ..., x_M\}$ given, where, $1 \le n < N \le M$; $n, N, M \in \mathbf{Z}$., $N - n > 1$.

Time series segment $\{x_n, ..., x_N\}$ will be called a stability segment if.

$$\forall\forall i, j{:}\ i \in \{n, n+1, ..., N\},\ j \in \{n, n+1, ..., N\},\ i > j :$$

$$\frac{x_i - x_j}{i - j} = x_e = \frac{x_N - x_n}{N - n}.$$

Definition 2. For x_e from definition 1: if $x_e < 0$, then the segment of the time series is a stable decline, if $x_e > 0$, the segment is a stable growth, if $x_e = 0$, then it is a plateau.

Let's introduce the following definition for a real time series, which cannot be strictly stable (that is, be exactly a straight line of growth or decline in a certain segment).

Definition 3. Time series segment $\{\tilde{x}_n, ..., \tilde{x}_N\}$, $N - n > 1$ is a stability segment if there is x_e from definition 1, for which the sum of deviations $\sum_{k=n}^{N} \delta_k$ is low enough, where $\delta_k = x_k - \tilde{x}_k, (k = \overline{n, N})$.

Remark. Given the introduced definitions, the criterion for the stability segment can be the deviation from the linear regression equation, that is $x_e = a$, where a is the coefficient from linear regression equation $y = ax + b$.

IV. Results

Let's consider the field of Digital Marketing. Estimated selection of prominent technologies requires adequate data for the analysis. To obtain the set of keywords for the research a generative pre-trained transformer model was utilized. The model response had 300 items and it was considered as a satisfactory result. After the preprocessing the set consisted of 296 keywords.

Let's consider an example of using the parameter plane to select promising technologies and their classification formed on the basis of the parameter plane.

Suppose that for the field of Digital Marketing it is necessary to highlight growing technologies, characterized by an increase in the number of patents, and it is necessary to distinguish four classes: technologies that are growing rapidly and have a large number of patents; rapidly growing technologies, the number of patents of which is significant for the field in question; technologies with a growing number of patents and specific to the chosen field; and potentially promising technologies, the growth of which is significant, but the number of patents is relatively small.

To solve this problem, let's construct a parameter plane and define four classes using the conditions that are shown on the parameter plane with dotted lines (see Fig. 4). Fig. 4 shows the points characterizing the selected keywords for the Digital Marketing topic. It can be seen that points can be divided into classes. For practical purposes, the points are divided into 4 classes: class 1 – blue dots, class 2 – green, class 3 – yellow, and class 4 – red. It should be noted that keywords whose growth is less than the regression coefficient 10 were excluded from consideration during the initial analysis procedure. The interpretation and keywords included in each class are given below.

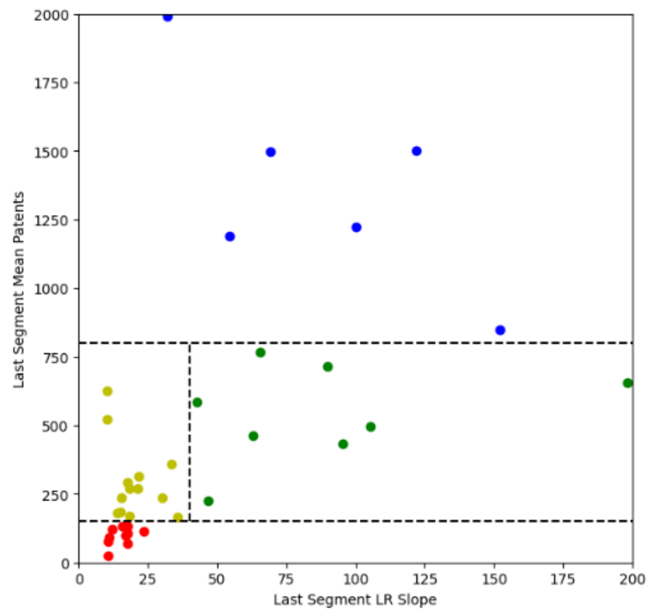


Fig. 4. Placement of the keywords on the parameter plane.

Class 1 (blue dots), characterized by a high number of patents (800 or more per year). This class includes general technological trends that are developing in the field as a whole, in this case, digital technologies, and go far beyond the scope of specific implementations and areas of application. The following keywords were assigned to this class:

1) Branding;
2) Content creation;
3) Customer relationship management;
4) Data analysis;
5) Data segmentation;
6) Market research;
7) Return on investment.

These areas of technological development are decisive in the area under consideration and their study in the context of competitiveness is fundamental.

Class #2 (green) of promising technologies is characterized by a significant number of patents (from 150 to 800), and a high growth rate in the number of patents. This class includes:

1) Brand loyalty;
2) e-commerce platforms;
3) Interactive content;
4) Predictive analytics;
5) Public relations;
6) Retargeting;
7) Social media platforms;
8) User-generated content.

Keywords included in this class are major emerging technologies.

Class 3 (yellow) includes technologies both with a possible drop in the level of patent activity, and those at a stable level, after which growth may begin. If the expert wishes, depending on the tasks at hand, this class can be divided into smaller ones. However, it is important to understand that knowledge of technologies of this class is important for deep specialists in the application field in question.

Class #4 (red) which includes keywords that show growth, but the number of patents (less than 150 per year) does not make it possible to predict technology development. However, for specialists studying trends based on other tools, such information may be useful, since it has been initially screened for sustainable growth.

Thus, topics have been found that should be included in topical educational content: general trends (class 1) and promising technologies, the knowledge of which is relevant for future professions.

The developed scalable tool in the form of interpretable visualization on the parameter plane allows an expert or artificial intelligence to carry out various classifications and clustering based on their applied tasks.

V. Discussion

Technologies that characterize the Digital Marketing domain are considered. It is noted that this data can also be obtained as the most mentioned terms [13] in the related news or in search queries, or as keywords for articles on the topic.

For each keyword, a patent search was performed using annual data. For each keyword, time series were created showing the number of patents per year containing that keyword. The years 2000-2021 were considered since the progress of a patent from the application stage to the registration stage takes a long period and does not allow one to obtain complete data for the last two years. The formation of time series can be associated with various difficulties: one can take into account only metadata, or consider, for example, only the background section of patents, or it is possible to consider a narrow scope, for example, a combination of the searched keywords together with other keywords that characterize the domain. When developing software systems and adapting the procedure described in the article, it is necessary to pay attention to the issue of forming time series.

From the initial set of 296 keywords, at the first stage, 186 words were excluded that did not pass the basic condition requiring the minimum number of patents. As an initial preprocessing of data, one can also set the boundary value for the expected value and variance.

Since the life cycles of technologies have different stages [10], and in addition, keywords can characterize not the technology as a whole, but only some part of its decomposition, in this work the time series are divided into segments – stable growth, stable plateau, stable decline. Thus, 110 time series are divided into those with stable growth in recent years – 55 keywords, stable plateau – 27 keywords, stable decline – 28 keywords. This approach allows one to obtain a numerical estimate of the change in dynamics – the slope, which is calculated as the coefficient of the linear regression equation on the last stable segment of the time series data. Stability segments have different lengths on the time series and can vary, for example, from 4 to 10 years, and obtaining a single numerical estimate in the form of a coefficient allows one to compare technologies on the same scale.

It is proposed to use a parameter plane consisting of two coordinates - the mean value of the number of patents in the last stable segment and the value of the growth/decline coefficient in the last segment. This plane allows one to classify emerging technologies, while the choice of methods depends on the application. An example of the classification of technologies in which growth is observed is considered. 4 classes were identified (see Fig. 4). Class #1 contained keywords characterizing general trends in the digital field, 7 words in total; class #2 contained keywords with a significant number of patents (from 150 to 800), and a high growth rate in the number of patents, with a total of eight keywords; class #3 included keywords for which a noticeable growth was visible, with the same number of patents as in the third class, a total of 13 words; class #4 contained keywords that had significant but minor growth and a limited number of patents, 11 words in total. Other methods of classification and clustering are possible, including the participation of an expert or the use of artificial intelligence.

Further work may be devoted to the formation of the design of experiments to compare the quality of various approaches [19-22] to the identification of topical technologies, the selection and assessment of the effect of sources of keywords and patent activity data on the completeness of inclusion of topical technologies, as well as the selection of clustering methods to automate the identification of groups of evaluated technologies. In addition, the process of automating the construction of educational programs based on data from open sources can be considered in future research.

VI. Conclusions

It is now general practice to use patents as a source for evaluating emerging technologies, skills, and educational areas.

The work explored the method of numerical estimates of emerging technologies based on the dynamics of changes in the number of patents.

Initial data was collected for the Digital Marketing domain. A generative pre-trained transformer model was used as a source to obtain the list of keywords representing the domain. For 296 keywords, time series were obtained with the annual number of patent documents containing mentions of each keyword.

To identify emerging technologies, a scalable numerical analysis tool was proposed. It includes two parameters - growth/decline rate and number of patents, both characteristics are calculated based on the last stable segment of the technology development life cycle.

The proposed methodology for identifying emerging technologies can be used to select the most significant technologies and subjects within the domain. The use of patent data for quantitative analysis can provide an advantage when designing curriculums, since promising technologies and skills can be identified before they are actively incorporated into the labor market.

The methodology in its current form does not imply automation of the search for threshold values and periods for collecting quantitative data. The choice remains with the expert, however, in the future, multi-criteria optimization methods can be considered to find effective threshold values for the proposed conditions. In addition, further research could include machine learning methods, supplement and refine the given conditions for determining relevant skills, and also consider the texts of patent documents in more detail to improve the accuracy of the assessment.

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