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**MODERNIZATION OF EDUCATIONAL PROGRAMS OF
PROFESSIONAL SKILL IMPROVEMENT USING PATENT
ACTIVITY DATA**

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Abstract

The study raises the issue of the need to verify the adequacy of the skills forming the educational program to the current realities. The initial data consists of a sample of 20 skills divided into 5 groups. The common methods of evaluating study programs are considered and the presence of a human factor is noted. The authors proposed to evaluate the indicators of technology development based on the annual number of published patents and labor market data, as it is an objective approach that excludes human participation. The main difficulties leading to the occurrence of large amounts of false positive results were noted, which required the development of filtering mechanisms. The analysis of the skills was conducted using data on patent activity and the state of the labor market. Professional predictive learning service was involved in order to do this, which was improved in accordance with the requirements of the study. The results show that there is a high level of correlation between patent activity and subsequent demand for specific skills in the labor market ($r = 0.8$). Most of the skills are recommended for the study, 10 of them are well-established in the labor market, 9 more skills are promising and gaining popularity.

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Keywords: Technology forecasting, patent analysis, education, training, curriculum review, predictive learning.



1. Introduction

While designing an educational program, the question always arises: which main technologies should be studied out of the available alternatives (Brusilovsky, et al., 2014). This is an important issue from the earliest days in education: for programmers, it is about which programming language is best suited to begin learning the profession, which version and which operating system is best fitted (Konecki & Petrlic, 2014). In the medical field, the number of saved lives can depend on the staff's experience with the most relevant skills (Neily, et al., 2010). Although, often this is determined by the existing hardware base, for example, it can be determined by the high-tech equipment for diagnosis in medical professions. It is impossible to teach functional magnetic resonance imaging without the equipment. Thus, the first issue, even for specialists in the field of education, is the choice of the best out of available options, for practical classes in the disciplines that will form the basis of the profession.

Currently there are a number of methods for assessing the relevance of training programs. One of them is the internal survey of the employees of the educational institution (Bird, van de Mortel, Holt, & Walo, 2015) in the format of a structured or unstructured interview, thereby attracting more experts to the issue. Indicators of achievements are considered for the assessment as well, for example, the level of employment among graduates (Crebert, Bates, Bell, Patrick, & Cragolini, 2004).

Since many professions are tied to the development of technologies, the indicator of innovation in the areas of economic activity and the corresponding professions can be determined using methods of the patent activity analysis (Altuntas, Dereli, & Kusiak, 2015; Lee, Kim, Kwon, & Woo, 2016).

It is proposed to use this fact to update the educational programs of professional education and professional development.

2. Problem Statement

The authors of the article were tasked to assess the relevance of mastering the skills and technologies included in the educational program of professional education courses. The collection of expert assessments is the most common method for solving such a problem (Tynjälä, Slotte, Nieminen, Lonka, & Olkinuora, 2006). The authors propose to evaluate existing training programs based on patent activity related to the corresponding technologies as an objective estimate without human involvement (Hagi & Yoffie, 2013).

According to the authors, it is correct to say that the set of skills determines the professionalism of a particular specialist at the specific time. For example, the most popular programmer in the labor market will be the one with a set of desired skills and knowledge of the required technologies, whether it be specific operating systems, programming languages or methodologies used. This makes it possible to call this programmer a professional and it is these skills that reflect the professional suitability. Obsolete programming languages, as well as cross-stitching, cannot be considered a professional skill. This applies to many high-tech and innovative professions. For example, a cardiac surgeon should be experienced both with the methods of surgery and with the technical means that are recognized as the most relevant presently (Figures 1 and 2), and not in the past (Figure 2). Thus, professional competence of a specialist should be considered as the presence of the set of relevant skills.

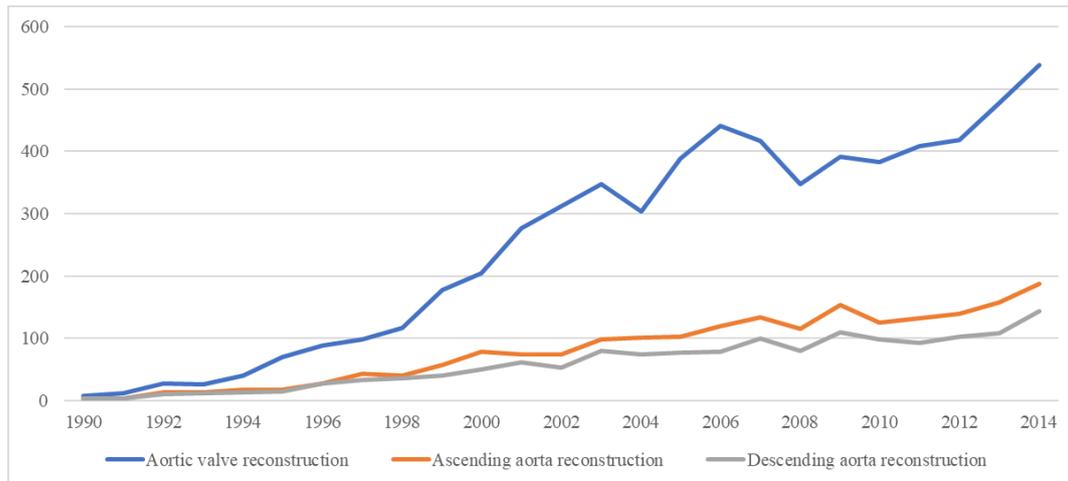


Figure 01. Data on patent activity in the field of cardiac surgery (source: Google Patents), Y-axis – the annual number of patents

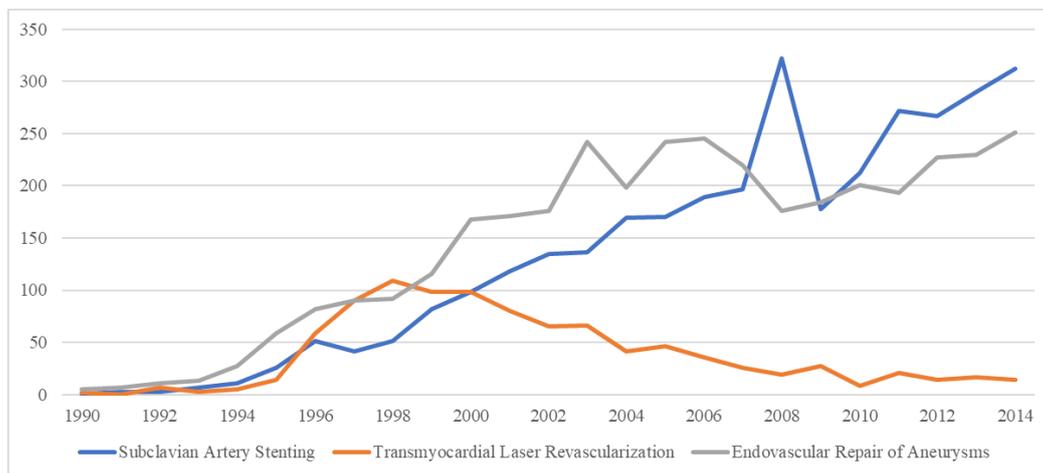


Figure 02. Data on patent activity in the field of cardiac surgery, example of obsolete skills (source: Google Patents), Y-axis – the annual number of patents

It is interesting to forecast the change of the demand for skills in the future. For this purpose, we propose a professional predictive learning approach, by which we mean learning the technologies and methods that will be in demand for a specified profession in the future. In other words, training ahead of the technology development.

The study analyzed 60 skills included in the training program of professional education courses. For the convenience of perception, the article lists 20 most representative ones. Also, for ease of perception, each of the skill is assigned with a skill code and skill group code (Table 1). The description of skill groups is presented in Table 2.

3. Research Questions

- What is the correlation between the demand for specialists in the labor market and the preceding patent activity?

- What specialized software solutions might be needed for the analysis of patent activity for individual skills?
- Which of the mentioned skills should be considered promising and demanded in the labor market?

Table 01. List of the sample skills for evaluation

Skill	Skill Code	Skill Group Code
C	S01	G01
Java	S02	G01
Python	S03	G01
HTML	S04	G02
CSS	S05	G02
HTML5	S06	G02
CSS3	S07	G02
Machine Learning	S08	G03
Deep Learning	S09	G03
Big Data Analytics	S10	G03
Search Engine Optimization	S11	G04
Internet Marketing	S12	G04
Email Marketing	S13	G04
Content Marketing	S14	G04
Social Media Marketing	S15	G04
Linux Administration	S16	G05
FreeBSD Administration	S17	G05
TCP/IP	S18	G05
Network Security	S19	G05
Computer Networking	S20	G05

Table 02. Skill groups

Skill Group	Skill Group Code
Programming Languages	G01
Web Development (Frontend)	G02
Analytics	G03
Marketing	G04
System Administration	G05

4. Purpose of the Study

The purpose of this study is to analyze the possibility of assessing the demand for professional skills in the labor market using patent activity data and specialized software tools.

5. Research Methods

Studies in the field of patent activity and demand in the labor market are labor intensive. Some of the stages can be automated. The authors developed a professional predictive learning service (Nikulchev, Ilin, Bubnov, & Mateshuk, 2017) for decision support that collects, homogenizes and visualizes data. It uses open data on patent activity, data on labor market and other kinds of data.

The involved sources have a number of features:

- The existence of homonyms that introduce noise into data.
- The existence of differences in the writing of technology names (for example, the use of acronyms and abbreviations).

The first feature is characterized by the fact that the percentage of false-positive results in patent searches, as well as when searching in other sources of data (scientific publications, vacancy databases), can exceed reasonable boundaries. For example, as was noted during the search for vacancies (Nikulchev, Ilin, Mateshuk, 2017), in some cases the share of false-positive results can be more than 94%. Because of this, the study will use the contextual keywords filtering method (Ilin, Mateshuk, Gilaztdinov, & Bubnov, 2017). Table 3 shows the contextual keywords used for filtering of the above-mentioned skill groups in a patent search.

Table 03. List of the sample skills for evaluation

Skill Group Code	Contextual Keywords
G01, G02, G03, G05	software, database, framework, application, developer, server, program, programmer, script, scripting
G04	marketing, sales

To illustrate the second feature, we give an example from the field of marketing: Search Engine Optimization (SEO). This area of expertise is in demand in organizations engaged in the promotion of goods and services in search engines. The skill mentioning occurs in patents both in the form of a full name and in the form of an abbreviation (fig. 3), however, in the second case, there is a large percentage of extraneous documents among the patents (fig. 4). Employers' vacancies often use SEO abbreviation (fig. 5). Considering this, it is reasonable to use the full name for some sources (patent databases, scientific publication databases) and an abbreviation for others (Internet recruitment agencies).

To conduct studies that require different variations in the spelling of keywords for different data sources, the service has been upgraded with a new mechanism that provides this capability. Figure 6 shows the ER diagram, where a table of keywords, which is responsible for storage of skills, is associated with a table of a similar structure (named *alternative_keywords*), containing alternative variants of writing. The relationship between this table and the data source is implemented using a string identifier that uniquely identifies the source.

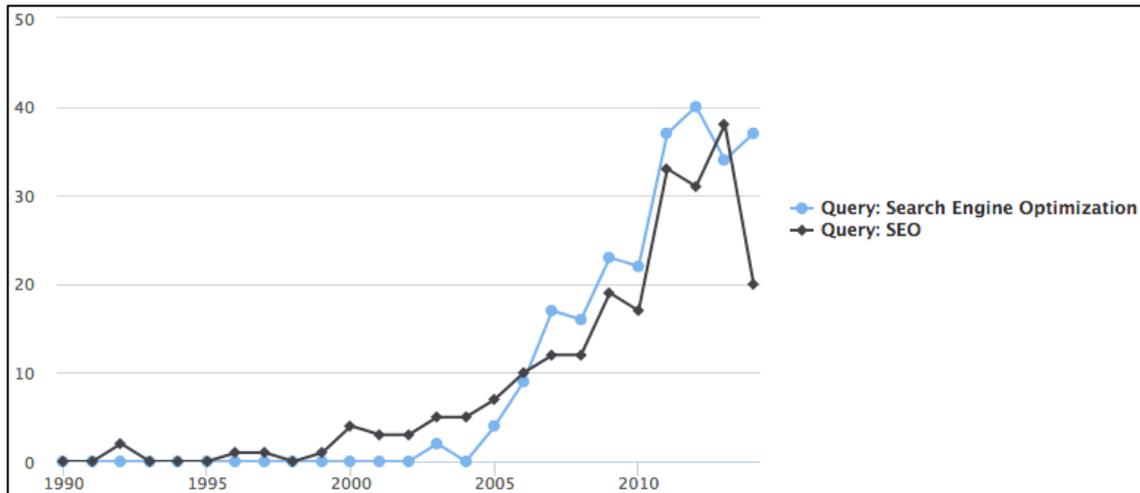


Figure 03. Data on the SEO skill from the USPTO service, the results are filtered with the use of contextual keywords (marketing, sales), Y-axis – the annual number of patents

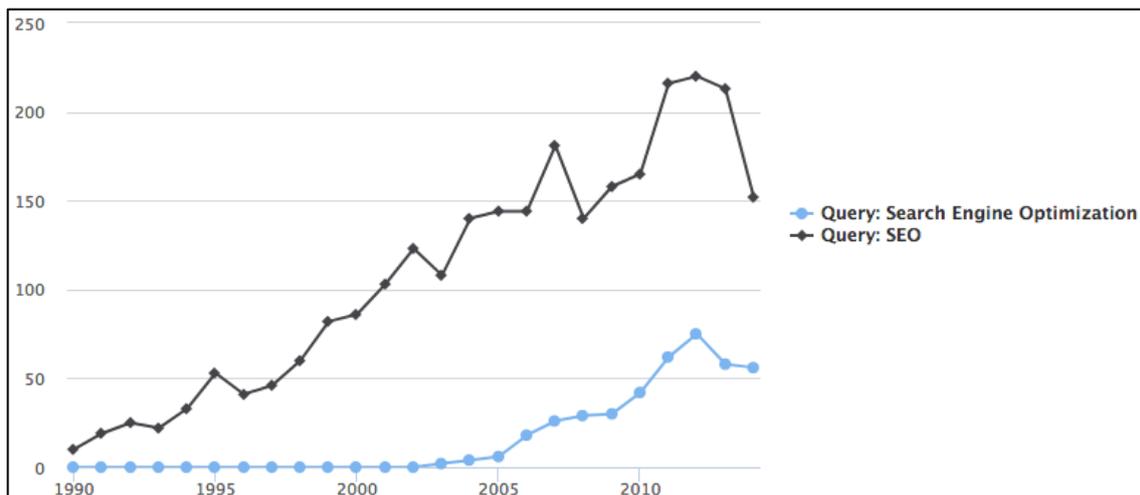


Figure 04. Data on the SEO skill from the USPTO service, the results were not filtered, Y-axis – the annual number of patents

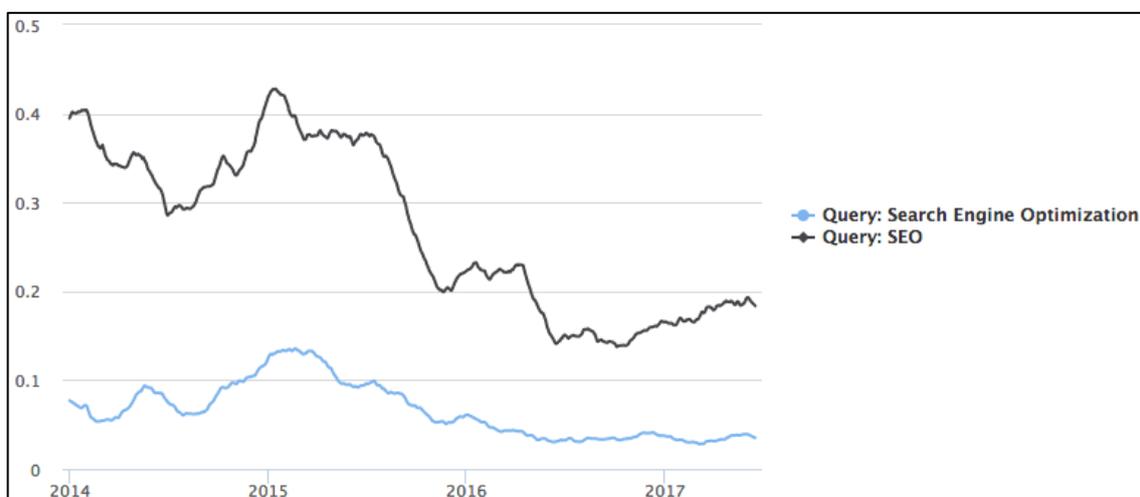


Figure 05. Data on the SEO skill from the online recruitment agency Indeed.com, Y-axis - the percentage of vacancies out of all the vacancies in the labor market

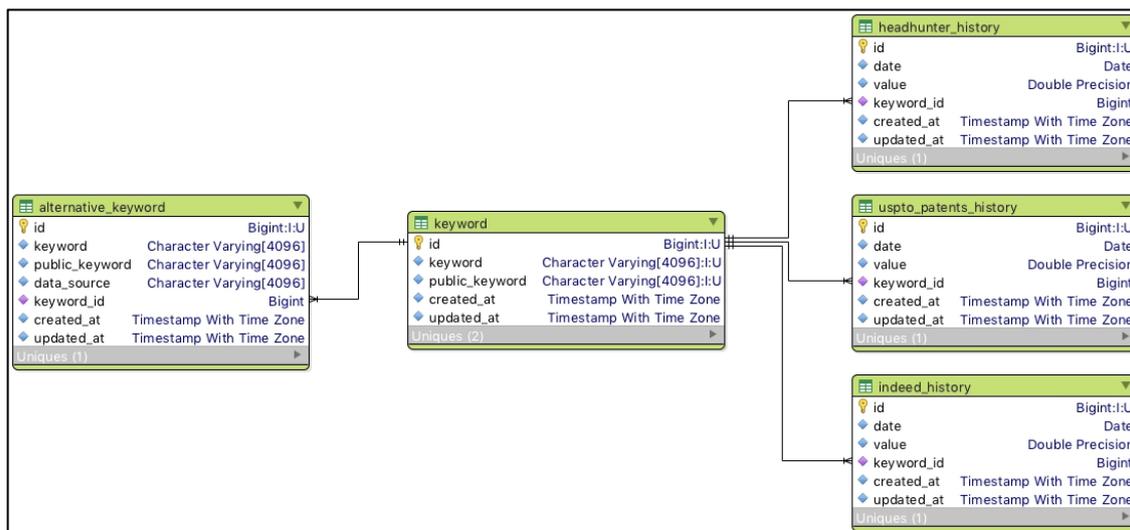


Figure 06. ER-diagram, illustrating the way in which alternative keywords are stored and their relationship to data sources

6. Findings

The collected data on patent activity (Table 4) indicates that the skills S02, S03, S04, S05, S08, S16, S18, S19, S20 can be considered well-established in the market, with a growing demand for them. At the same time, the skill S01 can also be considered well-established, but there is a decrease in demand for it (maximal demand falls on 1996-1998). It can be said that there is the rapid development of the market regarding the skill S06, it will be in demand. The skills S07, S09, S10 are promising, although they are at the early stage of development. All marketing skills (S11-S15) show a small steady increase in the annual number of patents, which indicates the development of the market. However, the total number of patents is small. Unlike S16, the skill S17 shows extremely low patent activity, from which it can be said that the field of expertise is not in demand.

The data on the skill S01 was normalized and represented as a percentage of the maximum number of patents per year. This is due to the specificity of the patent search in the USPTO service, which does not allow to identify patents related to the names consisting of a single letter or containing special symbols (which can be relevant for technologies such as C++ or C#).

Table 04. Patent activity regarding the sample skills

Skill	1990	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012	2014
S01*	31,93	40,59	71,78	91,34	91,09	88,37	85,89	83,91	73,76	67,08	59,16	64,85	42,08
S02	5	8	9	442	1911	3449	3922	4419	5194	6459	7519	11349	7261
S03	1	1	7	8	19	47	113	169	280	569	746	1591	1367
S04	0	0	8	671	1883	3985	3734	3824	4328	4891	5031	7225	4791
S05	46	67	100	124	156	308	248	341	457	604	698	1220	987
S06	0	0	0	0	0	3	0	1	0	1	101	520	388
S07	1	0	0	0	0	0	0	0	1	3	5	25	28
S08	7	19	25	49	80	169	246	397	636	921	1084	1788	2060

S09	0	0	0	0	1	2	1	1	0	0	2	4	53
S10	0	0	0	0	0	0	0	0	0	0	0	6	44
S11	0	0	0	0	0	0	0	0	9	16	22	40	37
S12	0	0	0	3	2	8	9	10	17	12	24	30	31
S13	0	0	0	0	0	3	3	18	11	28	15	26	24
S14	0	0	0	2	4	8	6	6	15	10	26	21	13
S15	0	0	0	0	0	0	0	0	0	0	2	6	10
S16	0	0	0	3	12	109	262	257	357	326	441	553	491
S17	0	0	0	3	1	2	11	17	18	7	30	21	17
S18	24	78	234	1072	2352	3968	4327	4624	5147	5770	5469	7350	5222
S19	6	12	46	107	194	373	479	649	785	719	755	1047	865
S20	6	18	42	100	238	301	373	396	378	358	404	603	480

To verify the compliance of the obtained data to the real state of the labor market, the vacancy shares in the labor market in the United States were collected. From these data, the mean values were calculated for the period from January 2014 to June 2017 (Table 5).

Table 05. The mean vacancy percentage in the labor market (USA, according to data from Indeed.com) for the period from January 2014 to June 2017

Skill	Vacancy Share (%)
S01	0,959720536
S02	1,608262607
S03	0,809376988
S04	1,204022790
S05	0,878797361
S06	0,350968613
S07	0,176563370
S08	0,150017934
S09	0,008187359
S10	0,358372186
S11	0,269257827
S12	0,069587299
S13	0,101806401
S14	0,056104254
S15	0,079025001
S16	0,467847123
S17	0,000567359
S18	0,390674714
S19	0,296862010
S20	0,165207664

The Pearson correlation coefficient was calculated for all of the skills except S01, as the data on patent activity for S01 was normalized and cannot be used for the evaluation (Table 6). There is a high level of correlation at the interval from 2010 to 2014 with the subsequent demand for skills in the labor market. Some decrease in the value of the correlation coefficient in 2014 may be due to the incompleteness of data that is present in the database of the USPTO patent office.

Based on the results it is possible to say with confidence that the majority of the presented skills are appropriate for studying: they are either well-established or developing. An exception to this is FreeBSD Administration, as evidenced by both low rates of annual patent activity and the minimal labor market demand for specialists.

7. Conclusion

According to the results of the study, it can be said that the analysis of patent activity can be used not only to assess technology and forecast their development, but also to assess the relevance of the skills associated with them. Moreover, it is possible to assess the relevance of the methods related to operational skills. A strong correlation between the annual number of patents and vacancies in the labor market presents the possibility of forecasting of the demand for skills.

Table 06. Correlation of patent activity and labor market demand for the skills in 2014-2017

Year	Correlation Value
1990	0,27839643
1992	0,184041682
1994	0,109807215
1996	0,486434536
1998	0,64312829
2000	0,676197869
2002	0,675273332
2004	0,685237234
2006	0,701815613
2008	0,728942863
2010	0,770600632
2012	0,801267924
2014	0,783115726

Mechanisms were implemented to apply the appropriate variants of the skills' names to use various data sources in the professional predictive learning service. A filtering mechanism based on contextual keywords for data from the USPTO service was implemented.

Using these mechanisms, 20 skills were analyzed. Programming languages C, Java and Python are popular and well established in the market, however C has some decrease in demand. Web development skills consist of well-established skills (HTML and CSS) and from relatively new ones which noticeably gaining in popularity (HTML5 and CSS3). Machine Learning is an established skill in the field of

analytics, and the skills of Deep Learning and Big Data Analytics begin to occupy their market share. All mentioned skills from the field of marketing show a small and stable increase in demand. System administration skills are also in demand, except for the FreeBSD Administration skill.

The results of the work can be applied for conducting similar studies assessing the relevance of educational programs, as well as for the further development of software tools for professional predictive learning.

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