Methodology for Job Advertisements Analysis in the Labor Market in Metropolitan Cities: the Case Study of the Capital of Russia

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Abstract. The article presents a methodology for analyzing perspective occupations in some region by means of job advertisements gathering and processing. We offer an approach to building ratings of popular specialties in the labor market in megacities. The object of the study is Moscow. The prerequisite for this study is the rapid development of labor markets in the capital cities, which must be monitored and analyzed due to some changes. The vacancies offered by employers form the professional qualification structure of demand in the labor market. Characteristics of vacancies (salaries, labor functions) are a guideline for regional labor markets. Also, the labor markets of large cities are distinguished by the large volume and diversity of the supply of work (demand for labor). Due to the large amount of information, to analyze all the labor offers on the market and summarize the results for an ordinary citizen seems to be a time-consuming task. Our approach illustrates the possibility of using programming technologies (the parsing and API of the sites of recruiting and recruitment agencies) for automatic collection of information about the proposed vacancies and their subsequent analysis. Using technologies of statistical data processing and Data Mining allows for filtering the source data, exclude emissions, group vacancies, evaluate key characteristics and build their private rankings. The obtained mass and job security ratings can be useful for career guidance agencies, as well as for schoolchildren, students and people planning retraining and retraining in adulthood, to assess the relevance and rational choice of a future profession. #CSOC1120

Keywords: Labor Market, Job Advertisement, Perspective Occupations, Vacancy Analyses, Group of Professions, Parsing, Data Mining.

1 Introduction

The professional realization is one of the most important stages in a person's life. The choice of a profession will be faced by young people who have not yet begun their professional activities, and by people with work experience who want to retrain.

Moreover, various reasons may influence the choice of a particular profession for different groups. For example, for pupils, when choosing a profession and the corresponding educational specialty, not rational, but emotional reasons may prevail [1]: "beautiful" or fashionable names of the profession (the so-called brand), a friend's example, the opinion of parents or the advice of an authoritative person. Future applicants choose an educational institution based on their personal preferences: the presence of an interesting specialty, high qualification of teachers, the possibility of free education, the location of the university, the availability of a good technical base, the status of the university, providing a dormitory [2]. Often the choice is based on a number of factors associated with the future profession. These factors are [3]: orientation to the relevance and prestige of professions; orientation to the prospects of professional and career growth with the quality of higher education received; future pay; family budget opportunities; obtaining a diploma from a prestigious university.

More pragmatic factors are important for older people, which may motivate them to even move to another region in search of work: the possibility of successful employment in the chosen profession or acquired specialty, salary level, working conditions, social package, etc. [4]. These factors are influenced by statistical indicators of professions, which can be estimated by studying job advertisements in the labor market of a certain region. Such indicators, for example, were proposed in [5]. This paper deals with comparative analysis of occupations in the regional labor market. Occupation is treated as a multi-dimensional space of characteristics, whereas a scalar form of a characteristic makes it possible to carry out a comparative analysis of occupations. Using cluster analysis of a pilot region indicators five meaningfully interpretable clusters of occupations were identified, reflecting their regional specificity. Based on the selected key characteristics of the professions, the following quantitative indicators were formed that made it possible to evaluate and classify the professional composition of the staffing of the economy: salary by profession in relation to the regional average; share of vacancies by profession; share of the profession in the regional labor market; the growth rate of the share of the profession in the market.

The All-Russian classifier of the professions of workers and positions of employees contains more than 8,000 thousand diverse professions [6]. Obviously, they are all represented differently on the labor market and have different values of the key indicators that characterize them. To extract and summarize useful information for oneself from so many professions is not an easy task for an ordinary job seeker. Here, information technology should come to the aid of an ordinary citizen, which can be effectively used at the stages: searching for job advertisements; extracting from the found vacancies information on key indicators of the professions in demand; processing and analysis of these key indicators.

The field of information technology is rapidly developing nowadays, that has a strong influence on the ways and directions of interaction between demand (employers) and supply (job seekers) in the modern labor market. There are many different job research studies based on job advertisements that differ in goals and methods for achieving them.

The development of information technology has led to the emergence of the concept *e-recruiting* (or *online-recruiting*) [7], that is, the use of Internet technologies to publish and search for vacancies and resumes, as well as to link job seekers and employers to each other. E-recruiting platforms actively develop using a variety of advanced technologies [8, 9]. Often e-recruiting systems are equipped with the functions of personalized search and ranking [10, 11] which makes them similar to recommender systems. In addition to the obvious advantages, e-recruiting has drawbacks, in particular, the process of mutual choice can be difficult due to formal and non-transparent evaluation of indicators instead of live communication [12], but there is no alternative to that approach.

One of key parts of e-recruiting is a continuously changing set of job advertisements (ads, offers, vacancies) – as a rule, unstructured or poorly structured texts on the sites of e-recruiting platforms, containing information on the vacancy and the employer, as well as the requirements for the applicant. Job advertisements analysis by means of Data Mining and Text Mining methods has become increasingly popular in recent years [13, 14]. The same methods can be applied to the job seekers' resumes published on the Internet. That approach opens a way to create smart information services, automatically connecting suitable jobs and resumes to each other [15, 16]. Intelligence of those services can be significantly increased by using ontologies of competencies, allowing to implement semantic searching [17, 18].

The analysis of competencies derived from job advertisements leads to the ability to characterize the current demands of the labor market. It is actively used for curricula management in universities and competency evaluating in organizations [19, 20]. The papers [21, 22] are devoted to the development of curricula management models and information systems for decision support by program directors and university administrations in the process of modernization of educational programs. The paper [23] describes an example of job advertisement analysis for curricula management problem solving.

Job announcements can also be used to analyze employers. The analysis of employers is equally important, especially from the job applicants' point of view. The attractiveness of an employer for a job applicant is traditionally described by the qualitative feature *employer branding* [24]. There is big amount of publications about employer branding analysis and evaluation. As a rule, data for research are obtained by interviewing students, job seekers or employees of enterprises. In particular, the article [25] reveals determinants of students' perceptions of employers. The paper [26] is devoted to the study of the need for different employer branding strategies in different cultures. The papers [27, 28] explore the attractiveness of companies for their employees depending on various factors. The paper [29] addresses the problem of the lack of attractiveness of foreign-based companies in some countries. The paper [30] examines the attitude of India's IT industry employees to employers. The paper [31] represents a good example of quantitative analysis of employer branding and the use of social media to improve employer attractiveness. An analysis of employers of the IT based on the study of job advertisements was carried out in [32].

The presented review of scientific sources shows that, despite a significant number of studies of job advertisements, there are no published approaches in the open press that allow one to analyze, classify and select the most relevant occupations in the labor market, identify their key characteristics and represent the results in an convenient form, useful for those who are going to choose and learn a new profession, for example, in the form of private ratings of professions (ranking).

Therefore, it seems important to create a methodology that could single out the most significant and demanded professions for the employer today and form from them the tools that are important for decision-making by potential job seekers.

2 Materials and Methods

Currently, there are many resources on the Internet dedicated to job search. These primarily include job search sites, which are specialized sites for posting job seekers resumes and publishing employer vacancies.

Employer vacancies may contain information about the requirements for the candidate, for example, level of education or work experience, as well as information about salaries, work schedules, type of employment, etc.

The purpose of this paper is to study the key characteristics of professions on the example of the Moscow labor market by analyzing data on available vacancies posted on the websites of "HeadHunter" [33], "SuperJob" [34] and "TrudVsem" [35].

The choice of these sites is due to the fact that the first two sites "HeadHunter" and "SuperJob" are the best private specialized recruitment agencies, and the site "TrudVsem" is a federal state platform where vacancies that come from enterprises and organizations to the public service are accumulated employment of the population. Thus, the parity of state and private partnerships is respected.

Thus, for the analysis of vacancies and the formation of key characteristics of professions, we suggested the following methodology for analyzing job advertisements on the labor market (Fig. 1):

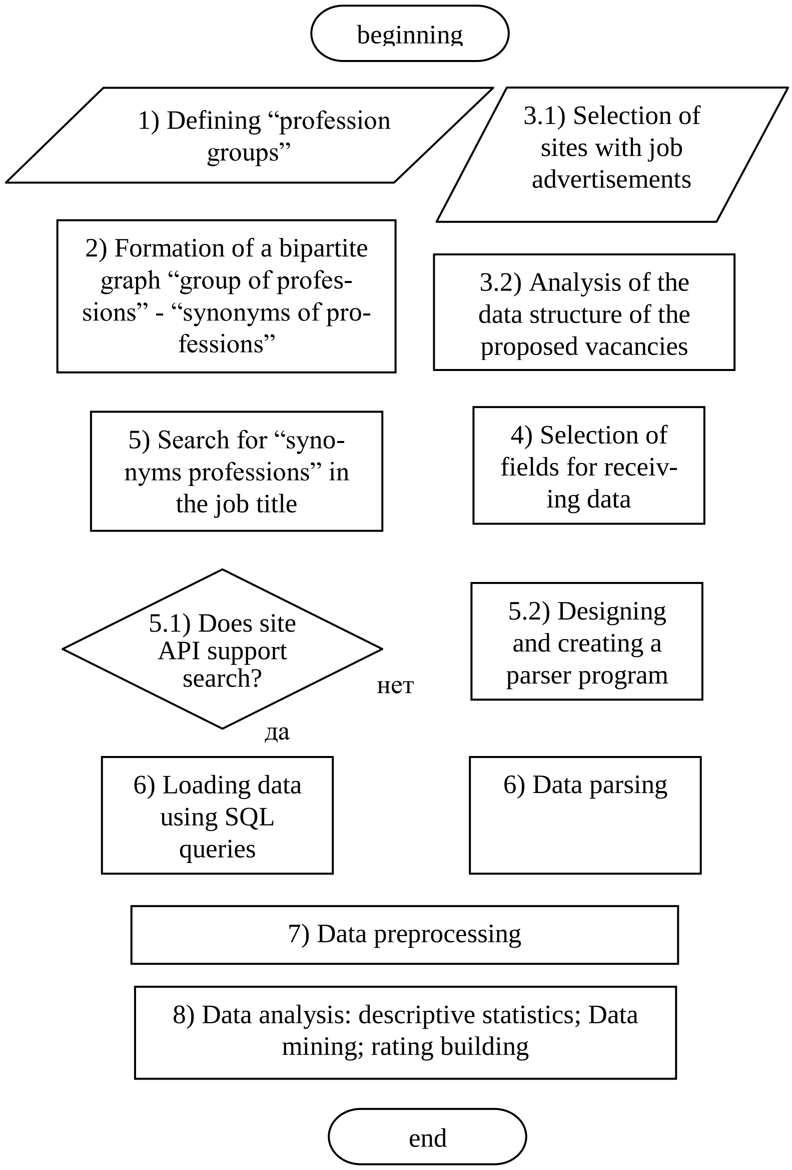

Fig. 1. An algorithm for the formation of key characteristics of professions based on the analysis of job advertisements.

We described in more detail the main stages of this algorithm:

1) Formation of a directory by expert means, which contains the so-called "groups of professions". Experts in this matter are representatives of the leading recruitment agencies we are considering, who own information about the

labor market and the most required professions, as well as representatives of career counseling agencies.

The concept of “group of professions” means an enlarged group of professions, which may include related professions from the same field of professional activity. Thus, not all thousands of professions in the labor market will be located and analyzed, but only the most popular ones.

2) Extension of the received reference book to a two-level one by compiling for each group of professions a “set of synonyms”, which may include the names of related professions that make up this group. This action takes into account the specifics of the three job search sites that we are considering, since different sites may name different professions. The aspect is also taken into consideration that some names of professions can be presented both in Russian and in English.

For instance, a group of professions "IT Specialist" may include such wordings of professions as "Programmer", "Software Architect", "Mobile Application Developer", "Ma-thematic programmer". The group of professions “Project-manager, project leader” may include the wording “Project Manager”, “Entrepreneur”, and “Project Manager”. The group of professions “The attending physician, diagnostician physician” includes the wording “Physician-diagnostician”, “General practitioner (family doctor)”, “Dentist”, “Physician-therapist”, “Emergency and emergency medical doctor”, “Surgeon” ”,“ General practitioner, general practitioner ”),“ Dentist, dental technician ”.

The formation of this set of synonyms is important, because in the full-text search for vacancies that will be performed on the selected sites, to improve the search results, we will use the setting of such a search parameter as a measure of proximity between the words found.

3) The choice of job search sites and analysis of the vacancies structure offered on them. Analysis of the methods of selecting information provided by sites: using the application program interface (API) for downloading data, studying the settings of search queries (vacancy fields in which to search for information, degree of relevance of information, degree of closeness of found words, etc.)

4) Definition of key fields in job advertisements, information from to obtain. For example, in our case study, we examined such characteristics of the profession in the vacancies found as salary, type of employment, work schedule, work experience, education. Such characteristics as language, age and gender were not considered in order to avoid discrimination on these subjective grounds.

5) Development and creation of a program (in our case, PHP), which carries out, at the first stage, the search for vacancies in the directory, and at the second stage, loads the required data from the vacancy into a specially created database for this according to the previously defined key fields.

In our case, the API sites “HeadHunter” and “SuperJob” allowed us to search only in the name of vacancies, and the API of the site “TrudVsem” did not provide such an opportunity. Therefore, for the site “TrudVsem” we had to develop a separate PHP parser program for parsing jobs using Web-scarping.

6) Importing job information from the database into an Excel file for subsequent statistical processing and analysis. In this case, for each vacancy, the file contained such fields as: ID of the group of professions, name of the group of professions, name of the profession, source of the vacancy, limits of salary, level of education, required experience, schedule and type of employment. For some vacancies, additional information about such factors as remoteness, temporality, and shift is also partially present.

7) Pre-processing and analysis of the source Excel file: eliminating emissions, encoding nominal variables. Aggregation of data on vacancies within each group of professions and calculation of all statistical indicators for the group: minimum, average and maximum salaries for the group, work experience for the group, etc. Formation of a pivot table in which there are only group of professions without specific vacancies and the corresponding statistical indicators for the group of professions under consideration.

8) Obtaining analytics from the pivot table: descriptive statistics, building scatter diagrams, clustering, analysis of key influence factors and building private rankings for the most significant key characteristics of group of professions. In our case, this is salaries (financial security of the profession) and the share of the profession in the market (demand for the profession).

The analysis used Analysis Services data mining tools, which are part of the Microsoft SQL Server database management system. For convenience, the analysis process was carried out in Excel using Excel Add-Ins Analysis Services MS SQL Server add-ons: table analysis tools and data mining client for Excel [36].

Using the methods of descriptive statistics, comparative analysis, filtering, sorting, highlighting exceptions (outliers) and classification, you can get additional (non-trivial) information about the professions represented on the labor market, which would help applicants, students or people located in active job search, make a more rational choice.

3 Results and Discussion

3.1 The structure of the source data

After performing step 6) of the described methodology, an Excel file was generated from the database of melon downloaded vacancies for further analysis, the data in which are presented in a tabular format and have the following set of columns:

1. Group ID - a unique identifier for a group of professions
2. Group of professions - the name of the group of professions
3. Source - the two-letter code of the website from which the vacancy was received (HH, SJ or TV)

4. Vacancy - job title on the website
5. salary from - the initial value of salaries
6. s / n to - the final value of salaries
7. Full day
8. Remote
9. Education
10. Experience
11. Temporary
12. Watch
13. Schedule
14. Type

The total number of vacancies with downloaded data from sources amounted to 90,027. The number of vacancies from various sources is presented in table 1. From table 1 it can be seen that the number of vacancies collected from the submitted sources covers 45.9% of the total vacancies submitted. This suggests that the collected number of vacancies is quite enough to describe the main trends of the entire labor market. It is likely that site administrators have limited the amount of data downloaded in order to protect information. Thus, the HeadHunter website did not allow downloading more than 2000 vacancies for one profession, and the SuperJob website did not allow downloading more than 500.

Table 1. Number of vacancies from various sources

Job site	Number of vacancies downloaded according to the list	The total number of vacancies on the site
HeadHunter	60328	116137
SuperJob	25385	70028
TrudVsem	4314	9561

The same result can be seen in Fig. 1, and the share distribution of offers on the labor market for real data is shown in Fig. 2. Thus, the largest share of vacancies for the entire labor market is provided by the HeadHunter website.

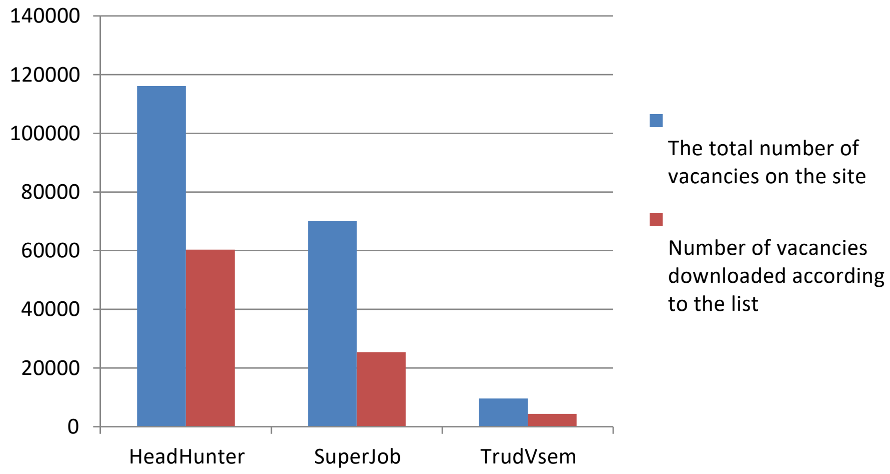

Fig. 2. Correlation of the total number of vacancies on sites and the number of downloaded vacancies.

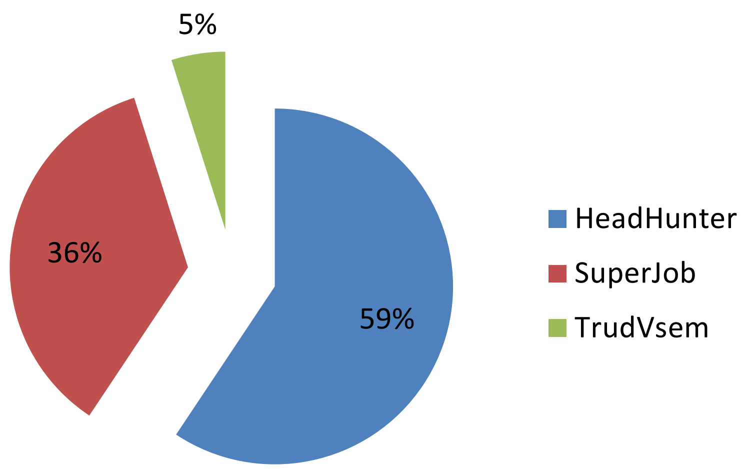

Fig. 3. The share of vacancies represented by sites on the labor market.

Figure 3 shows a cumulative summary of the vacancy rate in the market, sorted in descending order. The graphic demonstrates that the number of vacancies collected covers 46% of the labor market. Also Fig. 3 illustrates that to describe 40% we need only a third of these vacancies. This gives reason to believe that the collected number of vacancies is enough to describe the main trends of the entire labor market.

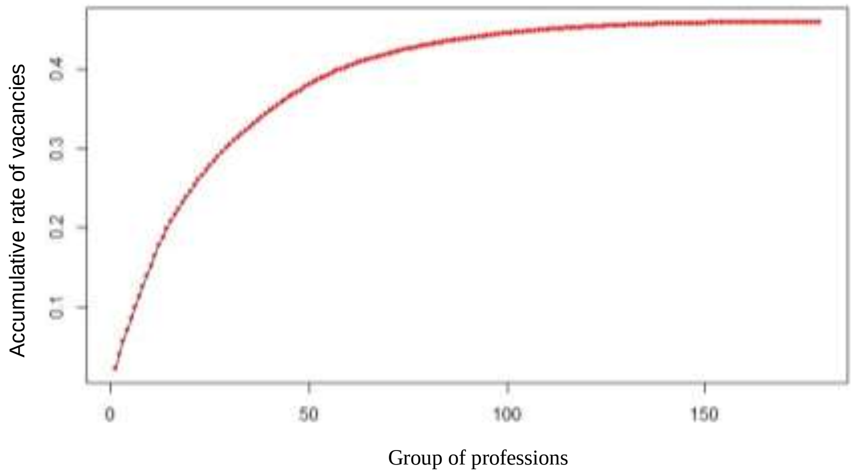

Fig. 4. The share of vacancies in the market cumulative total of the number of vacancies (job demand accumulation curve).

3.2 Data preprocessing

Before analysis, the data were pre-processed. The following columns were added:

1. Is there a salary – «1» if the vacancy has at least one of the fields “salary from” or “salary to”.

2. Average salary - If a vacancy has only one of the salary from or salary to fields, then this column will be equal to the non-empty field, if both are accessible, then their arithmetic average value will be taken, if not one is accessible, then the field is empty.

The field “experience” in the source data has values in various types of data, for some vacancies it is indicated in the form: “From X years to Y years”, “No experience”, ”0 years”. We decided to bring all the values to a numerical form from 0 to 20. So, if a gap was specified in the value, the arithmetic mean was considered. If it was indicated that the experience was not important, the number 0 was taken.

The education column also had to be standardized. The meanings of “Secondary Special” and “Secondary Vocational” were converted to “Secondary”. “Incomplete higher education” was replaced by “Incomplete higher education”, and empty values, where education was not indicated by the employer, were replaced by “Does not matter”.

3.3 Descriptive statistics

Having built a diagram of the dispersion of work experience with respect to average income and highlighting points on it depending on the source (Fig. 4), we can see that the data sources complement each other well. “TrudVsem” covers the area of low, average wages and high work experience. “HeadHunter” covers the area of high salary and high experience, while “SuperJob” covers the area of average salary and average work experience. This suggests that websites are not direct competitors of each other but represent different segments of the labor market.

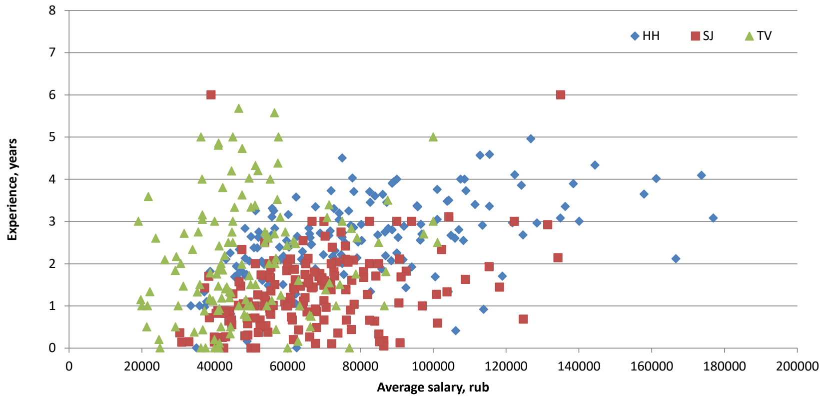

Fig. 5. Correlation of salary and work experience for different sites

Figure 5 also shows a scatter chart of work experience relative to average income but depending on the level of education. The shape and color indicate the education required to obtain work. The graph shows that employers requiring higher education from applicants also require 2-3 years of work experience. This means that it is difficult for university graduates to find work in their specialty and they have to start with those jobs where higher education is not required.

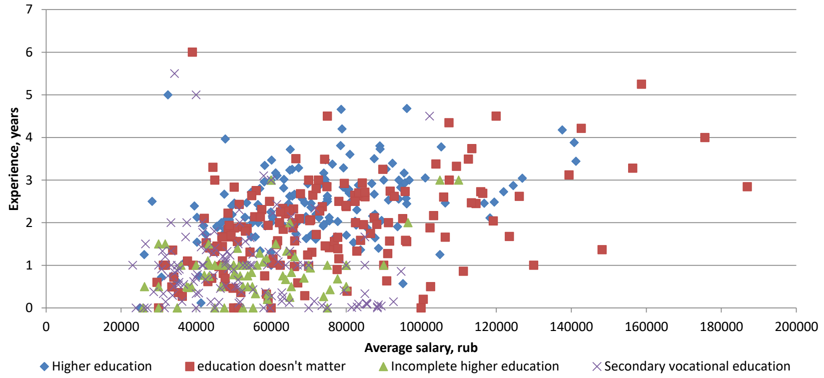

Fig. 6 Correlation of salaries and work experience for different levels of education

In the source "HeadHunter" there is a field "type of work". We built a diagram of the scattering of work experience and average income and highlighted points with different types on it (Figure 6) for those vacancies in which this field is filled, you will notice that a higher salary is usually offered for the project type of work, but it also requires more experience. For an internship, experience is not at all necessary, but wages are not high either.

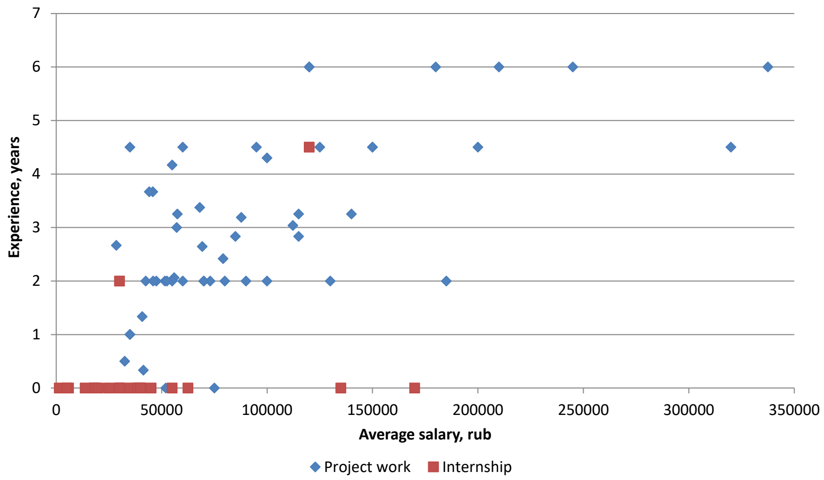

Fig. 7. Correlation between salary and work experience by type of work ("HeadHunter")

We analyzed the data on the average salary for each group of professions and built scatterplots for each site. Figure 7 demonstrates that on average for the same groups of professions, the highest salaries are offered by "HeadHunter" (80200 rub), the average salary level is offered by "SuperJob" (60500 rub), and the lowest salaries are offers "TrudVsem" (49600 rub).

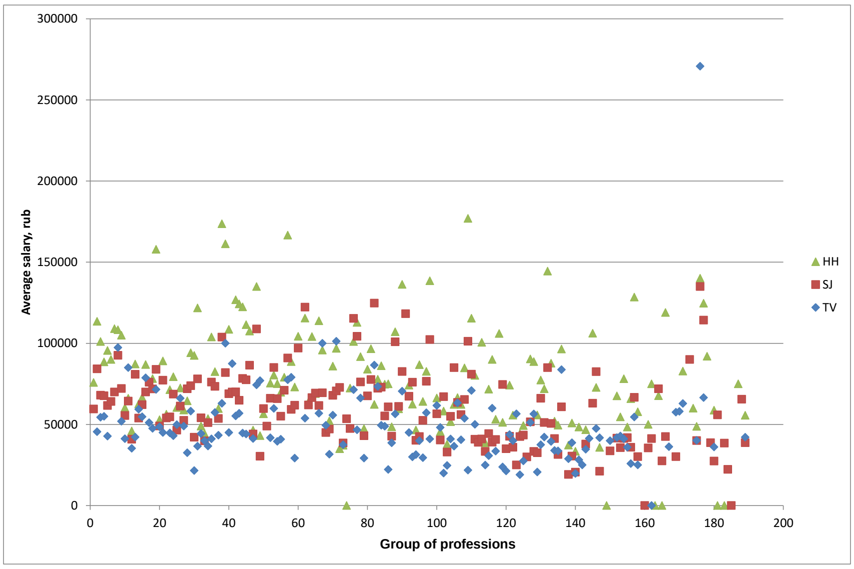

Fig. 8. Salary levels for different groups of professions for different sites

Figure 8 illustrates the Lorenz curve, which shows the inequality in the distribution of average wages among occupational groups. Before plotting, the average salary for each group of professions was sorted in ascending order, then all groups of professions were divided into 10 groups, and the share of group income was calculated. The Lorenz curve [37] graphically shows how close the market is to equilibrium, and the Gini coefficient [38] expresses this in numerical form. The Gini coefficient is calculated as the ratio of the area of the segment S_1 to the total area of the triangle $S_1 + S_2$: $G = S_1/(S_1 + S_2)$. The coefficient takes values from 0 to 1, where 1 means complete inequality. In our case, the Gini coefficient value takes the value 0.182, and this is closer to zero than unity, which suggests that vacancies with different salaries are equally represented on the labor market.

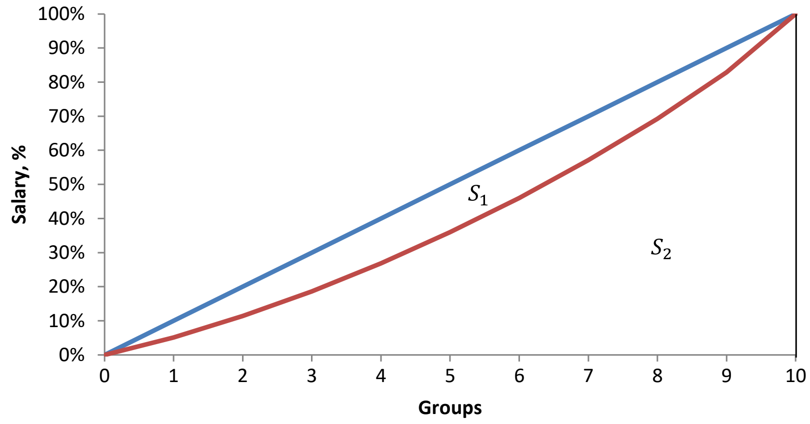

Fig. 9. Lorenz curve

3.4 Ratings of groups of professions

We sorted a list of occupational groups by a certain key criterion and got rankings according to relevant indicators.

So, for instance, in terms of the number and demand of professions in the labor market, we can judge by the number of job advertisements (vacancies) that are published on job search sites.

Therefore, Table 2 presents the ranking of professions in terms of their mass. Obviously, the chances of employment in these professions will be high due to increased demand for them from employers.

According to the results of a comparative analysis of tables 2 and 3, it turns out that only three of the thirty groups of professions, or only 10% of intersections, are common elements.

The inverse form of the dependence of the mass of groups of professions and salaries is confirmed by the graph in Figure 9. The graph demonstrates the mass curve and the curve of the share of vacancies with the maximum wage in a given group of professions. Preliminarily, the data were sorted in the reverse order (at the beginning there are the most massive groups of professions). It is clearly seen that the "mass" groups of professions have the smallest percentage of vacancies having the maximum wage for this group.

Table 2. Top 30 professions by the number of vacancies for all sources

Group of professions	Number of vacancies	Percentage of total
Chief Specialist (designer, engineer, mechanic)	4480	4.98%
IT specialist, development engineer, process engineer	3560	3.95%
Private business entrepreneur	3028	3.36%
Sales Manager, Medical Representative, ...	2946	3.27%
Project-manager	2925	3.25%
Bartender, waiter, barista	2651	2.94%
Administrator (salon, hotel, hall, store, etc.)	2640	2.93%
Cook	2535	2.82%
Accountant	2532	2.81%
Key Account Manager	2524	2.8%
Administrative Manager (Head)	2509	2.79%
Specialist in working with customers	2492	2.77%
Secretary, office manager, bank clerk	2108	2.34%
AXO specialist, office manager	1953	2.17%
HR manager, staff recruitment	1924	2.14%
Design Engineer, Design Engineer	1587	1.76%
Educator, teacher (education)	1536	1.71%
Purchasing, Procurement Manager, Merchandiser	1481	1.65%
Team Leader (IT)	1474	1.64%
Implementation and Maintenance Engineer	1398	1.55%
HR Manager, Trainer	1382	1.54%
Marketer, Media Analyst, Market Researcher	1360	1.51%
Nurse, nurse, paramedic	1324	1.47%
Logistic, production optimization engineer	1213	1.35%
Advertising Specialist, Brand Manager	1181	1.31%
Operative, bodyguard	1076	1.2%
Procurement Specialist	1067	1.19%
Merchandiser	1047	1.16%
Clerk, laboratory assistant, methodologist	988	1.1%
Commercial Director (Sales Manager)	934	1.04%

Another important indicator is the level of salaries for groups of professions. Table 3 shows the ranking of the highest paid vacancies in the labor market of Moscow.

Table 3. Top 30 occupations by salary level for all sources

Group of professions	Average salary	Min salary	Max salary
Pilot, navigator, skipper	212095	179231	234872
Team Leader	167291	148144	194641
Executive Director	141663	119890	190468
Systems Analyst	131210	104161	157723
Trader	129498	94713	254348
Technical Director	123600	105102	182333
Mobile app developer	118764	95983	140966
Investment Analysis Specialist	118237	76754	142500
Head physician	110952	93477	134466
Head of R&D	110395	92200	134622
Game designer	106000	93333	110000
Commercial Director	105031	84624	141950
Auditor Analyst, Business Analyst	104792	91872	118526
Surgeon	104106	84725	147572
Art Director	103913	90000	115000
Product Manager	103686	89542	128123
Lawyer - Consultant	99318	60500	156785
Architect	99235	86187	115425
Robot Engineer	98750	95000	120000
Chief Project Engineer	98140	88493	102058
IT specialist, development engineer	96243	82937	108783
Development Manager	95013	78698	127743
Expertise and property management	94060	65000	105060
Realtor	93516	70220	172200
Financial Consultant	93031	60799	155925
Head of Analytical Department	92818	72060	134706
Regional specialist	91970	84400	112777
ERP Systems Consultant, SAP Consultant	91818	72764	92520
Financial Controller	91026	82179	99562
3D designer, interface designer	90968	78717	103090

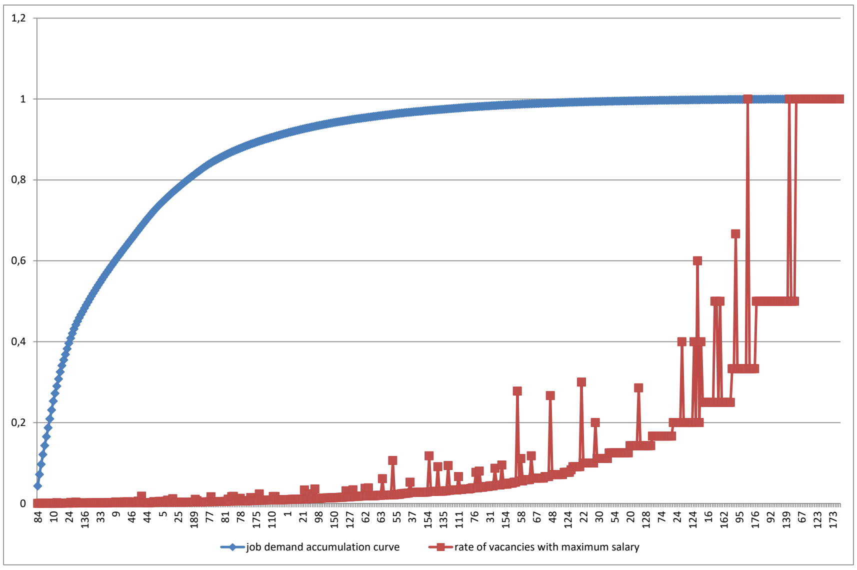

Fig. 10. Correlation of mass and probability of getting the maximum salary in this group of professions

4 Conclusions

The results can be useful to applicants when choosing a future profession, as well as job seekers. The ratings of professions based on the level of salaries and demand on the labor market will help them make rational choices and orient themselves when making important decisions.

An interesting result was the analysis of key factors of influence, which showed that neither the level of education, nor work experience, nor a group of professions strongly affect the level of salaries earned. This result does not correspond to human stereotypes about the impact of education on the level of salary or level of work. But in practical life there are situations of the opposite nature, while the table contains a lot of blank lines. Therefore, this issue should be studied better and with a larger and more complete set of data.

Also, based on the result of the analysis of the connection between the representation of the profession on the labor market and salaries, it can be concluded that the "mass" (popular) professions for the most part are not highly paid, and there is very little chance of getting the maximum salary. At the same time, “rare” professions are mostly highly paid.

A similar principle was observed in the analysis of categories, which showed that the largest number of professions were the least paid. This result seemed interesting, logical and motivational. If one wants to earn more, she or he needs to strive to work on yourself, acquire rare skills and go to areas where most people will not go.

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