Skills demanded by the Labor Market and supplied by Russian universities: An investigation

Artem Volgin and Suhas Parandekar

The World Bank, Global Practice Education

XXII APRIL INTERNATIONAL ACADEMIC CONFERENCE ON ECONOMIC AND SOCIAL DEVELOPMENT 2021

THE WORLD BANK IBRD • IDA | WORLD BANK GROUP

Human Capital and Skills

- The motivation for this study is to provide support to the human capital aspect of the development strategy of the Russian Federation as set out in the May decree of 2018. Russia's development goal is to become one of the top five economies in the world and to reduce poverty by half.

- The importance of human capital to reach this goal is recognized in the government's policy pronouncements and the World Bank analytical work in support of government policy.

- Skills are the core of human capital. The leading countries in the world learned to use the knowledge, skills, competencies of people in order to increase the national wealth.

Past Research: Skills and Online Data

- Soft skills are important for success in life (Heckman and Kautz, 2012).
- In Russia higher levels of non-cognitive skills are typical for people with university education and for highly qualified employees (Gimpleson, Zudina, Kapeliushnikov, 2020).
- Demand on skills based on the vacancies data: the labor market increasingly rewards social skills (Deming and Kahn 2017).
- LinkedIn collaboration with the World Bank: LinkedIn data are best at representing skilled labor in the knowledge-intensive and tradable sectors (Zhu, Fritzler, Orlowski, 2018).
- The World Bank researchers utilized HeadHunter vacancies data before: most occupations demand a variety of different socioemotional skills; cognitive and socioemotional skills appear as complementary (Muller and Safir, 2019).

Information about Skills

- Information about skills possession could be highly important for
  1. students to navigate their choice and increase returns to education
  2. universities to provide marketable skills
  3. companies to hire the most skilled graduates
  4. government to stimulate development of the 21st century skills
- We use the information from resume data provided by **HeadHunter.**

HeadHunter

- The biggest internet-recruiting company in Russia.
- Database of more than 50 million resumes.
- Publishes more than 600 thousand vacancies every day.

HeadHunter Data

- Size and granularity: millions of vacancies and resumes.
- High frequency data available on a daily basis.
- Contains unique information such as indication of skills.
- A lot of unstructured textual fields.
- Data is not representative of the Russian labor market as a whole but fairly representative of the set of workers who obtain employment through online medium.

Data Description

Sample of resumes of applicant with higher education from 2014 – 2020 provided by **HeadHunter**
N=259,133

Variables:

Year of CV creation	Education level
Region	University names
Gender	Faculty names
Age group	End year for each university
Expected salary	Skills list
Professional area	

Filtering:

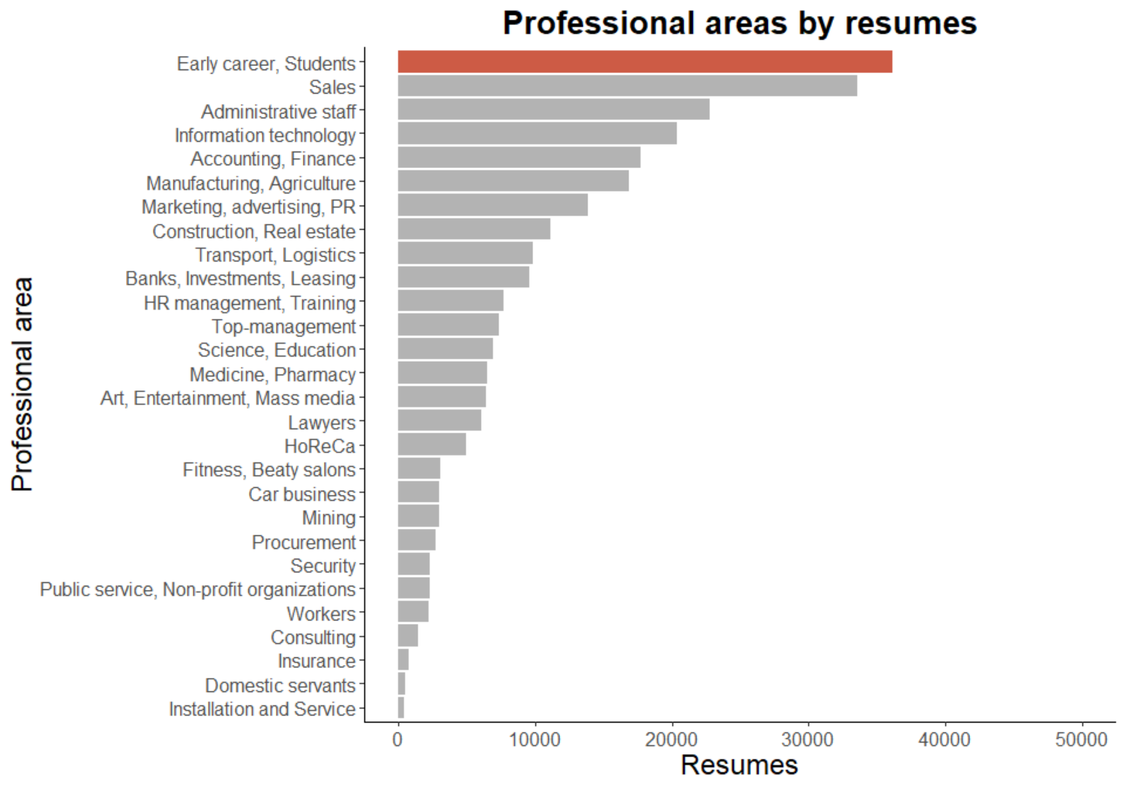
1. Finished education in 2000-2020
2. Only last obtained education
3. With indicated university, faculty and skills
4. Finished state universities

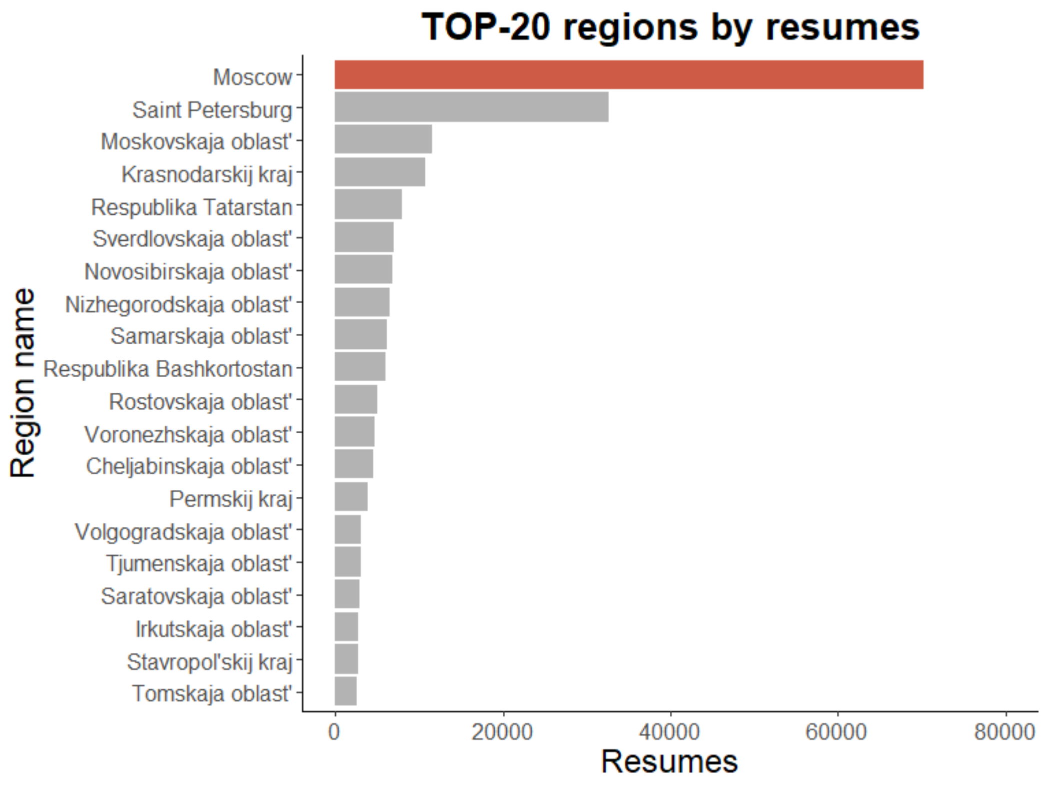
Official statistics from **graduate.edu.ru**

1. Number of graduates in 2013-2015 for each state university
2. Salary of graduates in 2013-2015 for each state university

First Look at the Data

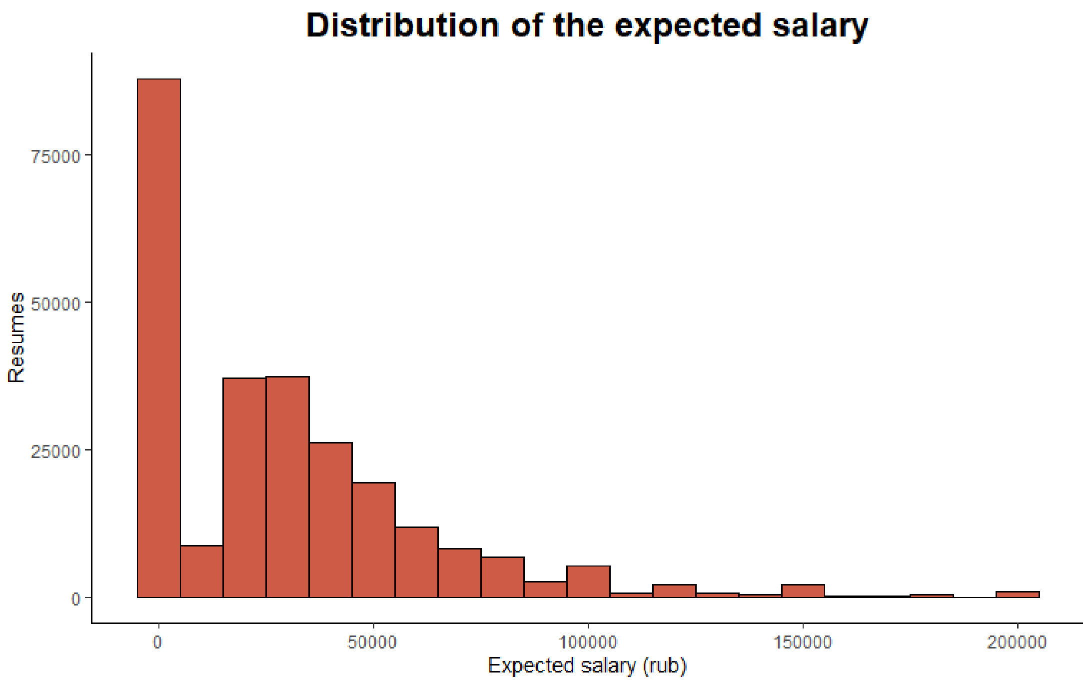
Professional area and region





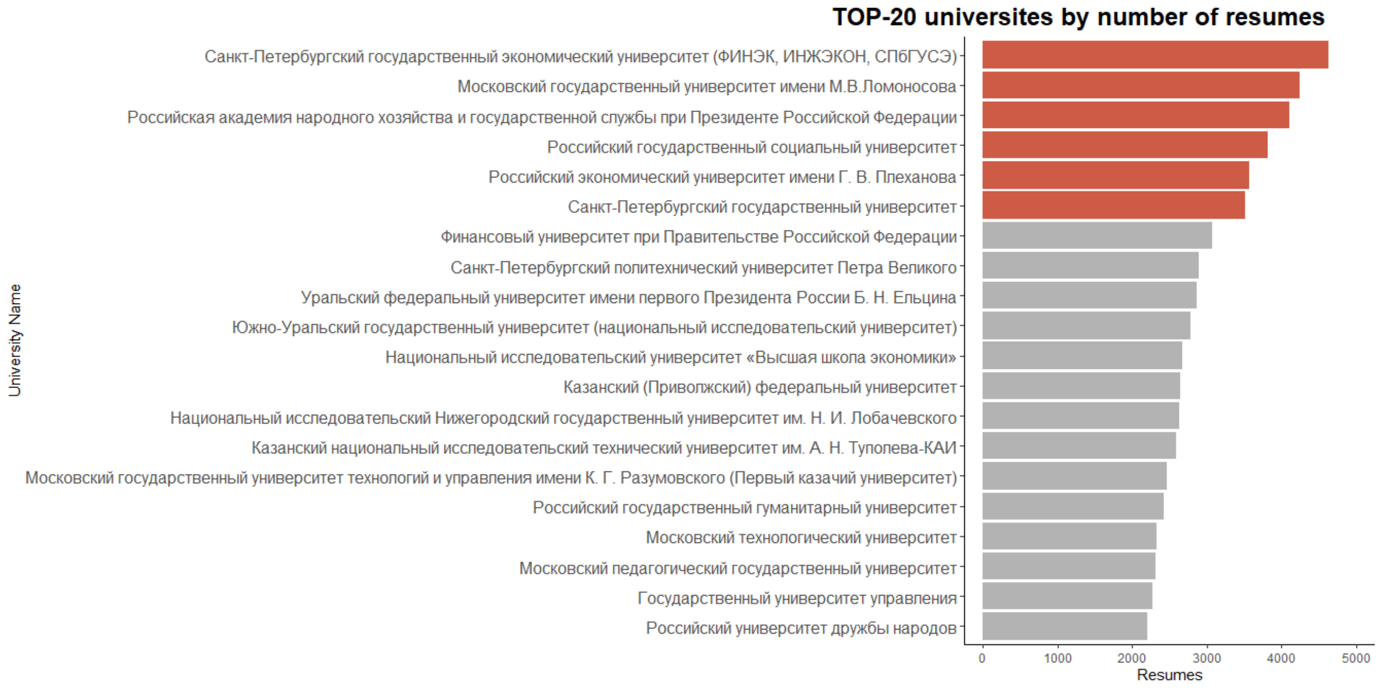
- A lot of early career applicants and students.
- Categorization with different bases: hierarchy, professional, and business areas.
- Bias towards Moscow and Saint Petersburg.

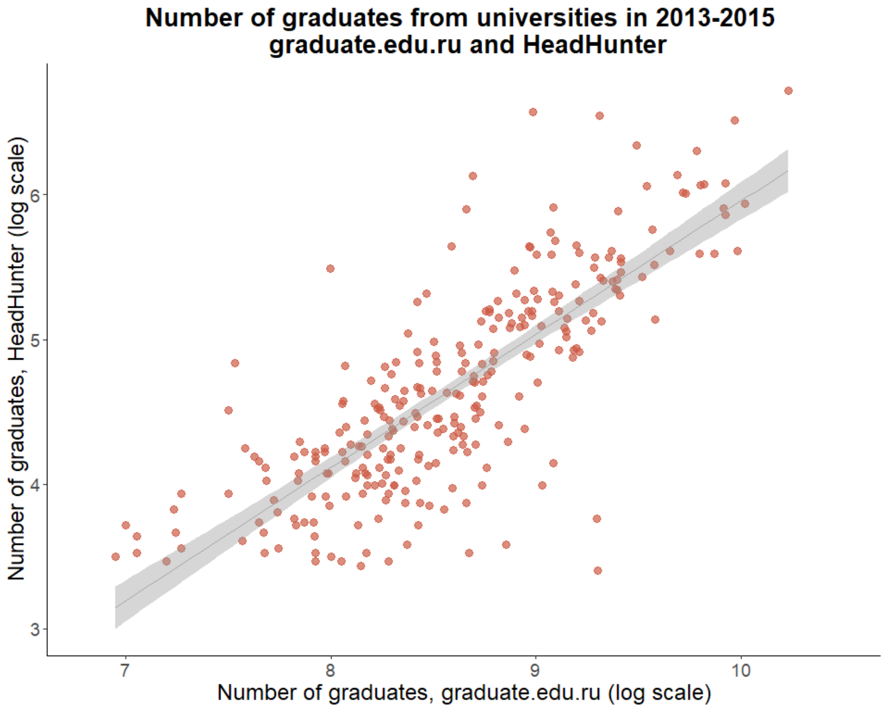
Expected Salary and Experience



- High percentage of resumes with 0 excepted salary and no experience (interns).
- Years of experience = Years of experience in the field, not the general working experience.

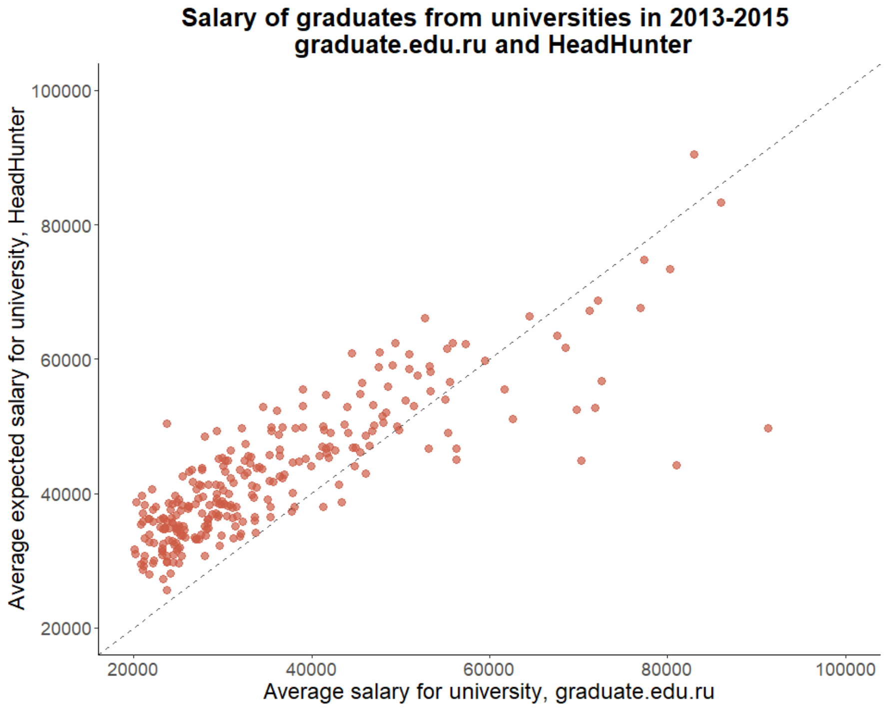
Number of Resumes by Universities





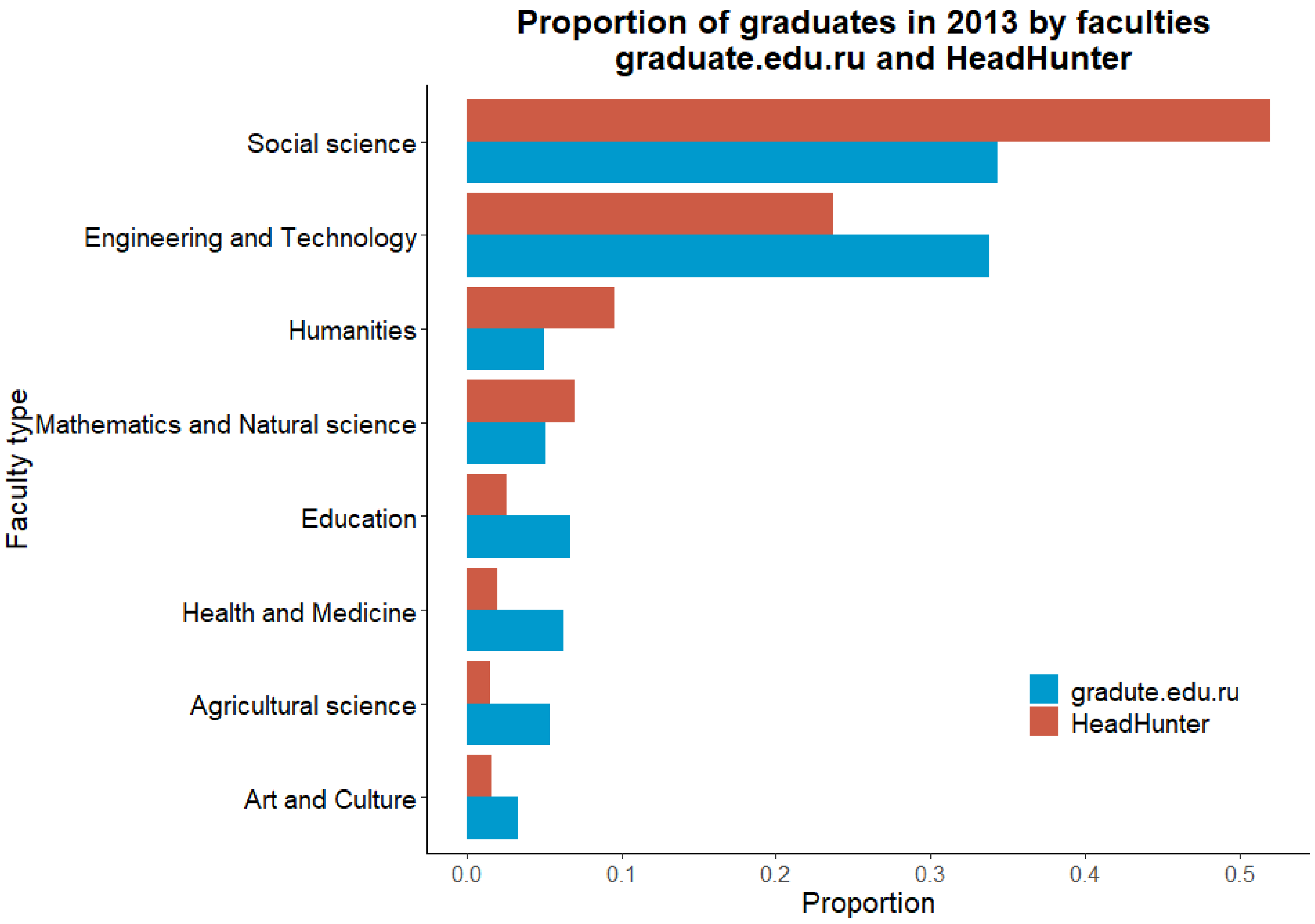
- Deduplication of the university names using Google Geocaching API.
- Number of graduates from each university in HeadHunter data highly correlates with official statistics.

Salary of University Graduates



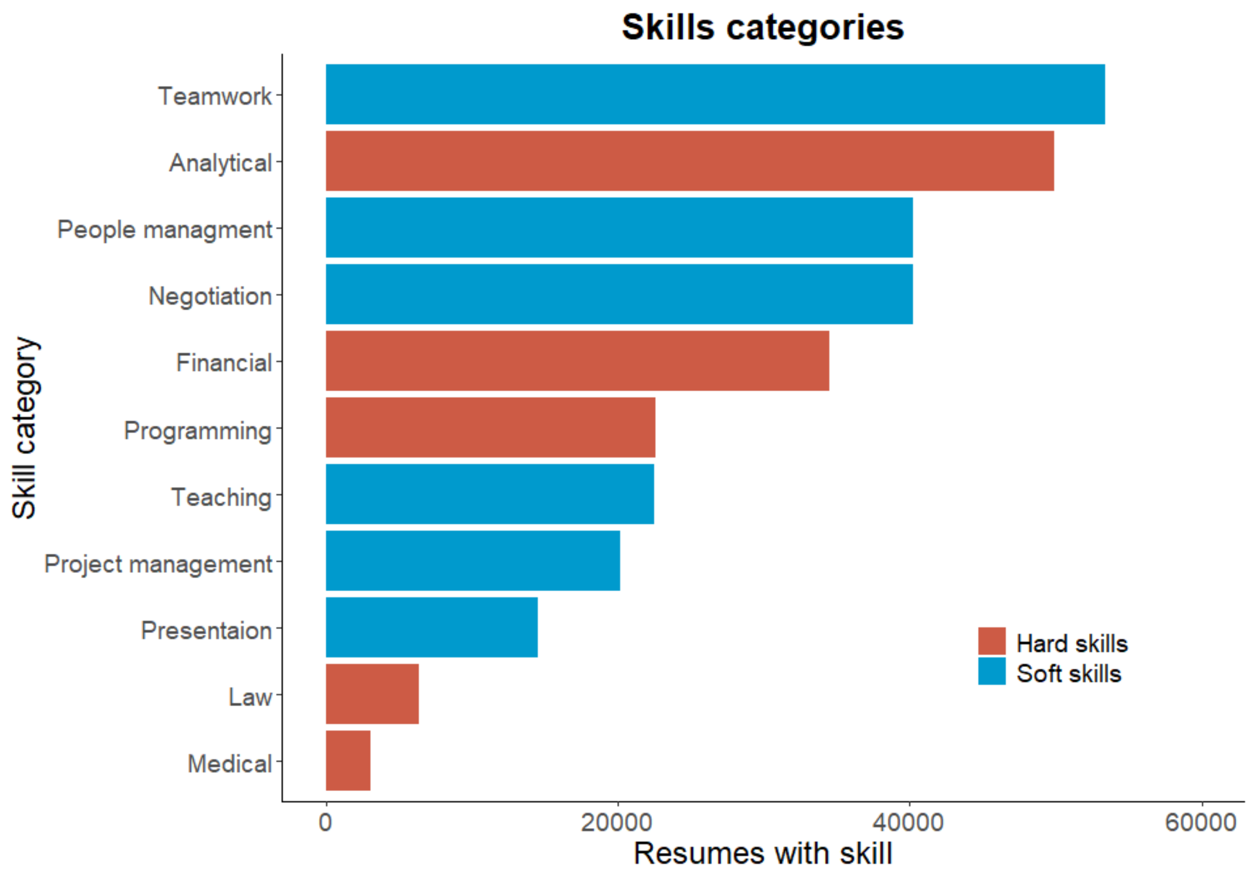
- Average salary of graduates from each university in HeadHunter data correlates with official statistics.
- Expected salary in HeadHunter data is usually higher than the obtained salary.

Faculties Distribution



- Faculties are coded based on the key words.
- Overrepresentation of Social Science and Humanities and lack of STEM graduates on HeadHunter.

Skill Categories Distribution



- Skills are coded based on the key words.
- Applicants mostly indicate teamwork, analytical skills, people management and negotiation abilities.

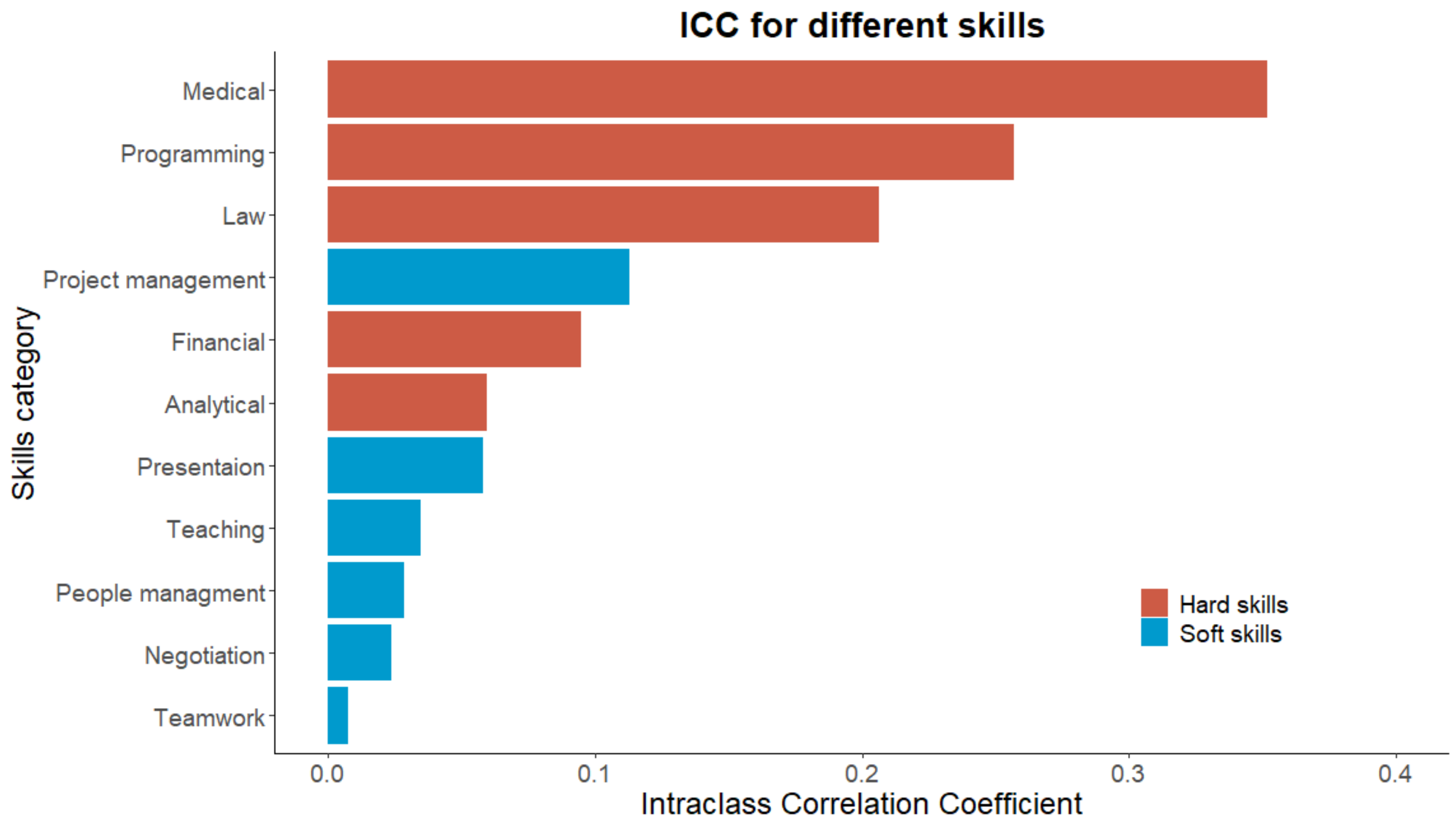
Skills Supplied by Universities

Research Questions

1. How important are Russian universities for the acquisition of skills?
2. Which universities are better at providing specific sets of skills?

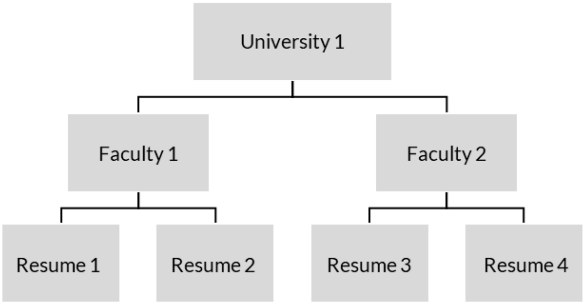
Importance of Universities for Skills

Null Models for each Skill



$$ICC = \frac{S_b^2}{(S_b^2 + S_w^2)}$$

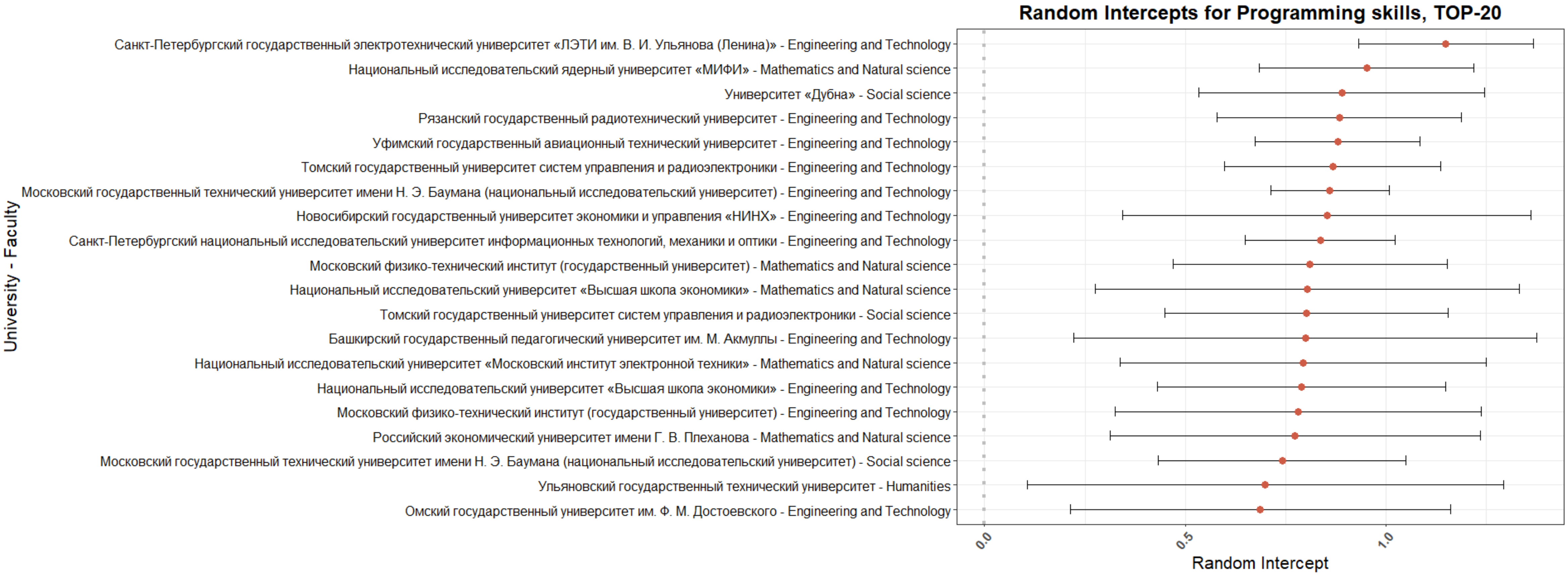
S_b^2 = between group variation,
S_w^2 = within group variation



- Universities play less important role in obtaining Soft skills than Hard skills.

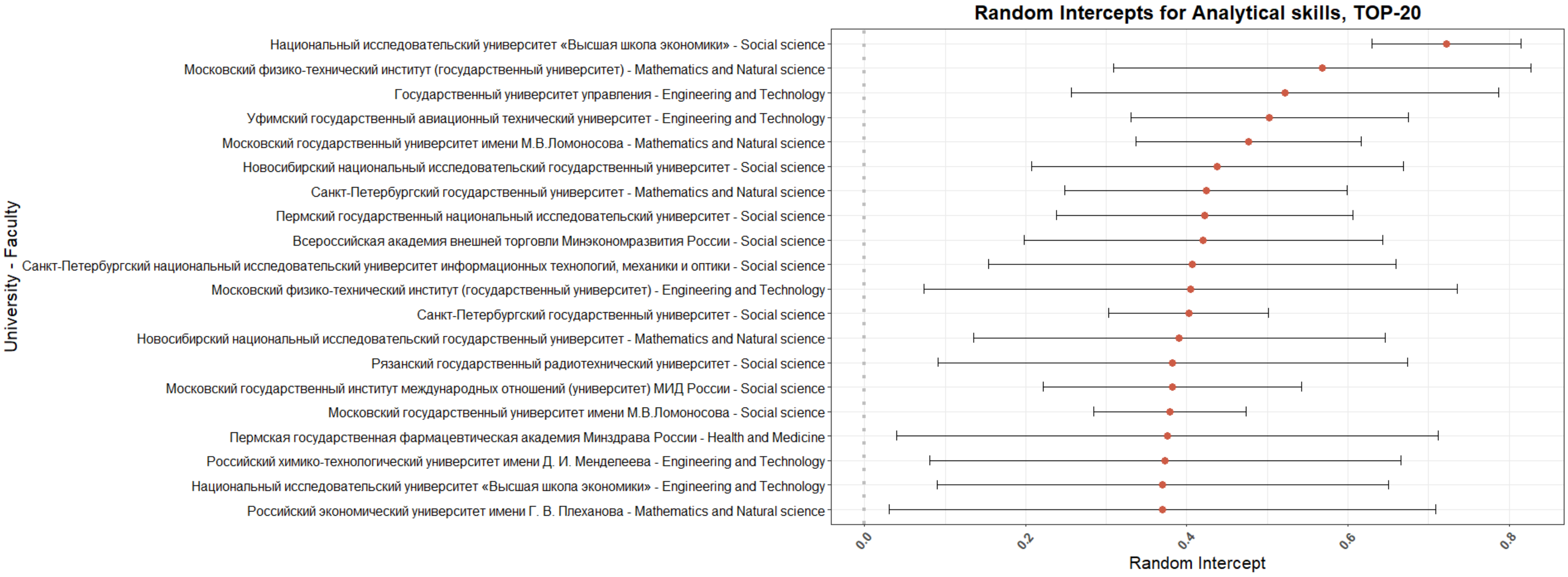
Programming Skills of Graduates

Random Intercepts of the Full model: University – Faculty



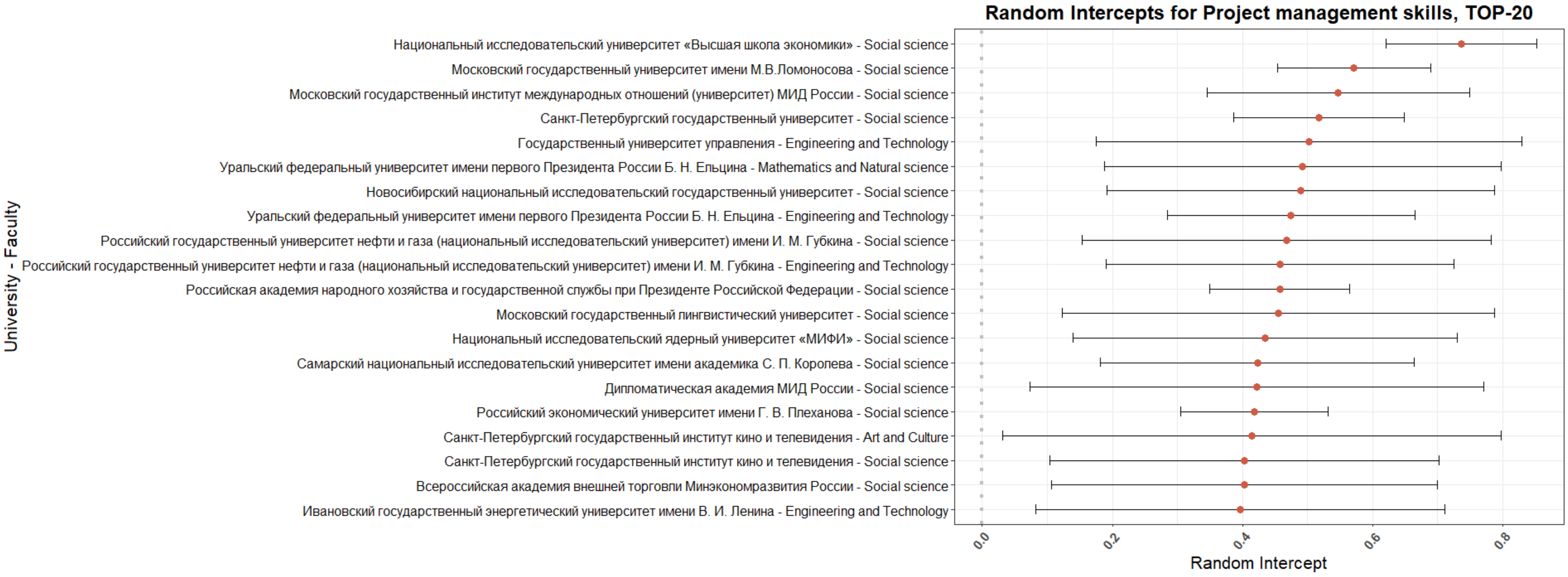
Analytical Skills of Graduates

Random Intercepts of the Full model: University – Faculty



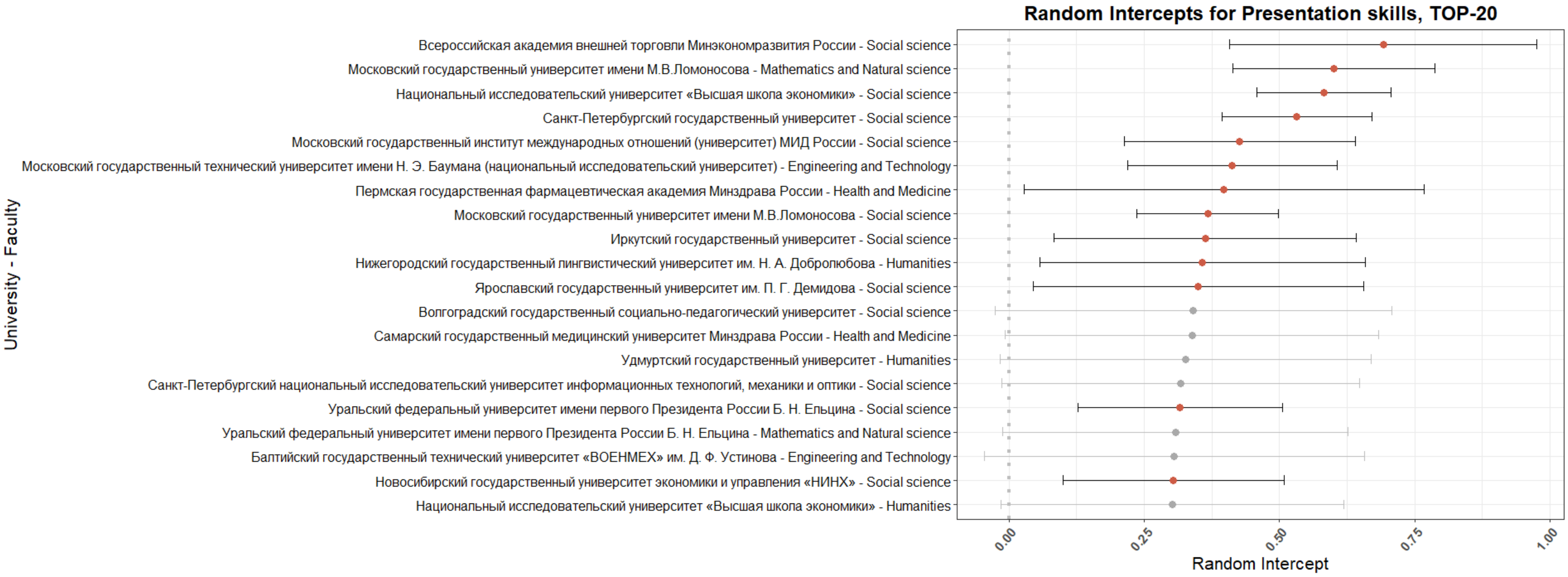
Project Management Skills of Graduates

Random Intercepts of the Full model: University – Faculty



Presentation Skills of Graduates

Random Intercepts of the Full model: University – Faculty



Conclusion

Conclusion

- The size of the data allows us to estimate highly detailed models.
- We should always keep in mind potential bias while working with such data.
- Universities play less important role in providing Soft skills.
- Top universities are better at providing both Soft and Hard skills.

Limitations

- Lack of detailed and comparable categorization of occupations.
- Relatively small sample size per faculty and university.
- Absence of information about skills’ proficiency.

Future Avenues

- Professional trajectoires of ex-students.
- Internal migration after graduation.
- Cohort analysis of graduates.
- Connection with vacancies data.

Thank you!

APRIL INTERNATIONAL ACADEMIC CONFERENCE ON ECONOMIC AND SOCIAL DEVELOPMENT 2021

THE WORLD BANK
IBRD • IDA | WORLD BANK GROUP

Deduplication of University Names

Google Geocaching API

University name	Coordinates	One entity
Московский государственный университет	55.704, 37.528	
Moscow State University	55.704, 37.528	
МГУ	55.704, 37.528	*Московский государственный университет имени М.В. Ломоносова*
МГУ имени М.В. Ломоносова	55.704, 37.528	
Московский государственный университет имени М.В. Ломоносова	55.704, 37.528	

Coding of Faculty Names

Faculty specialization	Key words
Mathematics and Natural science	математи | физик | химия | химичес | статисти | геолог | географ | биолог | гидро | эколог | физмат | кибернет | земля | недропольз | естествен | природный
Engineering and Technology	технолог | техничес | инженер | строител | информа | транспорт | компьютер | энергети | программир | бурен | оптика | энерго | вычислите | трактор | материал | прибор | производ | промышлен | автомат | связь | механик | механич | эксплуат | электро | техник | машин | газос | минерал | механиз | металл | робот | нефтян | нефть | газовый | аэро | космиче | двигател | ядерны | архитек | автомобил | дорожн | горный | авиаци | аппарат
Health and Medicine	медицин | медико | сестринск | здравоохран | фармацев | лечеб | стоматоло | фармация
Agricultural science	агроном | садовод | лесное | зоотехн | лесной | лесозаготов | дерево | сельское | почвовед | природо | овощевод | ветеринар | растительный | водоснабжение
Social science	социол | социал | бизнес | эконом | финанс | политолог | психолог | менеджмен | бухгалте | товаровед | политич | урбанис | торгов | регионовед | отношени | политик | реклам | обществен | журнал | маркет | логист | банков | демограф | менеджемент | туризм | сервис | гостини | юридич | юриспру | юрист | право | медиа | аудит | таможен | коммерц | налог | судебный | муниципальный
Education	педагог | детство | дефектолог | логопед | педиатр
Humanities	археолог | философ | региовед | теолог | лингвист | истори | филолог | гуманитар | язык | перевод | африка | восток | архив | физический культура
Art and Culture	дизайн | искусств | хореограф | музыка | художествен

Coding of Skills

Skills Category	Example of skills
Analytical	Маркетинговый анализ, Data Analysis, Сбор и анализ информации
Programming	SQL, Git, JavaScript, Linux, C++
Financial	Налоговая отчетность, Бюджетирование, Расчет затрат, Управление закупками
Legal	Претензионная работа, Гражданское право, Трудовой кодекс РФ
Medical	Фармакология, Стоматология, Педиатрия, Дерматология
People Management	Управление персоналом, Руководство коллективом, Оценка кандидатов, Кадровая стратегия
Project Management	Управление проектами, Agile, Организация PR кампаний
Negotiation	Проведение переговоров, Навыки ведения переговоров
Presentation	Навыки презентации, Публичные выступления, Public Speaking
Teamwork	Работа в команде, Лидерские качества, Teamplayer, Умение работать в коллективе
Teaching	Обучение персонала, Способность обучать других, Наставничество

Null Models Specification

Resume (1st level):

$$ln\left(\frac{P(Y_{ijk}^{s})}{1-\ P(Y_{ijk}^{s})}\right) = b_{0jk}$$

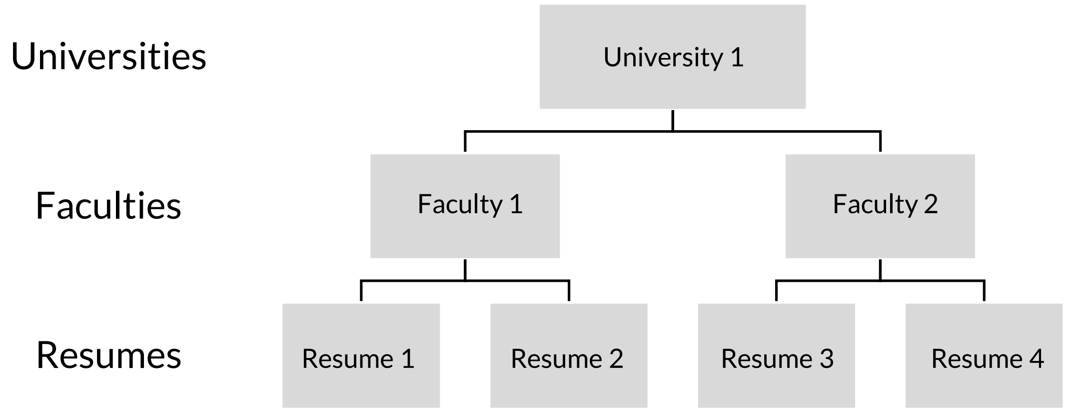
Faculty (2nd level):

$$b_{0jk} = \pi_{00k} + r_{0jk}$$

University (3rd level):

$$\pi_{00k} = \gamma_{000} + u_{00k}$$

where a resume *i* is nested within a faculty *j*, which is nested within a university *k*, Y_{ijk}^{s} is a dummy variable for a skill, *s* denotes a distinct skill of interest, r_{0jk} and u_{00k} are the second- and third-level errors respectively.



Full Models Specification

Resume (1st level):

$$ln\left(\frac{P(Y_{ijk}^{s})}{1-\ P(Y_{ijk}^{s})}\right)$$
$$=\ b_{0jk}+b_{1jk}(CV\ creation\ year)\ +\ b_{2jk}(graduation\ year)$$
$$+\,b_{3jk}(experience)\ +b_{4jk}(region)\ +b_{5jk}(professional\ area)$$
$$+\,b_{6jk}(gender)\ +b_{7jk}(age)\ +b_{8jk}(student\ status)$$
$$+\ b_{9jk}(education\ level)$$

Faculty (2nd level):

$$b_{0jk}=\pi_{00k}+r_{0jk}$$
$$b_{ijk}=\ \pi_{i0k}\text{ for } i\neq 0$$

University (3rd level):

$$\pi_{00k}=\gamma_{000}+u_{00k}$$

where a resume *i* is nested within a faculty *j*, which is nested within a university *k*, Y_{ijk}^{s} is a dummy variable for a skill, *s* denotes a distinct skill of interest, r_{0jk} and u_{00k} are the second- and third-level errors respectively.