Federal State Autonomous Educational Institution for Higher Education

National Research University Higher School of Economics

Faculty of Computer Science

Educational Program

Applied Mathematics and Information Science

GROUP TERM PAPER

Research project

Kinship Relations in Famous Russian Families in the XVIII and XIX Centuries and the Distribution of Influence in Them

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Moscow, 2021

Content

Abstract

Nowadays, quite a large number of works are being carried out to study the history of our society.

Our work is focused on the study of economic life in Russia in the 18th and 19th centuries.

We have an assumption that the Russian nobility of that period was highly indebted.

To prove or disprove this theory, we conducted research.

We collected data on dates, families, and financial institutions and created a database with all available data for this period.

Afterwards, we explored the data using various methods of data analysis and network analysis.

Most influential families and persons of Russian nobility have been observed.

Аннотация

Сегодня проводится довольно большое количество работ по изучению истории нашего общества.

Наша работа направлена на изучение экономической жизни в России 18 и 19 века.

У нас есть предположение, что дворянство 18-19 веков было сильно закредитовано.

Чтобы доказать или опровергнуть эту теорию, мы провели исследование.

Мы собрали данные о датах, семьях и финансовых учреждениях и создали базу данных со всеми доступными данными за этот период.

Следующим шагом мы исследовали полученную информацию с использованием различных методов анализа данных и сетевого анализа.

Были выделены наиболее влиятельные семьи и персоны.

Keywords

- Russian Empire
- Price revolution
- Borrower
- Creditor
- Debt
- Loan
- Obligation

Introduction

The aim of this work is to study the distribution of influence among famous families in the 18th and 19th centuries. There are many aspects on which you can assess the influence, one of them is debt obligations. The formation of the nobility of the Russian Empire took place not only under the influence of political ideas and within the framework of debates on political issues, but largely due to mutual debt obligations. That is why, firstly, we need to assess the debt burden of the nobleman. There is a strong belief that the nobility was indebted, but how much?

Reviewed period is 1760 - 1812 years. The chronological framework of the study is explained by the period of the Golden Age of the Russian nobility, which traditionally covers the period from the accession of Catherine the Second to the Patriotic War of 1812. Additional grounds for allocation of this period was the introduction of banknotes in 1768 - 1769 years. Banknotes were introduced for the entire period of operation of banks. This period was characterized by relatively high inflation according to Boris Mrionov’s research:

“The peculiarity of the "price revolution" in Russia was that it occurred not as a result of an influx of precious metals from Europe and America, but under the influence of the local emission of money, and not gold and silver, but paper and copper. The purchasing power of the latter did not match their intrinsic value. However, their emission then led not so much to inflation as to the fact that simultaneously depreciated silver and gold money, in other words, to the fact that the prices of goods grew not only in paper and copper, but also in silver and gold money.”[1]

[1] Boris Mirinov, "Price Revolution" in Russia in XVIII century, History questions, 1971, № 11, p. 49-61

Price index of the 8 most important agricultural products in Russia in the 18th century[8]
(original prices are in grams of silver. 1701 - 1710 = 100).

Goods|Unit	*1711 - 1720*	*1721 - 1730*	*1731 - 1740*	*1741 - 1750*	*1751 - 1760*	*1761 - 1770*	*1771 - 1780*	*1781 - 1790*	*1796 - 1801*
Rye, quarter	*149*	*246*	*209*	*242*	*209*	*293*	*340*	*527*	*555*
Oats, quarter	*144*	*204*	*185*	*244*	*222*	*252*	*304*	*448*	*588*
Wheat, quarter	*133*	*178*	*162*	*179*	*173*	*211*	*292*	*403*	*551*
Barley, quarter	*153*	*218*	*174*	*215*	*197*	*256*	*325*	*484*	*587*
Buckwheat, quarter	*153*	*200*	*166*	*208*	*184*	*234*	*315*	*460*	*523*
Hemp seed, quarter	*135*	*155*	*196*	*252*	*192*	*260*	*323*	*410*	*507*
Beef meat, pood	*144*	*181*	*238*	*306*	*288*	*406*	*413*	*563*	*706*
Cow butter, pood	*135*	*147*	*157*	*190*	*197*	*241*	*278*	*336*	*545*[2]

As one can see,the price for most of the goods has increased by almost 4 times in 100 years. Therefore, we think that this period is the most interesting, because the rise in prices of important products can cause an increase in the number of loans.

[2] Boris Mirinov, "Price Revolution" in Russia in XVIII century, History questions, 1971, № 11, p. 49-61

Literature review

At the moment, the nobility of Russia in the 18-19 centuries is studied mainly in the framework of political and social spheres, there is little research in the economic sphere. As far as we know, there are no similar studies on this topic. However there are some studies that overlap with our research.

- Elena S. Korchmina, “Do not give bribes in honor”: *pochest’* and *vzyatka* in post-Petrine Russia, Russian History, 2015, №2, p. 3-13

- Fuad T. Aleskerov, Vyacheslav I. Yakuba, “Matrix-Vector Approach to Construct Generalized Centrality Indices in Networks”, SSRN Electronic Journal, 2020, DOI:10.2139/ssrn.3597948

- Boris Mirinov, "Price Revolution" in Russia in XVIII century, History questions, 1971, № 11, p. 49-61

- Karnovich E. Remarkable wealth of individuals in Russia. SPb., 1885.

- Frumenkova T.G. Preserved, Loan and Widow Treasury of the St. Petersburg Orphanage in the Reign of Catherine II. Entrepreneurship and social life of St. Petersburg. Essays on history. Issue 2.SPb., 2003.

Data and results obtained as a result of our work can serve as a good confirmation for existing works, and can also help in further studies.

Therefore, it is necessary to collect all the data obtained in one database for subsequent placement in open sources.

Goals and Objectives

1. Collect a database of loans among the nobility for the 18th - 19th centuries.
2. Analysis of obtained data.
3. Based on new methods of network analysis and centrality indices to reveal most significant persons and families
4. Do comprehensive overview of the problem area
5. Draw conclusions about the debt burden of the Russian nobility in the 18th and 19th centuries

Distribution of the tasks

Sergey Yukhatskov:

1. Data collection
2. Assigning each user a unique ID and creating a table with them
3. Writing a function to allocate the gender for each borrower in a separate column
4. Performing analysis using graphs
5. Performing analysis using the numpy and matplotlib libraries
6. Performing analysis using network analysis

Paul Yurlov:

1. Data collection
2. Writing functions for data preparation
3. Creating the adjacency list and matrix
4. Performing analysis using the numpy and matplotlib libraries
5. Performing analysis using network analysis
6. Regression analysis

Data description

For the first time, we are introducing into scientific circulation a set of unpublished documents on the financial obligations of Russian nobles, both to individuals and to various banking organizations. The complex of handwritten sources is translated into a database in the format of linked Excel tables.

The data is a list of people who have borrowed or lent some money. Initially, we only had the lender, the borrower, the amount of the debt, the date of transaction and the date of repayment. The borrower can be a person or a group of people. The lender can be a person, an organization, or a group of people, such as brothers.

After we received the list of lenders and borrowers we decided to add much more information about each person to the table: their ranks, titles, social class, genders, family statuses. All this additional information was obtained from open sources.

From all the received data, we made 3 tables:

Main table

- In this table data is a table of borrowers and creditors. The table contains the following columns:

1. Sequence number
2. Name of borrower
3. The borrower's surname in the masculine gender
4. Availability of a guarantor (Field contains surname of guarantor)
5. Unique ID of the borrower
6. Gender of the borrower
7. Availability of a grade of the borrower (zero or one)
8. Grade of the borrower
9. Rank of the borrower

10. Availability of a rank of the borrower (zero or one)
11. Dignity of the borrower
12. Family status of the borrower
13. Class of the borrower
14. Name of the creditor
15. The creditor’s surname in the masculine gender
16. Unique ID of the creditor
17. Gender of the creditor
18. Availability of a grade of the creditor (zero or one)
19. Grade of the creditor
20. Rank of the creditor
21. Availability of a rank of the creditor (zero or one)
22. Rank of the creditor
23. Family status of the creditor
24. Creditor’s estate
25. Debt amount in the silver rubles
26. Debt amount
27. Repayment period
28. Debt closed or rewritten
29. Availability of debt
30. Security deposit
31. Deposit amount
32. Description of the deposit
33. Method of giving a debt
34. Transaction year
35. Transaction day
36. Transaction month
37. Date of transaction
38. Year of closing of the transaction

39. Day of closing of the transaction
40. Month of closing of the transaction
41. Date of closing of the transaction
42. Number of days of debt
43. Source of information
44. Callouts

Example of the table:

	Заемщик	Фамилия в мужском роде Заемщика	Поручитель	ID заемщика	Пол заемщика	Есть/нет чина	Чин заемщика	Ранг заемщика	Есть/нет титула	Титул заемщика	Семейное положение	Сословие заемщика	Кредитор	Фамилия в мужском роде Кредитора	ID кредитора
0	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Кропотова Настасья Александровна	Кропотов	id_personal_451
1	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Гагарин Петр Иванович	Гагарин	id_personal_191
2	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Гагарин Петр Иванович	Гагарин	id_personal_191
3	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Сакстон Анна Андреевна	Сакстон	id_personal_806
4	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Мордвинова Варвара Леонтьевна	Мордвинов	id_personal_551
5	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Прозоровский Иван Иванович	Прозоровский	id_personal_735
6	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Салтыкова Елена Сергеевна	Салтыков	id_personal_813
7	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Голицына Наталья Николаевна	Голицын	id_personal_243
8	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Зануца (Zanouzzi) Василий Антонович	Зануц	id_personal_356
9	Гагарины Николай и Сергей Сергеевичи	Гагарин	Отсутсвует	id_personal_198	М	0			1	князь	малолетний	Дворянство	Зануца (Zanouzzi) Василий Антонович	Зануц	id_personal_356

Fig. 1. Example of the table of borrowers and creditors.

Table of IDs

- In the Table of IDs each line represents information about a unique person. The table contains following columns:

1. Person's Name, Patronim, Surname
2. Rank
3. Name of the rank
4. Title

5. Unique ID

Example of the table:

Имя	Чин	Ранг	Титул	id
Абиетская Варвара Ивановна	Коллежский Секретарь	10 ранг	-	id_personal_0
Абрютина Мария Петровна	-	-	-	id_personal_1
Абрютина Мария Петровна , Отец Надворный Советник Абрютин Петр Петрович	-	-	-	id_group_4
Адамович Иван Степанович	Генерал-Майор	3 ранг	-	id_personal_2
Акинфов Алексей Алексеевич	Действительный Статский Советник	4 ранг	-	id_personal_3

Table. 1. Example of the table of IDs.

Matrix of network interactions

- Matrix of network interactions is required for network analysis, the first line contains IDs of creditor, the first column contains IDs of debtors and intersection contains amount of debt. This table is required for network analysis.

Example of the table:

Заемщик\Кредитор	id_personal_451	id_personal_191	id_personal_191	id_personal_806
id_personal_198	11904	0	0	0
id_personal_198	0	9523	0	0
id_personal_198	0	0	2380	0
id_personal_198	0	0	0	1428

Table. 2. Example of the table of matrix of network interactions.

Data transformation and preprocessing

All acquired data was collected by all members of the team, so it was almost impossible to avoid human errors, such as: typos, missing values, deviations from standard format, therefore data preparation was required. For that purpose we used following computer languages and tools:

- Python3 as the main language
- Jupyter Notebook as Interactive shell for Python3
- Pandas - Python software library for data processing and analysis.
- Numpy - an open source project aiming to enable numerical computing with Python.
- Gspread - Simple Python3 interface for working with Google Sheets API.
- Google Sheets as a storage for our data

Data preprocessing functions

As a result we created the following functions, required for data preparation:

- `def transform_names(x)` is used to transform names to uniform format
- `def rang_(input_string)` is used to transform one rank string to uniform format
- `def clean_rangs(df)` is used to transform all ranks to uniform format
- `def transform_title(df)` is used to transform all string data to uniform format
- `def transform_prices(x)` is used to transform all prices to uniform format
- `def clean_data(df)` is used to apply all previous functions to our data

Data transformation functions

At first all data was stored at the main table, but we also needed a matrix of network interactions for network analysis and a table with unique IDs for each person. Therefore we created the following functions, required for data transformation:

- `def get_sparse_matrix_names(df)` is used to create matrix of network interactions using names as nodes
- `def get_sparse_matrix(df)` is used to create matrix of network interactions using IDs as nodes
- `def get_ids(df)` is used to generate unique IDs
- `def export_table(df, gc_, url_, sheet)` is used to export tables to Google Sheets
- `def export_sparce(df, gc_, url_, sheet)` is used specifically to export matrix of network interactions to Google Sheets

All presented functions can be found in the GitHub repository, the link to which is in the links section

Data analysis

Distribution of the amount of credits

Since our table contains data on borrowers and creditors, the first idea is to draw a graph of the number of borrowers and the amount of debt.

Before plotting the chart, we took the amount of debt and dropped the fractional part.

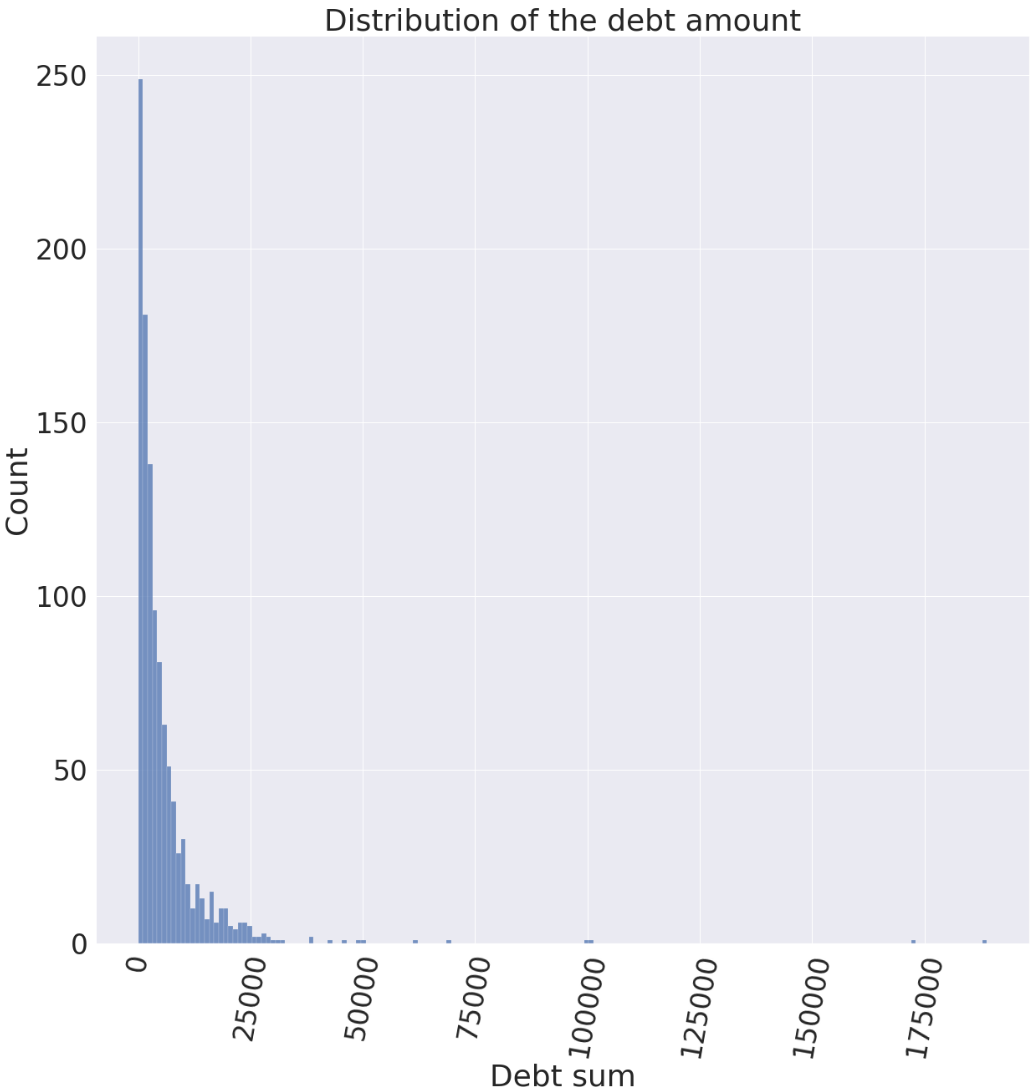

Fig. 2. Distribution of the debt amount.

As we can see, most of the debts are taken for a small amount. But there are three debts for big sums: 100.000, a little less than 175.000 and between 175.000 and 180.000.

Also we drew a more detailed graph for a small amount of the debts.

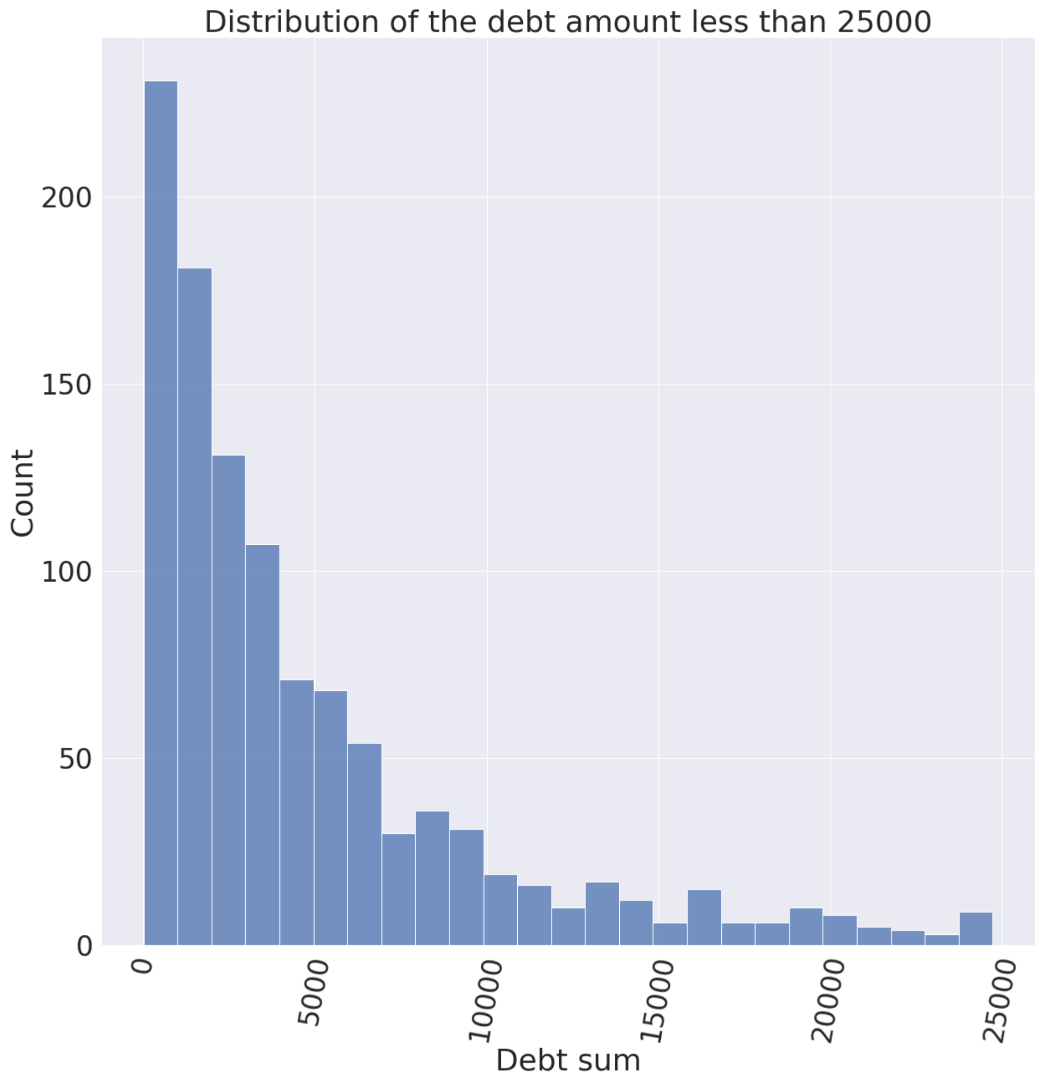

Fig. 3. Distribution of the debt amount less than 25.000.

This graph shows that people mostly borrowed up to 5.000. And the most popular were debts of about 1000 silver rubles. We see that the maximum number of borrowers of one amount is slightly more than 300.

Now we can look at the graph of the distribution of the remaining amounts.

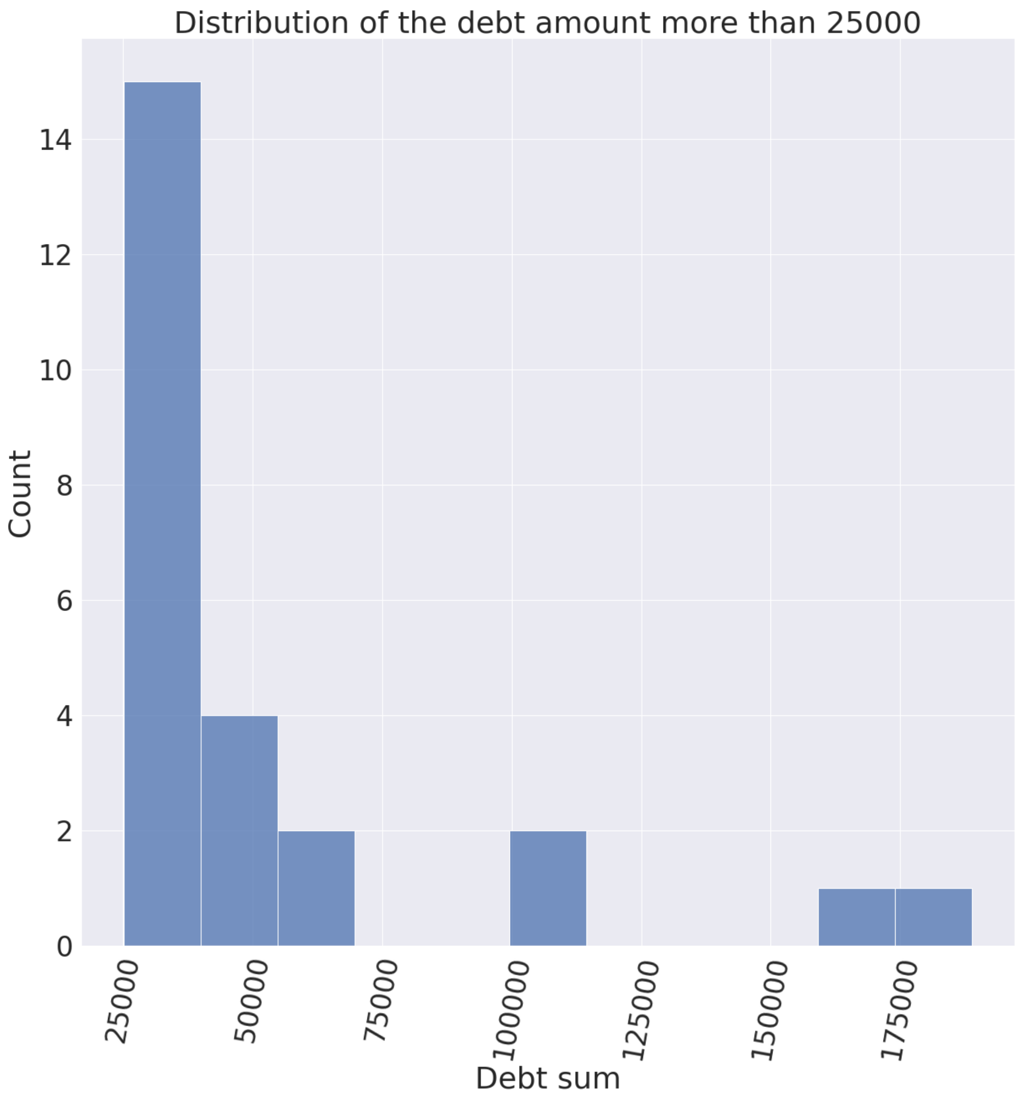

Fig. 4. Distribution of the debt amount is more than 25.000.

For other borrowers, the most popular debt amount is about 25.000 and there are a little more than 14 people who took this amount.

95% asymptotic confidence interval

It would be nice to understand how well our data describes the period we have chosen. For this, we plotted a 95% asymptotic confidence interval for the mean loan amount. We can do this because the asymptotic confidence interval uses the central limit theorem as a basis, which works for any means, regardless of which distribution they came from, and the CLT is also quite sensitive to outliers, so we removed all credits with an amount over 25000. The interval confidence turned out to be (4479.943252996244, 5090.193026930091). Its width is 610.25.

The 95% percent confidence interval shows that with a probability of 0.95 the mean lies within the obtained interval. Given the complexity of data collection and the fact that most of the data may have been lost, we consider this result to be good and that our data well describes the chosen period.

Gender distribution

We also have an assumption that women could borrow on an equal footing with men. To test this suppose, we will take look at a series of graphs and tables:

Debtors sex	Amount of credits	Creditors sex	Amount of credits
Ж	392	Ж	95
М	676	М	160
СОВ[3]	43	О[4]	824
		СОВ	3
		Ф[5]	29

Table. 3. Table of count debts by sex.

[3] СОВ - совместный, joint credit, when there were several creditors or borrowers.

[4] О - организация, the creditor is an organization, such as a bank.

[5] Ф - физическое лицо, individual person.

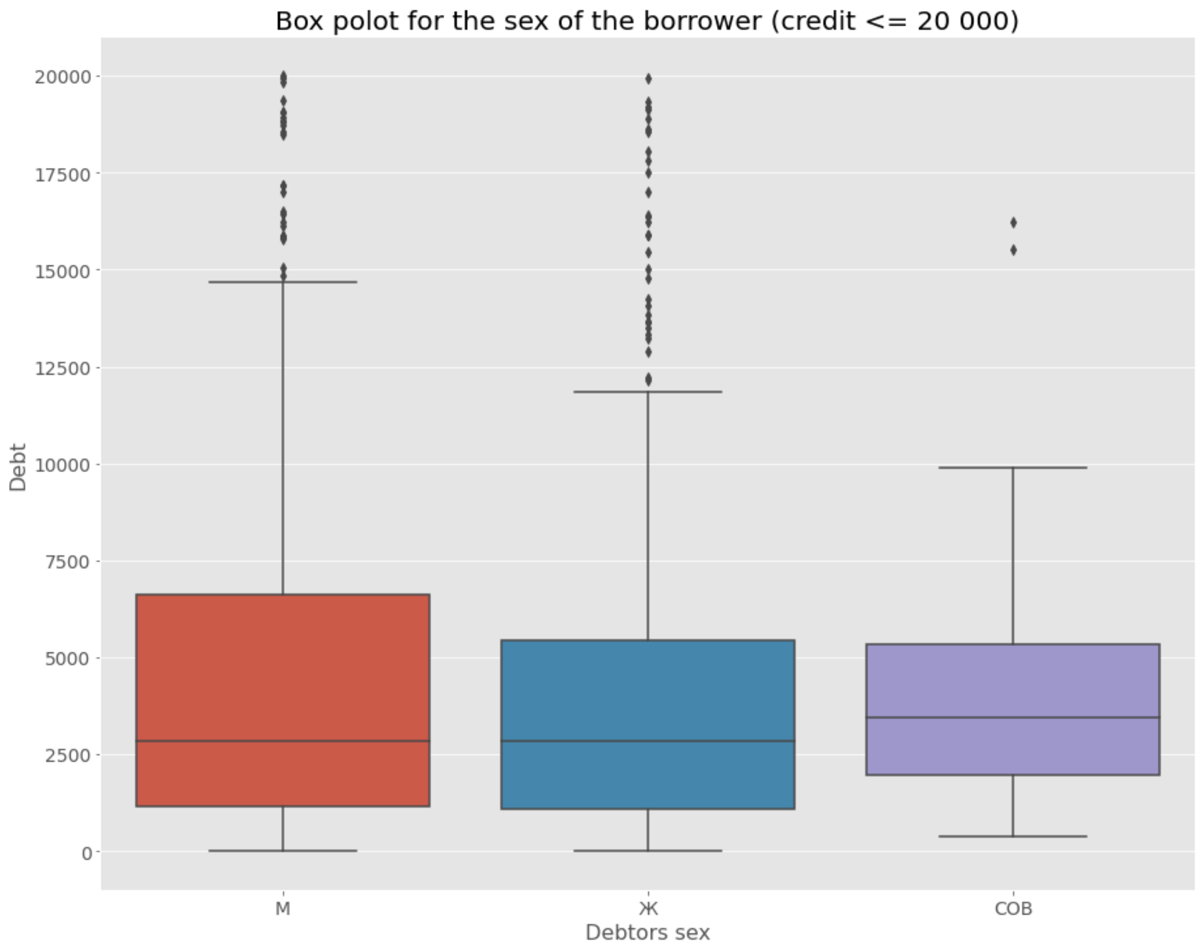

Fig. 5. Distribution of the borrowers amount under 20.000 and by sex.

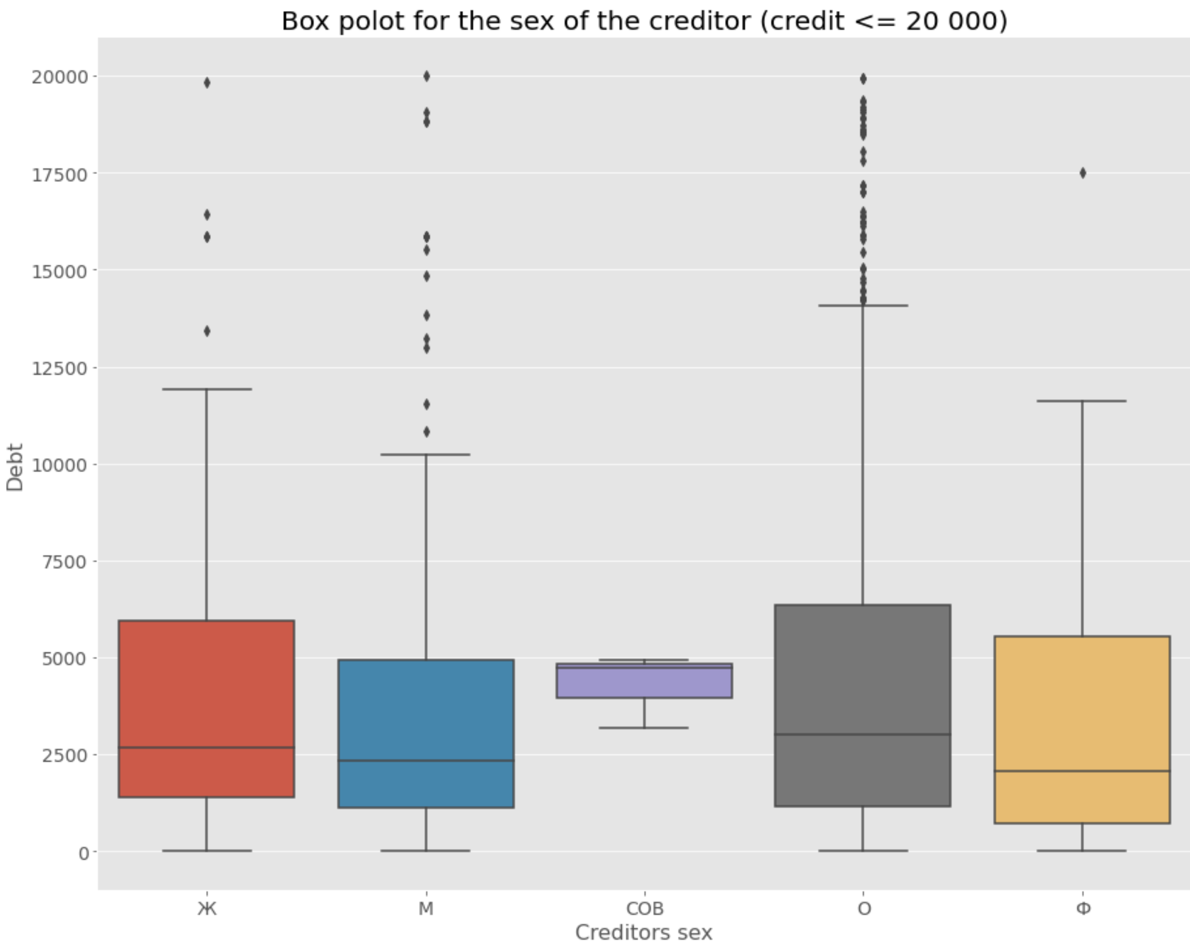

Fig. 6. Distribution of the creditors amount under 20.000 and by sex.

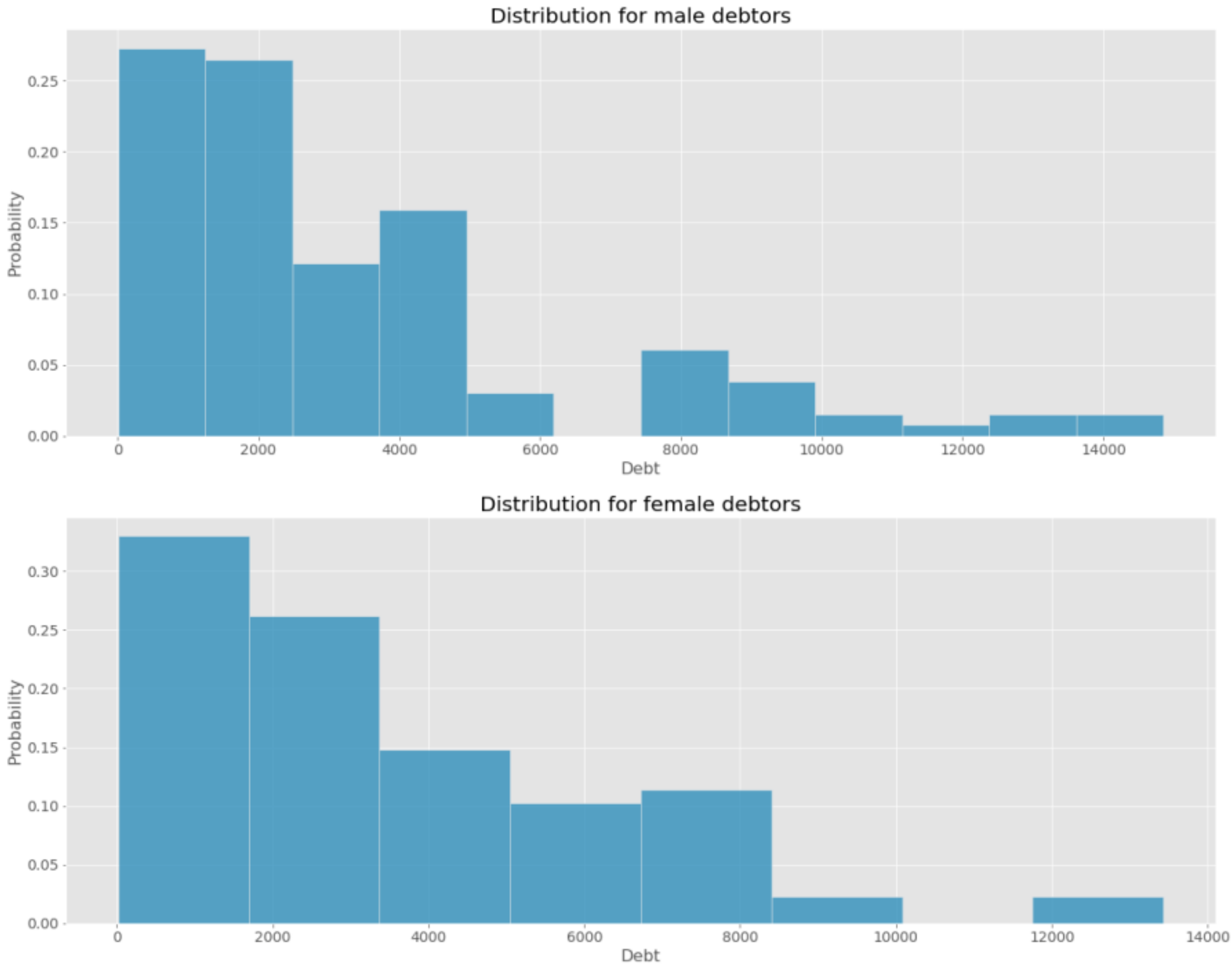

Fig. 7. Distributions of the debts by sex.

As we can see, the table shows that men, on average, took out more loans than women, but at the same time box plots show that median for both genders is almost identical which could mean that women could borrow on an equal footing with men. That is also supported by an almost similar distribution of debts that are under 20 000. However this result can only serve as a first step towards the proof of the assumption, but not as proof as is.

Distribution of the amount of debts over time

We are moving to drawing the distribution of the number of credits by year.

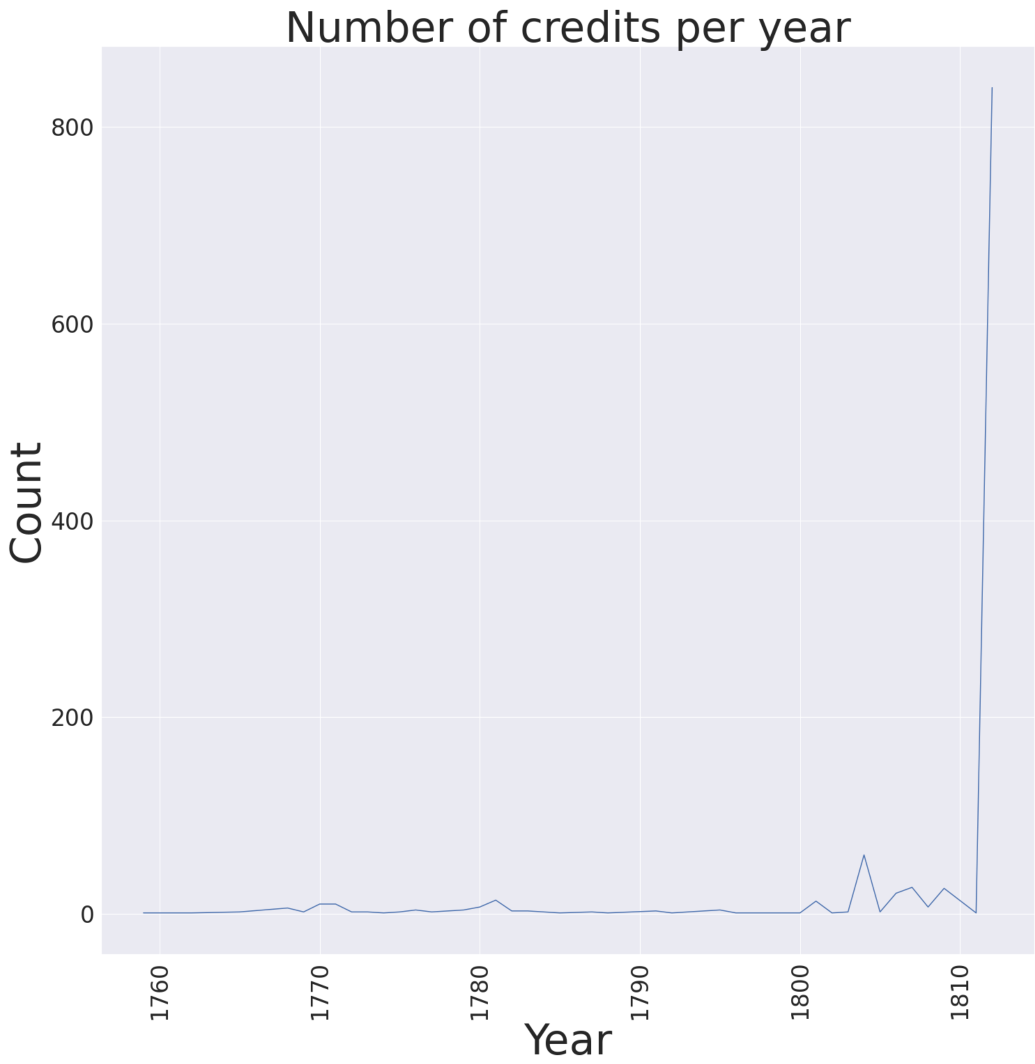

Fig. 8. Distributions of the number of credits per year.

We can note that after 1810 there was a sharp increase in the count of the debts.

This can be easily explained. The fact is that in 1812 there was a war between the Russian and French Empires. Most likely, people had a premonition of the imminent war and prepared for it.

Now one can look at the on distribution of the number of credits excluding year 1812:

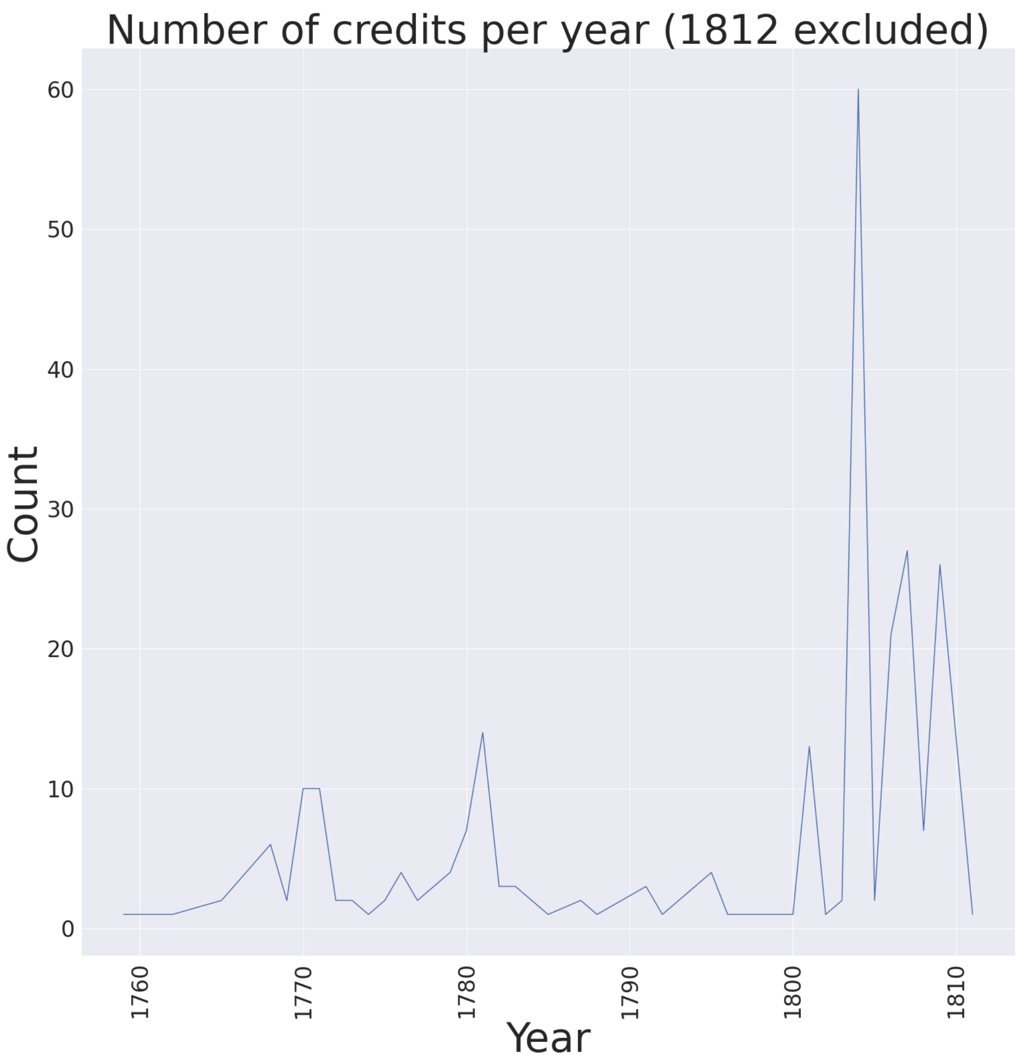

Fig. 9. Distributions of the number of credits per year 1758-1811.

As we can observe, there are a few other increases in the count of the debts: in 1771, in 1781, in 1804 - 1805. Some of them also could be explained by some important events in the world:

- Russian-Turkish War 1768 - 1774 could explain increased quantity of debts in April 1770 - February 1771 and in January 1773
- Annexation of Crimea to the Russian Empire in 1783 during Potemkin's military campaign to "pacify the Crimea" in 1782-1783 could explain increased quantity of debts in January 1781
- Battle of Austerlitz 20 November 1805 could explain increased quantity of debts in September 1804 - January 1805

After plotting the graph with the distribution of the number of credits by year, we became interested in whether people could have taken out debts in a certain month more often. For example, in the modern world, before the New Year, the number of purchases in stores increases. People buy gifts. So maybe there was some kind of addiction in the past?

However we cannot use data as is for that purpose because, as we remember, there was a big leap in the quantity of debts in april of 1812. That is why we need to exclude 1812, before making any assumptions. Also we will logarithm the axis of quantity to make the result more visible.

Fig. 10. Log of quantity for each month excluding year 1812.

We can see an increase in the number of debts from October to January and a decline from January to May.

This observation can be explained by the harsh conditions of winter and lack of supply during this period.

Network analysis

For both groups of debtors and creditors we calculated centrality indices, such as: Copeland in-degree index, Bundle index, Pivotal index. Now we will look at them more closely.

Copeland in-degree index for debtors

The Copeland index is simply just a sum of weights of the incoming edges from connected vertices. In our case weights are normalized credit amounts.

In the following table, we can see the 10 largest and 10 smallest values.

Debtors name	Name of rank	Rank	Title	Copeland in-degree share
Гагарины Николай И Сергей Сергеевичи	-	-	Князь	0.062765
Голицын Александр Николаевич	Действительный Камергер	4 ранг	Князь	0.059018
Булгаков Яков Иванович	Действительный Тайный Советник	2 ранг	-	0.034703
Бибиков Петр Иванович	Подполковник	7 ранг	-	0.031072
Гагарин Сергей Сергеевич	Гофмейстер	5 ранг	Князь	0.027944
Голицыны Малолетние	-	-	Князь	0.024033
Гагарина Варвара Николаевна	Гофмейстер	5 ранг	Князь	0.01109
Гагарин Сергей Сергеевич	Действительный Тайный Советник	2 ранг	Князь	0.01063
Каверин Павел	Тайный Советник	3 ранг	-	0.009803
Гагарины Дети Сергея Сергеевича	-	-	Князь	0.009243
Булгакова Агафия Петровна	Гвардии Секретарь	12 ранг	-	0,000003
Кологривов Андрей Семенович	Генерал От Кавалерии	2 ранг	-	0,000004
Лунина Катерина Алексеевна	Титулярный Советник	9 ранг	-	0,000004
Зубкова Наталья Петровна	Майор	8 ранг	-	0,000004
Замятнина Прасковья Андреевна	Коллежский Асессор	8 ранг	-	0,000004
Юсупов Николай	Действительный Тайный Советник	2 ранг	Князь	0,000004
Закревский Дмитрий	Генерал-Майор	4 ранг	-	0,000004

Андреевич				
Высоцкий Николай Петрович	Генерал-Майор	4 ранг	-	0,000005
Дурасова Аграфена Алексеевна	Генерал-Лейтенант	3 ранг	-	0,000005
Аникеев Василий Петрович	Надворный Советник	7 ранг	-	0,000005

Table. 4. Copeland in-degree index for debtors.

Bundle index for debtors

In this index, we predefine a quota for each node and number k which represents the maximum number of nodes which can simultaneously influence a vertice. For each vertice the value of the Bundle index is equal to the number of the subsets of incoming edges from not more than *k* vertices, with the sum of weights not less than the quota. This index is computed in the following way:

$$S \subseteq V \setminus \{i\},\ |S| \leq k,\ \forall j \in S,\ w_{ij} \neq 0$$

$$BI_i(S) = \begin{cases} 1, & if \sum_{j \in S} w_{ij} \geq q_i \\ 0, & else \end{cases}$$

In our case for all nodes q = 1% and k = 3

In the following table, we can see the 10 largest and 10 smallest values.

Debtors name	Name of rank	Rank	Title	BI index share
Булгаков Яков Иванович	Действительный Тайный Советник	2 ранг	-	0.6882733
Гагарины Николай И Сергей Сергеевичи	-	-	Князь	0.271723
Голицыны Малолетние	-	-	Князь	0.0363133
Булгаков Иван Михайлович	Гвардии Секретарь	12 ранг	-	0.003354
Прозоровская Анна Михайловна	Генерал-Фельдмаршал	1 ранг	Князь	0.0000025
Львов Владимир Семенович	Гвардии Капитан	7 ранг	Князь	0.0000025
Ефремов Дмитрий Михайлович	Штык-Юнкер	13 ранг	-	0.0000025
Голицын Александр Николаевич	Действительный Камергер	4 ранг	Князь	0.0000025
Бибиков Петр Иванович	Подполковник	7 ранг	-	0.0000021
Каверин Павел	Тайный Советник	3 ранг	-	0.0000011
Симонов Алексей Дмитриевич	Бригадир	5 ранг	-	0,0000004
Жилле Беми Акинтович	Коллежский Асессор	8 ранг	-	0,0000004
Секерин Василий Андреевич	Коллежский Асессор	8 ранг	-	0,0000004

Перхуров Василий Иванович	Надворный Советник	7 ранг	-	0,0000004
Лопухин Николай Ардалионович	Действительный Статский Советник	4 ранг	-	0,0000004
Левшин Гаврила Федулович	Коллежский Асессор	8 ранг	-	0,0000004
Брюхатова Соломонида Васильевна	Прапорщик	14 ранг	-	0,0000004
Елагина Анна Петровна	Генерал От Кавалерии	2 ранг	-	0,0000004
Наумова Мария Петровна	Майор	8 ранг	-	0,0000004
Безобразов Александр Сергеевич	Прапорщик	14 ранг	-	0,0000004

Table. 5. Bundle index for debtors.

Pivotal index for debtors

This index is almost similar to the Bundle index, but it is calculated for pivotal nodes. The node j_p is called pivotal for i from V in the set $S = V$ without i if:

$$\sum_{j\in S} w_{ji}^{0} \geq q_i, \text{ but } \sum_{j\in S\setminus\{j_p\}} w_{ji}^{0} < q_i,$$

In the following table, we can see the 10 largest and 10 smallest values.

Debtors name	Name of rank	Rank	Title	PI index share
Булгаков Яков Иванович	Действительный Тайный Советник	2 ранг	-	0.6378361
Гагарины Николай И Сергей Сергеевичи	-	-	Князь	0.1444768
Булгаков Иван Михайлович	Гвардии Секретарь	12 ранг	-	0.0434078
Голицыны Малолетние	-	-	Князь	0.0280207
Бибиков Петр Иванович	Подполковник	7 ранг	-	0.0006479
Прозоровская Анна Михайловна	Генерал-Фельдмаршал	1 ранг	Князь	0.0004859
Львов Владимир Семенович	Гвардии Капитан	7 ранг	Князь	0.0004859
Ефремов Дмитрий Михайлович	Штык-Юнкер	13 ранг	-	0.0004859
Голицын Александр Николаевич	Действительный Камергер	4 ранг	Князь	0.0004859
Кольцов-Масальский Андрей Александрович	Действительный Тайный Советник	2 ранг	Князь	0.0003239
Симонов Алексей Дмитриевич	Бригадир	5 ранг	-	0.000162
Жилле Беми Акинтович	Коллежский Асессор	8 ранг	-	0.000162
Секерин Василий Андреевич	Коллежский Асессор	8 ранг	-	0.000162
Перхуров Василий Иванович	Надворный Советник	7 ранг	-	0.000162
Лопухин Николай Ардалионович	Действительный Статский Советник	4 ранг	-	0.000162
Левшин Гаврила Федулович	Коллежский Асессор	8 ранг	-	0.000162
Брюхатова Соломонида Васильевна	Прапорщик	14 ранг	-	0.000162

Елагина Анна Петровна	Генерал От Кавалерии	2 ранг	-	0.000162
Наумова Мария Петровна	Майор	8 ранг	-	0.000162
Безобразов Александр Сергеевич	Прапорщик	14 ранг	-	0.000162

Table. 6. Pivotal index for debtors.

As we can see, Gagarin Nikolay Sergeevich and Gagarin Sergey Sergeevich had the most amount of debts. The second place goes to Golitsyn Alexander Nikolaevich and the third goes to Bulgakov Yakov Ivanovich. As one can notice, there is a certain pattern that the most indebted families were Gagarins, Golitsyns and Bulgakovs.

Copeland in-degree index for creditors

In the following table, we can see the 10 largest and 10 smallest values.

Creditors Name	Name of rank	Rank	Title	Copeland in-degree share
Московский Опекунский Совет	-	-	-	0.4990275
Государственный Банк	-	-	-	0.146546
Кнауф	-	-	-	0.034749
Государственный Заемный Банк	-	-	-	0.026517
Частные Руки	-	-	-	0.0239296
Голицын Дмитрий Михайлович	-	-	Князь	0.0226379
Голицын Михаил Михайлович	Действительный Камергер	4 ранг	Князь	0.0224888
Бутурлин Аркадий Иванович	Действительный Камергер	4 ранг	-	0.0154906
Оболенский Николай Петрович	Премьер-Майор	8 ранг	Князь	0.0153372
Санкт Петербургский Опекунский Совет	-	-	-	0.0132857
Петр Яковлевич	-	-	-	0.0000014
Машковы Дочери Петра Ивановича Машкова	-	-	-	0.0000031
Рогозина Аграфена Симоновна	Полковник	6 ранг	-	0.0000044
Михаил Андросинов	Погребщик	-	-	0.0000069
Сендерс Петр	Майор	8 ранг	-	0.0000075
Плотников	-	-	-	0.0000083
Антон Селевестров	-	-	-	0.0000083
Скаретин Яков Федорович	-	-	-	0.0000098
Патрикеева Наталья Андреевна	-	-	-	0.0000143
Полякова Екатерина Устиновна	-	-	-	0.0000152

Table. 7. Copeland in-degree index for creditors.

Bundle index for creditors

In the following table, we can see the 10 largest and 10 smallest values.

Creditors Name	Name of rank	Rank	Title	BI index share
Московский Опекунский Совет	-	-	-	0.9283769
Государственный Банк	-	-	-	0.0693722
Частные Руки	-	-	-	0.0015987
Голицын Михаил Михайлович	Действительный Камергер	4 ранг	Князь	0.0003938
Тамбовский Приказ Общественного Призрения	-	-	-	0.0000703
Голицын Дмитрий Михайлович	-	-	Князь	0.0000370
Гагарин Сергей Сергеевич	Гофмейстер	5 ранг	Князь	0.0000370
Санкт Петербургский Опекунский Совет	-	-	-	0.0000370
Воронцов Роман Илларионович	Генерал-Аншеф	2 ранг	Граф	0.0000056
Голицын Сергей Михайлович	Действительный Тайный Советник	1 ранг	Князь	0.0000028
Пекина Екатерина Семеновна	Действительный Статский Советник	4 ранг	-	0,00000040
Чаадаев Иван Петрович	Гвардии Капитан	7 ранг	-	0,00000040
Сакстон Анна Андреевна	-	-	-	0,00000040
Рюмин	Коллежский Советник	-	-	0,00000040
Голицына	-	-	Князь	0,00000040
Андронова Надежда Николаевна	-	-	-	0,00000040
Яковлев Дмитрий Андреевич	Надворный Советник	7 ранг	-	0,00000040
Ессен Катерина Николаевна	Генерал-Лейтенант	3 ранг	-	0,00000040
Рахманова Александра Григорьевна	Статский Советник	5 ранг	-	0,00000040
Никласова Сестра	-	-	-	0,00000040

Table. 8. Bundle index for creditors.

Pivotal index for creditors

In the following table, we can see the 10 largest and 10 smallest values.

Creditors Name	Name of rank	Rank	Title	PI index share
Московский Опекунский Совет	-	-	-	0.9753394
Государственный Банк	-	-	-	0.024365
Частные Руки	-	-	-	0.0002361
Голицын Михаил Михайлович	Действительный Камергер	4 ранг	Князь	0.0000222
Тамбовский Приказ Общественного Призрения	-	-	-	0.0000018
Голицын Дмитрий Михайлович	-	-	Князь	0.0000014
Санкт Петербургский Опекунский Совет	-	-	-	0.0000014
Гагарин Сергей Сергеевич	Гофмейстер	5 ранг	Князь	0.0000014
Воронцов Роман Илларионович	Генерал-Аншеф	2 ранг	Граф	0.0000007
Голицын Сергей Михайлович	Действительный Тайный Советник	1 ранг	Князь	0.0000005
Пекина Екатерина Семеновна	Действительный Статский Советник	4 ранг	-	0,0000002
Чаадаев Иван Петрович	Гвардии Капитан	7 ранг	-	0,0000002
Сакстон Анна Андреевна	-	-	-	0,0000002
Рюмин	Коллежский Советник	-	-	0,0000002
Голицына	-	-	Князь	0,0000002
Андронова Надежда Николаевна	-	-	-	0,0000002
Яковлев Дмитрий Андреевич	Надворный Советник	7 ранг	-	0,0000002
Ессен Катерина Николаевна	Генерал-Лейтенант	3 ранг	-	0,0000002
Рахманова Александра Григорьевна	Статский Советник	5 ранг	-	0,0000002
Никласова Сестра	-	-	-	0,0000002

Table. 9. Pivotal index for creditors.

Here we can see that mostly people took credits in the Moscow Trusteeship Council and other organizations. However we can see that there are also some individuals in tables: Golitsyn Mikhail Mikhailovich who was famous Russian commander, Golitsyn Dmitry Mikhailovich, Gagarin Sergei Sergeevich, Vorontsov Roman Illarionovich, Obolensky Nikolay Petrovich, Buturlin Arkady Ivanovich and the famous merchant Knauf.

Thus we can assume that the most influential families were Golitsyns, Gagarins, Vorontsovs and some individuals:Obolensky Nikolay Petrovich, Buturlin Arkady Ivanovich, Knauf

As one can notice there are two families that took a great amount of credits and gave loans as well, those are Golitsyns and Gagarins. These families are the most financially active.

Graph Analysis

Previously, we have already conducted several types of analysis. In this block, we decided to build a connection graph.

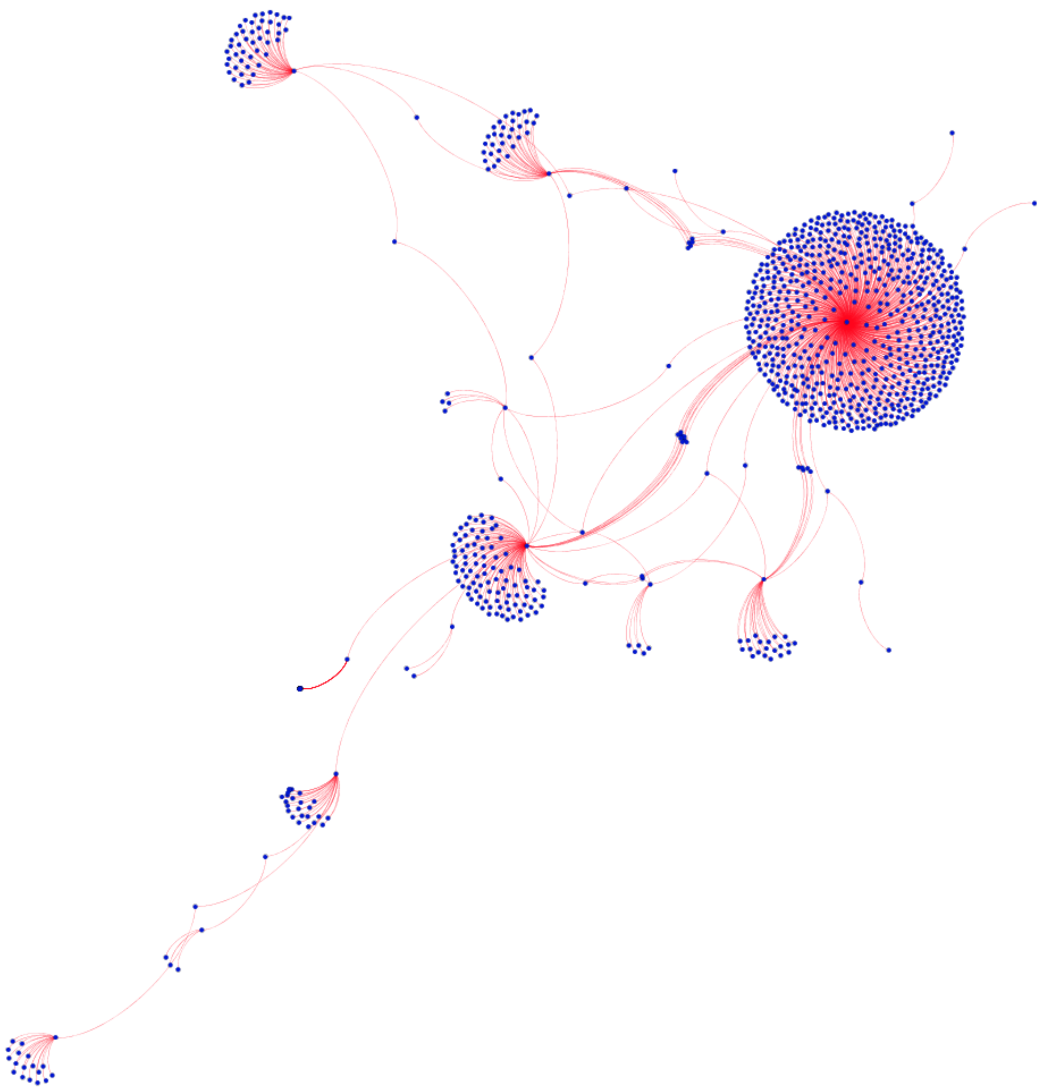

Fig. 11. Relationship graph

Even without further analysis, it is clear that there is a center on the right that connects a large number of lenders and borrowers. This center is the Moscow Board of Guardians. On the next graph, the Moscow Guardian Council is colored pink and has the largest vertex size.

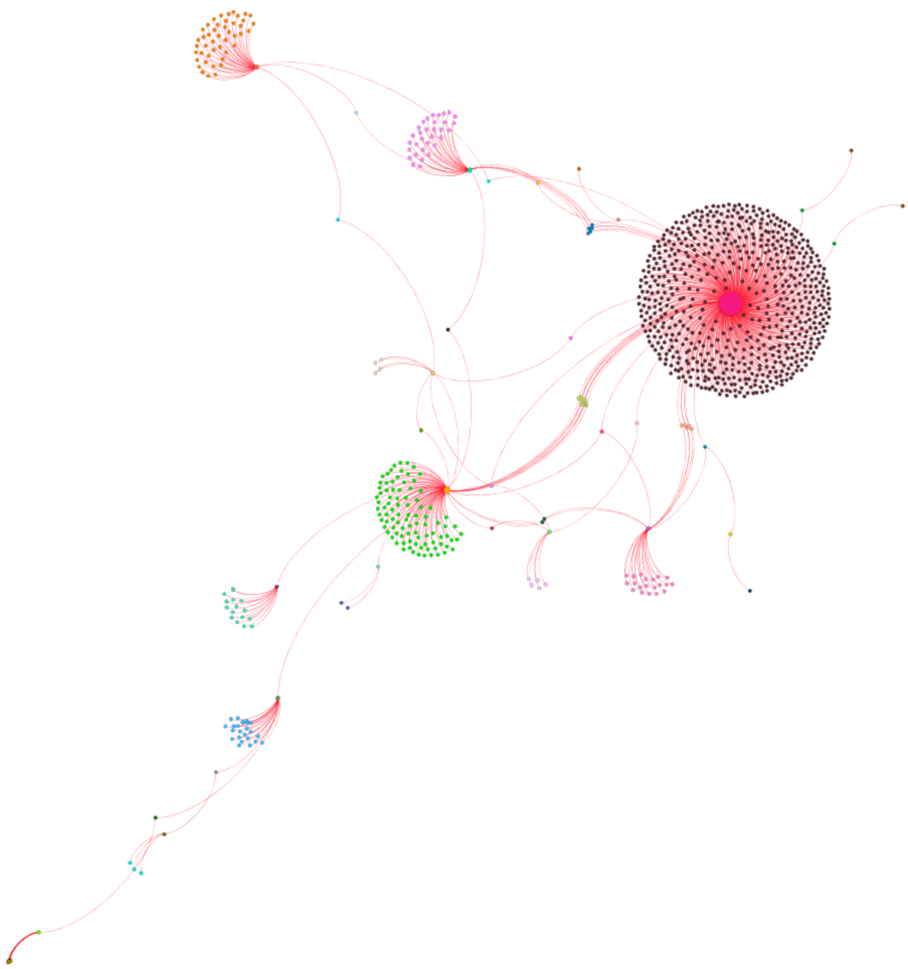

Fig. 12. Distribution of degrees on the graph

This graph shows the degree distribution, vertices with the same color have the same number of vertices. We can also note that the closer a person is to the Moscow Board of Guardians the more connections they have.

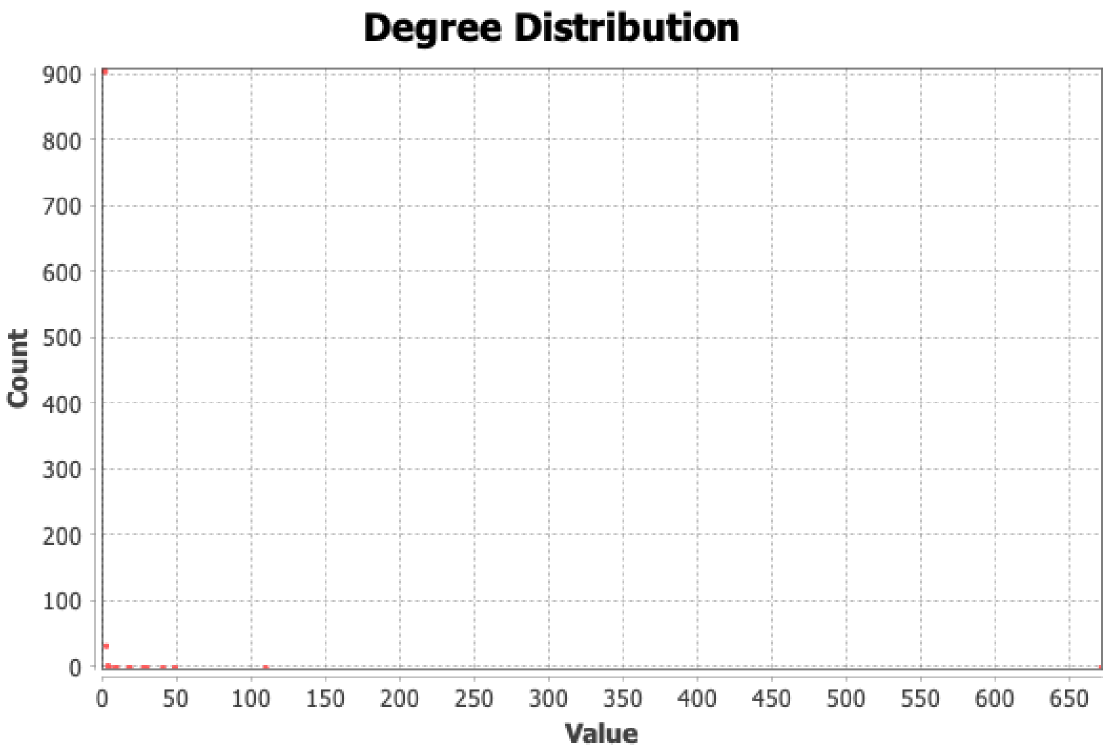

Fig. 13. Degree Distribution

Average Degree is equal to 2,059. As already mentioned, the Moscow Board of Guardians has the highest degree and it is also visible on the distribution chart. It is located on the right.

In our graph, each edge has its own weight. In our case, the weight is the amount of the loan. Calculate the weighted average power.

Fig. 14. Пraph with weighted edges.

The thickest edges mean it was a big loan. We see that the largest amount of debt people took from a limited number of people, So for example, at the top of the graph we see two thick edges that depart from one lender.

There is a theory that some people know each other through N handshakes. In our graph, the most distant vertices are known after 8 handshakes

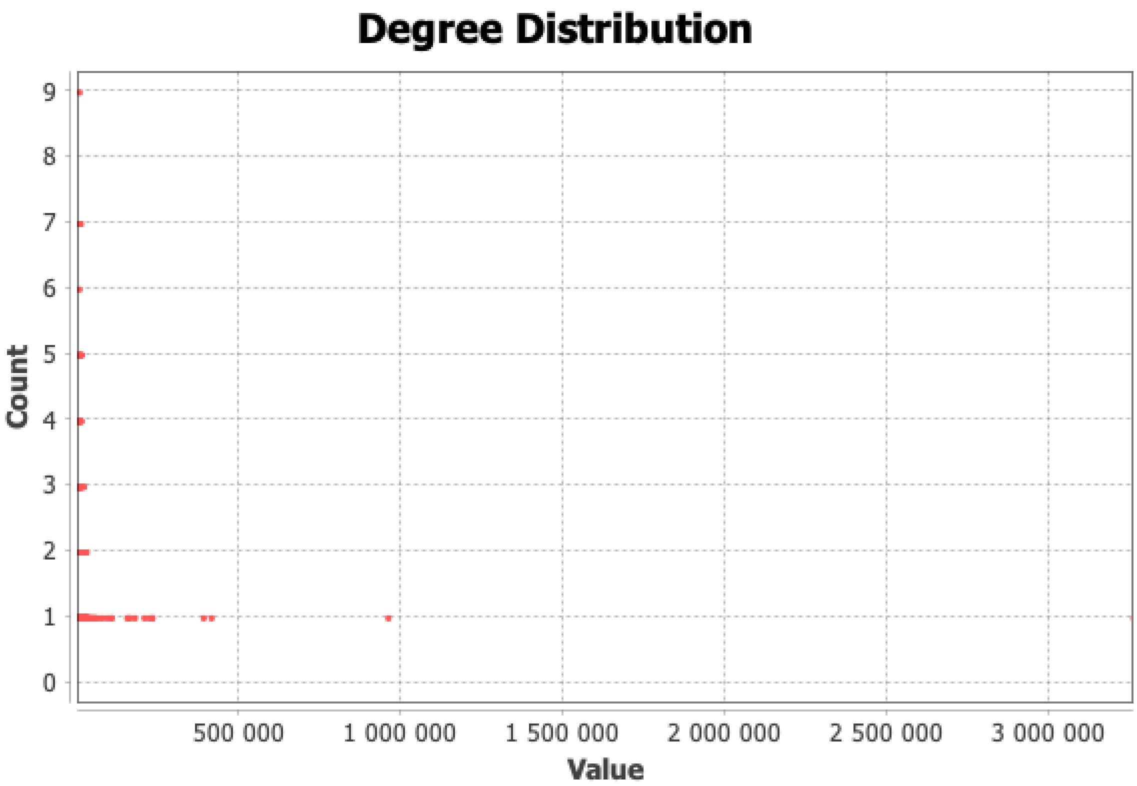

Fig. 15. Weighted Degree Distribution

Average Weighted Degree: 12563,302. In our case the average degree distribution is the average amount of debt.

Regression analysis

In this chapter, we performed regression analysis. We wanted to find what information could affect the amount of the credit for debtors. Therefore we created a data set containing: all credits with amount less than 20000, debtor's gender, rank, name of the rank, title, feature that returns 1 if debtor has got the title or else 0, social class and as target value we have chosen debt amount. We didn't use a year or a month of deals because they would have highly affected regression. Our choice has fallen on Lasso regression, which can identify useless features by giving them a zero weight. Gender, name of the rank and title were encoded by One Hot Encoding. After all data preprocessing we received final data set containing 1050 rows and 17 features As a result, we created the following table:

features	weights
Grouped_gender	-1067.469
Title_Knyaz'	-129.23
Rank	-73.005
No_title	-56.942
Female_gender	0
Social_class_merchant	0
Social_class_no_information	0
Title_Baron	261.459
Male_gender	389.218
Title_Count	723.227
Social_class_nobility	875.504
Yes/No_tilte	1619.789

Table. 10. Regression weights.

As we can see, the most important features are the presence of title, social class nobility, title Count, title Baron. That means that the higher the debtor was in social hierarchy the bigger debt he could have taken.

Conclusion

Summarizing everything written above, we have achieved the following results:

- We have collected and processed a significant amount of data, creating one of the most biggest datasets of debts of 18-19 centuries
- We analyzed the received data
- As a result of the analysis, we have put forward several interesting assumptions that we hope will be useful in future research.
- We have identified the most significant persons and families of chosen period of time

Relying on data we can say that in that period of time the Russian nobility was highly indebted due to various reasons and there some families that were indebted more than others.

Drawing the conclusion, we can most certainly say that this topic is very interesting and requires further research, because there is a lot left to do.

Bibliographic record of data sources:

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2. *РГАДА. Ф, 1262. оп. 1. д. 141 а*
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13. *ЦИАМ. Ф. 4. оп. 1. д. 3225*
14. *ЦИАМ. Ф. 4. Оп. 1. д. 3233*
15. *ЦИАМ ф. 4 оп.1 д. 3247*
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18. *ЦИАМ ф 4 оп 1 д 3238*
19. *ЦИАМ ф. 4 оп.1 д. 3241*
20. *ЦИАМ. Ф, 4. оп. 1. д. 3236*
21. *ЦИАМ. Ф. 4. оп.1. д. 3230*
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28. *ЦИАМ. Ф. 4. оп. 1. д. 3232*
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33. *ЦИАМ. Ф, 4. Оп. 1. Д. 3228*
34. *ЦИАМ. Ф. 4. Оп. 1. д. 3239*
35. *ГАСО. Ф, оп. 1. д. 3 л.12*
36. *ГАСО. Ф. 6. оп. 1. д. 3 д. 12 об*
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40. *ГАТО. Ф. 161. Оп. 1. д. 1432*
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43. *ОПИ ГИМ Ф.246*
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45. *НИОР РГБ Ф. 41*

Links

- Research project Kinship Relations in Famous Russian Families in the XVIII and XIX Centuries and the Distribution of Influence in Them // GitHub URL: https://github.com/paulyurlov/course_work_3rd_year_ami_cs_hse (дата обращения: 05.06.2021).
- Matrix of network interactions // Google Sheets URL: https://docs.google.com/spreadsheets/d/16hTQ2FlC2p8LDe2g3KUFJdogPwoLui6E-JN7Kbe5jyk/edit?usp=sharing (дата обращения: 05.06.2021).
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- Main Table // Google Sheets URL: https://docs.google.com/spreadsheets/d/1gzTqDTViRpI_Ts1z_JAkV6e1SyFICK8G0Hztqs9jzU8/edit?usp=sharing (дата обращения: 05.06.2021).