A Social Network of Russian “Kompromat”

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Abstract  “Kompromat” (the Russian word for “compromising material”) has been efficiently used to harass Russian political and business elites since the days of the USSR. Online crowdsourcing projects such as “RuCompromat” made it possible to catalog and analyze kompromat using quantitative techniques—namely, social network analysis. In this paper, we constructed a social network of 11,000 Russian and foreign nationals affected by kompromat in Russia in 1991–2020. The network has an excellent modular structure with 62 dense communities. One community contains prominent American officials, politicians, and entrepreneurs (including President Donald Trump) and appears to concern Russia’s controversial interference in the 2016 U.S. presidential elections. Various network centrality measures identify seventeen most central kompromat figures, with President Vladimir Putin solidly at the top. We further reveal four types of communities dominated by entrepreneurs, politicians, bankers, and law enforcement officials (“siloviks”), the latter disjointed from the first three.

Keywords  kompromat · Russia · politics · social network analysis

1 Introduction

“Kompromat” is a Russian word for “compromising material.” Kompromat has been efficiently used to harass political and business elites. It is widely considered to be essential in shoring up authoritarian durability [7]. Kompromat regimes often appear in states with low fiscal capacity and very high police capacity and harbor widespread criminality combined with systematic blackmail [2].

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The practice of kompromat is nothing new: it dates back to the Soviet period (Stalin, Beria, and the KGB) [6]. However, social media advances provided massive and affordable opportunities for authoritarian regimes to use kompromat against the opposition and competing factions [9]. Simultaneously, online crowdsourcing projects such as “RuCompromat” [11] make it possible to catalog and systematize kompromat, make it broadly available to researchers, and potentially disarm it by exposing its sources.

In this paper, we explore the most extensive online collection of the post-Soviet (mostly Russian) kompromat hosted by the “RuCompromat” team from the perspective of social network analysis—the process of modeling a social environment as a pattern of regularities in relationships among interacting units [16]. In our case, the interacting units are the persons subject to kompromat or related to kompromat in any other way (e.g., reporters and politicians [5]). Their co-involvement in compromising scenarios defines relationships among them. We identify 33 dense groups (network communities) of actors: politicians, entrepreneurs, and law enforcement officials, in the first place—associated with specific kompromat cases. Eventually, we classify the cases in four basic types that differ in the principal actors’ participation.

The rest of the paper is organized as follows: In Section 2 we describe the data set, its provenance, and its structure; in Section 3 we explain the network construction and analyze it; in Section 4 we present the results and discuss them. Finally, in Section 5 we conclude and lay the ground for further work.

2 Dataset

We collected the dataset in September 2020 from the site “RuCompromat” [11]. The site provides information about approximately 11 thousand persons, both Russian and foreign nationals. For each person, the site provides references to media articles (only for the years 2013–2020) that mention potentially compromising facts about the person, a list of other people mentioned together with the person, and a list of organizations (e.g., companies, banks, and government offices) related to the person.

As an example, an article called “Patrushev Jr. and the Orthodox retirees. Unprofitable Rosselkhozbank goes to the aid of “Peresvet,” published by the “Ruspress” agency [12], mentions banker Valery Meshalkin and the son of the former FSB director Nikolai Patrtyshev. Thus, “RuCompromat” lists the two as related.

The dataset contains co-references for 11,118 persons for the time frame from 1999 to 2020. We have not validated the references’ accuracy and take the “RuCompromat” contributors’ opinions as the ground truth.

3 Network Construction and Analysis

The first step in social network analysis is the construction of a social network. The network consists of 11,118 nodes representing persons, and 37,544 edges representing relationships between the persons. The density of the network is ≈0.0006. The network is unweighted (all edges have the same weight of 1), undirected (if person
A is connected to person B, then B is also connected to A), and strongly connected (it is possible to get from any person A to any person B by following edges without leaving the network). The diameter of the network is 12. Fig. 1 shows the central part of the network—its dense core.

Fig. 2 shows the node degree distribution in the network. The distribution has a “long tail” and can be approximated by the power law with the exponent $\alpha \approx -1.85$ (for the nodes with three or more neighbors). This exponent is typical for massive online social networks [13]. The majority of persons are connected poorly, only to one (2,100) or two (2,051) other persons. On the other end of the spectrum, there are the highest-connected (most embedded) persons: Vladimir Putin (President of Russia; 960 connections), Igor Sechin (CEO of Rosneft’, the Russian state oil company; 283), Dmitry Medvedev (former President and Prime Minister; 272), Sergey Chemezov (CEO of Rostec Corporation; 261), Sergey Sobyanin (Mayor of the City of Moscow; 236), Aleksandr Bastrykin (head of the Investigative Committee; 220), Aleksey Navalny (opposition leader; 208), and Arkady Rotenberg (co-owner of Stroygazmontazh construction group; 203)—cf. Fig. 1 and Table 2.

We used the Louvain community detection algorithm [1] to partition the network into 62 network communities: groups of persons that are more closely connected to
Fig. 2 The node degree distribution has a “long tail” and can be approximated by the power law $f_d \sim d^{−1.85}$ for $d \geq 3$.

Each other than to the persons from the rest of the network. Each of the communities is denser than the whole network (Table 1). The sizes of the communities range from 3 persons to 1,470 persons. The partition modularity is 0.64 on the scale from -0.5 (no community structure) to 1.0 (perfect community structure).

As it is customary in social network analysis, we excluded the smallest 29 communities with fewer than 100 persons from the study. For each node in the remaining communities, we calculated the clustering coefficient and several centralities: degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality.

The degree centrality, or simply the degree of a node, is the number of the node’s connections. A person with a high degree centrality has been affected by more kompromat cases.

To understand closeness centrality, let us consider two randomly chosen persons: Vladimir Putin and Zhou Yongkang (a late senior leader of the Communist Party of China, CPC). Due to the network’s sparse nature, it is improbable that they shared a direct connecting edge. Putin is more likely connected to another person: say, Xi Jinping (the General Secretary of the CPC)—who, consequently, was connected to Zhou. We say that Putin is two hops apart from Zhou.

In a different scenario, Putin is connected to Genry Reznik (a prominent Russian lawyer), who is connected to Yury Antonov (a retired activist from St. Petersburg), who is connected to Inna Pashchenko (a WWII veteran; all three are actual
A Social Network of Russian “Kompromat” members of the “RuCompromat” dataset). Therefore, Putin is three hops apart from Pashchenko.

There is a path from Putin to the other person in both scenarios, and the length of the path is two and three, respectively. In general, the average length of the shortest paths from a person to all other people in the network is called the closeness centrality of that person. A person with a high closeness centrality has been more likely indirectly affected by or involved in more kompromat-related cases.

Quite expectedly [15], the degree centrality is positively correlated with closeness centrality (their correlation is $r \approx 0.867$). On these grounds, we excluded the degree centrality from the results.

Any person along a path is somewhat similar to any other person along the same path. The shorter is the distance between two such persons, the more similar they are, to the extent that two immediate neighbors share the same kompromat. The number of the shortest paths that pass through a person is called the betweenness centrality of the person. A person with a high betweenness centrality is similar to more persons along the adjacent paths—in other words, that person is more typical. Thus, betweenness centrality appears to be a sensible measure of typicality.

Let us assume that each person has a quantitative “kompromat score” that somehow measures the extent to which the person was subject to kompromat. Let us also assume that a compromising document “smears” all referenced persons proportionally to the kompromat scores of everyone involved in the case. In other words, being mentioned together with a rapist and a thief paints a person as partially a rapist and partially a thief, regardless of the actual case context: “Tell me who your friends are, and we will tell you who you are.” Such a score is called the eigenvector centrality. The eigenvector centrality measures a person’s influence on the network—in this study’s context, the person’s toxicity.

The last network attribute is the clustering coefficient [17]. It measures how many immediate network neighbors of a person are also directly connected. A high clustering coefficient is a sign of a tightly knit group. In a fully-connected clique, the clustering coefficient is 1. In a “hub-and-spoke” network, it is 0.

Table 1 shows the mean values of each community’s network attributes, sorted in the decreasing order of the betweenness centrality, and the number of persons in the communities. Note that the mean closeness centrality in all communities is almost the same. On the contrary, the clustering coefficient is negatively correlated with the betweenness and eigenvector centralities (Fig. 3). The dense communities (higher clustering coefficient) are, on average, smaller, less typical/more peripheral (lower betweenness centrality), and less toxic (lower eigenvector centrality).

Table 2 shows the top ten persons in each centrality category. Only five persons: German Klimenko (Vladimir Putin’s Internet advisor), Dmitry Kamenshchik (owner of Moscow Domodedovo airport), Boris Mints (former owner of the Future Financial Group), Mikhail Oreskhin (the Minister for Economic Development), and Gennady Timchenko (former co-owner of Gunvor Group Ltd)—appear once. Most of the top performers shine in several categories: Vladimir Putin (#1 in all four categories), Sergey Chemezov (appears in 4 categories), Dmitry Medvedev (4), Igor Sechin (4), Aleksandr Bastrykin (3), Aleksey Navalny (3), Oleg Deripaska (the founder of Basic Element, one of Russia’s largest industrial groups; 2), German Gref (CEO of Sber-
Table 1 Mean community parameters, sorted in the decreasing order of the Betweenness centrality: Size (number of persons), Closeness centrality, Eigenvector centrality, Clustering Coefficient, and Density. The mean betweenness centrality of the top six communities is above the network average.

| Community label       | B    | S   | C   | E    | CC   | D    |
|-----------------------|------|-----|-----|------|------|------|
| 1 Putin Vladimir      | 0.54 | 1.470 | 0.24 | 7.80 | 0.53 | 0.0124 |
| 2 Bastrykin Aleksandr | 0.39 | 749  | 0.23 | 3.44 | 0.61 | 0.0065 |
| 3 Sobyanin Sergey     | 0.38 | 940  | 0.23 | 4.00 | 0.56 | 0.0208 |
| 4 Sechin Igor         | 0.35 | 199  | 0.23 | 2.93 | 0.58 | 0.0124 |
| 5 Rotenberg Arkady    | 0.35 | 382  | 0.23 | 3.99 | 0.57 | 0.0035 |
| 6 Kostin Andrey       | 0.33 | 233  | 0.23 | 3.30 | 0.64 | 0.0075 |
| 7 Chemezov Sergey     | 0.31 | 322  | 0.23 | 3.83 | 0.59 | 0.0206 |
| 8 Nabuiilina Elvira   | 0.30 | 390  | 0.22 | 2.70 | 0.58 | 0.0144 |
| 9 Shuvalov Igor       | 0.29 | 176  | 0.22 | 1.97 | 0.62 | 0.0152 |
| 10 Lashkov Yury       | 0.29 | 298  | 0.22 | 2.12 | 0.59 | 0.0309 |
| 11 Rogozin Dmitry     | 0.28 | 293  | 0.22 | 3.11 | 0.59 | 0.0228 |
| 12 Poltavchenko Georgy| 0.28 | 230  | 0.21 | 2.43 | 0.61 | 0.0118 |
| 13 Gref German        | 0.27 | 353  | 0.22 | 2.06 | 0.61 | 0.0123 |
| 14 Kerimov Suleyman   | 0.27 | 225  | 0.23 | 2.65 | 0.63 | 0.0341 |
| 15 Chayka Yury        | 0.27 | 338  | 0.22 | 2.75 | 0.60 | 0.0451 |
| 16 Mutko Vitaly       | 0.27 | 121  | 0.22 | 2.09 | 0.63 | 0.0129 |
| 17 Abramovich Roman   | 0.26 | 465  | 0.23 | 3.21 | 0.61 | 0.0242 |
| 18 Ismailov Telman    | 0.25 | 105  | 0.21 | 2.34 | 0.63 | 0.0185 |
| 19 Tolokonsky Viktor  | 0.25 | 264  | 0.21 | 2.08 | 0.65 | 0.0108 |
| 20 Poroshenko Petr    | 0.25 | 385  | 0.23 | 2.74 | 0.63 | 0.3636 |
| 21 Trump Donald       | 0.24 | 289  | 0.22 | 2.87 | 0.59 | 0.0130 |
| 22 Kadyrov Ramzan     | 0.24 | 202  | 0.23 | 3.95 | 0.64 | 0.0163 |
| 23 Ivanov Sergey      | 0.24 | 230  | 0.22 | 2.98 | 0.62 | 0.0434 |
| 24 Vekselberg Viktor  | 0.23 | 331  | 0.22 | 1.92 | 0.65 | 0.0154 |
| 25 Khodorkovsky Mikhail| 0.23 | 142  | 0.22 | 3.91 | 0.65 | 0.0139 |
| 26 Avetisyan Artem    | 0.23 | 100  | 0.22 | 2.58 | 0.62 | 0.0151 |
| 27 Miller Aleksy      | 0.23 | 107  | 0.21 | 2.06 | 0.64 | 0.0365 |
| 28 Yakumin Vladimir   | 0.22 | 340  | 0.23 | 4.59 | 0.59 | 0.0174 |
| 29 Chayka Igor        | 0.21 | 307  | 0.23 | 2.92 | 0.61 | 0.0123 |
| 30 Mordashev Aleksey  | 0.21 | 156  | 0.22 | 1.58 | 0.64 | 0.0194 |
| 31 Mikhailov Sergey   | 0.20 | 182  | 0.22 | 2.18 | 0.61 | 0.0316 |
| 32 Prigozhin Evgeny   | 0.20 | 152  | 0.22 | 1.67 | 0.65 | 0.0235 |
| 33 Radaev Valery      | 0.19 | 130  | 0.22 | 2.01 | 0.66 | 0.0214 |
| Overall               | 0.32 | n/a | 0.23 | 3.56 | 0.60 | 0.0006 |

They represent almost all principal groups of kompromat stakeholders: business, politics, law enforcement, banking, government, and press—with a notable exception of the criminal underworld.

4 Discussion

In the rest of the paper, we investigate the composition of the communities, their relationships, and kompromat cases’ typology.
Fig. 3 Mean eigenvector centrality and clustering coefficient for the major 33 communities (see Table 1). The size of a dot represents the number of persons in the community.

Table 2 Top ten persons, sorted in the decreasing order of the betweenness centrality, closeness centrality, eigenvector centrality, and degree. The dagger \( ^\dagger \) marks the persons who appear in more than one column.

| Betweenness | Closeness (Typicality) | Eigenvector (Toxicity) | Degree (Direct involvement) |
|-------------|------------------------|------------------------|----------------------------|
| Putin \( ^\dagger \) V. | Putin \( ^\dagger \) V. | Putin \( ^\dagger \) V. | Putin \( ^\dagger \) V. |
| Sechin I. \( ^\dagger \) | Medvedev D. \( ^\dagger \) | Medvedev D. \( ^\dagger \) | Sechin I. \( ^\dagger \) |
| Bastrykin A. \( ^\dagger \) | Kostin A. \( ^\dagger \) | Sechin I. \( ^\dagger \) | Medvedev D. \( ^\dagger \) |
| Medvedev D. \( ^\dagger \) | Sechin I. \( ^\dagger \) | Chemezov S. \( ^\dagger \) | Chemezov S. \( ^\dagger \) |
| Chemezov S. \( ^\dagger \) | Zakharchenko D. \( ^\dagger \) | Rotenberg A. \( ^\dagger \) | Sobyannin S. \( ^\dagger \) |
| Sobyannin S. \( ^\dagger \) | Klimenko G. | Navalny A. \( ^\dagger \) | Bastrykin A. \( ^\dagger \) |
| Zakharchenko D. \( ^\dagger \) | Kamenschchik D. | Timchenko G. | Navalny A. \( ^\dagger \) |
| Navalny A. \( ^\dagger \) | Mints B. | Bastrykin A. \( ^\dagger \) | Rotenberg A. \( ^\dagger \) |
| Gref G. \( ^\dagger \) | Chemezov S. \( ^\dagger \) | Deripaska O. \( ^\dagger \) | Deripaska O. \( ^\dagger \) |
| Kostin A. \( ^\dagger \) | Oreshkin M. | Kostin A. \( ^\dagger \) | Gref G. \( ^\dagger \) |

Fig. 4 presents a birds-eye view of the original kompromat network, called an induced network. Each node in the induced network stands for a community in the original network. Node size represents the number of persons in the community. The induced network edges are weighted; their weight (thickness) represents the number of individual edges in the original network. The communities are named after the most prominent persons—the persons with the highest betweenness centrality.
The node color represents the mean betweenness centrality of the community nodes: darker nodes have a higher centrality. (One exception is the node labeled “Trump Donald”—it is painted pink because it contains disproportionately many foreign nationals.)

Table II additionally shows the top five most prominent persons in each community (some names have been spelled in Russian and English in the original dataset, which resulted in duplications; also, Igor Slynuyav changed his unpleasantly sounding name to Igor Albin and was recorded in the same community under two names).

The community #21, labeled “Trump Donald,” stands out among other communities. Not only its most prominent representative is a foreign national and the president of a sovereign nation, but the nation—the USA—is also well outside of Russia’s zone of influence. At a closer look, the community contains other prominent American officials, politicians, and entrepreneurs such as businessmen Ilon Mask, Bill Gates, and Jeff Bezos, U.S. government officials Robert Mueller and Rex Tillerson, and a disgraced lawyer Michael Cohen. The community is also the home to the Russian prime minister Mikhail Mishustin and Maria Butina, who pleaded guilty to conspiracy to
Table 3 Top five most prominent persons (in terms of betweenness centrality) in each community (see also Table 1). The dagger † denotes English-language duplicates. The star ⋆ denotes foreign nationals. The equal sign = denotes the same person known under two different names.

| Community label | Other persons |
|-----------------|---------------|
| 1               | Putin V., Medvedev D., Navalny A., Deripaska O., Timchenko G. |
| 2               | Bastrykin A., Zakharchenko D., Sugrobov D., Titov B., Chubays A. |
| 3               | Sobyanin S., Magomedov Z., Gusertiev M., Mints B., Ananyev A. |
| 4               | Sechin I., Sechina M., Leontyev M., Rakhanmanov A., Avdolyan A. |
| 5               | Rotenberg A., Peskov D., Rotenberg B., Lisin V., Rotenberg I. |
| 6               | Kostin A., Evtsushenkov V., Rakhimov U., Gagiev A., Khamitov R. |
| 7               | Chemezov S., Prokhorov M., Manturov D., Khudaynatov E., Ignatova E. |
| 8               | Nabullina E., Tokarev N., Bedzhmanov G., Pugachev S., Markuz L. |
| 9               | Shuvalov I., Shuvalov I.†, Kesaev I., Levenchenko S., Filev V. |
| 10              | Lazhkov Yu., Chayka A., Yurevich M., Dubrovsky B., Rashnikov V. |
| 11              | Rogozin D., Lavrov S., Patrushev N., Komarov I., Vinokurov A. |
| 12              | Poltavchenko G., Beglov A., Albin I.†, Slyunyaev L.†, Oganessian M. |
| 13              | Gref G., Usmanov A., Mamut A., Durov P., Dmitriev V. |
| 14              | Kerimov S., Matvienko V., Turchak A., Golodets O., Petrenko S. |
| 15              | Chayka Yu., Shoygu S., Serdyukov A., Vasilyeva E., Ivanov T. |
| 16              | Mutko V., Rashkin V., Ablyazov M.†, Rodchenkov G., McLaren R.† |
| 17              | Abramovich R., Vorobyev A., Potanin V., Sobchak K., Lebedev V. |
| 18              | Ismailov T., Usoyan A., Mitrofanov A., Dzhaniev R., Varshavsky A. |
| 19              | Tolokonsky V., Morozov S., Shantsev V., Khinshtein A., Nazarov V. |
| 20              | Poroshenko P.†, Yanukovich V.†, Surkov V., Belykh N., Kolomoysky I.† |
| 21              | Trump D.†, Cherkalin K., Mishustin M., Belousov A., Tkachev I. |
| 22              | Kadyrov R., Ulyukayev A., Nemtsov B., Timakova N., Galchev F. |
| 23              | Ivanov S., Gordeev A., Skrynnik E., Ivanov A., Korolev O. |
| 24              | Vekselberg V., Golunov I., Golubev V., Varshavsky V., Blavatnik L.† |
| 25              | Khodorkovsky M., Skripal S., Petrov A., Litvinenko V., Lebedev P. |
| 26              | Avetisyan A., Calvi M.†, Nazarbaev N.†, Maduro N.†, Dzhabiev R.† |
| 27              | Miller A., Slipenchuk M., Khludeykov P.†, Lurakhmaev V., Lainin M. |
| 28              | Yakunin V., Belozorov O., Tikhonova E., Tikhonova K.†, Gorbuntsov G. |
| 29              | Chayka I., Traber I., Zhirinovsky V., Skoch A., Yarovsky I. |
| 30              | Mordashov A., Shvets A., Novak A., Cyril (Patriarch), Khotimsky S. |
| 31              | Mikhaylov S., Malofeev K., Strelkov I., Kaspersky E., Girkin I. |
| 32              | Prigozhin E., Prigozhin E.†, Kliman L., Gerassimenko A., Uss A. |
| 33              | Radaev V., Savelyev V., Lebedev A., Shishov O., Vantsev V. |

act as an unregistered foreign agent of Russia within the USA [14]. The community’s composition suggests that it concerns Russia’s controversial interference in the 2016 U.S. presidential elections[14].

In the final stage of the analysis, we identified several types of communities, based on the affiliations of their most prominent members with one of the following categories: “business,” including state corporations (53 people in Table 3), “politics” (50), “law enforcement” (known in Russia as “siloviks,” or “people of force” [10]; 16), “banking” (15), “government officials” (13), “criminal world” (6), “press” (5), and “others” (4). Sometimes, there was more than one affiliation per person: for example, Igor Sechin, as the CEO of Rosneft’, is an entrepreneur, but since Rosneft’ is a state oil company, he is also a government official. In such cases, we selected the most notable affiliation.
Table 4 Kompromat types: “business” $T_1$, “politics” $T_2$, “banking” $T_3$, and “law enforcement” $T_4$.

| Type        | $T_1$ | $T_2$ | $T_3$ | $T_4$ |
|-------------|-------|-------|-------|-------|
| Business    | 39    | 7     | 4     | 3     |
| Politics    | 11    | 29    | 8     | 2     |
| Banking     | 4     | —     | 11    | —     |
| Law Enforcement | 1   | 2     | 2     | 11    |
| Government  | 5     | 2     | 3     | 3     |
| Criminal    | 6     | —     | —     | —     |
| Press       | 5     | —     | —     | —     |
| Other       | 2     | —     | 1     | 1     |
| # of communities | 15 | 8     | 6     | 4     |

As a result, we described each community with eight numbers—in other words, represented it as a point in 8-dimensional space, to a total of 33 points. For example, of the five most prominent persons in community #1, two are entrepreneurs, two are politicians, and one is as journalist. The numbers for that community are (2, 2, 0, 0, 0, 0, 1, 0).

Such multi-dimensional points could be arranged into groups by applying k-means clustering—a method that aims to partition the observations into k clusters in which each observation belongs to the cluster with the nearest mean. We chose $k = 4$ in the expectation of a match with contemporary Russian kompromat’s typology that includes political, economic, criminal, and personal types of incriminating material [6]. Table 4 presents the results of the classification. Each network community and, by inclusion, all individual members of those communities, belong to one of the four types.

The results, while different from the taxonomy proposed in [6], appear consistent. Each kompromat type has the specific, dominant category of participants: entrepreneurs ($T_1$), politicians ($T_2$), bankers ($T_3$), and “siloviks” ($T_4$). However, types $T_1$ and $T_3$ also have a significant secondary population of politicians, and $T_2$ additionally includes entrepreneurs. Thus, the first three types represent a corrupted symbiosis of industrial and banking capital and political power, biased towards one of the factions, depending on the type.

The fourth type, $T_4$, comprises the “siloviks” and has few representatives from the other categories. The difference suggests that the kompromat cases involving law enforcement officials, though not entirely isolated, differ from those that have affected the political and economic block.

5 Conclusion and Future Work

In this paper, we analyzed a social network of 11,000 Russian and foreign nationals, including politicians, entrepreneurs, bankers, law enforcement officials, and high-profile criminals, affected by kompromat: compromising materials. The data for the study was downloaded from “RuCompromat,” a Russian online encyclopedia of kompromat. The network is modular and has an excellent community structure. Each
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network community brings together persons who participated in similar kompromat cases. We calculated the network attributes (such as various centralities and clustering coefficient) and identified the most prominent persons in the whole network and each community. By looking at the top community members’ affiliations with various socio-economic groups, we introduced a four-type taxonomy of the communities. Three types represent industrial and banking capital and political power; law enforcement officials (the “siloviks”) dominate the fourth.

“RuKompromat” offers an additional level of information: organizations involved in the kompromat cases. In the future, this information can be used to construct and analyze a joint socio-organizational network. Since organizations are usually easier to classify than individuals, adding them to the dataset could help us automatically assign persons to the categories, which would improve the kompromat cases’ typology.

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