Selection Methods for Geodata Visualization of Metadata Extracted from Unstructured Digital Data for Scientific Heritage Studies

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Abstract. The present study explores the methods of geodata visualization extracted from the metadata of scientific publications for use in scientific research using the scientific heritage of Georgy Gause. It is based on the results of case studies to assess the possibilities of digital information resources, metadata extraction from digital resources, and using methods for their quantitative processing. We have studied methods of extracting metadata from digital information systems that do not have export tools. Our concentration is on methods and technologies of geodata extraction, and their subsequent visualization are considered. They are considered and applied methods of a dynamic clustering of geodata markers. Based on geodata visualization, we interpreter the results. The possibility of using extracted metadata in scientific visualization systems that support standard formats is evaluated.

Keywords: Scientific information · Digital information resources · Metadata extraction · Geodata extraction · Geodata visualization · Dynamic clusterization · Digital scientific heritage · Georgy F. Gause

1 Introduction

Currently visualization technologies are widely used in various scientific disciplines. An intensively growing field in this respect is geodata visualization [2, 4, 25, 34, 48]. These methods are of special importance for big data [18, 32]. Various methods of big data processing are often employed within humanities and are part of the "digital humanities". Our objective here is to apply the methods of geodata visualization. The data was extracted from the metadata of scientific publications. As case studies, we have used the scientific heritage of a famous ecologist, Georgy Gause, to be analyzed from a science studies viewpoint. The study is based on formerly conducted research into the possibilities of using digital informational resources in the science studies [39, 40]. To do so, we have extracted metadata from digital resources and employed the methods of its quantitative evaluation [38].

In the framework of the present study, we solved the following tasks:

– Selection of wide spread geodata visualization tools (available to every researcher, for they do not require financial investments or special computer skills)
– Extraction of data about the organizations/affiliations from the metadata of scientific publications;
– Extraction of geodata from the above data on organizations/affiliations of the publication authors;
– Ultimate visualization of the extracted information along with dynamic clusterization of markers.

2 Related Works and Literature Review

Research is currently underway in various fields related to the extraction of big data from various digital resources. Including the extracted geodata. Some digital resources for retrieval of geodata provide an API. For example, the Marketing API is used to extract geodata from Facebook [4]. The harvesting machine using the Twitter API is used to extract geodata from messages micro-blogging platform Twitter [41]. A special web application based on ArcGIS API for JavaScript technology was developed to access the geodata database of the Geophysical Center of RAS [25]. In bibliometric studies, geodata are extracted from the metadata of scientific publications placed in digital information systems (for example, the author's country) [33]. Various systems and services are being developed to extract metadata [19], including using the OAI-PMH metadata exchange Protocol [11, 17, 37]. Methods of automatic extraction of metadata from the texts of scientific articles are widely used [44, 47].

Different software platforms and software are used to visualize geodata. One popular solution is OpenStreetMap (OSM), a platform that allows users to create or edit maps using GPS-enabled devices or aerial imageries [51]. Other popular solutions include such systems as PostGIS [6, 30, 42] and GeoServer [21, 45].

When positioning geographic features, the quality of the data is an important issue. In modern studies, different approaches to the accuracy of geolocation are considered [3, 14, 29]. One solution to the quality of data in GIS is the use of metadata [9, 16, 26].

When visualizing big geodata, problems arise when using visual analysis methods. To solve this problem, clustering methods are developed that are aimed at visually combining datasets not based on their spatial localization [15]. Methods of clustering of spatial objects are increasingly used in humanitarian studies [7, 50].

3 Methods and Approaches

To solve the above tasks, several steps should be completed [22]:

– Collection of information on the objects;
– Spatial localization of the data;
– Creation of a map design;
– Selection and implementation of a visualization technology.

To implement this approach, the following methods were identified:

- Extraction of metadata from digital informational systems, which do not offer importing tools;
- Spatial identification of visualization objects;
- Mapping the objects of spatial visualization.

In addition, to meet our objectives, we investigated the methods and corresponding technologies of dynamic clusterization of spatial objects by changing map scales.

Choosing technologies for our tasks, we proceeded from the assumption that they should be available for every researcher' independently of their information technologies and computer science skills. This allow employing the suggested methods in humanities without appealing to computer scientists. We also concentrated on free software and open source technologies.

4   Information Extraction from Metadata of Scientific Publications and Its Preliminary Interpretation

To conduct our case studies, we selected a Russian-based electronic scientific library (Elibrary, http://elibrary.ru), which is the most voluminous Russian scientific information system that includes the overwhelming majority of Russian scientific journals in all scientific disciplines. Furthermore, this informational system includes full texts of scientific publications as well as detailed metadata embracing, among others, abstracts and key words. In addition, the majority of scientific publication full texts are in the open access, which allows using Elibrary in science studies. The search engine of the Elibrary offers many their options allow the filtering of information and selecting of scientific publications by apply many criteria simultaneously. Search results can be used for scientometrics. For example, one can classify publications according to their topics, key words, affiliations, authors etc. However, statistics is presented in only one window of the browser whereas the only visualization tool is a column-like diagram. Another issue of Elibrary is the lack of tools for exporting metadata and statistical calculations. This constraints the use of selected publications and the search results for further automatic processing for scientific purposes. Consequently, the first task was to extract statistical reports. For publication selection, we used the search query "Gause & the competitive exclusion principle". The search engine found 190 publications. To estimate the validity of search entries, we used statistical report "distribution by topics".

For the purposes of further processing, the extracted data was highlighted by means of operational system's standard interface tools. By using "copy-paste" technology, the results were placed into an MS Excel table, and a circular diagram was created (Fig. 1).

The majority of publications (64%) fit into the biology category; there are also publications in agriculture and forestry, medicine and health care, environmental protection, human ecology, and biotechnology, which embrace 17% of the publications. From a historical viewpoint, it these statistics that support the assumption that Georgy Gause's principle of competitive exclusion is of primary importance for general biology and will be only marginally cited in the applied science.
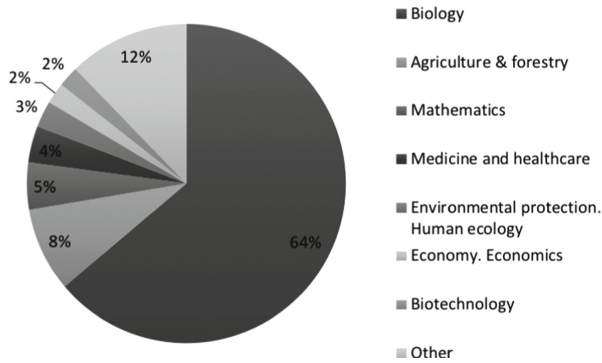
Fig. 1. Distribution of scientific publications by topics.

Using the same method as above, we imported the statistics extracted by means of the search entry "distribution by affiliations". The final list of affiliations was verified and classified into three categories: research organizations (scientific), educational organizations, and other organizations. In a special column, a type or organization was indicated along with its name. The circle diagram built on that data demonstrated the author's affiliations classified into organization types (Fig. 2).
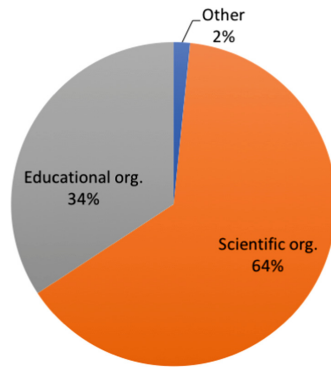
Fig. 2. Distribution of affiliations in accord with the type of organizations.

As one can see, purely research organizations dominate this diagram, that hinting to the assumption that Gause's theory was a theoretical breakthrough and is of importance for current research. To make a more precise inference, one should be able to extract purely educational publications (textbooks, published lectures) from the publications surveyed as well as consider the general index of publication activity of educational and research organizations.

5   Investigation into the Mechanisms of Dynamic Clusterization of Geodata Markers

The next step included an investigation into possibilities of dynamic clusterization of geodata markers by using authors affiliations as an indicator. By doing this, we have proceeded from the principle of simplicity and broad availability of methods and tools. Google service for programmers allows using Maps JavaScript API (https://developers. google.com/maps/documentation/javascript/tutorial), which creates customized maps with the own content and imagery for display on web pages and mobile devices. Including Maps JavaScript API allows using marker clusters to display a large number of markers on a map. It is also possible to use the MarkerClusterer library in combination with the Maps JavaScript API to combine markers of close proximity into clusters, simplifying the display of markers on the map.

This approach requires special computer skills and experience with JavaScript. Another difficulty with this method is the necessity to present geolocations considering a certain variable (Fig. 3) by manually operating with the large amount of data on geolocations.

```
var                    locations                 =                      [
                {lat:    -31.563910,    lng:    147.154312},
                {lat:    -33.718234,    lng:    150.363181},
                {lat:    -33.727111,    lng:    150.371124},
```

Fig. 3. The structure of the variable "location" along with data on geolocation of objects (sample)

Another power tool for big data processing and cluster map designing is the service Splunk Cloud (https://www.splunk.com/en_us/software/splunk-cloud.html). This is a sophisticated tool requiring significant programmer skills and knowledge of interface commands [10]. In addition, this is not a free service and currently blocked by the embargo on the Russian federation.

Other popular free solutions for processing great amounts of geodata is PostGIS (http://geoserver.org) and GeoServer (http://postgis.net). However, to work with these one needs a very powerful computer and advanced skills in computer science [43].

We have found several other popular open source non-commercial licensing programs [20, 23, 25, 27, 35]. On this basis, Mapbox tools was selected [1, 28]. For further operation, an account in Mapbox was created.

6 Spatial Localization of Geodata and Dataset Establishing

Mapbox tool is able to process geodata in the GeoJSON format. To create a dataset of extracted organizations services, Google Maps (https://www.google.com/intl/ru_RU/maps/about/mymaps/) and Yandex Map Constructor (https://yandex.ru/map-constructor) were used. Determination of geographical coordinates of the organizations happened on the map in Maps Google service account. This was made by using organization names in the search engine. If necessary, an organization name has been proved either on the site of this organization or in other open sources.

On this stage, we have created a map with statically indicated markers of various organizations. After that, data was exported into the file in KML format [24, 31, 36, 46]. This format allowed to saving spatial coordinates of each organization (latitude and longitude). The import of geodata from this file was completed in the Yandex Map Constructor account. Doing this, we have inverted latitude and longitude, because in these two services the sequence of the presentation is different. To create a dataset, a geodata import in GeoJSON file format was made [8].

7 Establishing of a Map in the Mapbox

An account was created to work in the mapbox. Creation of the map happened in the Studio Mapbox tool in the Mapbox account. To do so, we first selected a map style "Streets", which is quite laconic and visualizes both countries and cities. After that, the data was imported from a file in a GeoJSON format. Tilesets were used to visualize markers on the map. The tileset is a collection of raster or vector data broken up into a uniform grid of square tiles at 22 preset zoom levels. Data from the dataset was imported into tileset. For the purposes of dynamic clusterization, vector type and zoom extent: z0–z10 (data will be visible above zoom 10, but may appear simplified) were selected. Then, the created style was opened in the style editor. Next, a new layer with this tileset as the source was created. On the created map, layers and styles were combined with markers.

8 Establishing the Dynamic Clusterization

To create a dynamic clusterization by changing a map scale, a method of Mapbox GL JS' built-in functions to visualize points as clusters was used [13]. In an html-code, sample corresponding locations were presented:

– An API access token to configure Mapbox GL JS, Mobile, and Mapbox web services like routing and geocoding. It was generated in the Mapbox account;
– Reference to the created map style;
– Reference to the file of GeoJSON format with dataset.

In addition, a clusterization adjustment was conducted in accordance with the number of markers and map size, which reflected the whole geographical space of Russia.

MAMP was used to visualize maps with dynamic clusterization. MAMP is a free, local server environment that can be installed under macOS and Windows with just a few clicks. MAMP provides all the tools needed for testing or development purposes, for example [5, 12, 49]. After its installation, into root directory a file with html-code and a GeoJSON format file with dataset were copied. After starting MAMP, the html-file was opened in the browser: http://localhost:8888/index.html. By alternating the map scale markers were combined into clusters (Fig. 4).


Fig. 4. Clusterization of the markers of author's affiliations.

The same approach was used for clustering publication quantities per organization. For this purpose, based on the created file with geolocations in the GeoJSON format, an analogous file was created in which an organization's geolocation was given one more time in accordance with the number of publications from Elibrary (Fig. 3). After completing these steps, we had an analogous map (Fig. 5).

Based on the extracted information one can make following conclusions:

– Major clusters of Russian organizations conducting research relevant to Gause's competitive exclusion principle are situated in Moscow, St. Petersburg, and in the Urals. To the minor extent but quite evenly affiliations are distributed in South Siberia and Far East region.

– Publication activity corresponds to the identified clusters of organizations: Moscow, St. Petersburg, and the Urals (equally), then Far East region and South Siberia.
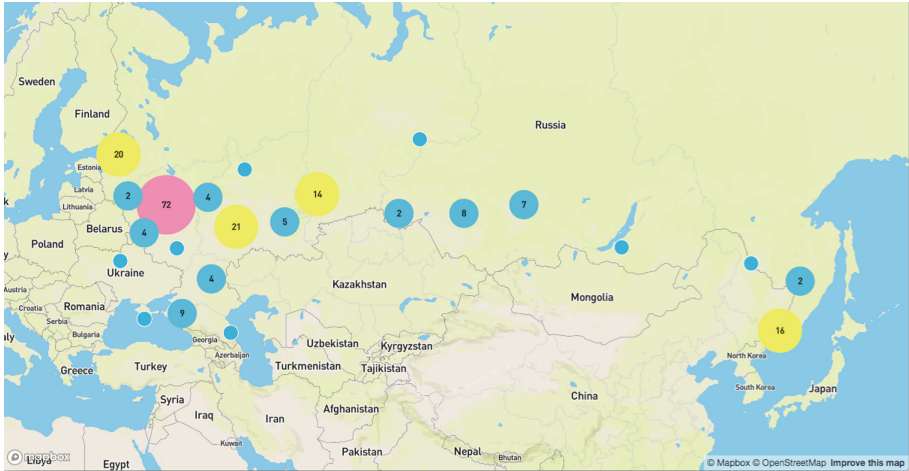
Fig. 5. Clusterization of publications markers corresponding to author's affiliations.

9   Conclusions

This study of data extracted from the online scientific library (http://elibrary.ru) allows making the following conclusions:

– Elibrary offers various tools that allow the extracting of analytical information about the publications it offers;
– The analysis of data has shown that the majority of Russian-language scientific publications is distributed in accordance with the topics of biology, ecology, medicine and its related fields;
– This completely corresponds to the research directions Gause is associated with. He is best known for his contribution into the evolutionary theory, ecology, and medicine (discovery of antibiotics);
– The metadata was extracted by means of the technology of data extraction from informational systems, which do not offer exporting tools;
– Proceeding from the principle of "open access", only widely available methods and technologies were used. Researchers without special computer skills can apply the described technologies as well. This allows recommending this approach for studies in humanities without appealing to experts in computer science;
– Methods and technologies of establishing datasets based on spatial localization of geodata were employed;
– Maps with dynamic clusterization of markers were created by using open access technologies and alternation of maps scales;
– The analysis of achieved visualization allowed the detecting of clusters of organizations and corresponding scientific publications. The visualizations reflected the appeal of researchers to the scientific heritage of Georgy Gause.

Further development of our current approach presupposes comparative studies of data extracted from various informational digital resources. This will allow a quantitative approach for the problem of Russian researcher impacts on both international and Russian science development.

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