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The Categorization of the Darkweb

MASTER'S THESIS

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Declaration

Hereby I declare that this paper is my original authorial work, which I have worked out by my own. All sources, references and literature used or excerpted during elaboration of this work are properly cited and listed in complete reference to the due source.

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Abstract

The future Categorization of the Dark Web abstract

Keywords

Web Application, Dark-web, Python, RestApi, Django REST, Type-Script, React, Redux, d3 Graph

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1 Introduction

2 Data set analysis

The data set we were working with consisted of pages which had been scraped¹ from the dark web and stored in Elasticsearch (ES) [10]. This chapter will describe the clear web, deep web, and the dark web, the Elasticsearch database, and the structure of the stored pages.

The Internet consists of networks from all over the world. The networks are connected and together they comprise a global network. The Internet can be divided into the clear web 2.1, and the deep web 2.2 [6].

2.1 Clear web

The content of the clear web is indexed by search engines and is publicly accessible. The users are identified by their IP addresses and are usually not anonymous unless some privacy tools are used. The most used browsers worldwide according to market share are Chrome, Safari and Firefox [41]. The size of the clear web is difficult to determine. However, it is estimated to contain about 5.93 billion pages as of March 2020 [16].

2.2 Deep web

The content of the deep web is not indexed by search engines and is not accessible publicly. Emails or medical information are examples of resources in the deep web. A user needs to be authorized to access this data. It is more problematic to measure the size of the deep web because of the fact the content is not indexed. The size was estimated to be 4,000 to 5,000 times larger than the clear web [14].

A portion of the deep web is the *dark web*, also called darknet.

1. Scraping is a method used for collecting data from web pages with automated software rather than doing so manually.

2.2.1 Dark web

The dark web provides anonymized services and user identities. It is therefore leveraged for activities like accessing or publishing illegal or censored material, e.g. the Bible, whistle-blower secrets, or child porn. It is also used for trading with illegal goods, such as drugs or guns. Another way to exploit the dark web is to offer or order illegal services, for instance money laundering, hacking or murder [5]. The onion router (Tor) 2.2.2 or the Invisible Internet Project (I2P) 2.2.3 are two of the networks comprising the darknet.

2.2.2 Tor

The Tor network [39] is accessible through the Tor browser or Tor proxy. Tor makes use of *onion routing* (ORing) [18]. ORing describes routing where each node, except for the originator and the target node, knows only its predecessor and successor. The originator chooses a list of nodes from which it creates a circuit between itself and the target node. Nodes in this circuit are determining their successor leveraging public-key cryptography. For example, *A* is the originator and *D* the target node. *A* creates a circuit consisting of itself and of nodes *B*, *C* and *D*. *A* creates a fixed-sized cell with encrypted information about the circuit nodes with a message using their respective public keys. *A* sends this cell to *B*. *B* removes one layer of the cell using its private key in order to get the address of its successor, in this case *C*. *B* cannot remove an additional layer to the successor of *C* because it lacks the private key of *C*. *B* sends the cell to *C*. *C* removes another layer and sends the cell to *D*. *D* removes the final layer and reads the information. Now *D* is able to communicate with *A* through *D* and *C* with only knowing about itself and *D*. Determining the original source and target node is therefore difficult. ORing was introduced in the 1990s to ensure privacy.

2.2.3 I2P

I2P [1] is another network of the dark web which anonymizes its traffic. It is accessible through the I2P browser. In contrast to Tor, communication in I2P is based on *garlic routing* (GRing) [2]. GRing is described as an extension of ORing. The established tunnels between

two nodes are unidirectional, meaning different tunnels are used for outgoing and incoming messages. Another difference from ORing is the bundling of messages. An individual message is called a *clove*². Each clove contains their own delivery instructions. These instructions are exposed at the target node. Cloves are bundled into a garlic-message. The bundling of cloves ensures more secure and efficient communication.

Both exemplified browsers provide anonymous access to the clear web as well as to the dark web. Both are open-source and free to use.

2.3 Elasticsearch

The data collected from the dark web was store in Elasticsearch. ES is a distributed, open source search engine [10] and offers a fast full-text search. Another benefit of ES are documentation and supported tools, such as Logstash [9] for processing of data or Kibana [11] for the visualization of data. ES can be used as a NoSQL database. Such a database consists of indexes, documents and fields as opposed to tables, rows and columns of SQL databases. One of the advantages of NoSQL databases is scalability, therefore they are suited for big amounts of data.

2.4 The data set

The dark web pages were acquired via web scraping. The scraped pages belonged to two different networks - I2P and Tor. The total number of pages was 221,844. Of those pages 212,851 were Tor pages and 8,993 I2P pages. The total number of unique domains was 5,178 of which 4,912 were from the Tor network and 266 were from the I2P network.

The fields of a page entry will be described in the following list 2.4. Each description will include a concrete example from the database. Fields beginning with an underscore are assigned to every document implicitly.

2. Michael Freedman, who defined garlic routing, called cloves *bulbs*.

_id is a unique identifier. For example

2d622b6fba6f203d790fedbb4f47963e2366c7fd.

_index informs about the collection the document belongs to. For example *tor*.

_type determines the type of the document. For example *_doc*.

content is the actual content of the page. For example *Purple Kush – 10g – WackyWeed Menu * Home * Contact us * About us .*

content_type describes the type of the content. For example *text/html; charset=UTF-8*.

domain of the url address. For example *wacky2yx73r2bjys.onion*.

h1 is the text with the h1 style. For example *Purple Kush – 10g*.

links to other pages this page links to. For example {

"link": "http://wacky2yx73r2bjys.onion/",

"link_name": "Home"

}.

raw_text is similar to *content*. It additionally may contain formatting elements such as *\n*. For example *Purple Kush – 10g – WackyWeed Menu\n\n * Home\n * Contact us\n * About us\n .*

raw_title is similar to title. It additionally may contain formatting elements. For example *Purple Kush – 10g – WackyWeed*

raw_url is the same as *url*.

title of the page. For example *Purple Kush – 10g – WackyWeed*.

updated_on depicts the time when the document in the database was last updated. For example *2019-10-22T19:41:09*.

url address of the page. For example

http://wacky2yx73r2bjys.onion/?product=purple-kush-10g.

3 Machine learning

A part of this thesis was the categorization of the scraped pages. Categorization in this context means the process of assigning categories (labels) to pages. The data set at hand contained a vast amount of pages, as we discussed in chapter 2. The manual categorization of this number of pages would therefore take too much time and in consequence was infeasible. An automatic system for text classification was required. A simple system with a list of words assigned to each label was introduced but was performing poorly. A more sophisticated tool for text categorization is machine learning. We decided to use supervised machine learning (ML).

This chapter describes ML. Secondly, supervised and unsupervised learning, types of machine learning, are characterized. Lastly, neural networks and their attributes detailed.

3.1 Machine learning

The term *machine learning* was first introduced by Arthur Samuel. In his paper *Some Studies in Machine Learning Using the Game of Checkers* [40] he proved it is possible for a program to develop better game-related skills than the skills of the programmer of the program.

ML is the process in which an application develops the ability to perform a certain task at least as well as a human would. The learning process is based on the evaluation of gained experience [29]. The algorithm requires an initial data set in order to train and validate. The size of initial the data set depends on the nature of the task and the selected ML type. During training the algorithm attempts to perform the given task and validates its own performance. The algorithm then adjusts its criteria for performing the task based on the validation results. These two steps are repeated a number of times defined by the programmer. The output of the algorithm is a model able to perform the task it was trained for.

ML is used across various industries and fields. The need for automated analysis is increasing with the growing popularity of *big data*¹

1. A data set too vast or complex for traditional or manual data processing.

[45] [4]. ML is used widely with Big Data. Another use for ML is in the automotive industry. Cars with assisted parking or breaking, or self-driving cars are examples[26]. Also, ML is used frequently in games for a more natural game experience [19].

There are several approaches in ML based on the different ways of training. We describe the three main approaches in the subsections following. Namely *reinforcement learning* in subsection 3.1.1 (RL), *unsupervised learning* (UL) in subsection 3.1.2, and *supervised learning* (SL) in subsection 3.1.3. The approach used in this thesis was *supervised learning*.

3.1.1 Reinforcement learning

It is suitable to use RL if behaviours in dynamic environments are to be learned [30]. A software agent receives an indication of the state of the environment. The agent then picks an action from a discrete set of agent actions. Next the state is modified by the action. The value of this modification is passed on as a scalar reinforcement signal to the agent. The objective for the agent is to maximize the long-run total of reinforcement signal values. This is achieved over time by leveraging a number of specialized algorithms together with methodical trial and error.

3.1.2 Unsupervised learning

3.1.3 Supervised learning

4 Clustering

One of the goals of this thesis was to visualize the structure of the scraped portion of the dark web. We chose to render the data as a web graph which is further outlined in section 4.1. As was described in chapter 2, the data set to be displayed was rather sizable. The problem with the visualization of such an amount of data is readability. All pages of such a data set cannot be displayed at the same time if additional information, such as the category with the url address of the page, needs to be provided to the user. Such rendering would be cluttered and readability would be affected negatively. It was therefore necessary to find a proper way to divide the graph into several subgraphs. We decided to adopt community structure introduced in section 4.1.1. For community detection we leveraged the well known Louvain algorithm (LA). LA is described in more detail in section 4.2.

In this chapter we characterize web graphs and its challenges. Next we talk about community structure and LA, the algorithm for dividing a graph into communities.

4.1 Web graph

The data is displayed as a graph. More precisely a web graph [25]. A web graph is a graph representation of the web. Nodes are portrayals of the pages and edges depict links between the pages. Web graphs tend to be built from an enormous amount of data. As such, they can be advertised in various ways. One of the visualizations is shown in figure 4.1. The depicted web graph displays all its data at once without any labels or details. The result may be useful for viewing the internet as a whole. However, for our purposes this view was not sufficient. One of the requirements of this thesis was the possibility of the inspection of the relationships between nodes in more detail. The big amount of data described in subsection 2.4 prevented the displaying of all page at once. The information the user would read from such a graph would be either incompatible with the requirements or incomprehensible as too much visual data worsens the quality of the user's information processing [34]. Therefore the requirement arose for the graph to be composed of a significantly smaller amount of nodes. As

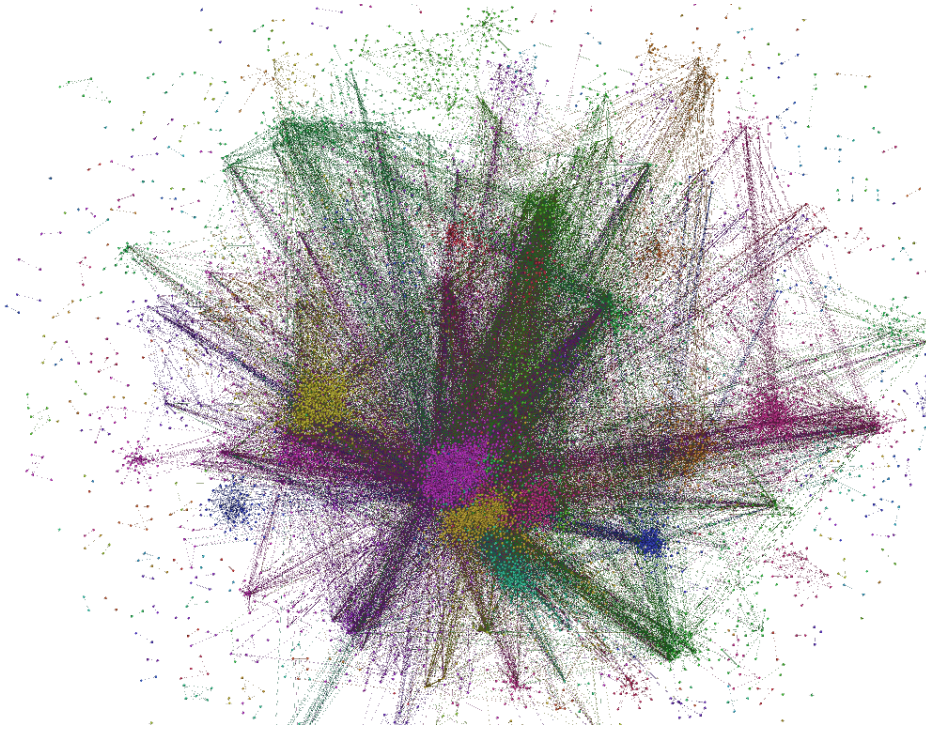


Figure 4.1: Web graph by Citeo made consisting of circa 600 000 domains and 16 billion links. [15].

a result the user would be able to obtain the sought knowledge without hindrances. The majority of the nodes in our graph were not isolated¹. The nodes were in fact part of a single connected component. It was therefore possible to partition the graph based on the density of its nodes into communities. Communities are described in detail in the next subsection 4.1.1.

4.1.1 Community structure

If a graph can be partitioned into several subgraphs so that nodes from one subgraph are internally connected densely and are connected scarcely to nodes from other subgraphs, we can claim it has a community structure. Each subgraph of such a graph is a commu-

1. An isolated node is a node with zero incoming and outgoing edges.

nity [20]. Each community can be portrayed as a meta node of the graph. This way the number of nodes in the graph is reduced. The quality of such a partition is measured using modularity. L. Wenye and D. Schuurmans describe modularity in their work [37] with the following words:

For a candidate partition of the vertices into clusters, the modularity is defined to be the portion of the edge connections within the same cluster minus the expected portion if the connections were distributed randomly [32].

4.2 Louvain algorithm

A widely used algorithm for finding communities in graphs is LA [7]. It is a greedy algorithm which maximizes modularity locally. The modularity value is a number between -1 and 1. Next we detail the principle of the algorithm. We example each step on node N_A belonging to a part of an example graph illustrated in figure 4.2.

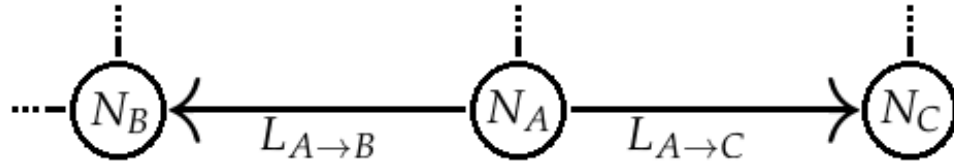


Figure 4.2: The visible portion of the exemplified graph depicts nodes N_A , N_B , and node N_C . There are links $L_{A \rightarrow B}$ and $L_{A \rightarrow C}$ between nodes N_A and N_B , and N_A and N_C respectively. Other links are displayed partially and are connecting the nodes to the rest of the graph.

1. Each node is assigned a community. Current modularity for each node is calculated.
 - Node N_A is assigned to community C_A . The modularity value $M_{A \rightarrow c_A}$ for N_A is 0.2.
2. Each node is disassociated from its community and randomly appointed to a community of one of its neighbours. This is repeated for each neighbour of the node. Modularity for each node after each such a transition is calculated.

- Node N_A has two neighbouring nodes, node N_B in the community C_B and node N_C in the community C_C . Node N_A is removed from C_A and appointed to C_B . Modularity value $M_{A \rightarrow cB}$ is -0.1 . Afterwards, N_A is removed from C_B and assigned to C_C . Modularity value $M_{A \rightarrow cC}$ is 0.5 .
3. Each node is now appointed to the community in which the maximum modularity value was achieved. This can also result in the node remaining in its original community.
 - The maximum modularity of N_A achieved in the previous step is $M_{A \rightarrow cC}$. N_A is therefore removed from C_A and appointed to C_C .
 4. Discard the empty communities.
 - Community C_A is now empty and is therefore discarded.
 5. Each community is now considered a node (community-node). Links between community-nodes are constructed from links of nodes of the same community-node (old-links). This is done by grouping together old-links which target nodes assigned to the same target community-node. These grouped links now represent weighed edges between community-nodes. Old links between nodes of the same community-node are represented by a self-loop on the community-node.
 - Community C_C is now considered a node N_{cC} and C_B is considered a node N_{cB} . A link $L_{cC \rightarrow cB}$ from N_{cC} to N_{cB} with a weight of 1 is created because of link $L_{A \rightarrow B}$. Also, a loop $L_{cC \rightarrow cC}$ is created on N_{cC} because of the link $L_{A \rightarrow C}$. The result of this step can be observed in figure 4.3.

LA is favoured for its simplicity, speed and accuracy. Since its introduction, in 2008, it was possible to detect communities in graphs with billions of nodes in a relatively timely manner. LA was compared to other algorithms for community detection [7]. Namely the algorithm of Wakita and Tsurumi [44], of Pons and Latapy [38], and of Clauset, Newman and Moore [13]. The used graphs were of sizes varying between 34 nodes and 77 edges to as much as 118 million nodes and

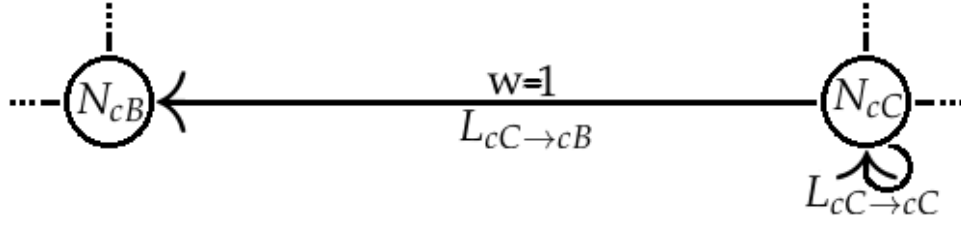


Figure 4.3: This graph is the result of applying the above listed steps to the previously shown portion of the example graph from figure 4.2. The visible portion of the graph contains nodes N_{cB} and N_{cC} , and a link $L_{cC \rightarrow cB}$ with a weight of 1 between them. A self-loop $L_{cC \rightarrow cC}$ on N_{cC} is present.

1 billion edges. The difference between the computing times of the previously stated algorithms grows with the size of the graphs and favours LA. In fact, it took 152 minutes for LA to detect the communities of the greatest graph whereas the computation time of the other algorithms was more than 24 hours. In terms of precision, LA was also the most precise one with slightly better modularities.

5 Development

An application was developed in order to fulfill the goals of this thesis. One task of the application was the categorization of the scraped pages into categories. This was to be done depending on the content of the pages. Another task was to provide a way to observe the structure of the pages, links between them, and their categories. One of the partner requirements was for the application to function on a UNIX system. Another requirement was a user friendly UI. Also, the option of retrieving all the available information about the pages was demanded.

This chapter first describes the implementation of the model for the categorization of the pages. Then the design and implementation of the application which is composed of a representational state transfer (REST) application program interface (API) and a front-end (FE) web application is detailed.

5.1 Categorization

One part of this thesis was to categorize the scraped pages into categories depending on their content.

5.2 API

The scraped pages of the dark-web were being stored in *ElasticSearch*. We created a back-end application (BE) in order to perform various operations on the data-set before sending it to the FE. Such operations involve resource intensive processing of large volumes of data, and caching. We decided to create a Python BE. The reason behind this decision was the requirement for the application to function on a UNIX system. Other reasons are described in subsection 5.2.1. The requirements for the BE was the categorization of the nodes along with their division into groups. The groups were either represented by nodes of the same category or communities. The BE also needed functionality to return details for specific pages or groups if requested.

5.2.1 Technology overview

Python is a widely used interpreted programming language known for readability and portability [24]. Python is open-source and is considered to have an extensive documentation and community available.

Python is popular in the science community because it is easy to learn and has simple syntax. There is therefore a great amount of useful libraries for research purposes such as *NetworkX*¹ [17] or *cylouvain*² [22] because of this. As we wanted to follow the REST architecture we decided to make use of the *Django* framework [21]. It is responsible for tasks such as running the server or managing web requests. Another advantage of Django is its *Django REST framework* (DRF). DRF offers a convenient way for creating restful endpoints and responses [33]. Both frameworks are open-source with helpful documentation and community.

We had to solve performance issues. It took approximately 30 minutes to retrieve and categorize about 220,000 pages from the database and circa xxx seconds to divide such a response into communities. We considered this wait time to be too long. Therefore we decided to cache the data of the first response. For that purpose *Redis* [31] was used. It is an open-source solution which we used as a key-value store. It supports basic data structures³ as values, but not custom objects. Since the API uses custom objects for *communities*, *pages* and *links*, an object serializer was leveraged along with Redis. We decided not to write our own but to utilise the Python *pickle* module⁴ [23] (pickle). The reason behind this decision was the simplicity of pickle. Pickle also fulfilled all our needs for serializing. Specifically the serialization or deserialization of data in the form of the previously mentioned models for Redis to store in an acceptable time. Pickle took xxx seconds to serialize xxx pages. The deserialization of the same number of pages took xxx seconds.

1. A library used for creating and working with graphs.

2. A library with a fast implementation of LA.

3. Simple structures, e.g. strings, numbers or sets.

4. A module used for converting Python objects to streams of bytes and vice versa.

5.3 Front-end

For users to be able to see the data acquired from the BE in a reasonable way a FE application was created. The goal of this FE was to visualize the scraped pages in a graph. The pages or communities, and links from the BE were to depict nodes, and links of the graph respectively. The category of the pages or communities was to be readable from the graph. Additional information about the nodes needed to be displayed or retrieved on demand.

5.3.1 User interface

We designed the UI the following way.

After the application is loaded the UI is composed of a *header* with the name of the application *Dark web categorization*, a *loader* and a *sidebar* on the right hand side. The application resembles at this point the image in Figure 5.1.

The *sidebar* contains several *input fields* and *buttons* in a column. At the very top of the *sidebar* a *drop-down button* (DD) is present.

The DD sets the mode according to which the pages are grouped into communities. There are two modes available, *link-mode* and *category-mode* as can be seen in Figure 5.2. If *link-mode* is selected, the pages are divided by the LA4.2 depending on the connections between them only. If *category-mode* is selected, the pages are divided into groups by categories. The pages in the groups are further divided into communities according to links between them, as if in *link-mode*.

An *input field* with a *submit button* was placed underneath the DD for the purpose of filtering nodes according to a search phrase as can be seen in Figure 5.3.

The last element shown is an indicator of the current level - how many times the user zoomed into a community. The indicator has a *zoom-out button* placed next to it.

The moment the data is retrieved from the BE the *loader* gets replaced for a graph. The graph-nodes represent either the communities the pages are partitioned into or the pages themselves. If the graph contains any isolated nodes (isolates) a *mock-community* is displayed containing all isolates. This community cannot be zoomed into. A community node is depicted as a *pie chart*. The individual sec-

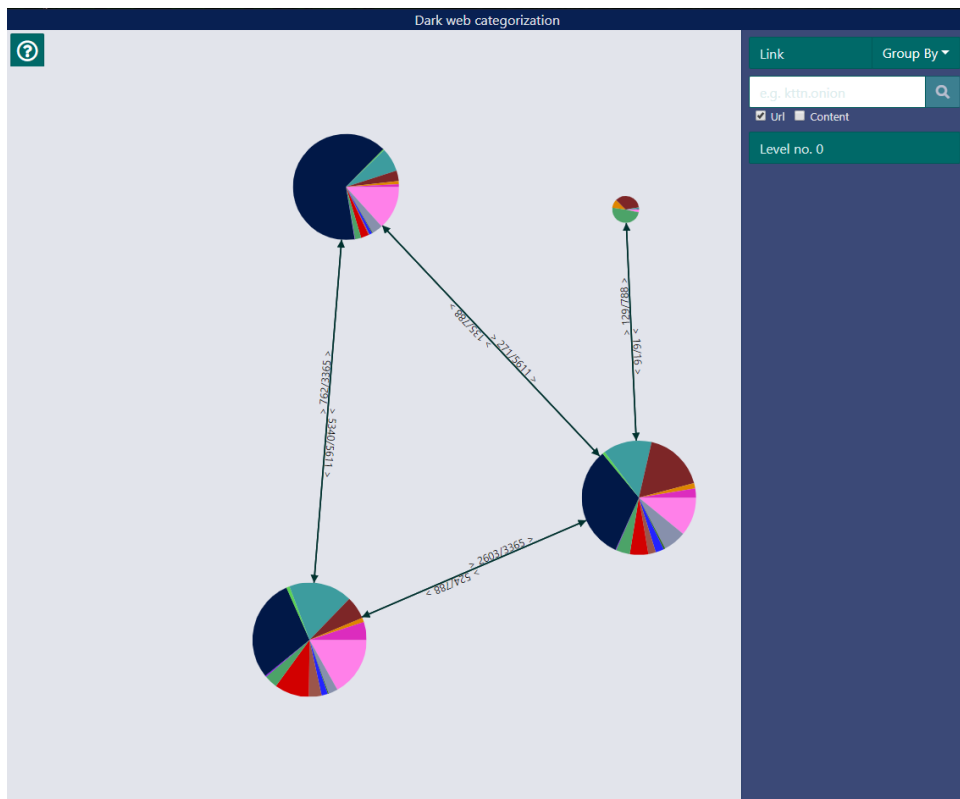


Figure 5.1: The view after the application has loaded.



Figure 5.2: The DD for the selection of the grouping-mode.

tors of the *pie chart* represent the categories of the pages belonging into the community. This is portrayed in Figure5.4. It was difficult to distinct between a small community of only one category and page nodes. A page node is therefore differentiated from a community



Figure 5.3: The input field with submit button for filtering.

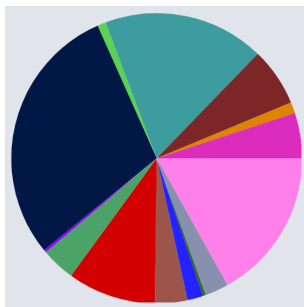


Figure 5.4: The representation of a community node. The individual sectors of the pie-chart illustrate the category-composition in the community.

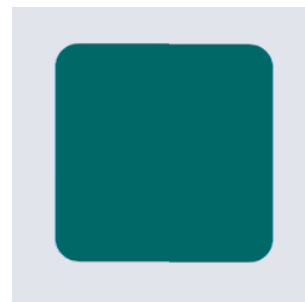


Figure 5.5: The representation of a page node. The colour of the square symbolizes the category of the page.

node by depicting the node as a square shaped symbol. The colour of the square corresponds to the category of the page. An example of a page is illustrated in Figure 5.5. It is possible for a level to depict communities and pages at once. The links between the nodes visualize the links between pages or communities.

After single-clicking a node additional information is exampled in the *sidebar*. The details vary depending on whether the node is representing a community or a single page. The details of an individual page are as follows:

Url which also serves as a unique identifier of the page.

Category of the page. Each page belongs to exactly one category.

Links to other pages displayed as a list of url addresses. There are up to ten links visible in the sidebar. The remaining links, if any, are

downloadable in a text file. Figure 5.7 contains a sidebar view with page details.

The details of a community consist of grouped information of its members and include the following:

Category composition which is aggregated from the categories of all the pages of the community. Each category is represented by its name and the percentage of its relevance in the community.

Page url addresses (urls) of members belonging into the community. There are up to ten urls visible in the sidebar. The remaining urls, if any, are downloadable in a text file.

Urls count represents the number of all the pages belonging into the community.

Figure 5.7 contains a sidebar view with community details.

In case of the need of further information a link, also present in the *sidebar*, can be clicked. If clicked, a *pop-up window* with detail-options is displayed. Details may include the *title*, *category*, *links* and *page-content*, depending on the user's selection. *Urls* of the pages are present by default. The window can be seen in Figure 5.8. After selecting the needed options and clicking the *download button*, a *text file* with the desired information is downloaded. The page or community-members with their details are depicted in JSON format. This functionality was required for the scenario of the user needing to download all available data about members of a specific community.

A graph node representing a community can be double clicked. After doing so, a new graph is shown. The data of this graph consists of the members of the clicked community. We call this process *zooming*. In case the parent community contains too many sub-communities, it is displayed as a single community-node. The zooming-in or -out of communities adjusts the *zoom-level*. This level is represented by a number and is visible below the *node-filter*. If the current zoom level is more than zero, i.e. at least one community-node was double clicked, a button for zooming out appears next to the *level indicator*. It is shown in Figure 5.9.

If further zooming is not possible, the user reached the maximum level. Each community may have a different maximum level, depending on the number of its pages and its structure.

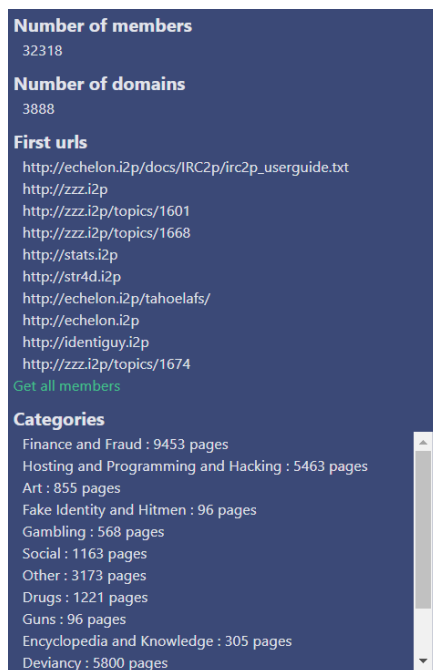


Figure 5.6: The sidebar with details of the selected community.

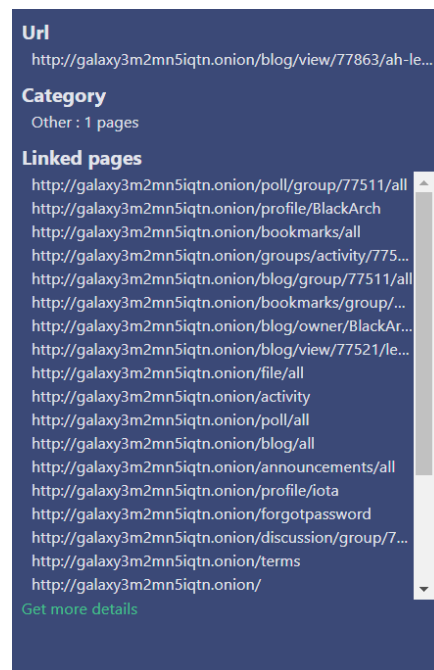


Figure 5.7: The sidebar with details of the selected page.

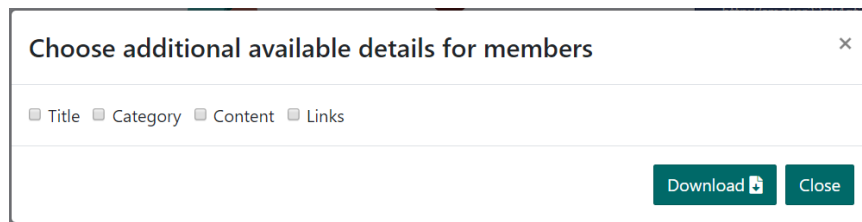


Figure 5.8: The pop-up window with detail-options for selection. These options dictate which details will be included in the downloaded text file.



Figure 5.9: The level indicator with the zoom-out button. After the zoom-out button is clicked, the user is shown the communities of the previous level.

5.3.2 Technology overview

JavaScript [36] (JS) is the most favoured programming language used for creating web applications [46]. It is an interpreted language supported by all modern browsers. It is open-source and as such disposes of a considerable community with convenient documentation. JS is not strongly typed and the code might therefore be complicated to read or navigate. For this reason the FE was written in *TypeScript* (TS) [35] which is a superset of JS with the advantage of being typed. There is a significant number of tools and libraries for implementing user interfaces (UI) in a clean and timely manner created for both JS and TS. One of such tools is the framework *React.js* [27] (React). React is one of the most favoured JS frameworks [28]. The advantages of using React are readable code and improved performance by managing the re-rendering of page elements.

To achieve a satisfying UX the app needed to be interactive and obtain new or modified data frequently. Repeated requests to the BE would mean longer wait time for the user. However, a proper mechanism for data-storing would present a convenient solution to this issue and make the requests unnecessary. A JS library which handles

the app state and works well with TS and React is called *Redux.js* [3] (Redux). Redux is a single store approach. This ensures easy hydration⁵. Redux also provides a custom set of TS typings and provides the developers with easy to use debugging tools. Another advantage of this library is the documentation.

The visualization of the web graph alone was realized using the *react-d3-graph* library [12] (RD3). RD3 is an implementation of the library D3.js [8] made more convenient for the use with React.js.

5.3.3 Implementation

The FE project consists of three folders and several configuration files. The folder `node_modules` contains imported libraries including *React.js*, *Redux* or *d3*. The next folder named `public` encloses a *.ico* file⁶ and a *html* file which is the default entry point when the application is started. The last folder `src` contains the source code itself.

As previously mentioned, the FE is written in TS which has the advantage of readability and easy navigation. There are, however, also disadvantages. One of them is the need of a TS file with the types (typing) for every used library. Typings for popular libraries are often downloadable as modules. If a library has no ready-to-download typings own ones need to be written. In our case the typings for the library *react-d3-graph* were custom made. They can be found in the folder `@types/react-d3-graph`. The file `common.d.ts` holds types used heavily across the application, e.g. *Action*. Types in this file are available without importing them to all files in the project.

Objects passed between functions also need to be typed. Those models are stored in the folder `models`. Each file contains one server-model and one client-model. The conversion between these models is conducted in specific helper functions. The advantage of this approach is the independence of client-models from the BE models.

The visual aspect is implemented using Less [42] which is a language extending CSS with improvements such as the possibility of using variables. The Less classes are divided into files depending on

5. The process of an object being provided with information

6. A picture with the dimensions 16x16 pixels used by the browser to represent the web page or application. It is usually displayed in the tab in which the application is opened.

the element they are meant to modify. These files were placed into the folder `styles`.

The remaining folders each represent a different part of the UI. The structure of their sub-folders is similar. Therefore it is sufficient to describe them as a whole. Folders named `utils` contain files with helper functions such as converters between server and client models. `Constants` contains folders with string constants or simple functions which return a string depending on the input. The rest of the folders represent some part of the Redux framework.

The most basic files which only include string constants are situated in the folders named `actionTypes`. These are utilised as action types in actions. An action is a simple objects containing a type and an optional payload. Actions themselves are returned by action creators (AC). AC are functions returning an action and can be found in folders called `actions`. They can be as simple as those present in the file `nodesActionCreators.ts`. But they can be more complicated such as the AC `fetchNodes.ts` and dispatch multiple simple ACs. The purpose of an AC is to be injected into reducers, i.e. dispatch them.

`fetchNodes` and the folder it is placed in share the same name. For easier testing purposes the main logic of this AC is put into a function which receives the simple ACs as dependencies. When this AC is called it first dispatches a simple AC to indicate the fetching has begun. After that an identifier (`id`) is created. This `id` is later used to create an error object in case of failure. Next, the fetching itself begins. The fetching in `fetchNodes` is realized with the library *isomorphic-fetch*. The `fetch` function of this library expects the first argument to be the url address of the resource. The second argument is an object describing further details of the request and is optional. Such an object may contain the request method, headers or the payload. If the request does not result in error the response status is checked. After the fetching is complete a success AC with the acquired response is dispatched. If an error is caught during the fetching a failure AC is dispatched. The payload of this AC is an error-object with the `id` and error message if any.

The dispatching of actions enables the changing of the state via reducers situated in the `reducers` folders. The state is a single im-

mutable⁷ object and is used in the whole application. A reducer is a pure function⁸ receiving the current state and the dispatched action as its arguments. It then returns the newly computed state. A reducer creates a new state only if the type of the given action is recognized. If not, the previous state is returned unmodified. The state object received or returned by the reducer does not need to be the entire state (app-state). A reducer may be responsible for just a part of the app-state. However, the root reducer is responsible for the whole app-state.

The folders components contain files with React components. They define the skeleton of the UI with the specified behaviour. The folders containers hold files with React containers. A container is a file with access to the app-state. It is responsible for passing data to components.

7. The object cannot be adjusted directly. Instead, a new modified object is returned and the original one stays unmodified.

8. The return value of a pure function is only dependent on its input values. A pure function has no side effects.

6 Conclusion

6.1 Evaluation

6.2 Future work

The Leiden algorithm (LeA) might be used in the future instead of LA. LeA is another algorithm for community detection on large graphs. The paper in which LeA is described claims LA has a major flaw which is eliminated in LeA [43]. It needs to be taken into consideration if it becomes adopted widely.

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