The Missing Path: Diagnosing Incompleteness in Linked Data

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Abstract—The Semantic Web is an interoperable ecosystem where data producers, such as libraries, public institutions, communities, and companies, publish and link heterogeneous resources. To support this heterogeneity, its format, RDF, allows to describe collections of items sharing some attributes but not necessarily all of them. This flexible framework leads to incompleteness and inconsistencies in information representation, which in turn leads to unreliable query results. In order to make their data reliable and usable, Linked Data producers need to provide the best level of completeness. We propose a novel visualization tool “The Missing Path” to support data producers in diagnosing incompleteness in their data. It relies on dimensional reduction techniques to create a map of RDF entities based on missing paths, revealing clusters of entities missing the same paths. The novelty of our work consists in describing the entities of interest as vectors of aggregated RDF paths of a fixed length. We show that identifying groups of items sharing a similar structure helps users find the cause of incompleteness for entire groups and allows them to decide if and how it has to be resolved. We describe our iterative design process and evaluation with Wikidata contributors.

Index Terms—Linked Data, Semantic Web, Incompleteness, Wikidata

1 INTRODUCTION

As the web is evolving from a Web of Documents to a Web of Data — also known as Semantic Web and Linked Data — the issue of completeness becomes a critical concern regarding its quality [8][16]. We present an approach relying on multidimensional projection combined with statistical summaries to help Linked Data producers diagnose incompleteness in their data.

Linked Data are used by communities, institutions, research laboratories, and companies to combine and share data, and let them be queried jointly. It becomes possible to get, with a unique query, answers...
that would otherwise have requested access to several databases, each with its own technical idiosyncrasies and data model. But merging heterogeneous data into a common model often results in incomplete attributes, and incomplete data produce unreliable query results. To make data consumers trust and use their data, data producers need to ensure that their data are as complete as possible. For example, if the general chair of a conference wanted to query Linked Data sources to draw a map of the affiliation locations of all authors having published in a visualisation conference in the last 10 years, she would not want to miss important authors due to incomplete data. To curate their data, data producers need to diagnose the reasons for incompleteness. In that example, the reason for missing points on the map could be manifold. Some authors might have no affiliation because they are independent, or the affiliation is missing in the database. Some affiliation might be described as located in a city, others in a country, others as both or none. Some locations might have geo-coordinates encoded under different concurrent property names using different datatypes, other geo-shapes, and other no coordinates at all. The difficulty for producers is to identify when an information is missing ‘for good reasons’, or when it should be extracted from an external source, or fixed manually. There are tools and methods to assess the rate of completeness of a property, but they give a flat list of all entities to fix, mixing entities for which the cause of the lack might be very diverse. Inspecting and editing entities one by one is very long and tedious and does not reveal causes that might be shared by groups of entities.

We present The Missing Path, a tool to identify missing information related to groups of entities, to inspect them for diagnosing the reason why they are missing, and to export instructions and information to support actions to remedy their absence. Our visualisation tool is based on the UMAP [13] dimensional reduction techniques to create a 2D map of the entities based on missing attributes. The map reveals clusters of entities with similar missing structures. To our knowledge, the idea of describing high-dimensional items by feature they miss instead of feature they do possess is novel. Our tool allows users to inspect these clusters to diagnose what is missing. We show that identifying groups of items sharing a similar structure helps users find the cause of incompleteness for entire groups and allows them to decide if and how it has to be resolved. In summary, we contribute:

- A method to transform a set of entities into high-dimensional vectors, based on paths missing for each entity,
- A visualization tool called The Missing Path to explore the entities based on the vector representation combined with statistical summaries,
- A description of the iterative design process we used to improve and validate the utility of our approach while working with nine Wikidata contributors, following a methodology inspired by the “Multi-dimensional In-Depth Long-term Case Studies” (MILCS) of Shneiderman & Plaisant [26].

The Missing Path is available as open source at: https://github.com/midstand/the-missing-path and can be run online at: https://missingpath.hr.fr

2 LINKED DATA AND WIKIDATA

Linked Data are graph data. They are made of low level statements that can be chained to answer complex queries, possibly over several datasets. Statements are made of entities (nodes) and properties (links); authors, universities, cities, countries are entities; links describing that an author is affiliated to a university, or that a university is situated in a city are properties. Author A is affiliated to University B is a statement. A chain of statements is named a path. In previous work, we showed that path-based summaries for sets of entities are meaningful objects for data producers, especially in terms of completeness [5]. In other words, they need to know the percentage of authors with an affiliation (path of depth 1), but also the percentage of authors with an affiliation which has a location (path of depth 2). Linked Data’s digital format is called RDF, and access to Linked Datasets relies most of the time on SPARQL endpoints, equivalent to SQL endpoints for querying standard databases.

Wikidata is an example of a collaboratively created and edited Linked Dataset. It was founded in 2013 to overcome the limits implied by Wikipedia being full text [30]. As stated on the website, it “acts as central storage for the structured data of its Wikimedia sister projects including Wikipedia, Wikivoyage, Wiktionary, Wikisource, and others.” Having data stored in a Linked Data base allows to manage them in an interoperable and automatable format. Like many other Linked Datasets, it is made of heterogeneous data imported from various sources. What is less common, however, is that, once imported, the data are modified directly in Linked Data format. Contributors can have various roles [29], and the workflows and tasks of contributors who edit the data are very diverse [17]. Contributors can create bots (automated processes), perform manual editions through the standard user interface, or use one of the many tools available in the ecosystem. Typical workflows rely on custom queries to identify items that need to be fixed [31]. Then tools like QuickStatements, providing a simple syntax to make edits, can be combined with OpenRefine [20] in semi-automated workflows to update the list of entities. Such workflows are documented on users’ pages or on project pages.

3 RELATED WORK

We discuss the problem of incompleteness in Linked Data, the use of dimensionality reduction (also called multidimensional projection) for Linked Data, and the task of diagnosing issues in data cleaning activities.

3.1 Incompleteness

Though the definition of Linked Data quality can have many acceptations, most work on the topic mention the problem of completeness [3, 16, 24]. In the context of data consumption, completeness can be evaluated at retrieval time [23], as an indicator to help interpret the results of a query even when they are not complete. In the context of data curation, completeness is assessed by running full analyses of the dataset, with the goal to improve it. The completeness of a property can be computed for all entities in the dataset [1], but knowing that, for instance, n% of all entities miss a rdf:type [12], allowing to know that, for instance, n% of the Persons or of the Documents do not have a label. PROWD [32] even defines more elaborate patterns for the set of interest. In previous work [5], we also considered completeness of chains of properties, thus automatically simulating contexts of retrieval, but on a systematical basis, offering advanced filtering to deal with the many possibilities. Integraality, a completeness tool for Wikidata, offers to make groups according the values of one selected property [11]. While narrowing the context allows to take more precise actions, it multiplies the number of cases to consider. And it is hard to know which subset will be a consistent group, requiring a single action. Most of the time, some entities can be fixed, because the information exists and is missing, while some other cannot, the property being not relevant to them.

Our approach looks for an automatic way to identify consistent clusters with a limited number of entities in order to provide an information both understandable and usable for data producers.

3.2 Dimensional Reduction Techniques

Dimensional reduction techniques have many applications in general, mostly in visualization [19]. These techniques take a list of items described by vectors in high-dimensions (HD), and project them in the 2D plane, trying to respect the high-dimensional distances in 2D: items close in HD are located close by in 2D, and items farther away in HD are located farther away in 2D. Dimensional reduction has been used in Linked Data to analyze the content of datasets [33], perform learning [10], estimate the similarity of items [9], support recommendations [7, 18], and evaluate the distance between ontologies [4]. Node2Vec [6] focuses on exploring neighbourhood in graphs and was also applied for item recommendation [27]. Paulheim [23] advocates using vectors that preserve semantic and are interpretable.
Visualisation tools can support data curation tasks. As written by The Missing Path supports the identification of groups of items sharing a similar structure in order to inspect them, identify the causes of potential incompleteness, and decide if and how it shall be resolved, using the user interface shown in Fig. 1.

A dissimilarity that takes into account the indices of the Boolean values. This function computes the dissimilarity between Boolean vectors. The idea is to find the path that will enable to divide the datasets in parts that are under the quota of maximum results returned by a SPARQL endpoint.

When the path is selected, for each value, we query all the entities having this value at the end of this path and merge the results in a list. We then query all the entities not described by this path, to have a complete list of all the entities. With this complete list of entities, we send one query per entity and per depth to retrieve all the values, datatypes, and languages at the end of each path.

To give an order of idea, for the dataset D1 with 4,567 entities described by 401 paths of depth 1, the number of queries for the analysis would be around 5,300.

4.2 2D map of entities

The map is laid out on the left part of the screen (Fig. 3, left). It allows to identify clusters and outliers, and additionally gives a visual overview of the dataset heterogeneity in terms of completeness. Each point represents an entity, which coordinates are computed as follows.

4.1 Initial analysis

Prior to visualization and exploration, an analysis is done on data loaded through an API taking as parameters a SPARQL endpoint URL, a criteria to identify the entities to load, and a maximum depth of property paths to load and analyse. The criteria for the collection can be expressed in SPARQL, ranging from simply matching a type or a class, to an arbitrary complex specification. The analysis is then made in several steps:

- We retrieve all the path patterns up to the max depth, computing their completeness rate along the way.
- Starting with the most complete path, we look for the first path for which there are less than x unique values with a count higher than y, x and y can be set as optional parameters. The idea is to find the path that will enable to divide the datasets in parts that are under the quota of maximum results returned by a SPARQL endpoint.
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4.3 Data cleaning visualisation tools

Visualisation tools can support data curation tasks. As written by Kandel et al. [14]: “Determining what constitutes an error is context-dependent and so requires human judgment. [...] visualization tools can facilitate this process”. Indeed, visual interfaces can be used to perform cleaning actions more easily than scripting languages by graphically specifying changes [13]. The Wrangler tool [14] has shown the benefit of visualization for cleaning-up traditional database contents, and has led to the creation of the commercial product Trifacta [27]. While traditional databases and linked data share similar problems related to values consistency, the structural issues raised by linked data are harder because the Semantic Web is not closed like a database and integrity cannot be controlled as tightly. Furthermore, an ontology is more flexible and less constrained than a regular database schema, leading to more situations of undetected incompleteness, although they can also exist in regular databases.

4. THE MISSING PATH

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Fig. 2. Datasets D1, D2, D3, D4 and D6 (see Table 2). The number of clusters, their size and distribution provide a visual footprint of the shape of a dataset, relative to the set of paths selected to produce the map (highlighted in pink on the right side of each thumbnail).

Fig. 3. Datasets D1, D2, D3, D4 and D6 (see Table 2). Histogram on the frontpage: the steepness of the curve gives a visual footprint of the completeness of the most represented paths in the dataset. Scrolling down allows to see all paths. D1 is our demo dataset, it was not curated as a wikiproject, so very few paths are complete, and there is a sharp decrease with a long tail of little represented paths. D2 is maintained by an active team of 10 contributors, a large number of paths is complete. D3 is more balanced, it is a catalog of films curated before it was imported. D4 has been created and curated over a short time mostly by one contributor. D6 is a starting project mixing sets of data which were curated separately.

Among the large number of dimensionality reduction techniques available with different properties [19], we use UMAP [15] which is relatively fast and has excellent properties related to clustering.

4.3.1 Data cleaning overview

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giving the shape of a dataset relative to the set of properties selected to produce the map. Users can modify the list of paths taken into account to build the vector with the projection button \(\text{\textcircled{A}}\) and recompute the map with a maximum of 50 paths considered, i.e., the underlying vectors are limited to 50 dimensions. Our Python API, based on UMAP-learn \(\text{[23]}\), takes a few to 20 seconds to recompute the map depending on the size of the dataset and on the datasets listed in Table 2.

While the position of the entities is based on missing information, their color is linked to the content of present information. Paths for which the summary of values has more than one value are candidates for color coding. By default, the most covered candidate path is used. For instance, the default for dataset D1 is \(\text{wd:t:P31}\) instance of, its summary is composed of two values: \(\text{wd:Q1004 Comics}\) and the aggregate Other. Entities are colored in blue for the former, in green for the latter, and with a gradient if they hold several values. Users can select another path to color the entities with the color button \(\text{\textcircled{B}}\), through the color button in the top bar. When a subset of entities is selected, the selected entities are colored in pink and others in black so users can keep track on the map of entities that are selected.

4.3 Paths histogram for the collection

Next to the map giving a visual overview of the entities, the histograms (Fig. 1, right) focus on and provide details on the paths. They show all paths used for the set, ordered by completeness. This gives another visual signature of the completeness, showing at first glimpse the quantity of paths fully complete. Fig. 3 shows paths summaries for the datasets displayed in Fig. 2. The map and the histogram are aligned and coordinated.

Each row represents a path, the length of the gray bar is mapped to its percentage of completeness. Clicking on a path opens it, showing a summary as detailed in Sect. 4.5.

Paths labels are displayed on the left of each row. By default, they appear when users hover a path, when they hover a predefined zone on the map, as in Fig. 5 or when a path is open. Labels can be toggled on permanently as in Fig. 1 with the labels button \(\text{\textcircled{A}}\).

4.4 Paths histogram for a selection

To make sense of a subset of entities, users need to identify its distinctive features, what defines it in comparison to the whole set of entities. Our interface shows the summary of the whole set and selected subset side by side. The visual overview can be compared at a glance. For instance in Fig. 1 comparing the two histograms show that the subset is very homogeneous: although it misses important information (no grey bar in the right column), the 16 paths that are described are fully complete (full grey bar in the right column), while only 8 of them are fully complete for the full set. Paths that are missing in the subset are highlighted in yellow, to make it clear that this is what the tool is detecting. To help users explore the subsets, the tool always draws their attention on which paths to inspect in order to understand the specificity of a selection (how it differs from the full set), by coloring them in pink.

To compute statistically significant differences, we use the distributions of the values at the end of a path as displayed in the summaries, including the ‘other’ aggregate, for the subset and for the full set. We normalize them and perform a Kolmogorov-Smirnov test, using the scipy.stats.ks_2samp function from the SciPy library \(\text{[25]}\). We repeat this operation with the summaries of the datatypes and Languages. If there appears to be a significant difference (p-value < 0.1) in either the values, the datatypes or the languages, the path is colored in pink.

4.5 Detailed summary for an open path

Each path can be opened to be inspected, comparing the statistics for the whole set and the subset, as detailed in Fig. 4. The summary is based on unique values. All values with a number of occurrences lower than 5% of the total number of values are merged in an ‘other’ bucket. When open, a path displays the distribution of the values at its end, as well as of their datatypes and languages. The graphical elements can also be used to select entities by clicking on them, as displayed in Fig. 6.

4.6 Creating, inspecting, and refining a selection

Selections are made of conditions — i.e., selection criteria in the database sense, the conditions being combined by a conjunction (an ‘and’ operator) — coming from the map, the histograms, and the summaries. Hovering the map highlights predefined zones (Fig. 5). The + button in the center of the zone allows adding the zone as a condition. Clicking on the map switches from region selection mode to a lasso mode to allow selecting zones that are not predefined. Graphical elements in the histograms and the summaries can be added to and removed from the selection. The selection control bar in Fig. 7 supports users in understanding what happens when they add a condition, validating the selection, seeing the list of entities selected and clearing the selection.

a) Toggle list of conditions. Each condition is represented by a checked box. When at least one condition has been added, (a) and (b) become pink, to indicate that the selection can be queried. Clicking (a) toggles the list of conditions, as shown in Fig. 8. The query is written in pseudo code, and can be modified: conditions can be removed from the list or toggled to their inverse condition, and the scope of the query can be toggled from ‘whole set’ to ‘current selection’.

b) Inspect selection. The selection is defined by the combination of conditions. When the inspect button is clicked, the query is sent to our Python API. The new list of entities in the selection is retrieved, and Fig. 7 is updated first. Then the summary for the entities is computed, and displayed under the selection control bar (Fig. 7).

c) Toggle list of selected entities. Clicking this button toggles the list in Fig. 9. Entities can be removed from the list. Clicking the ‘Update selection’ button at the bottom updates the paths summary for the selection.

d) Export selection. This button triggers the download of 3 csv files that can be used to keep track of the query: condition.csv contains the list of conditions used to get the selection, selection.csv contains the list of entities in the selection (URI + label) and summary.csv contains the summaries for the subset and full set.

e) Clear selection. Clears the current selection and its summary.

5 SCENARIO OF USE

We designed our tool to help users see what is missing in their dataset and make sense of it. Let us describe the interface from the point of view of a contributor. Alice, who wants to curate Wikidata entities of class Q1004 Comics, describing comic books. She opens the tool, sees the map of entities in Fig. 1. As she moves the mouse, yellow zones delimiting clusters of entities appear, and paths that are missing for the zone are highlighted in yellow. Her attention gets caught by a small cluster, for which many pieces of information that are important to describe comics are missing, such as P407 language of work or name, P495 country of origin, P123 publisher, P577 publication date and P136 genre. She decides to inspect this group in more details: she adds this zone to the conditions for selection using the + symbol and validates the selection with the magnifier button. The selection bar announces a total of 20 entities and the summary appears under it. Some of the paths are colored in pink, indicating that their summary for the selection might be significantly different from the full set. Alice hovers the paths highlighted in pink to see their labels and starts by opening rdfs:label. She notices that there are 20 distinct labels, all of them in French. Then, she inspects schema:description. Its summary reveals that a single value is repeated 20 times: “stripverhaal van Robbedoes en Kwabernoot” (“comic strip Spirou & Fantasio” in Dutch, a popular comic strip originally written in French). The 20 descriptions are in Dutch. She inspects schema:dateModified and sees that 20 entities were last modified on the same day. The P179 part of the series property indicates that 20 are part of the same series. Alice finds that those entities appear to have very similar needs. According to her quality standards, labels and descriptions should be available in similar languages (as opposed to labels being in French only and descriptions in Dutch only). From what
Fig. 4. Summary of values for a path: the whole set is presented on the left, in comparison to the selection on the right. The summary details values representing more than 5% of the total, and aggregates others: for the whole set, only 3 of the 54 unique values are well represented enough to be detailed; the 51 remaining are merged in the ‘other’ rectangle, represented with a dotted texture. Hovering a rectangle displays the label and count of the value it represents. Each value, including the aggregate, can be clicked to be added as a condition for a selection.

Fig. 5. Hovering a predefined zone on the map highlights it in yellow, and gives access to the + button, to use it as a condition for a selection. It also displays and highlights in yellow the names of the paths missing for the entities in this zone.

Fig. 6. The user can click on an element of the summary to add it to the selection (top). Once added, it becomes dark pink, and clicking again will remove it (bottom).

Fig. 7. The selection bar contains controls to inspect and refine the conditions for a selection and its result. The number of checkboxes in (a) shows how many conditions are pending (here, there is one). Clicking on (a) displays the query in pseudo code (see Fig. 8). Clicking on (b) retrieves the list of entities matching the conditions and their summary. When a selection has been retrieved, (c) indicates the number of the list of entities in the selection, clicking on it displays the list in (d) enables to export the selection, and (e) to clear it.

Fig. 8. Conditions for a selection are expressed in pseudo code, to let users understand how the tool retrieves entities. They can refine them by toggling the elements that are underlined: ‘having’ can be switched to ‘not having’, resulting in the inverse condition, and the whole set to ‘the current selection’.

Fig. 9. List of entities in the current selection. The label is in the preferred language when available. Clicking on the URI opens it in a new window.
she knows, Spirou and Fantasio comics are known enough that it should be easy to find the author, language, publisher, and publication date. It is likely that the information can be found from the same sources for at least some of the albums. If she is lucky, one of the sources might even be the URI of the series that all entities belong to. It definitely looks like she will be able to save time by fixing those entities at once. Now that she has identified that this cluster needs a certain type of action, she would like to make sure that she will check all the entities belonging to the series, even if they miss slightly different information and are not in the initial cluster. In order to do so, she clicks on the value shared by 20 entities to add it to conditions for selection. She then opens the conditions and reads the query: “SELECT entities HAVING the path :P179 among the current selection”. She toggles the scope definition from “current selection” to “full set” and validates the selection with the magnifier button. The selection bar now announces a total of 35 entities, all part of the “Spirou and Fantasio” series. She clicks the export button and downloads the files describing this group for fixing it later.

She then hovers the next zone. The paths highlighted in yellow indicate that entities in this zone also miss similar important information, the main difference being that they have a skos:altLabel, but no attribute wikibase:timeStamp. Note that even if the properties discriminating two neighbour zones do not appear to be meaningful properties, this structural approach helps detect coherent subsets. In order to inspect the new cluster, she adds the zone to conditions for selection using the + symbol, and validates the selection with the magnifier button. The new selection replaces the previous one. The selection bar announces 127 entities. 100% of them have a P179 part of the series, so she opens the summary for this path that is now colored in pink, hoping that she can detect interesting groups. The summary announces 25 unique values, and 3 values stand out because they are well represented. Those values are URIs and she hovers them to dereference them in the URI bar above the map; she sees the corresponding labels: “Sammy” (25), “Bobo” (21), and “Natacha” (14). The rest of values are merged in an ‘other’ group (67). She clicks on the first value to add it to conditions for selection, and validates the selection with the magnifier button. She exports this selection. She repeats the same actions with the two other subgroups. Now she can refer to the csv files she has exported to fix each of those 3 groups.

This exploratory approach enables her to quickly detect small groups that are coherent and thus easy to fix. Let’s now see how she can use the tool starting from the summary of paths. She clears the current selection, and clicks on the eye pictogram to display all path labels. She figures out at first glance, from the length of the grey bars in the histogram, that less than half of the entities have an author. She decides to make this a priority to fix. She opens the author summary, which confirms a completeness of 42 percent, and she clicks on the bar to add it to conditions for selection. She opens conditions to read the query: “SELECT entities HAVING the path :P50 among the whole set”. She toggles the condition from ‘HAVING’ to ‘NOT HAVING’ and validates the magnifier button. The selection bar displays: 1929 entities for the selection. The summaries for paths are mainly composed of ‘other’ values. Wondering how to deal with this huge list, she considers refining the selection by combining conditions. She sees the property P3589 Grand Comics Database Series ID in the list. She decides to inspect entities having no author but such an identifier, which might mean that the information about the author will be accessible. The result of the query is indeed more manageable: 49 entities. She exports the selection, the workflow should be easy since the source is the same and it might even be automatable. There are still 1880 entities without authors. She tries another strategy, looking for the series for the selection. The summaries for paths are mainly "whole set". She toggles the condition from ‘HAVING’ to ‘NOT HAVING’ and validates the magnifier button. The selection bar now announces a total of 35 entities, all part of the “Spirou and Fantasio” series. She clicks the export button and downloads the files describing this group for fixing it later.

After going through the informed consent form and collecting demographic information, the interview was guided by the following question: 1. Which Wikidata projects do you contribute to? 2. How do you decide which data you will update in priority? 3. Did it ever happen that you wanted to contribute and didn’t know where to start? 4. Can you tell me about the last item you edited? 5. Do you propose items for others to update? How do you select them? Then we gave a quick overview of the tool and asked participants if they would be interested in visualising a dataset with it.

We communicated with participants by email (and a mix of twitter direct messages and email for one of them). We conducted an additional video interview with four of them.
6.4 Data collection and analysis

We recorded the first interview. For the second and third interview, we without giving a reason.

We received a total of 111 emails or Twitter direct messages, with an average of 2 messages per participant.

Table 2. Data collections visualised in the tool for the evaluation, available in 'anonymous'. During the interviews, we regularly used the tool on other participants having used the tool on another computer. We, other 408 actions logged as 'anonymous' can be attributed to him or browser privacy settings interfered with our log collection mechanism, so this is not accounted either. Over 4 months we conducted a total of 22 interviews, without planning that this would be necessary, so this is not accounted either. Over 4 months we conducted a total of 22 interviews, with an average of 12.33 messages per participant (median 11). We extracted a total of 61 selectColor (55). P1 had no logs at all — his web browser privacy settings interfered with our log collection mechanism, although he reported using the tool. We don't know which part of the other 408 actions logged as 'anonymous' can be attributed to him or to other participants having used the tool on another computer. We, as authors, had a separate identifier and our actions were not included in 'anonymous'.

During the interviews, we regularly used the tool on behalf of the participants, while they were guiding us through sharing screens. We had not planned that this would be necessary, so this is not accounted either. Over 4 months we conducted a total of 22 interviews, with an average of 2.44 interviews per participants (median 3), and we received a total of 111 emails or Twitter direct messages, with an average of 12.33 messages per participant (median 11). We extracted a total of 78 issues. Only three were filed directly by a participant; we accounted either. Over 4 months we conducted a total of 22 interviews, without giving a reason. The Illuminati dataset worked particularly well in this respect. As P7 explained: “First thing is that we have different items: some exist, others are lost (mainly in the 1944/45 bombing of archives), but we know what they contained (because their textual content was published already in 1787). It is clear that lost items have different P-statements (as we will no be able to speak about paper formats, or give shelf marks on things that are now ashes). We have, secondly, two sources of data: Some are part of recent work done by our team in Gotha since 2013 (with a focus on Schwedenkiste Vols. 12–14.) Other data we have inherited from a project that created an Access-database between 1998 and 2007. Their database was not that versatile, they had just five columns — but I am extremely happy that they allowed us to merge their data. This explains some of the differences. Our research — of the two teams from 1998 to 2020 — has focused on different materials (the Halle team did letters, we did documents on every day work of Military Churches — Illuminati lodges), not the same materials but with an overlap while we also collectively ignored other topics (and files). This is briefly the history behind the data — a research of 22 years. I still wonder how this history will resurface in your picture; it will take me a while to understand your work but it looks bright — the use case we created is extremely realistic, close to the research proposal which I will have to hand in next year.

P9 was planning to import and manage his own catalog of movies in Wikidata. Since he was still at a planning step, we selected the BFI movie database, which was about similar in size and type of information to what his own data would later be. P9 had no time to use the interface on his own, so during his third interview, one of the authors used the interface guided by him through a shared screen, in line with the MILCS method. He started by hovering the zones. He figured out there was a cluster of 16 entities without titles. He inspected the summary and found out those entities all had a label, which meant the titles would be very easy to fix. A double check through the histogram showed that there were 125 entities with no title but a label. Another cluster had no directors. This led him to use the histogram to look for all entities having no directors, which amounted to 1380 entities. Looking on the map he could see they were spread into about 20 different clusters, depending on what else was missing. Hovering the clusters then gave him an overview of the possible combination of missing attributes. He inspected two of them in more details. Trying to imagine how he could use the tool later with his own data, he said he would probably want to configure the projection with the paths he wished to achieve a full coverage for, and then work on the data until they end-up in one big cluster.

6.5 Results

We analyse the results with regards to the iterative design process and the validation of the approach.

We name our participants P1 to P9, according to their unique identifier. We logged a total of 298 actions attributed to our participants, distributed as follows: add condition (46), remove from condition (20), retrieve subset (74), compute projection (21), clear selection (21), load collection (61) selectColor (55). P1 had no logs at all — his web browser privacy settings interfered with our log collection mechanism, although he reported using the tool. We don't know which part of the other 408 actions logged as ‘anonymous’ can be attributed to him or to other participants having used the tool on another computer. We, as authors, had a separate identifier and our actions were not included in ‘anonymous’. The Illuminati dataset worked particularly well in this respect. As P7 explained: “First thing is that we have different items: some exist, others are lost (mainly in the 1944/45 bombing of archives), but we know what they contained (because their textual content was published already in 1787). It is clear that lost items have different P-statements (as we will no be able to speak about paper formats, or give shelf marks on things that are now ashes). We have, secondly, two sources of data: Some are part of recent work done by our team in Gotha since 2013 (with a focus on Schwedenkiste Vols. 12–14.) Other data we have inherited from a project that created an Access-database between 1998 and 2007. Their database was not that versatile, they had just five columns — but I am extremely happy that they allowed us to merge their data. This explains some of the differences. Our research — of the two teams from 1998 to 2020 — has focused on different materials (the Halle team did letters, we did documents on every day work of Military Churches — Illuminati lodges), not the same materials but with an overlap while we also collectively ignored other topics (and files). This is briefly the history behind the data — a research of 22 years. I still wonder how this history will resurface in your picture; it will take me a while to understand your work but it looks bright — the use case we created is extremely realistic, close to the research proposal which I will have to hand in next year.

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Volunteers had already spent a large amount of time, filling holes in their data and somehow erasing part of the history that would make the exploration starting from the map most useful. They became more familiar with the tool in different ways. P1 still relied on the map to spot simple problems. He explained he was a programmer, used to visualisations, and that he thought of his data in terms of what was missing so the map was intuitive for him: “I see it as a way to start the exploration, see the outlines”. He had already spent a lot of time curating this set of data and knew them well. However, there are more than 14,000 entities in the set, and he worked more specifically on those related to the French Fifth Republic, so the map was useful to spot problems he was not aware of. For instance, the first cluster he inspected during the second interview was a set of 47 deputies having no place of birth. He commented: “There should not be entities without place of birth. This group can easily be fixed, the information is available through the Sycomore French deputies database and they all have a Sycomore ID” (wdt:P Sycomore ID). During the third interview, another cluster showed entities (deputies) with no given name. He explained: “All deputies should have a given name. This can be fixed easily from the labels.” He thought that even if the focus might switch from the map to the histogram as you get to know your data better and they become more homogeneous, there can always be new stages when you incorporate new sets of entities and want to bring them to the same level of quality as the rest of the data, when the map could prove to be useful again.

P2 customized the map to remove from the paths vectors all the paths that were not of prior importance for him. This reduced the map to a few clusters that he found meaningful. “Now I am satisfied. This is the image I wanted, when all the irrelevant criteria that complexified the map have been removed.” Then he started his exploration from the histogram. He used the combination of conditions to find the list of all monuments qualified as churches — having wd:Q16976 church building as a value for wdt:P31 instance of — but with no identifier wdt:P3963 Clochers de France ID, specific to churches. He expressed the wish to see the entities highlighted on the map, a feature described in Sect. 4.2 that we added following his demand. While explaining that wdt:P18 image was not a relevant path for the projection in his opinion, because it was normal that some entities had no images, he exclaimed “I know what I am going to do this afternoon!” He had figured out he could select all the entities having no wdt:P18 image but a wdt:P373 Commons category, because if they have a commons identifier then he knew he could find an image. He added “I could have done the same with SPARQL but I would never have had the idea. The tool gave me the idea.”

Also starting from the histogram, P5 ignored the map. She checked paths names and sounded positively surprised by the completeness of the property wdt:P3450 sports season of league or competition “I did not think it was so complete”. Towards the end of the study, P7 wrote to us “All in all I feel we should really have your tool since one of our best participant has started to set statements in items where he feels they are insufficient.” Although it was not possible to include this participant in the study for time and technical reasons — security restrictions at work stopped him from connecting to the video conference, but we had a one hour interview. He was indeed performing a very similar work to our tool, adding a factgrid:prop/P17 Dataset complaint property with values indicating what information the items were missing. We used the tool to select the 146 entities of our dataset he had tagged so far, and we found interesting to see that the entities highlighted on the map formed distinct clusters (see Fig. 10). He estimated the time he spent to add such information to 2 to 4 minutes per entity. When the dataset contains 7,938 entities, using 3 minutes on average per entity, it would require 397 hours to complete the work. He explained that he would later retrieve with SPARQL subsets of items based both on what they were missing and what they had in common. Then he would contact historians to ask them if they could find the information he needed in their archive. For instance, when he found a group of persons for whom he had no information about the secret society they were a member of, but who obviously were linked because they had been described in the same document, he checked if there were other persons described in the document for whom the society would be known, in order to identify which archives might contain information. This workflow can be reproduced with our tool: starting from a cluster missing the information, the user can identify what the cluster has in common, refine the query to identify all the entity having this in common in the whole set, and find the values for the entities which do not miss information. Although this last step is possible in our tool, we had not identified it as useful for the diagnosis. In our use case, we used the extension of the query to the whole set as a double-check in order not to forget entities. This opens new perspectives, and implies that we might need to refine the export in order to keep track of steps, and be able to separate the cluster for which information is missing, and the larger step that helps find missing information.

6.5.2 Iterative design

Along this iterative process, participants suggested 32 new features, and reported 15 problems. We developed 20 of the new features, marked 3 as irrelevant in the context of our work, and kept 9 for future work. We solved 13 problems, marked one as an exception, and one for future work.

An interesting feature, suggested by P5, was the possibility to combine conditions to make a selection. The first version of the tool only allowed to inspect elements of the interface one by one. We realized that the possibility to refine selections with more flexibility, to filter out items from a group, or add other items with similar characteristics, was a great help improve the usability of the clusters. However, when we implemented this feature, we ended up with an interface that was too complicated. Several participants then complained that the tool was difficult to use. P2 reported being discouraged, partly because he had been sick, and partly because it was not obvious to him how to use the tool. P3 said “Lots of clicks, it’s not easy to understand how to use it”. He wrote to us “My feeling is that what you do is excellent BUT my brain has problem understanding the UI. I had the same feeling in the beginning when using the product OpenRefine: it took me some weeks to be friend with the product”. We decided to simplify the interaction and move the option to make inverse selection into the query editor, as written in the scenario. The interactions, as described in Sect. 4.6 is now manageable, albeit with some complexity due to the Linked Data semantics. In the end, this means we made two significant changes to the interaction model during the evaluation and we think this made it difficult for some users to get familiar with the tool.

P7 suggested to highlight the paths for which the summary appears to be significantly different in the subset than in the full set. In a first version, inspecting a cluster to understand its specificity necessitated to look at each path one by one, which was long and uneasy. Participants did not know where to start, and it could happen that they repeatedly opened paths for which the summary consisted in ‘other’ aggregates. We added the automatic detection of significant differences,
Fig. 11. Evolution of the layout for dates summaries during the iterative process. This is the summary for the path schema:[dateModified] on the dataset D1 Comics. In the first version (top) the dates were grouped by unique values, which very often resulted in an ‘other’ aggregate, laid out with a dotted texture. After participants’ feedback we implemented binning for dates (bottom), which results in 4 groups, from right to left: “2018” (4150), “2019” (4423), “2020” (460) and ‘other’ (100) — hovering the rectangles reveal the value and counts. Each value can be used as a condition for selection.

as described in Sect. 4.4 and highlighted them in pink. Even if this does not mean that all paths in pink will be useful for the diagnosis, this feature saves substantial time and provides guidance.

The way we presented summaries also evolved during the process. We had first presented summaries for integers as boxplots, thinking it could be interesting for users to select only outliers, or median. We realised that our users could not read boxplots and ignored those summaries, so we switched to a representation by unique values similar to the text values. On the other hand, there was no special treatment for dates and times, and this resulted most of the time in a single ‘Other’ aggregate. P1 asked if we could group dates, so we implemented binning by hour, day, month or year. This feature greatly improved the readability of some paths, for instance the modification date, as we can see in Fig. 11. When he first used the tool, P1 also tried to select the ‘other’ aggregate as a condition for selection, which was at the time not possible. We added this feature.

Among the simple features that made a difference, several participants pointed out the need to choose the preferred languages when content URIs were shown in the URI bar; we added this option in the settings.

The most critical issue we faced was the understanding of the map. In the first version, the interface gave access to information missing only after a selection was made. P3 stated that he found difficult to understand what paths were missing. We decided to create an default zones on the map, and to display missing path names on hover to make the interface self-explanatory. We also added the yellow color to highlight what was missing. After this, users reacted much more positively to the map: “I understand now” (P2), “Now I understand it better” (P3).

Other problems consisted in generic usability problems, like the buttons being too small or not giving enough feedback, or in bugs.

Cleaning Linked Data is an emerging activity and the process used by different users can be very diverse; work practices will probably evolve with time and appropriate tools to become more standardized. Meanwhile, the study revealed that there can be different phases in the curation of a dataset, and that our tool is flexible enough to support them in different ways. We had first imagined the clusters as an overview of issues made by users to support the actions to fix these issues.

Having heard of the tool, Wikidata product managers became intrigued, interested, and asked for a demonstration. As one of them told us when we demonstrated the tool, “One of the big problems our contributors face in keeping the data quality and completeness high is the fact that it is very hard to see the big picture due to Wikidata’s modelling being centered around individual entities. Your tool is addressing this issue”. We will continue to interact with the Wikidata community and other Linked Data producers to improve our tool and help improve the Semantic Web.

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REFERENCES

[1] S. Auer, J. Demter, M. Martin, and J. Lehmann. Lodstats—an extensible framework for high-performance dataset analytics. In International Conference on Knowledge Engineering and Knowledge Management, pp. 353–362. Springer, 2012.

[2] V. Balaraman, S. Razniewski, and W. Nutt. Reconc: Relative completeness in wikidata. In Companion Proceedings of the The Web Conference 2018, WWW 18, p. 17871792. International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE, 2018. doi: 10.1145/3184558.3191641

[3] C. Bizer and R. Cyganiak. Quality-driven information filtering using the wiqa policy framework. Journal of Web Semantics, 7(1):1 – 10, 2009. The Semantic Web and Policy. doi: 10.1016/j.websem.2008.02.005

[4] J. David and J. Euzenat. Comparison between ontology distances (preliminary results). In A. Sheth, S. Staab, M. Dean, M. Paolucci, D. Maynard, T. Finin, and K. Thirunarayan, eds., The Semantic Web - ISWC 2008, pp. 245–260. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008.

[5] M. Destandau, O. Corby, J.-D. Fekete, and A. Giboine. Path outlines: Browsing path-based summaries of linked open datasets. ArXiv e-prints, abs/2002.09949, 2020.

[6] A. Grover and J. Leskovec. Node2vec: Scalable feature learning for networks. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD 16, p. 855864. Association for Computing Machinery, New York, NY, USA, 2016. doi: 10.1145/2939672.2939754

[7] S. Harispe, S. Ranwez, S. Janaqi, and J. Montmain. Semantic measures based on rdf projections: Application to content-based recommendation
systems. In On the Move to Meaningful Internet Systems: OTM 2013 Conferences, pp. 606–615, 09 2013. doi: 10.1007/978-3-642-41030-7_44

[8] A. Harth and S. Speiser. On completeness classes for query evaluation on linked data. In Twenty-Sixth AAAI Conference on Artificial Intelligence, 2012.

[9] A. Hogan, A. Polleres, J. Umbrich, and A. Zimmermann. Some entities are more equal than others: statistical methods to consolidate linked data. In 4th International Workshop on New Forms of Reasoning for the Semantic Web: Scalable and Dynamic (NeFoRS2010), 2010.

[10] Y. Huang, V. Tresp, M. Nickel, A. Rettigter, and H.-P. Kriegel. A scalable approach for statistical learning in semantic graphs. Semantic Web, 5(1):5–22, 2014.

[11] The story of integraality, or my quest to make it at the wikimedia hackathon. Accessed on April 25, 2020.

[12] S. Issa, P.-H. Paris, F. Hamdi, and S. S.-S. Cherfi. Revealing the conceptual schemas of rdf datasets. In International Conference on Advanced Information Systems Engineering, pp. 312–327. Springer, 2019.

[13] S. Kandel, A. Paepcke, J. Hellerstein, and J. Heer. Wrangler: Interactive visual specification of data transformation scripts. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI 11, p. 3363372. Association for Computing Machinery, New York, NY, USA, 2011. doi: 10.1145/1978942.1979444

[14] S. Kandel, R. Parikh, A. Paepcke, J. M. Hellerstein, and J. Heer. Profiler: Integrated statistical analysis and visualization for data quality assessment. In Proceedings of the International Working Conference on Advanced Virtual Interfaces, AVI 12, p. 547554. Association for Computing Machinery, New York, NY, USA, 2012. doi: 10.1145/2254556.2254659

[15] L. McNees, J. Healy, and J. Melville. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. ArXiv e-prints, abs/1802.03426, Feb. 2018.

[16] P. N. Mendes, H. Mühleisen, and C. Bizer. Sieve: linked data quality assessment and fusion. In Proceedings of the 2012 Joint EDBT/ICDT Workshops, pp. 116–123. Citeseer, 2012.

[17] C. Müller-Birn, B. Karran, J. Lehmann, and M. Luczak-Rösch. Peer-production system or collaborative ontology engineering effort: What is wikidata? In Proceedings of the 11th International Symposium on Open Collaboration, OpenSym 15. Association for Computing Machinery, New York, NY, USA, 2015. doi: 10.1145/2788993.2789036

[18] C. Musto. Enhanced vector space models for content-based recommender systems. In Proceedings of the Fourth ACM Conference on Recommender Systems, RecSys 10, p. 361364. Association for Computing Machinery, New York, NY, USA, 2010. doi: 10.1145/1864708.1864791

[19] L. G. Nonato and M. Aupetit. Multidimensional projection for visual analytics: Linking techniques with distortions, tasks, and layout enrichment. Submitted to Semantic Web Journal, 2013.