Path Outlines: Browsing Path-Based Summaries of Linked Open Datasets

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Abstract—The Semantic Web is made of structured sources of information, such as DBpedia or GeoNames, also known as Linked Data (LD). They can be linked and queried together. The information they contain is atomized into triples, each triple being a simple statement composed of a subject, a predicate and an object. Triples can be combined to form higher level statements following information needs. This granularity makes it difficult to produce overviews of the content. We introduce the concept of path-based summaries, which carries a higher level of semantics for data producers, and the tool Path Outlines to support LD producers in browsing path-based summaries of their datasets. We present its interface based on the broken (out)lines layout algorithm and the path browser visualisation. We report a characterisation of LD producers’ needs, and show that our approach, reifying path outlines, was informed by this observation. We compare Path Outlines with the current baseline technique (Virtuoso SPARQL query editor) in an experiment with 36 participants. We show that participants prefer Path Outlines, find it easier and more comfortable to use, and that it is faster and leads to better task completion and less errors.

Index Terms—Linked Data; Semantic Web; Visualisation; Summarisation

1 Introduction

As explained by Bizer et al., “In recent years the Web has evolved from a global information space of linked documents to one where both documents and data are linked. Underpinning this evolution is a set of best practices for publishing and connecting structured data on the Web known as Linked Data (LD). [...] These best practices have been adopted by an increasing number of data providers [JAÅ], leading to the creation of a global data space containing billions of assertions — the Web of Data” [1].

To keep this Web of Data usable, LD providers, our users, need to ensure the quality of the assertions (statements) in their datasets. To this aim, several methods exist and can be combined. The quality of ontologies (data models) is evaluated on their ability and efficiency to express knowledge from a domain [2], and on their compatibility, in cases where several are combined [3]. The quality of data is evaluated on their formal conformity with ontologies [4] and with good practices [5], [6]. Most of the time, LD are created from the transformation of existing data sources, so the quality constraints can also be implemented when transforming the data [7].

However, data assessed with such methods can still present quality problems, such as nonsensical statements or incomplete information, and it remains difficult for data providers to have an overview of what their data can express. While the necessity of summaries to produce overviews of the content is acknowledged [8], an overview of what their data can express. While the necessity of summaries to produce overviews of the content is acknowledged [8], it is hard to determine the right unit to summarise meaningful pieces of information. Existing approaches are either at an atomic level, too focused for the user to make sense of the information globally, or at an ontological level, too abstract.

In this article, we describe a tool, Path Outlines, designed to support LD providers in improving the quality of their datasets, based on visualization and summarisation of paths that, we believe, offer a better level of abstraction than previous work.

To support LD producers in performing their data curation tasks our contribution includes:

• the concept of path-based summaries with an API to analyse such summaries,

• a visualisation tool, Path Outlines, to present them, based on two new visualisation techniques, and

• a controlled experiment to evaluate the tool.

After giving a brief introduction to the basic concepts of Linked Data, we discuss related work regarding LD summaries, their visualisation, and issues relative to retrieving summary information. We introduce Path Outlines, the tool that supports LD producers in browsing path-based summaries of their datasets. We present its interface based on the broken (out)lines layout algorithm and the path browser visualisation. We report our observation of LD producers and characterisation of their needs. We explain how it led us to reifying chains of statements into Path Outlines, and operationalising the needs into path-based tasks. We relate an interview-based evaluation of the relevance of such tasks with LD producers. Finally, we report an experiment-based evaluation of Path Outlines with 26 participants, in which we compare with the Virtuoso SPARQL query editor as a baseline, and we discuss the results of the evaluation.

2 Basic Concepts of Linked Data

The syntax of Linked Data is defined in the Resource Description Framework W3C Recommendation (RDF) [9]. A Dataset is a collection of statements named triples. Triples are composed of a subject, a predicate and an object, as shown in Figure 1. Subjects and predicates are always Uniform Resource Identifier (URIs). Objects can be URIs (ℓ. 4–9) or literals (ℓ. 1–3). The same URI can be the subject and object of several triples (ℓ. 5, 6, and 7 or ℓ. 6, 8 and 9). The triples form a network that can be represented as a node-link diagram (c). The special predicate rdf:type (ℓ. 4, 7 and 8) expresses that a subject entity has for type a class.

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Fig. 1. Basic concepts of Linked Data. Samples extracted from Nobel and DBpedia datasets. Full datasets contain respectively 87,422 and 185,404,534 triples (on 2019-09-07). of resources. Predicates and classes of resources are defined in data models called ontologies. For instance, the predicates of the 3 first triples, and the object of the 4th, belong to the FOAF [10] (friend of a friend) ontology, a model (ontology) dedicated to the description of people and their relationships. In principle, URIs should be derefencable: querying them on the web should return their RDF description. Literals can be typed, and string literals can be associated with a language. [Figure 1-a, grey colour]. URIs can be prefixed for better readability, as in [Figure 1-c]: the beginning, common to several URIs, is given a prefix (a short name), e.g. foaf: instead of http://xmlns.com/foaf/0.1/.

Linked Datasets are interlinked: a dataset can reference an entity produced in another one (red colour). When this happens, they can be queried jointly, through federated queries, and a chain of statements can jump from one dataset to another: the triples in Nobel Dataset la Sorbonne is in Paris, Paris entity in Nobel is equivalent to Paris entity in DBpedia can be completed by those from DBpedia: Paris’ latitude is 48.856701, Paris’ longitude is 2.350800.

As seen in the example, the information is separated into atomic pieces that can be retrieved and combined following needs. For instance, a question like “When was Marie Curie born?”, could be answered with triple 2. “What was her affiliation?” could be answered by chaining triples 5, 6 and 9. Placing Marie Curie on a map displaying laureates by affiliation, could be achieved by chaining triples 5, 6 and 9 and 10 to get the latitude, and 5, 6 and 9 and 11 to get the longitude. A chain of statements is commonly called a path in the graph.

Linked Data is used by communities such as Wikidata, institutions such as national libraries and archives, research laboratories, and companies to combine and share data, and let them be queried jointly. There are few tools to manage Linked Data content natively datasets are more often produced by transforming existing data sources, with transformation tools for ad-hoc scripts. The workflows are very diverse, even among similar producers: video archives of 2019 professional meeting Semantic Web In Libraries (SWIB) show each data producer describing a specific workflow. However, they have in common to be very fragmented, because of the many diverse sources they come from. As a result, the producers have no overview of their data, and when errors occur, their discovery is delayed until a user finds them out, or never.

3 Related Work

We will discuss the types of summaries which are currently available, the visualisations of these summaries, and the difficulty of writing and running queries for summary information. By summary we mean description of the content of a dataset, sometimes characterised by descriptive statistics.

3.1 Dataset Summaries

Finding the right unit to summarise a Linked Dataset content is not trivial. A first approach is to focus on simple statements, following the structure of the data. Auer et al. present features like the number of occurrences of a property (e.g., foaf:name),

1. https://www.w3.org/2001/sw/wiki/Tools
2. http://www.mkbergman.com/sweet-tools/
3. https://www.youtube.com/playlist?list=PL7fMsenBLiQ3FnY59f-nIHpmy2r5Nmtc
the number of entities in a class (e.g., foaf:Person), or the datatype of objects (e.g., xsd:date) aggregated over the whole dataset [11]. This summary is complete and accurate, but does not reveal much about the content: it is possible to know that there are $n$ names in a dataset, but what do those names describe? or that there are $n$ persons in the dataset, but how are they described? how many of them do have a name? To answer such questions, more context can be added by considering properties for entities with a specific type, that is counting the number of foaf:Person having a foaf:name [12], [13], [14]. Others also take into account the type of the objects of the triples (not only of their subjects). This allows to count the number of Persons having a birthplace that is a City on the one hand, and the number of Persons having a birthplace that is a Country on the other hand [15], [16], [17].

Adding more context leads to more interpretable summaries, the trade-off being to leave aside parts of the graph, such as statements involving untyped or literal objects.

Another approach is to construct a subgraph as the summary, producing some sort of a-posteriori model, inferred from the data. ÀNebiriAG et al. compute the smallest graph containing all patterns, with variations regarding the definition of a pattern [18]. These subgraphs are very dense, and are query-oriented, not meant to be read by humans. Troullinou et al. limit the subgraph to the most represented classes, and the most represented direct properties between them [8]. The restrictions make it graspable, yet very incomplete. Weise et al. [19] give access to more elaborate statements, also starting from the most represented classes, and considering the most represented properties, which can be chained without involving untyped entities. Those subgraphs preserve access to chains of statements, but the statistics are produced for single statements only. Since the number of paths that can be extracted from a graph is extremely large, considering chains of statements would require to decide where to start and where to stop.

Khatchadourian and Consens [14] also provide a summary of the links between datasets. However, they account only for entities described with a similarity link owl:sameAs, belonging to the same class of resources and described by the same properties in both datasets. In other words, they summarise linked entities only if they are very strongly similar, while we think the power of interlinking rests on the fact that diverse descriptions can be complementary.

In contrast to previous methods, our approach considers paths as the basic unit for summaries. We define path-based summaries as descriptive statistics about chains of statements starting from a set of entities sharing the same rdf:type, with a specified maximum depth. They enable us to summarise complex statements, that can be extended to another dataset, in a readable manner.

### 3.2 Visualising LD Summaries

The few summaries presented as visualisations use simple lists or different types of node-link diagrams. Simple lists have the advantage of being readable but they provide no overview [11]. On the other hand, diagrams give a full picture but can be harder to interpret. UML diagrams can be accurate for single statements [12]. The use of classic node-links is very similar to ontology visualisation [20], [21], [22]: in both cases, groups of entities or literals are presented as nodes, and properties as links. For ontologies, the class of a group of entities can be a separate node representing the class entity, as expressed in RDF [23], or, by metonymy, the name of the class is often used to label the group of entities [24]. Only the second method is used for summaries since it makes statements more readable [8], [19]. LD-VOWL [19] presents its summary subgraph as a node-link diagram as an interface to display statistics: selecting a node in the diagram gives access to statistical information about all similar nodes and properties starting from them in this original graph.

As its name implies, almost everything in Linked Data is a link: entities, properties, classes and datatypes are URIs, which by definition are links [25]. Technically, the connection between two datasets is made possible by joins: the fact that a same URI exists in two datasets enables querying them jointly. Semantically, one tends to think of these joins as links. The representation used by LOD Cloud—a frequently chosen to illustrate the Semantic Web—is a node-link diagram where each dataset is displayed as a node and the presence of joins between two datasets is displayed as a link between them.

In the related domain of ontology alignment tools with instance matching features, Kotis and Lanzenberger point the need to visualise linked items in their respective contexts [26]. “Interpreting an entity of one ontology in the context of the knowledge of another ontology is a cognitively difficult task since it requires the understanding of semantic relations among entities of different ontologies” [27].

Node-link diagrams are the most common representation for paths in graphs that are not necessarily linked data [28], and their readability has been studied. Huang and Eades remarked that people tried to read paths from left to right and top to bottom, even when the task requires another direction [29]. Van Amelsvoort et al. demonstrated that reading behaviours were influenced by the direction of elements [30]. Ware et al. showed that good continuity and edge crossing and path length did influence the following of a path [31]. A specific type of node-link diagrams, node-link trees, seemed to be more efficient for tasks related to following paths, traversing graphs [28], [32], and reading paths [33]. A survey on the readability of hypertext did mention many studies showing that the multiplication of possibilities impacts readability negatively [34], supporting the same idea. In an approach that has similarities with ours, PathFinder [35] did lay all possible paths for a subgraph flat.

4. http://lodstats.aksw.org/  
5. https://lod-cloud.net/
The list was very long and has to be paginated even when the subgraph was very small.

Therefore, existing visualizations of LD provide some level of summaries, but they have difficulties to find the right level of representation and interaction, and they present readability issues. Our visualisation represents path summaries as graphical objects that can be manipulated, preserving their readability as sequences of statements, and thus enabling users to make sense of them.

3.3 Querying Summary Information

SPARQL, the main query language for Linked Data, provides aggregation operators to count occurrences. These operators can be applied to the different types of summaries we mentioned: simple patterns, patterns specifying the type of the subject and/or of the object, and more complex statements, following paths in the graph by chaining triples. However, complex queries raise both technical and conceptual issues, as reported by Warren et al. [36].

From a technical point of view, the cost of a query increases with number of entities and length of paths, and the fact that a query is federated, resulting in possible network and server timeouts and errors. SPARQL query optimisation [37] and Federated Distributed SPARQL query processing [38] are two intertwined research areas.

From a conceptual point of view, thinking of paths patterns in graphs is not a simple mental operation. If finding the right unit to summarise and visualising them is difficult, forming a mental model cannot be simple either. Among tools to assist writing queries, some offer the possibility of discovering the model iteratively, enabling at each step to browse the available possibilities for extending the current path [39]. This applies to one dataset only, not to others that would be queried jointly. And the tool does not present summaries, so the query must then be edited manually to add aggregation operators, which adds a level of complexity.

Altogether, there is still a need for a tool to enable the summarisation and visualisation of paths in a Linked Dataset, and the display of links between datasets in context.

4 User Study: Characterizing LD ProducerÄžs Needs

Our motivation to design our Path Outlines tool comes from the detailed analysis of meeting notes collected by one of the co-authors of this article over two years to identify the problems encountered by professional data producers during a research project conducted by three public institutions, to interlink their musical catalogues [40].

4.1 Participants

The group of producers was composed of 4 women and 3 men, employed by three public institutions. The meetings notes concerned 26 meetings where the producers discussed the work accomplished and tried to solve problems together. There was a mean of 5.31 core participants per meeting. In addition to the core participants, a coordinator attended 5 meetings, and there was a total of 21 guests over 11 meetings.

4.2 Data Analysis

Relying on the notes, we summarized the producers’ activities and listed the problems they encountered in each meeting. We characterized the problems in a bottom up approach.

4.3 Results

4.3.1 Managing Expressivity

This concern appeared in 22 meetings. Data producers developed a number of ad-hoc tools such as custom-made node-link diagrams, spreadsheets with specialized scripts to filter, and documents for listing properties and classes. Although this enabled them to improve their understanding of the model and to communicate together, readability and interpretability remained difficult. For instance, in the last observed meeting, after more than a year and a half of work, there were still discussions about the level of abstraction (Work, Expression, Manifestation) at which the title could and should be in the current version of the model.

4.3.2 Fitting Data to Model

This problem appeared in 18 meetings. Data producers had written themselves the mapping rules to transform their data into RDF, and knew them rather well, but they did not know how well they fitted their data. Until a specific interface was developed, which occurred nearly a year after the first data were transformed, they had to use spreadsheets or raw RDF xml files to check if the model did enable to express the data accurately, selecting both representative and random items. Knowing how well a property was represented, and what there really was in common between data coming from the different producers’ databases was complex.

4.3.3 Encoding Data

This concern appeared in 8 meetings when working on mapping rules. Librarians did the inventory of possible cases relying on their (impressive) memory, but they were concerned by the cases they probably missed. As an example, the original information for the date of creation of an Expression could be a category (beginning of the XVIIIth century), a text note containing both time and other information, or a date in different formats—knowing that library models use non-standard options to express ranges or uncertainty. The rules to process such information were many and complicated, and varied from a database to another. It was nearly impossible to get a sense of the partition of the resulting data.

4.3.4 Querying Data

This concern appeared in 14 meetings. Producers were building this common model in order to enable joint querying of their databases. While the abstraction of the model seemed to ensure a common structure with pivot elements to which different properties could be attached depending on the available information, it was then difficult to imagine how user needs could be expressed in queries addressing entities originating from all the producers’ databases.

4.3.5 Interlinking

This concern appeared in 6 meetings. To decide on the vocabularies to use to create similarity links, data producers needed to know the type of information it would give access to, but also the coverage for their data. For instance, linking with the GeoNames ontology would in theory give access to geo-coordinates. But there were places, typically for traditional music, likely not in GeoNames. These might be solved by using GeoEthno, but in the end it was impossible to estimate the coverage of the information really added by interlinking.
5 User study 2: validating the approach

To address these “specific user problems” [41], we needed to provide some intermediate level of understanding, between the precise example and the abstract model, in other words a summary. We relied on path-based summaries, and operationalised this approach in a series of low-level path-based tasks, presented in Figure 3. These tasks basically consist of three actions: browse, filter and inspect, that can be associated with the different features of a path and its extensions. To check if this approach did fulfil data producers’ needs, we interviewed 11 of them for a partial validation. We selected 6 tasks involving all concepts — identification, inspection, coverage, features and extensions — illustrated with examples inspired from the situations we observed.

5.1 Participants

We conducted a fifteen to thirty-minute interview with 11 LD producers recruited via email calls on Semantic Web mailing lists and Twitter. Participants belonged to industry (4), academia (4) and public institutions (3). The Datasets they usually manipulated contained data from various domains, ranging from biological pathways to cultural heritage through household appliances. All participation was voluntary and without compensation.

5.2 Set up and Procedure

The interview was supervised online through the videoconference system Renater “Rendez-vous”[6].

We presented each type of task, together with a precise example, which could be adapted to the participant’s domain. We asked participants if they did already perform such a task; and if so, how often and by which means; if not, for what reason. Finally, we asked if those tasks reminded them of other similar or related tasks.

5.3 Results

We collected answers in a spreadsheet and analysed them with R.

5.3.1 Current Status

A few participants already performed such tasks, as reported in Figure 4. Some did perform similar tasks, but for direct properties only (4)[7] or on the original data before the transformation in RDF (5), especially for validating the datatype. In these cases, the tasks had been identified as needed, but the available solution was incomplete.

Participants already performing such tasks used SPARQL query editors (16) or content negotiation in the browser (3). The main reason given for not performing a task, or performing it too rarely was no tool (14). These tasks are actually possible with SPARQL, but we interpret this as a sign that participants either did not know how to write the queries, or regarded it as so complicated that they would not even consider it as an option. The second main reason was time concerns (13): the task was regarded as doable, but the time it would have taken to write such queries was too sizeable.

5.3.2 Interest for the Tasks

Two participants had difficulties in relating to the tasks, and did not express interest. Their use of linked data was focused on querying single entities rather than sets. They did not feel the need for an overview. Most other participants, however, declared a strong interest for the tasks (Figure 4). Three had already identified their needs, others sounded really enthusiastic that we were able to elicit the tasks for them. In some cases, participants needed rephrasing or further examples to really understand the tasks.

Six participants spontaneously mentioned clearly seeing the interest of a tool enabling those tasks for reusers, in a discovery context. Only one participant suggested a related task: identify outliers in values of paths typed as numerical values. This corresponds to task E with more advanced statistics.

5.4 Summary

This interview confirmed that data producers were aware of their difficulties, but needed help to elicit their needs and the tasks to address them, as well as tools to support those tasks. This is why we have implemented our tool Path Outlines.
6 Path Outlines

We present Path Outlines, a tool to support data producers in curating their datasets, letting them browse and inspect path-based summaries of their datasets. We posit that the path level is the appropriate level of abstraction to represent meaningful information for sets of entities in Linked Data, offering a granularity that matches our users' tasks, beyond simple statements. Our tool is based on a user interface using several visualizations to explore the paths. We introduce a new layout algorithm called broken (out)lines that allows displaying a large number of paths and the path browser visualization to compact the representation of paths. We also introduce an application program interface (API) called LDPath to analyse the paths.

6.1 Definition

We define a path outline as a set of resources related to a set of values by a sequence of RDF properties. Resources are defined by a similarity criterion, e.g. their rdf:type. Values are the URIs or literals reached by following the chain of properties all the way to the last statement in the chain, for all resources in the set. Core features of a path outline are described in Table 1. Going to the end of all chains in the dataset would produce too many over long statements to be technically feasible, so we set a limit that can be adjusted depending on the specificity of the model and the computing resources available.

For instance, considering the full Nobel dataset, from which a sample is presented in Figure 1, a path of depth 1 relative to the set of laureates, and describing those whose birth date is known in the dataset, can be expressed as nobel:Laureate/foaf:birthday/*. Its coverage is 96 percent and could be expected to be 100 percent after data curation since the information is likely to be available after some research.

Figure 6 shows the path outline of depth 3 describing the laureates having an affiliation, which has the city, which has a similarity link to another resource. In this case, the coverage is unlikely to reach 100 percent, as some laureates might not have an affiliation. The number of unique values is higher than the number of laureates having an affiliation, some of them having several affiliations.

We created a syntax inspired from XPath. The template string consists of a set of resources at the beginning of the path, defined by a similarity criterion, e.g. their rdf:type. Values are the URIs or literals reached by following the chain of properties all the way to the last statement in the chain, for all resources in the set. Intermediate sets of resources are conceptual objects representing summaries of chains of statements starting from similar entities and using similar properties.

| Feature | Definition |
|---------|------------|
| Start set | Entry point rdf:type of the start set |
| Coverage | Percentage of entities in the start set for which this path actually exists |
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| Statements | Depth | Number of statements from the start set to the set of values |
| Statements | Properties | URIs of the property in each statement, from the start to the end |
| Types | rdf:type of intermediate sets of entities, from the start to the end |
| Values | Count | Number of total values (or URIs) at the end of the path = number of instances of the paths |
| Unique count | Number of unique values (or URIs) at the end of the path |
| Datatype | Except for URIs datatype of the values at the end of the path |
| Language | For strings, if specified: list of languages of the values |
| Language | Min / max | Numerical values: minimum and maximum value Strings: first and last value, in alphabetical order |

6.2 User Interface

Path outlines are conceptual objects representing summaries of chains of statements in a Linked Data graph, as depicted in Figure 5. We designed an interface reifying them into graphical objects in order to let users manipulate them to perform data curation tasks. We will present it through the eyes of Alice, a fictional data producer.

6.2.1 Overview and broken (out)lines

Alice opens Path Outlines to clean one of her datasets. She sees several datasets laid out with a circle packing algorithm in order to let users manipulate them to perform data curation tasks. We will present it through the eyes of Alice, a fictional data producer.
which are linked to it also come to the foreground, as small bullets laid out on the side (Figure 8-f). The different sets of entities belonging to her dataset and sharing the same rdf:type are laid out inside in another circle packing, their size corresponding to the number of entities (Figure 8-1). The filter panel allows her to filter them by size and name (Figure 8-6). She can hover a set to display its name, and click on it to open it. Other sets become smaller and are aligned on the side to be easily available (Figure 8-8). The available path depths (Figure 8-7) are laid out with the broken (out)lines algorithm presented in Figure 7. By default, paths of depth 1 are selected and displayed in the browser (Figure 8-9). The mechanism is inspired by systems which present an overview of a graph for the user to select one of different cuts in it [44], [45]. It allows the interface to present a very large number of paths. For instance, the analysis of Data.bnf (LD produced from the National Library of France, BNF) with a maximum depth of 5 gives more than 63,000 paths for 9 sets of entities. With such cuts, the largest group of paths are paths of depth 4 for the set “Event” with 4392 paths, as shown in Figure 8-f. We will see how Alice can inspect these 4392 paths in the path browser.

6.2.2 The path browser visualisation: paths as readable sequences

The path browser visualisation can be described as a Sankey diagram [46], [47] where the nodes are merged, and information about the flow is available through interactivity. Paths being sequences of properties, it is possible to represent them with a Sankey, as shown in Figure 9-a. However, the number of paths that can be displayed is limited, and it is difficult to follow the edge that the labels relate to and to identify sequences. The path browser keeps the links, but merges the nodes, so that the links do not need to be curved any more, and become rectangles Figure 9-b. Merged nodes are turned into vertical rectangles representing entities, allowing to display their rdf:type when it is known. The structure of RDF triple statements is visible, as well as their chains.

To browse the paths, Alice can click on a property in one or several columns. The large rectangles allow easy hovering and clicking interactions, making it easy for her to filter on properties by direct manipulation. When she hovers a property, information on how the flows merge and divide (Figure 8-e) is displayed, since it is no more visible at first glance, as it was in the Sankey. Selected properties form a pattern, and all paths that do not match this pattern are filtered out. She can use the filter panel offers to filter by statistical features (Figure 8-10), and to have an overview of the available range for each feature. She can combine property and statistical filters. When she hovers or selects a single path, its statistical description appears in the statistical panel (Figure 8-11). This panel also offers a list of linked datasets to which the selected path can be extended. When she selects a linked dataset, a column is added on the right (Figure 8-12), to let her browse possible extensions to the path. The filter panel (Figure 8-13) and statistical panel (Figure 8-14) now apply to the extended paths. A line shows the target dataset, inviting users to click it and explore its paths. With our visualisation, the 4392 Event paths of depth 4 in Data.bnf (made of 13 properties at depth 1, 12 at depth 2, 25 at depth 3, 55 at depth 4, and 110 at depth 5) can be displayed (Figure 8-f) in a readable manner, which would not be possible with a Sankey diagram.

6.2.3 Scenario of use

We present two scenarios of use of Path Outlines to further illustrate the interest of the functionalities of this tool.

Scenario 1: A member of the DBpedia community would like to check the quality of music albums described in the DBpedia dataset. She opens Path Outlines, searches DBpedia in the filter panel (Figure 8-a2). A dozens of datasets remain, all other are filtered out (Figure 8-a1). Hovering them she can see each one corresponds to a different language. She clicks on the French version which opens in the foreground (Figure 8-b3). To find music albums among the many sets of entities, she types music in the filter panel (Figure 8-b6). Five sets of entities correspond to this keyword (Figure 8-b5), she hovers them and identifies schema:MusicAlbum, which she selects. This isolates the set, displays its broken (out)lines (Figure 8-c7), and opens the path browser (Figure 8-c8). By default, paths of depth 1 (such as http://dbpedia.org/ontology/composer or http://dbpedia.org/ontology/formaat) are displayed. The interface announces that there are more than 41 000 albums, with 87 paths of depth 1. She wants to check properties with a bad coverage, to see if there is a reason for this. She uses the cursor in the filter panel (Figure 8-c10) to select paths with a coverage lower than 10 percent. She hovers available paths and inspect their coverage. She notices that the property http://fr.dbpedia.org/property/writer is used only once. A property which sounds very similar, http://dbpedia.org/property/writer, is used more than 800 times. To identify the entity, she needs to modify, she clicks on the button “See query”, that opens the SPARQL endpoint in a new window, prefilled with a query to access the set of DISTINCT values at the end of the path. She will now do similar checks with other paths of depth 1 and paths of depth 2.

Scenario 2: A person in charge of the Nobel Dataset would like to know what kind of geographical information is available for the nobel:Laureates. Could she draw maps of their birth places or affiliations? She knows there are no geo coordinates in his dataset, but some should be available through similarity links. She opens Path Outlines, searches nobel in the filter panel, and opens her dataset. She then selects the nobel:Laureates start set. She starts to look laureates having an affiliation aligned with another dataset. She selects paths of depth 3. In the first column, she types affiliation. This removes other properties than nobel:affiliation from this column, and properties which are not used in a path starting with nobel:affiliation from other columns. Among properties remaining in the second column she can easily identify dbpedia:city, which she selects. In the third column, she selects owl:sameAs property. A single path being now selected, summary information appears in the inspector: 72 percent of the laureates have an affiliation
Fig. 8. Overview to detail. a) The user selects a dataset among available datasets. b) The dataset opens in the foreground; interlinked datasets are placed aside. The user selects a start set c) Paths are displayed in the paths browser. When a single path is hovered or selected, details are available in the detail panel. d) The user selects extensions of a path in another dataset. e/f) The user selects paths of depth 4. When hovering a property, its label and description are displayed in a tooltip.

aligned with an external dataset. She selects the link to display extensions in DBpedia. A list of 78 available properties to extend the path in DBpedia appear. She types geo in the search field. A list of 4 properties containing geo:lat and geo:long remains. She inspects the summary information of the extended paths: only 32 percent of the laureates have geo coordinates in DBpedia. She repeats the same operations for birth places: 96 percent have a similarity link to an external dataset, among which 61 percent have geo coordinates in DBpedia. She can now assess the coverage of the dataset regarding the laureates and their locations, and report the missing information for improvements.

6.2.4 Implementation
The front-end interface is developed with NodeJS, it uses Vue.js and d3.js frameworks. The code is open source.

6.3 LDPath API for Path Analysis
In order to analyse the paths, we developed a specific extension to the semantic framework CORESE. Given an input query, it discovers and navigates paths in a SPARQL endpoint by completing the input query with predicates that exist in the endpoint. LDPath first computes the list of possible predicates and then, for each predicate, counts the number of paths. This behaviour is done recursively for each predicate until a maximum path length is reached. The values at the end of each path are analysed to retrieve

9. https://gitlab.inria.fr/mdestand/spf
the features listed in Table 1. LDPath can also, for each path, count the number of joins of this path in another endpoint, and compute the list of possible predicates to extend the path by one statement. The values at the end of the extension are also analysed. The software package consists in recursively rewriting and executing SPARQL queries with appropriate service clauses. The API of this extension is made available for other purposes, and can be queried independently of Path Outlines.

7 User study 3: evaluating Path Outlines

We conducted a $2 \times 2 \times 3$ within-subject controlled experiment, with a mixed design (counterbalanced for the two first variables, and ordered for the last one), to compare Path Outlines with the virtuoso SPARQL query editor (hereafter SPARQL-V). The first independent variable was the tool, with two modalities: Path Outlines vs SPARQL-V. We chose a non-graphical tool as a baseline because we were unable to find a graphical tool that was able to support our tasks, whereas we identified SPARQL query editors as the most straightforward means to realise them, as confirmed by the producers we interviewed. The second independent variable was the dataset, with two modalities: Nobel dataset vs PersÃ£l dataset. The third independent variable was the task, with 3 modalities: 3 equivalent tasks with small adaptations to the dataset, ordered by difficulty. The dependent variables we collected were the perceived comfort and easiness, the execution time, the rate of success and number of errors, and the accuracy of memorising the main features of a dataset.

7.1 Hypotheses

Our hypotheses are:

H1 : Path Outlines is easier and more comfortable to use than SPARQL-V
H2 : Path Outlines leads to shorter execution time than SPARQL-V
H3 : Path Outlines leads to better task completion and less errors than SPARQL-V
H4 : Path Outlines facilitates memorising the main features of a dataset compared to SPARQL-V

7.2 Participants

We recruited 36 participants (30 men and 6 women) via calls on semantic web mailing lists and twitter, with the requirement that they should be able to write SPARQL queries. Five of the participants in the interview also registered for the experiment. Job categories included 12 researchers, 10 PhD students, 9 engineers and 3 librarians. 29 produced RDF data and 31 reused them. Their experience with SPARQL ranged from 6 months to 15 years, the average being 5.07 years and the median 4 years (note: SPARQL has existed since 2004, the standard was released in 2008). 12 rated their level of comfort with SPARQL as very comfortable, 11 as rather comfortable, 10 as fine, and 3 as rather uncomfortable. 18 used it several times a week, 13 several times a month, 2 several times a year and 3 once a year or less. All participation was voluntary and without compensation.

7.3 Setup

The experiment was supervised online through the videoconference system renater “Rendez-vous”. Due to technical problems it was replaced by Skype in 4 cases and “Appear In” (now called “Wereby”) in 2 cases. It was run face-to-face for 3 participants. We used a LimeSurvey form to guide participants through the tasks and collect the results. The form provided links to our tool, to a web interface developed in JavaScript, and to a SPARQL endpoint we had set up for the experiment. In 5 cases, due to restrictions in the network, we replaced the endpoint by the Nobe1 public endpoint. We used two datasets, Nobel and PersÃ£l, which had been analysed with our tool and are hosted in our endpoint. Two participants stopped after two tasks because of personal planning reasons, so we asked the last two participants to complete only two tasks to keep the four configurations balanced for all tasks.

7.4 Tasks

We limited the experiment to 3 tasks, to keep the total time under one hour, knowing that it is tiring for participants to write queries in a limited time, especially when the experimenter is watching. The tasks were ordered by difficulty: Task 2 necessitated to consider paths of several depths, and Task 3 involved path extensions in another dataset. The tasks on Nobel Dataset were:

- Task 1 (T1): Consider all the awards in the dataset. For what percentage of them can you find the label of the birth place of the laureate of an award?

10. https://project.inria.fr/corese/
11. www.limesurvey.org/
• Task 2 (T2): Consider all the laureates in the dataset. Find all the paths of depth 1 or 2 starting from them and leading to a temporal information. Indicate the datatype of the values at the end of the path.
• Task 3 (T3): Imagine you want to plot a map of the universities. The most precise geographical information about the universities in the dataset seems to be the cities, which are aligned to DBpedia through similarity links (owl:sameAs). Find one or several properties in DBpedia (http://dbpedia.org/sparql) that could help you place the cities on a map.

The tasks on PersAl'e Dataset were equivalent, with small adaptations to the context.

7.5 Procedure
We sent an email to the participants with a link to the video conference. As they connected, we gave them a link to the form with a unique token, valid only once, associated with their anonymous unique identifier. Participants were invited to read the consent form. We rephrased the main points and invited them to accept it if they agreed to continue. We started with a set of questions about their experience with SPARQL. Then we introduced the experiment and explained how it would unfold.

The first task T1 was displayed, associated with a technique and a dataset. We read it aloud, and rephrased the statement until it made sense to the participants. Performing such tasks on sets of entities in a Linked Dataset was a new concept for some of the participants. Participants were asked to describe their plan before they performed the task. We rated the precision: 0 for no or very imprecise planning, 1 for imprecise planning, 2 for very precise planning. The time to actually perform the task was limited to eight minutes. If they were not able to complete in time, they were asked to estimate how much time they think they would have needed. Then they rated the difficulty of the task and the comfort of the technique.

The next task was the equivalent task T1 associated with the other technique on the other dataset. We counterbalanced the order of the technique and dataset factors, resulting in 4 configurations. After the set of two equivalent tasks, participants were asked which environment they would choose if they had both at their disposal for such a task.

The same was repeated for tasks T2, and then T3.

At the end, participants answered a multiple choice query form about the general structure of a dataset: number of triples, classes, paths of length 1 and length 2. To finish with, they were invited to comment on the tool and make suggestions.

7.6 Data collection and analysis
We collected the answers to the form, screencasts of the web browser and notes. Answers to the form and notes were merged in a spreadsheet and analysed with R.

7.7 Results
7.7.1 Perceived comfort and easiness
In general, participants found Path Outlines more comfortable than SPARQL-V (Figure 10). Several participants said that they would need more time to become fully comfortable with Path Outlines. Five minutes of practice was indeed a very short time, but the level of comfort reported with Path Outlines is already quite satisfactory.

The level of comfort reported when performing tasks with SPARQL-V was lower than the level initially expressed. We interpreted this as being due partly to the fact that it is uncomfortable to code when an experimenter is watching, and partly to the difficulty of the tasks. Being very familiar with SPARQL does not mean being familiar with queries involving both sets of entities and deep paths. This supports the idea that a specific tool for such tasks can be useful even for experts. Three users mentioned being less comfortable with Virtuoso than with their usual environment. However, Virtuoso was the tool most frequently listed as usual by participants (23). Participants perceived the same tasks as being easier when performed with Path Outlines than with SPARQL-V, as shown in Figure 10. We think this is due to the fact that Path Outlines enables them to manipulate directly the paths, saving them the mental process of reconstructing the paths by chaining statements and associating summary information to them. Those results are in agreement with H1.

7.7.2 Task execution time
We counted 8 minutes for each timeout or dropout. Participants were quicker with Path Outlines on the three tasks, as shown in Figure 11, in agreement with H2. We applied paired samples t-tests to compare execution time with each technique for each task.

There was a significant difference for the three tasks:

T1: $t = 16.775, p < 2.2^{-16}, m = 287.1389$,
T2: $t = 6.4312, p < 2.8^{-07}, m = 161.3333$,
T3: $t = 17.815, p < 2.2^{-16}, m = 292.1875$

which shows that participants were significantly faster on each task with Path Outlines than with SPARQL-V.

Those who did not complete the tasks were asked to give an estimation of the additional time they would have needed. We did not use self-estimations to make a time comparison since not all participants were able to answer, and such estimations are likely to be unreliable since time perception and self-perception being influenced by many factors. However, we report them as an indicator: for participants with a very precise plan, it ranged from 30 seconds to one hour; with an imprecise plan, it ranged from 15 seconds to 45 minutes; and with no plan it ranged from 4 minutes to several hours. Task 2 required them to look at paths of two different depths, which we had identified as a non optimal aspect of our interface. Although participants were longer on this task, Path Outlines still outperformed Virtuoso SPARQL query editor, but several participants expressed the wish to see both depths at the same time.

7.7.3 Task completion and errors
Using our tool, only one participant timed out on task 2, all others managed to complete each of the tasks within 8 minutes. With SPARQL-V, there were 37 dropouts (9 on T1, 10 on T2 and 18 on T3) and 15 timeouts (9 on T1, 5 on T2 and 1 on T3). Among the tasks completed in time, 28 did had erroneous or incomplete results with SPARQL-V (11 on T1, 13 on T2 and 5 on T3) versus 13 with our tool (on T2), as summed up in Figure 10.

The main errors on T1 were that some participants counted the number of paths matching the pattern instead of the number of documents having such paths (either by counting values at the end of the paths or by counting entities without the DISTINCT keyword). It occurred 9 times in SPARQL-V, and never with our tool. Four participants were close to making the mistake but corrected themselves with SPARQL-V, and one did so with our tool.
Another error occurred only once with SPARQL-V: the participant started from the wrong class of resource.

T2 presented the particular difficulty that temporal information in RDF datasets can be typed with various datatypes, including xsd:string and xsd:integer. The most common error was to give only part of the results, either because of relying on only one datatype, or because it was difficult to sort out the right ones when displaying all of them. It occurred 12 times with both techniques. The mean percentage of correct results was 75 percent with our tool, versus 50 percent with SPARQL-V. With SPARQL-V, one participant happened to give all paths as an answer, including non temporal ones, which we regarded as partial success.

For T3, one participant gave an answer that did not meet the requirement with SPARQL-V, stating that it would be too complicated. Another error which happened 5 times was that the query timed out, although it was correct. There are tricks and workarounds, but in most cases the time needed to write the query and realise it would time out was already too long to start figuring out a workaround. This is a common problem with federated queries on sets, also reported by Warren and Mulholland [56].

Overall, our results are in agreement with H3.

### 7.7.4 Memorising the main features of a dataset
At the end of the experiment, participants answered MCQ questions about the structure of both datasets. Answers were very sparse, most participants did not remember the information at all, and there was no significant difference between the techniques. We cannot make any conclusion from the data we collected. We think this is related to the fact that participants were fully focused on finishing the tasks in time, and did not have time to look at contextual elements of the interface. Therefore, the results are not in agreement with H4.

### 7.7.5 Preference
Most participants preferred Path Outlines (34 on T1, 31 on T2 and 29 on T3) versus Virtuoso SPARQL query editor (2 on T1, 5 on T2 and 3 on T3), as shown in Figure 11.

### 7.7.6 Other user comments
Several participants expressed the need for such a tool as Path Outlines in their work, and asked if they could try it on their own data. Most of them liked the tool and made positive comments. One participant wrote an email after the experiment to thank us for the work, saying that “such tools are needed due to the conceptual difficulties in understanding large complex datasets”. It is interesting to note that the participant happened to be one of the two participants who had difficulties to relate to the tasks during the interview.

### 8 Discussion and future work
Although Path Outlines was designed for users who are not very comfortable with SPARQL-V, it seemed difficult to find enough beginners as participants, so we had to open the call to any level of expertise. We were positively surprised to see that with an average level of experience and expertise which was rather high, participants still performed so significantly better with our tool. While novice users are often more efficient and comfortable with our interface based on recognition than with a query editor based on recall [49], this is not always the case with more experienced users. We think this might be due to the fact that querying over sets did not seem to be a usual operation for most of the participants.

Linked Open Data are by definition huge and incomplete, so it might be natural to not even try to get overviews, since such queries are likely to either time out or return results that are difficult to interpret. However, as human beings, we need to compare, evaluate, see resources in the context of other similar resources. Considering subsets of the LD world, and being able to see how they relate is probably needed to leverage the use of LD. The new standard of property paths for SPARQL queries, offering a simpler syntax for chains of properties when there are no constraints on intermediate entities, is a sign that there is a need to consider paths deeper in the graph. However, the difficulty remains for experts to think at the same time deep and broad. Path-based summaries are a conceptual tool that helps understanding what can be achieved with such queries.

The concept still needs to be refined and developed. We used as a similarity criterion for the starting set a single rdf:type, but we could extend to any SPARQL constraint, opening the possibility to consider more specific sets of interest. At the moment, our paths are “weakly typed” [18]: they consider statements going through intermediate entities belonging to different rdf:type as being similar. It would also be worth investigating the benefits of filtering on types. The cost for computing the analysis would be higher, but we could imagine several modes of summaries, depending on the time and resources available to compute the summary.

Although it seemed logical to start by looking at shorter paths before longer ones, there are cases when users would prefer to see several depths at the same time, as for Task 2. With the current interface this means repeating the same task with different depths. In the absence of a better solution, we considered this as acceptable, though not optimal. The challenge is not trivial, but would definitely be worth further investigations.

As a prototype, our tool works on small to medium datasets. For larger datasets, it would make sense to compute the analysis on a sample and extrapolate. This would raise design challenges regarding the representation of uncertainty. In the current state of the prototype, we do not provide access to the raw data. To identify entities summarised by a path, we only provide a link to the SPARQL endpoint with the query to fetch the results. It would definitely be valuable to integrate statistics with the content [50], although this would come with new technical and design challenges.

While we studied a specific user group, participants in our interview and experiment spontaneously mentioned the interest of such a tool for Data Reusers when discovering a dataset. The tool could also be adapted for Ontology Builders, for instance to support navigation on inferred class hierarchy [51], and let them discover to which statements inferences can lead. Studying Semantic Web users and building tools to leverage the use of

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**Fig. 11. Execution time and preference: comparison of Path Outlines and SPARQL query editor on each task. a) Participants are quicker with Path Outlines and b) prefer Path Outlines to SPARQL query editor.**
the technology is needed if we want to use it to overcome challenges in HCI@AI [52], so that initiatives such as the CHIP interactive tour guide or Telebuddies [53], [54] do not remain at the margin of the community. Semantic web data being graph data, the principle of a path browser could also be generalized to other graph data, addressing key concerns such as gaining overviews [55], [59], structuring high-dimensional data in a low number of dimensions [57], [58], [59], building visual analysis tools [60], and representing irregular and heterogeneous semi-structured data [61], [62].

9 Conclusion

Linked data producers face a challenge: the particular structure of their data implies new tasks that need to be elicited and empowered. We observed them in situations where they felt hindered in the understanding of their data and characterised their needs. To address these needs, we reified chains of statements into paths, and operationalised this approach into tasks. We interviewed 11 data producers and confirmed that they were enthusiastic with the elicitation of their needs and related tasks, and interested in a tool to meet them. We designed Path Outlines, a tool to support data producers’ tasks, relying on an API to analyse the paths. Our tool enables users to browse and inspect large collections of paths. We compared Path Outlines with Virtuoso SPARQL query editor, SPARQL being the most common way to realise such tasks. Path Outlines was rated as more comfortable, easier, performed better in terms of time and lowered the number of abandonments, although participants had, on average, 5 years of experience with SPARQL, versus 5 minutes with our tool.

We believe that the development of the Semantic Web will rely on tools such as Path Outlines to make sure the quality of Linked Data remains high, and that the Path object as we use it can overcome some of the complexity created by atomizing data as RDF triples at the heart of the Semantic Web.

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