Keywords: Linked Data, Visualization Pipeline, Linked Data Visualization, RDF Visualization, Visual Exploratory Search.

Abstract: Over the recent years, Linked Open Data (LOD) has been increasingly used to support decision-making processes in various application domains. For that purpose, an increasing interest in information visualization has been observed in the literature as a suitable solution to communicate the knowledge described in LOD data sources. Nonetheless, transforming raw LOD data into a graphical representation (the so-called visualization pipeline) is not a straightforward process and often requires a set of operations to transform data into meaningful visualizations that suit users’ needs. In this paper, we propose a LOD generic visualization pipeline and discuss the implications of the internal operations (import → transform → map → render → interact) for creating meaningful visualizations of LOD datasets. To demonstrate the feasibility of this generic visualization pipeline, we implement it as the tool LDViz (Linked Data Visualizer). We demonstrate how LDViz supports access to any SPARQL endpoint through multiple use cases, allowing the users to perform searches with SPARQL queries and visualize the results using multiple visualization techniques.

1 INTRODUCTION

The publication of Linked Open Data (LOD) using RDF (Resource Description Framework) datasets on the Web provides valuable information to support decision-making processes in diverse application domains (Gandon, 2018). Nevertheless, the value of these data depends on the capacity to find relevant information that describes the phenomenon embedded in data. We can observe an increasing interest in using visual and interactive techniques to explore LOD resources via multiple criteria and levels of abstraction by the Semantic Web community for accomplishing three main goals: (i) to explore the relevant concepts of an application domain via ontology representation; (ii) to inspect RDF Graphs (e.g., “for debugging triplets”) (Antoniazzi and Viola, 2018); and (iii) to analyze the instances based on their types/classes. Contrariwise to typical visualizations, which uses specific datasets whose structure and nature are known, enabling one to easily define indicators and visualization techniques that are suitable to support the data exploration, visualizing linked data requires a preceding RDF graph processing to retrieve suitable data that may originate from different endpoints. Moreover, it may sometimes require combining data from different endpoints, resulting in datasets that may contain quality issues (e.g., missing data, inconsistency) and which structure and nature are unknown to the visualization. Although the design process of every visualization tool follows a well-known pipeline (i.e., import → transform → map → render → interact) (Card et al., 1999; Telea, 2014), we could not find any definition of these stages and the issues that arise from applying such visualization pipeline for LOD exploration.

Particularly, a visualization pipeline for LOD data should take into account the linked nature of these datasets by leveraging/supporting/exploiting these links, while being capable of processing and visualizing the data appropriately. This requires a high
level of flexibility in every step of the pipeline, which
could be seen in the drafting of SPARQL queries in
a way that appropriately addresses the links in the
linked data, the possibility of tuning the parameters of
the graphic display and the associated interaction, and
the availability of multiple visualization techniques that
can help users see data according to diverse and
complementary viewpoints.

Contributions. The primary goal of this paper is
to introduce a LOD generic visualization pipeline. Our
goal is to present the function and expected output
of the different steps of the pipeline, and the
underlying issues, so the scientific community can
easily employ it to develop LOD visualization sys-
tems. As a proof of concept, we developed the Linked
Data Visualizer (LDViz). This visualization tool inte-
grates a SPARQL query management interface, a data
transformation engine, and a visualization interface to
support the automatic visualization of data extracted
from any SPARQL endpoint. We show how our im-
plementation allows any expert user to access the
SPARQL endpoint of their choice, perform searches
with SPARQL queries, and visualize the results via a
visualization interface, MGExplorer, designed to as-
sist the exploration of any multivariate network.

The remaining of this work is organized as fol-
lows. Section 2 summarizes previous contributions
for LOD visualization. Section 3 presents the pro-
posed generic visualization pipeline for LOD. Sec-
tion 4 presents the tool developed as a proof-of-
concept of the pipeline. Section 5 describes a set of
use case scenarios to demonstrate the feasibility and
generality of our approach. Section 6 discusses our
results and concludes the paper.

2 RELATED WORK

In this section, we present previous LOD visualiza-
tion solutions focusing on representing mainly three
aspects of RDF datasets: (i) OWL or RDF Schema;
(ii) the RDF graph; and (iii) custom datasets repres-
ted according to data types. Table 1 summarizes
previous works according to supported data format,
access methods, represented aspects of data, visual-
ization and interaction tools.

OWL/RDF Schema Visualization. Kremen et al.
(2018) represent the structure of RDF datasets and the
relationship with other datasets by using class/pro-

properties statistics, spatial and temporal information, and
a dataset summary. Similarly, Anutariya and Dangol
(2018) use a node-link diagram to visualize schema
information inferred via SPARQL queries using ontolog-
ical characteristics of the triples in the LOD data

sources.

RDF Graph Visualization. Aiming at simplifying
the exploration of large RDF graphs, previous works
support progressive visual exploration of LOD given
a resource or an RDF dataset as starting point (Jacksi
et al., 2018; Deligiannidis et al., 2007; De Vocht
et al., 2015). Using a node-link diagram and selec-
tion operations, the user can incrementally reveal/hide
neighboring resources to explore and visualize rel-

vant data of very large RDF graphs (Deligiannidis
et al., 2007), while discovering linked RDF graphs in
the Web (Jacksi et al., 2018), and inspecting informa-
tion and internal relations of data subsets (De Vocht
et al., 2015). Chawuthai and Takeda (2015) visualize
RDF graphs sparsified via graph simplification, which
removes redundant triples; triple ranking according
to topics interesting for the user; and graph filtering
through property selection. The goal is to interpret all
nodes and links as knowledge structures to keep only
interesting triples.

Frasincar et al. (2006) propose an RDF data for-
mat plugin for a general-purpose visual environment
for browsing and editing graph data, where users can
define new operations for data processing, visualiza-
tion, and interaction, and modify visual mapping by
changing the shape, size, and color of nodes and edges.
Likewise, Graziosi et al. (2018) provides a user-friendly
SPARQL query builder to support non-
programmers users in extracting data from the Web
and exploring it through a node-link diagram. The
nodes’ shape (circle, ellipse, polygon), color, border,
etc., can be modified via a customizable template for
the visualization of entities and properties.

Visualization per Datatype. To improve LOD visu-
alization by considering data characteristics, Brunetti
et al. (2013); Thellmann et al. (2015); Peña et al.
(2016) analyze the RDF vocabulary of the input data
to visualize it accordingly, e.g., data containing prop-
erties such as xsd:date and ical:dtstart would
be visualized through timeline or calendar visual-
izations. The S-Paths visualization tool (Destandau
et al., 2021) supports the visualization of resources
sets based on semantic paths by identifying and rank-
ing a set of visualization techniques suitable to ex-
plore the data. Interaction allows to explore different
resources sets and/or use different visualization tech-
niques to get another perspective to the dataset via dif-
ferent semantic paths.

The Visualbox tool (Graves, 2013) generates
graph, temporal and geographical visualizations to
explore SPARQL result datasets; it also exports the
visualisation in a format suitable for incorporation
in hypertextual documents. In a similar way, the
JavaScript wrapper proposed by Skjøveland (2012),
generates visualizations of SPARQL result sets via HTML elements embedded with SPARQL SELECT queries, which are rendered to contain the specified visualization type on page load or function call.

Although a visualization pipeline is necessary to build any visualization (Munzner, 2014), previous works on LOD visualization do not describe how they deal with the different steps of the pipeline, which are often tuned to represent the results of a particular query. Hence, we provide a description of every step of the pipeline and ways of applying it to linked data using multiple queries. Furthermore, the advantage of our approach compared to existing solutions relies on the flexibility that enables users to define meaningful datasets via SPARQL SELECT queries applied to any SPARQL endpoint, so that they can explore multiple aspects of RDF datasets and the LOD Cloud. It also allows users to perform exploratory searches using various complementary visualization techniques instantiated on demand according to the task at hand, instead of a single visualization technique that represents the whole dataset, restraining the analysis to a single view to the data.

### 3 LOD VISUALIZATION PIPELINE

A visualization pipeline is a step-wise process of creating visual representations from data. It usually follows a data-driven approach as shown in Fig. 1 and includes import, transform (optional), mapping, and rendering steps. Additionally, the interaction step allows the users to intervene in the data processing chain according to their needs. Hereafter, we describe a generic visualization pipeline and discuss the implications and design challenges at each step for the visualization of LOD datasets.

**Import.** This step refers to identifying triplestores and queries that allow retrieving relevant data to support the resolution of domain-related tasks. For that, users must know which endpoints are available and which RDF vocabulary compose them. Data can be extracted from endpoints via querying interfaces using SPARQL templates or SPARQL query builders to create SPARQL queries interactively or via online published RDF. Moreover, they might take advantage of the linked data principles (dereferencing, “follow you nose”) and semantic Web standards by using the GRAPH and SERVICE SPARQL clauses to retrieve

<table>
<thead>
<tr>
<th>Ref</th>
<th>Year</th>
<th>Tool</th>
<th>Input Data</th>
<th>Rep.</th>
<th>Data Access</th>
<th>Visualization</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deligiannidis et al. (2007)</td>
<td>2007</td>
<td>PGV</td>
<td>RDF Dataset</td>
<td>Per Datatype</td>
<td>RDF Dump</td>
<td>SPARQL</td>
<td>C, F, V</td>
</tr>
<tr>
<td>Destandais et al. (2021)</td>
<td>2020</td>
<td>S-Paths</td>
<td>RDF Dataset</td>
<td>Per Datatype</td>
<td>RDF Dump</td>
<td>C, G, H, P, PT</td>
<td>C, F</td>
</tr>
<tr>
<td>Frasincar et al. (2006)</td>
<td>2018</td>
<td>N/A</td>
<td>RDF Dataset</td>
<td>RDF Graph</td>
<td>RDF Dump</td>
<td>H, PT, R</td>
<td>C, F, M</td>
</tr>
<tr>
<td>Jacksi et al. (2018)</td>
<td>2018</td>
<td>LOD Explorer</td>
<td>RDF Dataset</td>
<td>RDF Graph</td>
<td>JSONP</td>
<td>R</td>
<td>D, F</td>
</tr>
<tr>
<td>Chawuthai and Takeda (2015)</td>
<td>2016</td>
<td>N/A</td>
<td>RDF Dataset</td>
<td>RDF Graph</td>
<td>SPARQL</td>
<td>construct</td>
<td>R</td>
</tr>
<tr>
<td>Peña et al. (2016)</td>
<td>2016</td>
<td>N/A</td>
<td>SPARQL Result Sets</td>
<td>Per Datatype</td>
<td>SPARQL / RDF Dump</td>
<td>C, G, P, R</td>
<td>?</td>
</tr>
<tr>
<td>De Vocht et al. (2015)</td>
<td>2015</td>
<td>LOD/VisSuite</td>
<td>RDF Dataset</td>
<td>RDF Graph</td>
<td>SPARQL</td>
<td>R</td>
<td>C, F</td>
</tr>
<tr>
<td>Destandais et al. (2015)</td>
<td>2015</td>
<td>VizSuite</td>
<td>RDF Dataset</td>
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<td>R</td>
<td>C, F</td>
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<td>2014</td>
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<td>R</td>
<td>C, F, V</td>
</tr>
</tbody>
</table>

Table 1: Summary of related work: publication reference, year, name (if provided), input data type, represented information, data access, visualization type (C: comparison, CL: clustering, D: distribution, G: geographical, H: hierarchical, P: proportional, PT: patterns, R: relationship, T: temporal, TT: text and table), and interaction operations (C: chart customization, E: data filtering, M: visual mapping, V: view operations).
and combine data from different knowledge graphs possibly in different endpoints.

**Transform.** This step deals with data quality issues due to the data on the Web is often incomplete, redundant, and inconsistent. For that, operations like filter, enrich, re-sample, and calculate are needed to transform the dataset according to what is expected in the visualization. LOD connectivity can be used to complete the dataset (e.g., by retrieving data from different endpoints) or via disambiguation algorithms (i.e., by determining the contradictions or inconsistencies in the dataset). Existing solutions in the literature often deliver visualizations based on the data type (e.g., numeric, categorical, temporal, geographic, etc.), which provide little added value to solve domain-related tasks. Thus, this step should include algorithms capable of deriving interesting indicators to the application domain, ensuring the delivery of meaningful visualizations capable of supporting decision-making processes.

**Visual Mapping.** This step addresses the visual representation of every transformed data via visualization techniques capable of representing the relationship between data items (e.g., hierarchy, grids, etc.) and a meaningful mapping to visual variables (e.g., shape, color, etc.). One should also choose whether and how to visualize the links within LOD data (e.g., via graphs). The mapping can be performed as part of the query setup (by associating SPARQL query variables to visual variables) or interactively on the user interface. In any case, allowing the user to modify the visual mapping is a suitable strategy to include semantic meaning in the application domain (e.g., using standard color codes in the domain).

**Rendering.** The goal here is to make the best use of screen space to display data. The graph nature of LOD implies that information can be retrieved via alternative paths. Thus, a suitable visualization approach is the usage of multiple views that are synchronized (via linking and brushing operations (Keim, 2002)) and (i) can be freely arranged on the display or (ii) are placed in a tab-based interface where each view is rendered in a separated window.

**Interaction.** Once the data is visually represented, the user should be able to interrogate the data through interactive operations (e.g., selection, pan and zoom, linking and brushing, and text search). The connectivity property of LOD also allows the dynamic enrichment of the analysis by allowing the user to query endpoints during the exploration phase. It is interesting to notice that user interaction might affect any previous steps in the visualization pipeline.

### 4 LINKED DATA VISUALIZER

In this section, we present the Linked Data Visualizer (LDViz), an implementation of the proposed generic visualization pipeline for LOD datasets based on web technologies, i.e., JavaScript, the D3 (Data-Driven Documents) library to create visualizations, and the nodejs library to manage the linked data access server that handles data retrieval through SPARQL queries. LDViz covers the steps of the pipeline as follows.

**Import.** Data import is handled via SPARQL queries. The generality of LDViz relies on the fact that users can query any SPARQL endpoint as long as it can return result sets in a JSON format. We provide an interactive interface where the user can test and debug SPARQL queries or import predefined queries, which they may modify at will.

**Transform.** Data transformation occurs in three moments: at the definition of the SPARQL query, which determines the information to be retrieved from the SPARQL endpoint, at the transformation engine, where the SPARQL results sets are cleaned and trans-
formed into a suitable data model for the visualization; and when the user filters the input dataset in one view to explore it in another, which requires reshaping the data to fit the visualization technique.

**Visual Mapping.** Visual mapping occurs in three ways: by transforming the SPARQL results set in a suitable format for visualization, by mapping the data variables to the visual variables of each technique, and by allowing users to tune certain variables, e.g., by defining colors to represent them.

**Rendering.** This is handled by MGExplorer (Cava, 2017), a visualization interface to explore multidimensional network data.

**Interaction.** Via the MGExplorer interface, we provide selection operations that enable the user to subset the input data to be explored via different visualization techniques, which present complementary views to the data.

### 4.1 Data Model

The data model corresponds to a custom graph model defined through a SPARQL query, which uses arbitrary query patterns on RDF graphs to generate the edges ?s p ?o of the graph one wants to visualize, where ?s and ?o represent the nodes of the graph and ?p corresponds to labeled edges between them. Listing 4 illustrates an example SPARQL query supported by LDViz. In this example query ?s and ?o will be bound to actors and ?p to films. The result of this SPARQL query will be used to build a visualization of the social network of actors co-starring in films. In addition to these three variables, the data model allows three other reserved variables that serve to describe the edges (?p) of the output graph visualization: ?type, ?label, and ?date. Variable ?type can be used to type the edges of the output graph (e.g., in a graph where films connect actors, films can be “typed” or classified by their genre). Due to human’s perceptual and cognitive limits towards visualizations, only a certain number of graphic elements can be drawn on the screen. Thus, we allow the variable ?type to be bound to only four different values describing the edges. If the variable ?type is bound to more than four distinct values in the SPARQL query result, the system automatically determines the three more relevant ones based on the number of bindings and considers the remaining values as the "Other" category. The ?label variable is intended to provide a description of edges in natural language (e.g., the value of rdfs:label properties describing resources). Finally, the ?date variable is used to provide a visual representation of the distribution of edges over time (e.g., if edges are films, it could correspond to the release year).

### 4.2 SPARQL Query Management Interface

The query management interface (Fig. 2) allows users to test and debug SPARQL queries or import predefined ones, which they can edit or clone according to their needs. The interface expects an address for the SPARQL endpoint of the targeted RDF dataset, a name for the SPARQL query (optional), and the query code itself. Note that the user can retrieve data from more than one endpoint by leveraging the full strength of the SPARQL language, including the SERVICE clause – depending on the SPARQL implementation available at the queried SPARQL endpoint. Action buttons at the bottom (Fig. 2d) allow to visualize the SPARQL query results using MGExplorer or export them as a JSON file.

```sparql
(a) { "nodes": [ "fst": {color": "green"}, "snd": {color": "orange"} ], "services": [ "Corese Browser": { "url": "http://corese.inria.fr/srv/service/covid?uri="} ]
(b) select * where { ?s p ?o
  bind("fst" as ?style1) bind("snd" as ?style2)}
```

Listing 1: Example of (a) GSS and (b) its usage in a SPARQL query.

Each query is associated with a Graph Style Sheet (GSS) that can be used to transform the default node-link diagram through a declarative specification of visibility, layout, and styling rules (Pietriga, 2006). For doing so, the user defines the styling rules as classes in a style sheet of reference (JSON format) (e.g., Listing 1a) and bind them to dedicated variables in the SPARQL query (i.e. ?style1 to style ?s, ?style2 to style ?o, and ?style for both). This information is then processed in the transformation engine, which associates the style classes to the visual variables used in the visualization. Moreover, the GSS supports a behavior feature that enables exploring data via an external service (e.g., the Corese browser (Corby et al., 2012), which allows browsing the original repository of open data) as long as an URL is provided (see Listing 1a).

### 4.3 MGExplorer

In our approach, data visualization is provided via MGExplorer (Menin et al., 2021), a tool that assists the exploration of multidimensional and multivariate graphs. Its main advantage is a flexible exploratory process that combines multiple views to allow comparing (i) two or more different subsets of...
Table 2: Classification of visualization techniques available in MGExplorer according to the type of analysis they provide.

<table>
<thead>
<tr>
<th>Node-link Diagram</th>
<th>ClusterVis</th>
<th>IRIS</th>
<th>GlyphMatrix</th>
<th>Bar chart</th>
<th>Listing</th>
</tr>
</thead>
<tbody>
<tr>
<td>network</td>
<td>clusters</td>
<td>pairwise</td>
<td>distribution</td>
<td>listing</td>
<td></td>
</tr>
</tbody>
</table>

data through a particular perspective generated by a particular view, and (ii) multiple perspectives of the same subset of data using several views. The views can be dragged, allowing the user to rearrange the visualization space in meaningful ways to the task at hand. They are connected via line segments to represent their dependencies and enable retracing the exploration path.

The bootstrapping process of MGExplorer consists in displaying a node-link diagram of the relationships within the dataset and a history panel, which are both interactive and visible throughout the whole exploration process. Other views can be created, and the history panel is progressively completed with provenance information that indicates the dependencies between views in a hierarchical representation, which allows for prompt recovering of the multiple analytical paths that emerge from a particular view. Further, users can hide any of the currently displayed views, which they may revisit later using the history panel.
thus cleaning the display area in a way that help them to focus on what is relevant to the task at hand. The input data is the reference data for selection operations throughout the whole exploratory process. The system supports data and view selection, allowing users to specify subsets of interest from the whole input graph and suitable views to explore them. Upon the element selection, the system filters the input dataset accordingly, and the resulting subset undergoes a process that transforms and maps it to the chosen visualization technique. An exploration history records information regarding the selection operation, the data subset, the chosen view, and the transformed data.

Table 2 summarizes the set of visualization techniques available in MGExplorer. The Node-link diagram shows nodes as items and edges between them as relationships. This diagram is used to provide an overview of any network defined within the dataset according to some criteria (e.g., keywords, co-publications, etc.).

The IRIS technique allows isolating a data item of interest (at the center) and showing all other data items with which it has a specific relationship in a circular view (Cava et al., 2014). The data attributes of the pairwise relationships are encoded by the height and color of a bar placed between the item of interest and each related item. The user can place any item in the field of view center by clicking on it, switching the focus of the IRIS.

The GlyphMatrix (Cava and Freitas, 2013) technique is based on a matrix where rows and columns represent data items in a cluster, and the cells contain glyphs encoding attributes that describe a pairwise relationship. The default glyph is a star-plot-like shape, with a variable number of axes used to encode values of selected data attributes. By pointing a glyph in the matrix, it is possible to enlarge the glyph to see the data attributes’ details.

The Bar Chart technique shows the distribution of data attributes’ value for an item or set of items. For example, in one of our use case scenarios, the x-axis encodes temporal information, while the y-axis encodes the counting of co-publications. The data is displayed as a single bar per time period or multiple colored bars to represent categorical information of attributes.

The Listing technique lists the items that form the relationship between two or more nodes in the graph. Each item of the list is linked to a descriptive web page in the dataset, where the user can obtain more information about it.

4.4 Transformation Engine

The transformation engine of LDViz consists of a converter module from SPARQL JSON results to the MGExplorer data model and a set of algorithms (i.e., mappers) that process subsets of data defined during the exploratory process via visual querying operations and map the resulting data to a particular visualization technique, also interactively chosen by the user.

From SPARQL Results to MGExplorer Data Model. The system receives the SPARQL JSON results set, which undergoes a transformation process to extract an attributed graph, encoded in the JSON format, that will serve as input data to MGExplorer. Besides identifying the mandatory and optional variables from the dataset, the process also derives indicators to describe the relationship between each pair of nodes, such as the total count of items and the count of items per type, when this information is provided.

MGExplorer Mappers. Every selection operation triggers a transformation process that filters and transforms the data and maps it to the selected visualization technique via: the ClusterVis mapper, which extracts clusters of nodes grouped according to the existing links among them, e.g., in a co-authorship network, the algorithm detects groups of authors co-authoring the same publication(s); the IRIS mapper, which extracts pairwise relationships between the selected node and the other nodes in the subset; the GlyphMatrix mapper, which extracts pairwise relationships by analyzing every possible combination of pairs of nodes within the subset; the Bar chart mapper, which extracts the distribution of items in the subset according to a particular attribute (e.g., date); and the Listing mapper, which extracts the list of links in the graph and their descriptive information (if provided). Regardless of the resulting relationship type, every mapper keeps information on the count and type of items per relationship.

5 USE CASE SCENARIOS

In this section, we demonstrate the flexibility of LDViz to accommodate and represent different aspects of an RDF dataset via three case studies exploring (1) the interactive visualization of an RDF graph and its ontology, (2) the interactive visualization of RDF
Use Case 1: Exploring RDF Graphs and Their Ontologies.

When working with the Semantic Web, a recurrent task is to inspect the RDF graph and its ontology for learning its content. In this use case, we consider exploration tasks where the user wants to (1) display the RDF graph with no particular goal in mind and (2) get an idea of the ontology used in the RDF graph. Thus, we generate four visualizations with the SPARQL queries in Listing 2, which, although they are applied to DBpedia, are generic enough to retrieve information from any SPARQL endpoint.

Fig. 3a depicts the node-link diagram representing the 1000 first statements in the DBpedia graph, which is an extract of the DBpedia RDF graph. DBpedia is a large-scale, multilingual knowledge base that extracts structured information from the Wikipedia project and other sources. It contains about 400 million triples describing various aspects of the world.

Figure 3: Node-link diagrams representing an extract of DBpedia’s (a) RDF graph, (b) class hierarchy, (c) property hierarchy, and (d) signatures of properties linking classes (orange) and properties (light green).

1SPARQL endpoint: http://fr.dbpedia.org/sparql

graph summarizations, and (3) visual mining of RDF graphs. Further, we show the generality of LD-Viz by illustrating those case studies on two distinct SPARQL endpoints giving access to the DBpedia FR dataset, which gathers about 400 million triples describing the content generated in the Wikipedia project, and the HAL dataset, which gathers scientific publications from the HAL open archive, a storage of scholarly documents from all academic fields.
where we can hover over the nodes to inspect related resources. Fig. 3b–d depicts the node-link diagrams representing the three typically explored aspects of an ontology: the class hierarchy, the property hierarchy, and the signatures of properties that connect properties to classes. Users can hover over the nodes to inspect and navigate within hierarchies and explore properties signatures by hovering over nodes that represent either properties to inspect their signature or classes to identify all the properties to whose signatures the selected class belongs, e.g., dbo:SoccerClub is related to three properties.

Besides allowing users to define nodes and relationships in meaningful ways for their exploration purposes, GSS can be used to assign meaningful visual elements to certain variables. For example, in Fig 3d, we use color to distinguish property (light green) and class nodes (orange), easing visual search and understanding of relationships between nodes of different types.

### Use Case 2: Exploring RDF Graph Summarizations

An RDF graph with millions of triples will generate a huge and cluttered node-link diagram. Structural RDF graph summarization addresses this issue by providing indices or summaries of RDF graphs to aggregate the triples in meaningful ways. Here we consider the visualization of (i) existing paths between classes of resources in an RDF graph, (ii) existing property paths between the resources of the graph, or (iii) paths showing the resource between classes and properties. The resolution of these tasks is possible via three visualizations generated with the SPARQL queries in Listing 3. The resulting node-link diagrams (Fig. 4) show classes or properties instead of resources of the RDF graph.

#### Use Case 3: Visual Mining of RDF Graphs

Here we show how LDViz enables RDF graph mining for exploring data describing a phenomenon of interest: network relationship of people. Listing 4 shows

Figure 4: Node-link diagrams representing DBpedia’s (a) class paths, (b) property paths, and (c) paths of type class → property → class.
the query used to retrieve the network of Robert Redford’s from DBpedia, including the name of actors (\(?s, ?o\)) that appear in a movie (\(?p\)) with Robert Redford, and a description of movies with the title (\(?\text{label}\)), release date (\(?\text{date}\)), and genre (\(?\text{type}\)). We found 278 results, creating a network of 26 nodes (actors) and 124 links (movies) shown in Fig. 5a. We see that Redford has 25 co-stars across four movies where details are available at the Listing view (Fig. 5b). The resources can be explored using the Corese browser (Fig. 5c) or any other service enabled in the GSS. The ClusterVis view (Fig. 5d) all Redford’s co-stars grouped by movies.

We use the SPARQL query in Listing 5 to retrieve the co-authorship network of Fabien Gandon from HAL, which results in 4680 triples. The corresponding graph contains 237 nodes (authors) and 1160 links (publications), which we visualize via the node-link diagram in Fig. 5d.

6 DISCUSSION AND CONCLUSIONS

In this paper, we presented and discussed the implications of designing a generic visualization pipeline for exploring LOD datasets. The proposed pipeline covers different means of accessing LOD datasets; it addresses various issues regarding data enrichment, filtering, and reshaping. It supports diverse visualization layouts (i.e., one or multiple view systems) and
interactive operations that enable dynamic addition, replacement and/or modification of the input dataset, visualization techniques, and visual mapping. We implemented the pipeline as a generic tool, LDViz, for exploring and understanding the Semantic Web of LOD. It provides access to any SPARQL endpoint by allowing users to perform searches with SPARQL queries and visualize the results via multiple visualization techniques. We developed LDViz using web technologies and made it available at (omitted for blind review), ensuring accessibility by anyone.

LDViz allows the definition of custom subsets of RDF data via SPARQL queries, which enables different ways of data exploration, such as: (i) inspecting and debugging the RDF graph and its ontology, (ii) exploring smaller RDF datasets via summarization to enable task resolution more efficiently by extracting meaningful information from data, and (iii) exploring graph mining result sets. When creating SPARQL queries, a great deal of time and effort is spent in testing and debugging to ensure that the resulting data is sufficient to accomplish the task at hand. Thus, we provide a query management interface where users can test and debug their queries, and import predefined queries, which they may use as templates to create new queries, simplifying the querying process. Furthermore, LDViz includes an interface where users without SPARQL knowledge can explore the result sets of predefined queries. We also provide a visualization interface to expert users in Semantic Web whose goal is to inspect or discover RDF/LOD datasets, and users of a given application domain whose goal is to analyze the data for supporting decision-making processes. For the purpose of strengthening the exploration capabilities, future work includes the implementation of a system of follow-up queries that allows one to import new data on-the-fly into the exploration process by either using predefined queries or creating new suitable queries.

We support exploration search via the MGExplorer, a visualization tool for progressively exploring multidimensional network data via multiple complementary views. Users can select subsets of data through visual queries and display the results in a separate view that shows a different perspective to the data. The multiple views can be hidden, revisited, and arranged in the display area in meaningful ways to support efficient data exploration while reducing cognitive overhead and clutter-related problems. While our use cases showed the support of different exploratory tasks, most data on the Web represent real-world phenomena, which are intrinsically spatio-temporal. Thus, future work includes expanding the visualization techniques and interaction tools to represent geospatial data.

The use case scenarios represent the resolution of well-known use cases for RDF visualization, which demonstrated the utility and feasibility of LDViz. However, user-based evaluations are essential and should be performed to determine the usability and suitability of the approach. Thus, future work includes developing user-based evaluations to investigate the usability of LDViz to assist the resolution of these and other use cases by expert users in Semantic Web, as well as to assist decision-making processes via visual mining of RDF graphs, involving expert users in diverse application domains.

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**REFERENCES**


