Use Cases for Linked Data Visualization Model

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ABSTRACT

There is a vast amount of Linked Data on the web spread across a large number of datasets. One of the visions behind Linked Data is that the published data is conveniently reusable by others. This, however, depends on many details such as conformance of the data with commonly used vocabularies and adherence to best practices for data modeling. Therefore, when an expert wants to reuse existing datasets, he still needs to analyze them to discover how the data is modeled and what it actually contains. This may include analysis of what entities are there, how are they linked to other entities, which properties from which vocabularies are used, etc. What is missing is a convenient and fast way of seeing what could be usable in the chosen unknown dataset without reading through its RDF serialization. In this paper we describe use cases based on this problem and their realization using our Linked Data Visualization Model (LDVM) and its new implementation. LDVM is a formal base that exploits the Linked Data principles to ensure interoperability and compatibility of compliant analytic and visualization components. We demonstrate the use cases on examples from the Czech Linked Open Data cloud.

Categories and Subject Descriptors

H.5.2 [**User interfaces**]: GUIs, Interaction styles; H.3.5 [**Online Information Services**]: Data sharing; H.3.5 [**Online Information Services**]: Web-based services

Keywords

Linked Data, RDF, visualization, discovery

1. INTRODUCTION

A vast amount of data represented in a form of Linked Open Data (LOD) is now available on the Web. Therefore, the focus of Linked Data experts now starts to shift from the creation of LOD datasets to their consumption and several new problems arise. Consider a Linked Data expert working for a modern company who has a task of finding suitable datasets in the LOD Cloud[1] that would enhance the company's internal data. As of today, he can search for the datasets in `http://datahub.io`, which is a CKAN[2] catalog instance, which provides full–text search and keyword and faceted browsing of the textual metadata of the datasets. To be able to decide whether a given dataset is

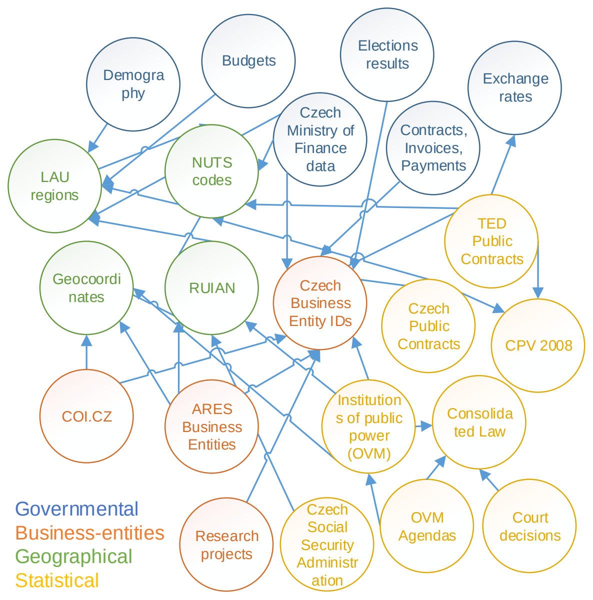


Figure 1: The 2015 Czech Linked Open Data Cloud

valuable for his use case or not, the expert needs to find out whether it contains the expected entities and their properties. In addition, the entities and properties can be present in the dataset, but they may be described using a different vocabulary than expected. A good documentation of datasets is rare, therefore, the expert needs to go through the dataset manually, either by loading it to his triplestore and examining it using SPARQL queries or by looking at the RDF serialization in a text editor. Only recently some other technical approaches started to emerge such as *LODeX* [2] that shows some statistics about the number of RDF triples, classes, etc. and tries to extract the data schema from a SPARQL endpoint. However, what the expert would really need is a simple process where he would provide the data and see whether the entities he expects, and maybe even some others he does not expect, can be found in the given dataset, and see them immediately. In this paper, we will focus on this part of dataset consumption. Now let us assume

[1] `http://lod-cloud.net/`
[2] `http://ckan.org/`

that the expert found a suitable dataset such as a list of all cities and their geocoordinates and saw its map visualization. This data could enhance his closed enterprise linked data containing a list of the company's offices. It would then be useful for the expert if he could just include the appropriate links from his dataset to the discovered one and see his offices on a map in a generic visualization. It would be even better if he could then refine this visualization instead of creating another one from scratch.

In this paper we define the use cases which have the potential to help Linked Data experts in their work. Then we briefly describe our *Linked Data Visualization Model* (LDVM) [4] and show its new implementation, using which we demonstrate that the use cases can be executed, which is the main contribution of this paper. We will demonstrate our approach using the datasets we prepare in our OpenData.cz initiative, which can be seen in Figure 1, namely Institutions of Public Power (OVM[3]) and registry of land identification, addresses and properties of the Czech Republic (RUIAN[4]).

This paper is structured as follows. In Section 2 we define the use cases we want to support by our approach. In Section 3 we briefly describe the principles and basic concepts of LDVM. In Section 4 we introduce our new proof–of–concept LDVM implementation and describe its components and relation to LDVM. In Section 5 we show a sample visualization pipeline. In Section 6 we show how we use our implementation to support the defined use cases. In Section 7 we survey related work and in Section 8 we conclude.

2. MOTIVATING USE CASES

In this section we motivate our work using a series of use cases with which we aim at helping Linked Data experts in various stages of their work.

2.1 What Can I See in the Given Data

The first use case is to show possible visualizations of data in a given dataset. The dataset must be given in an easy way - using either a link to an RDF dump or using direct RDF file upload, or using a link to a SPARQL endpoint that contains the data. The result should be a list of possible visualizations that could be meaningful for the dataset. When the user clicks on a possible visualization, he should see his data visualized by the selected technique, e.g. on a map, using a hierarchy visualizer, etc. This use case has several motivations. Firstly, one should be able to quickly sample a previously unknown dataset that may be potentially useful based on its textual description such as the one on `http://datahub.io`. Another motivation for this use case is the need to be able to quickly and easily show someone what can be done with his data in RDF. In addition, this use case can help Linked Data experts even during the process of Linked Data creation which usually happens in iterations. In the first iteration of creating Linked Data an expert usually writes a transformation of some basic information about entities in the source data such as their names and types. Then he reviews the created RDF data, selects another portion of the source data, amends his transformation, executes it and again observes the resulting, more detailed RDF data. He repeats this process until all of the source data, or at least the desired parts, is transformed to RDF. The iterations can be fast, when the expert knows the source data and the desired RDF form well, or they can be slow, when for example the expert shows the result of each iteration to a customer and discusses what part of the source data is he going to transform next. Either way, it would be better to have a visualization accompanying the data in each iteration, which would show how the data gets better and more detailed. Also, trying to visualize the resulting data provides additional means of validation of the transformation, e.g. when it is entities on a map, it is always better to see the result on a map than just an RDF text file. On the other hand, the visualization method needs to be quick and easy and not custom made for the data, because the data between iterations is only temporary as it lasts only until it gets improved in the next iteration. However, this is made possible by the Linked Data vocabulary reuse principle, all we need is a library of components supporting standard vocabularies and usage of the vocabularies in the data, which is a well known best practice. Finally, when developing advanced visualizations, the designer can start with the automatically offered one and refine it instead of starting from scratch.

An example of this use case is that when a dataset containing a hierarchy is provided, then a visualization using a hierarchy visualizer should be offered and it should display some meaningful data from the source dataset. To be specific, we will show this use case on a dataset that contains a hierarchy or regional units ranging from individual address points to the whole country.

2.2 What Can I Combine My Data With To See More

The second use case is to show which additional visualizations of the input data can be used when the data is simply linked to another dataset. One motivation of this use case is to visually prove the value of linking by showing the additional visualization options gained by it. Another motivation is the expert in a modern company that has its internal linked data and wants to see the improvement gained by linking it to the public LOD cloud. For this use case the user should be able to provide his data easily as in the previous use case. This time he is interested in seeing which additional visualizations of his data he can use when he linked his data to another dataset. The result should again be a list of possible visualizations which, however, use not only the input dataset, but also some other to achieve a better visualization. For example, a dataset with addresses of public institutions, linked to a geocoded dataset of all addresses yields a map visualization with no additional effort.

2.3 What Data Can I Visualize Like This

The third use case is a reverse one compared to the previous two. It is to show datasets or their combinations which can be visualized using a selected visualizer. The motivation for this use case is that the user sees a visualization that he likes and he wants to prepare his data so that it is compatible with the visualization. For that he wants to see which other datasets possibly combined with some transformations use this visualization. For this use case the user selects a visualization and he should get a list of data sets possibly with transformations which can be visualized by the selected visualizer. For example, the user selects a map visualizer and he should see that a dataset with a list of cities can be visualized this way.

[3]`http://datahub.io/dataset/cz-ovm`
[4]`http://datahub.io/dataset/cz-ruian`

3. LINKED DATA VISUALIZATION MODEL

To realize the use cases defined in the previous section we will use a new implementation of our Linked Data Visualization Model (LDVM), which we defined and refined in our previous work [4, 6, 8]. It is an abstract visualization process customized for the specifics of Linked Data. In short, LDVM allows users to create data visualization pipelines that consist of four stages: Source Data, Analytical Abstraction, Visualization Abstraction and View. The aim of LDVM is to provide means of creating reusable components at each stage that can be put together to create a pipeline even by non-expert users who do not know RDF. The idea is to let expert users to create the components by configuring generic ones with proper SPARQL queries and vocabulary transformations. In addition, the components are configured in a way that allows the LDVM implementation to automatically check whether two components are compatible or not. If two components are compatible, then the output of one can be connected to the input of the other in a meaningful way. With these components and the compatibility checking mechanism in place, the visualization pipelines can then be created by non-expert users.

3.1 Model Components

There are four stages of the visualization model populated by LDVM components. *Source Data* stage allows a user to define a custom transformation to prepare an arbitrary dataset for further stages, which require their input to be RDF. In this paper we only consider RDF data sources such as RDF files or SPARQL endpoints, e.g. DBPedia. The LDVM components at this stage are called *data sources*. The *Analytical Abstraction* stage enables the user to specify analytical operators that extract data to be processed from one or more data sources and then transform it to create the desired analysis. The transformation can also compute additional characteristics like aggregations. For example, we can query for resources of type `dbpedia-owl:City` and then compute the number of cities in individual countries. The LDVM components at this stage are called *analyzers*. In the *Visualization Abstraction* stage of LDVM we need to prepare the data to be compatible with the desired visualization technique. We could have prepared the analytical abstraction in a way that is directly compatible with a visualizer. In that case, this step can be skipped. However, the typical use case for Visualization Abstraction is to facilitate reuse of existing analyzers and existing visualizers that work with similar data, only in different formats. For that we need to use a LDVM *transformer*. In *View* stage, data is passed to a *visualizer*, which creates a user-friendly visualization. The components, when connected together, create a analytic and visualization pipeline which, when executed, takes data from a source and transforms it to produce a visualization at the end. Not every component can produce meaningful results from any input. Typically, each component is designed for a specific purpose, e.g. visualizing map data, and therefore it does not work with other data. To create a meaningful pipeline, we need compatible components.

3.2 Component Compatibility

Now that we described the four basic types of LDVM components, let us take a look at the notion of their *compatibility*, which is the key feature of LDVM. We want to use the checking of component compatibility in design time to rule out component combinations that do not make any sense and to help the users to use the right components before they actually run the pipeline. Therefore, we need a way to check the compatibility without the actual data.

Each LDVM component has a set of *features*, where each feature represents a part of the expected component functionality. A component feature can be either mandatory or optional. For example, a visualizer that displays points and their descriptions on a map can have 2 features. One feature represents the ability to display the points on a map. This one will be mandatory, because without the points, the whole visualization lacks purpose. The second feature will represent the ability to display a description for each point on the map. It will be optional, because when there is no data for the description, the visualization still makes sense - there are still points on a map. Whether a component feature can be used or not depends on whether there is the data needed for it on the input. Therefore, each feature is described by a set of input descriptors. An *input descriptor* describes what is expected on the inputs of the component. In this paper we use a set of SPARQL queries for the descriptor. We could also consider other forms of descriptors, but that is not in the scope of this paper. A descriptor is applied to certain inputs of its component.

In order to evaluate the descriptors in design time, we require that each LDVM component that produces data (data source, analyzer, transformer) also provides a sample of the resulting data, which is called an *output data sample*. For the data sample to be useful, it should be as small as possible, so that the input descriptors of other components execute as fast as possible on this sample. Also, it should contain the maximum amount of classes and properties whose instances can be produced by the component, making it as descriptive as possible. For example, when an analyzer transforms data about cities and their population, its output data sample will contain a representation of one city with all the properties that the component can possibly produce. Note that, e.g. for data sources, it is possible to implement the evaluation of descriptors over the output data sample as evaluation directly on the represented SPARQL endpoint. For other components, fast evaluation can be achieved by using a static data sample.

We say that a feature of a component in a pipeline is *usable* when all queries in all descriptors are evaluated `true` on their respective inputs. A component is *compatible* with the mapping of outputs of other components to its inputs when all its mandatory features are usable. The usability of optional features can be further used to evaluate the expected quality of the output of the component. For simplicity, we do not elaborate on the output quality in this paper. The described mechanism of component compatibility can be used in design time for checking of validity of the visualization pipeline. It can also be used for suggestions of components that can be connected to a given component output. In addition, it can be used in run time for verification of the compatibility using the actual data that is passed through the pipeline. Finally, this concept can be also used for periodic checking of data source content, e.g. whether the data has changed its structure and therefore became unusable or requires pipeline change. For a detailed description and thorough examples of compatibility checking on real world data see our previous paper [8].

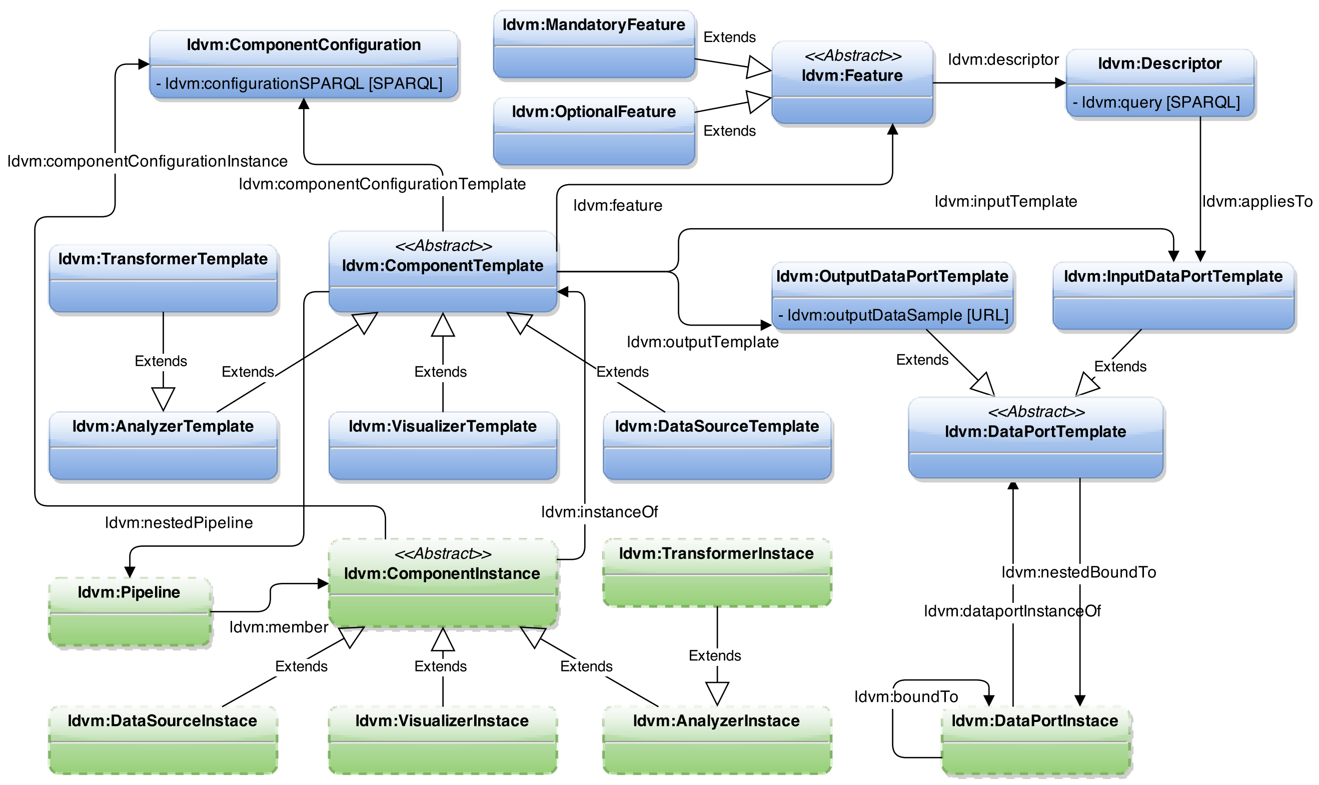


Figure 2: LDVM Vocabulary

4. ARCHITECTURE OF THE NEW LDVM IMPLEMENTATION

In our previous LDVM implementation version *Payola* [7] we had the following workflow. First, the pipeline designer registered the data sources he was planning to use, if they were not already registered. Then he started to create an analysis by selecting data sources and then added analyzers and transformers to the analytic pipeline. Then the pipeline was executed and when done, the pipeline designer selected an appropriate visualizer. There were no hints of which visualizer is compatible with the result of the analysis and this workflow contained unnecessary steps. The pipeline and its components existed only inside *Payola* with no means of their creation and management from the outside. Nevertheless it demonstrated some advantages of our approach. It showed that pipelines created by expert users can be reused by lay users and the technical details can be hidden from them. It also showed that results of one analysis can be used by various visualizers and also it showed that one analysis can run on various data sources.

In our new implementation of LDVM we aim for having individual components running as independent web services that accept configuration and exchange information needed to get the input data and to store the output data. Also we aim for easy configuration of components as well as easy configuration of the whole pipeline. In accordance with the Linked Data principles, we now use RDF as the format for storage and exchange of configuration so that any code that works with RDF can create, maintain and use LDVM components both individually and in a pipeline. For this purpose we have devised a vocabulary for LDVM. In Figure 2 there is a UML class diagram depicting the structure of the LDVM vocabulary. Boxes represent classes, edges represent object properties (links) and properties listed inside of the class boxes represent data properties. The architecture of our new implementation corresponds to the vocabulary. The data entities correspond to software components and their configuration. We chose the `ldvm`[5] prefix for the vocabulary. The vocabulary and examples are developed on GitHub[6]. Let us now briefly go through the individual parts of the vocabulary, which correspond to parts of the LDVM implementation architecture.

4.1 Templates and Instances

In Figure 2 there are blue and green (dashed) classes. The blue classes belong to template level of the vocabulary and green classes belong to the instance level. These two levels directly correspond to two main parts of the LDVM implementation. At the template level we register LDVM components as abstract entities described by their inputs, outputs and default configuration. At the instance level we have a pipeline consisting of interconnected specific instances of components and their configurations. The easiest way to imagine the division is to imagine a pipeline editor with a toolbox. In the toolbox, there are LDVM component templates and when a designer wants to use a LDVM component in a pipeline, he drags it onto the editor canvas, creating an instance. There can be multiple instances of the same LDVM

[5] `http://linked.opendata.cz/ontology/ldvm/`
[6] `https://github.com/payola/ldvm`

component template in a single pipeline, each with a different configuration that overrides the default one. The template holds the input descriptors and output data samples which are used for the compatibility checking together with the instance input and output mappings. Each instance is connected to its corresponding template using the `instanceOf` property.

4.2 Component Types

There are four basic component types as described in Section 3.1 - data sources, analyzers, transformers and visualizers. They have their representation on both the template level - descendants of the `ComponentTemplate` class - and instance levels - descendants of the `ComponentInstance` class. From the implementation point of view, transformers are just analyzers with one input and one output, so the difference is purely semantic. This is why transformers are subclass of analyzers.

4.3 Data Ports

Components have input and output data ports. On the template level we distinguish the inputs and outputs of a component. To `InputDataPortTemplate` the input descriptors of features can be applied. `OutputDataPortTemplate` has the `outputDataSample` links to the output data samples. Both are subclasses of `DataPortTemplate`. The data ports are mapped to each other - output of one component to input of another - as instances of `DataPortInstance` using the `boundTo` property. This data port instance mapping forms the actual visualization pipeline which can be then executed. Because data ports are not LDVM components, their instances are connected to their templates using a separate property `dataPortInstanceOf`.

4.4 Features and Descriptors

On the template level, features and descriptors (see Section 3.2) of components are represented. Each component template can have multiple features connected using the `feature` property. The features themselves - instances of either the `MandatoryFeature` class or the `OptionalFeature` class - can be described using standard Linked Data techniques and vocabularies such as `dcterms` and `skos`. Each feature can have descriptors, instances of `Descriptor` connected using the `descriptor` property. The descriptors have their actual SPARQL queries as literals connected using the `query` property. In addition, the input data port templates to which the particular descriptor is applied are denoted using the `appliesTo` property.

4.5 Configuration

Now that we have the LDVM components, we need to represent their configuration. On the template level, components have their default configuration connected using the `componentConfigurationTemplate` property. On the instance level, components point to their configuration using the `componentConfigurationInstance` property when it is different from the default one. The configuration itself is the same whether it is on the template level or the instance level and therefore we do not distinguish the levels here and we only have one class `ComponentConfiguration`.

The structure of the configuration of a LDVM component is completely dependent on what the component needs to function. It is also RDF data and it can use various vocabularies. It can be even linked to other datasets according to the Linked Data principles. Therefore it is not a trivial task to determine the boundaries of the configuration data in the RDF data graph in general. On the other hand, each component knows precisely what is expected in its configuration and in what format. This is why we need each component to provide a SPARQL query that can be used to obtain its configuration data so that the LDVM implementation can extract it. That SPARQL query is connected to every configuration using the mandatory `configurationSPARQL` property.

4.6 Pipeline

Finally, the pipeline itself is represented by the `Pipeline` class instance. It links to all the instances of LDVM components used in the pipeline. Another feature supporting collaboration of expert and non-expert users is pipeline nesting. An expert can create a pipeline that is potentially complex in number of components, their configuration and binding, but could be reused in other pipelines as a black box data source, analyzer or transformer. As this feature is not important in this paper, we do not further describe it. It is sufficient to say that the `nestedPipeline` and `nestedBoundTo` properties of LDVM serve this purpose.

4.7 Component Compatibility Checking

The component compatibility checks (see Section 3.2) are exploited in various places. The checks can happen during run time when the actual data passed between components is verified as it is passed along the pipeline. They can also happen in scheduled intervals when existing pipelines are re-checked to determine possible changes in data sources that can cause pipelines to stop being executable. This can be easily used for verification of datasets that change frequently. Another usage of the checks is during design of a pipeline in a future pipeline editor, which is not implemented yet, when a user wants to connect two components in a pipeline. However, the most valuable usage of component compatibility checking is in the pipeline discovery algorithm.

4.8 Pipeline Discovery Algorithm

The pipeline discovery algorithm is used to generate all possible pipelines based on a set of datasets and is therefore the core functionality for this paper and the use cases it demonstrates. It is inspired by the classical Breadth-first search (BFS) algorithm where, simply put, an edge between two nodes representing LDVM components in a pipeline exists if and only if the descriptor of the second one matches the output data sample of the first one. The edge then represents the possibility to pass data from the output of the first component to the input of the second component. The algorithm works in iterations and builds up pipeline fragments in all compatible combinations. We will demonstrate it on an example of two data sources (RUIAN, Institutions), a RUIAN geocoder analyzer, which takes two inputs, a Towns extractor, and a Google Maps visualizer.

It starts with the inputs of all available LDVM components (analyzers, transformers, visualizers) checking selected data sources, which form trivial, one member pipeline fragments. In Figure 3 we can see the trivial fragments in the top right part. In the first step every available component is checked with each selected data source. When a component's input is compatible with the output of the last component

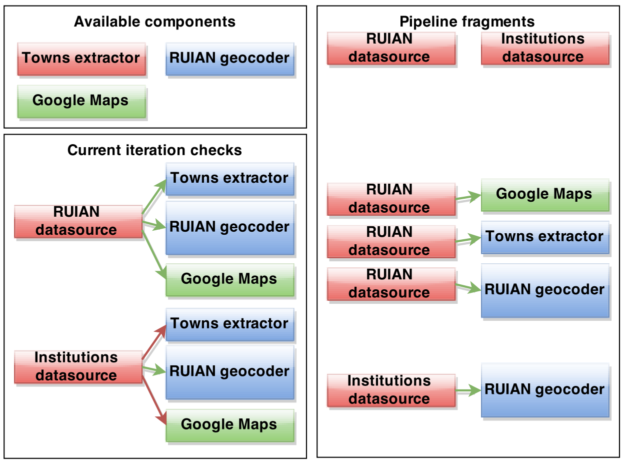


Figure 3: Pipeline discovery iteration 1

of a pipeline fragment (output of a data source in the first iteration), it is connected. A successful check is denoted by a green arrow and a unsuccessful one with a red arrow.

When all of the components inputs are connected, the component is added to the pipeline fragment and this fragment gets checked again by all LDVM component inputs in the next iteration. This is visible in Figure 4 – a pipeline fragments from iteration 1 ending with the RUIAN geocoder are not checked until both inputs of the geocoder are connected, which happens in iteration 2 and 3. When the algorithm reaches a visualizer and binds all of its inputs, the pipeline fragment leading to this visualizer is saved as a possible pipeline. This happens in Figure 3 with the 2 member pipeline and in Figure 4 iterations 3 and 4. When there are no new pipeline fragments to consider in the next algorithm iteration, we have generated all possible pipelines and the algorithm ends. In the example we generated 3 pipelines. Note that the generated pipelines are in a form of trees oriented from leaves to root where leaves are data sources and the root is the visualizer. Of course the complexity of this algorithm raises with the number of components and data sources to check. On the other hand the compatibility checks greatly reduce the number of possibilities and leave only the compatible ones. A more rigorous measurements of time consumed are part of our future work.

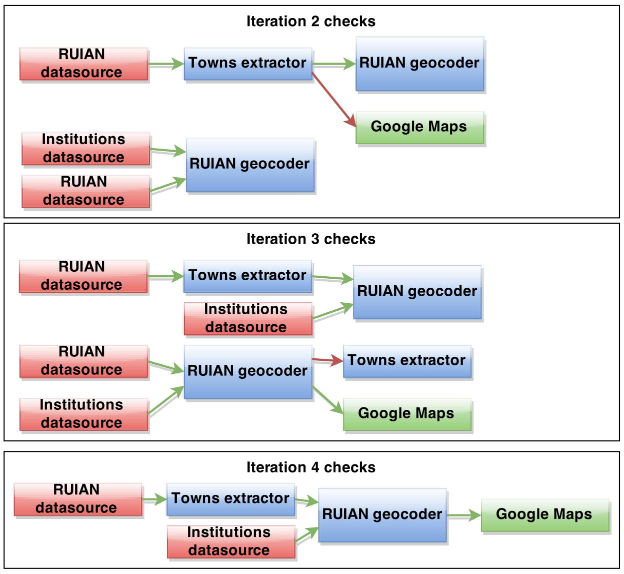
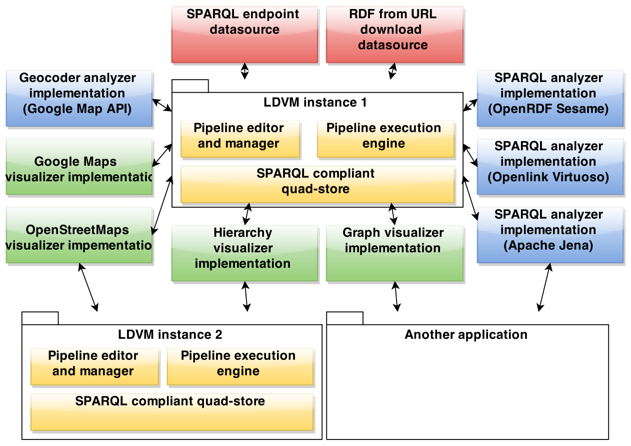


Figure 4: Pipeline discovery - more iterations

4.9 Component implementations

Note that we have not talked about the actual LDVM component implementations yet, only templates, which are abstract descriptions and default configurations, and instance, which are representations in a pipeline with inputs and outputs bound to other components. Our vision is to have LDVM component implementations as standalone web services configurable by RDF, reusable among LDVM instances and other applications. They would live separately from our LDVM implementation instance, which would then serve only as a pipeline editor, catalog and launcher (see Figure 6). The components would register to the LDVM instance with access data and a link to LDVM templates that can be processed using this component implementation. The RDF



SPARQL endpoint datasource
RDF from URL download datasource
Geocoder analyzer implementation (Google Map API)
LDVM instance 1
Pipeline editor and manager
Pipeline execution engine
SPARQL compliant quad-store
SPARQL analyzer implementation (OpenRDF Sesame)
Google Maps visualizer implementatic
SPARQL analyzer implementation (Openlink Virtuoso)
OpenStreetMaps visualizer impementatio
Hierarchy visualizer implementation
Graph visualizer implementation
SPARQL analyzer implementation (Apache Jena)
LDVM instance 2
Pipeline editor and manager
Pipeline execution engine
SPARQL compliant quad-store
Another application

Figure 6: LDVM implementation and LDVM components

configuration sent to the component implementation would contain the actual component instance configuration together with access information for getting input data, storing output data and a callback URL for sending execution result information. The execution result information would include the status (success, failure) and optionally logs to be displayed to the pipeline user. However, the complete freedom of the components is not a trivial development task, so it still remains a part of our future work. Now, the actual component implementations we use run on the same machine as the LDVM implementation and we have a hard coded list of which components can process which LDVM component templates. Nevertheless, this implementation limitation does not affect the use cases we show in this paper.

5. LDVM PIPELINE EXAMPLE

Let us now briefly demonstrate how a simple LDVM pipeline looks like from the data point of view. See Figure 5. Again, we will have blue for template level and green

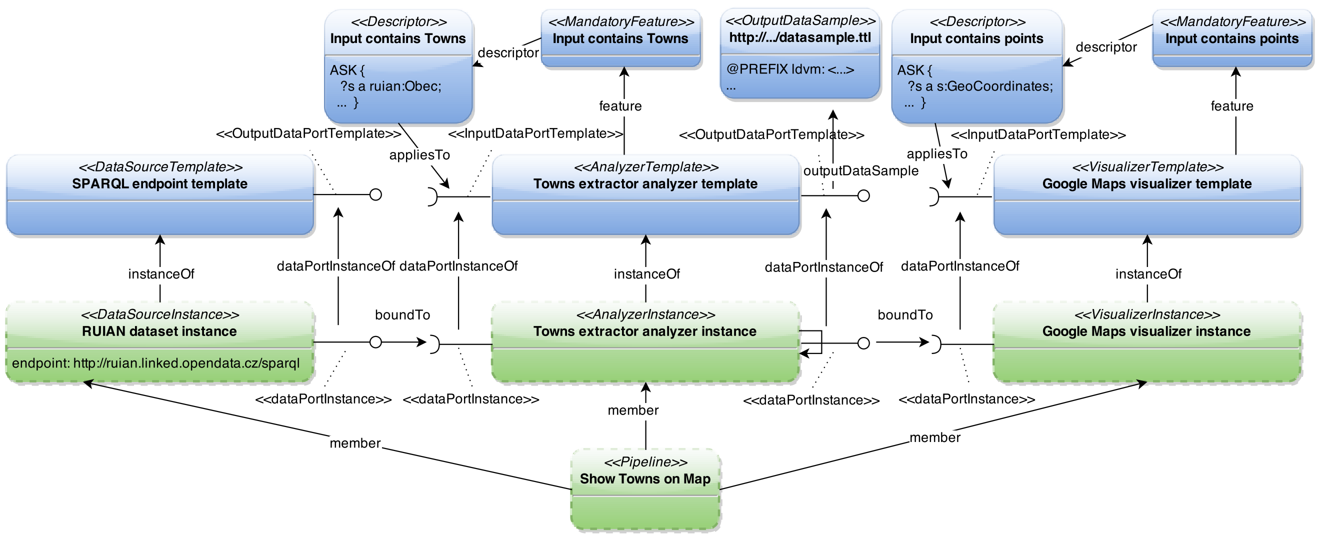
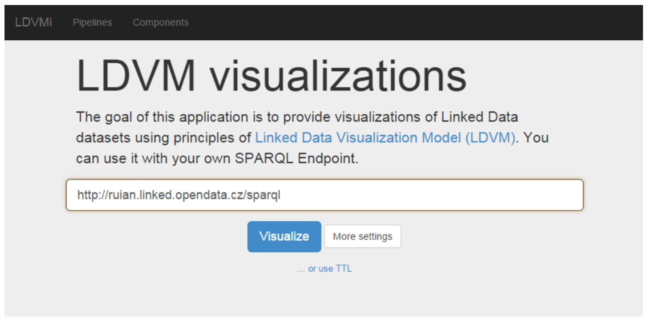


Figure 5: Sample LDVM Pipeline

(dashed) for instance level. The instance level is simpler, let us start with it. On the bottom we have a pipeline, which points to LDVM component instances that belong to the pipeline via the `ldvm:member` property. It is a simple pipeline consisting of one data source, one analyzer and a visualizer. The data source instance is configured to access our RUIAN SPARQL endpoint and it is an instance of a generic SPARQL endpoint data source template. The analyzer instance extracts information about Czech towns from the data source, which contains far more information. The descriptor of the analyzer's feature *Input contains Towns* is a SPARQL ASK query which checks for presence of a data source with towns information and is applied to the input data port template of the analyzer. The output data port template of the analyzer has a link to an output data sample, which is a Turtle file containing data about one Czech town as a sample. This brings us to the Google Maps visualizer, which only has input data port template with one feature and a descriptor checking for presence of geocoordinates in its input data. Note that the data port binding is done on the instance level, which is what will be seen and edited in a pipeline editor. On the other hand, features, descriptors and output data samples are all on the template level. Because RUIAN includes geocoordinates for each entity, the resulting visualization shows towns in the Czech Republic on a map.

6. REALIZATION OF USE CASES

In our new proof–of–concept implementation of LDVM (LDVMi) we aim at a more straight forward workflow utilizing the compatibility checking feature of LDVM. The goal is to provide the user with some kind of a meaningful visual representation of his data as easily as possible. This means that the user specifies the location of his data and that should be all that is needed to show some initial visualizations. This is achieved by our compatibility checking mechanism (see Section 3.2) using which we generate all possible pipelines that can be created using the data sources and LDVM components registered in the used LDVM instance. We are still in early stages of the new implementation, it runs at `http://ldvm.opendata.cz` and all the mentioned LDVM components should be loaded there. The use cases from this section should be executable there and anyone can experiment with any SPARQL endpoint or RDF data that is compatible with the loaded components.



LDVM visualizations

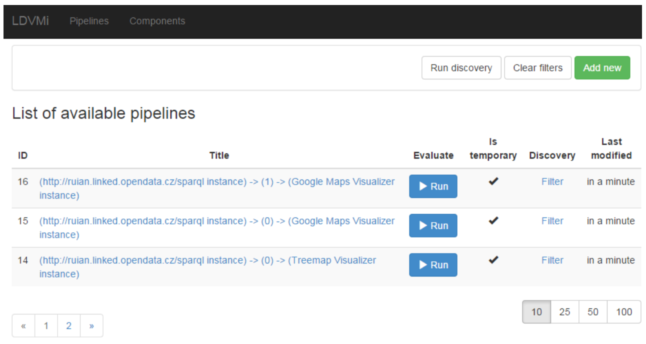
The goal of this application is to provide visualizations of Linked Data datasets using principles of Linked Data Visualization Model (LDVM). You can use it with your own SPARQL Endpoint.

http://ruian.linked.opendata.cz/sparql

Figure 7: Endpoint selection

6.1 What Can I See in the Given Data

In this use case we are in the role of a Linked Data expert that has a link to a dataset and wants to quickly see what can be seen in it. The actual offered visualizations depend solely on the set of analyzers, transformers and visualizers present in the LDVM instance. We assume that the expert has his LDVM instance populated with components that he plans to use and he checks a potentially useful dataset he has a link to. For the realization of this use case we will use the RUIAN dataset. It contains a lot of data among which is a hierarchy of regional units ranging from address points to the whole country modeled using SKOS. We have a link to the dataset in a SPARQL endpoint, so we point to it (see Figure 7). Next, we see the list of possible pipelines based on the evaluation of compatibility with the endpoint, see Figure 8. We can see that there are 3 pipelines. We can also see their data sources, their visualizer, and in between



List of available pipelines

ID	Title	Evaluate	Is temporary	Discovery	Last modified
16	(http://ruian.linked.opendata.cz/sparql instance) -> (1) -> (Google Maps Visualizer instance)	▶ Run	✓	Filter	in a minute
15	(http://ruian.linked.opendata.cz/sparql instance) -> (0) -> (Google Maps Visualizer instance)	▶ Run	✓	Filter	in a minute
14	(http://ruian.linked.opendata.cz/sparql instance) -> (0) -> (Treemap Visualizer instance)	▶ Run	✓	Filter	in a minute

Figure 8: Possible pipelines list

the number of analyzers the pipeline contains. The first two end with a Google Map visualizer – the dataset contains geocodes for all objects – and the third one with a TreeMap hierarchy visualization, which means that a hierarchy was found in our dataset and it can be visualized. We select the third pipeline and we see the hierarchy as in Figure 9. This proves that using a LDVM instance populated with

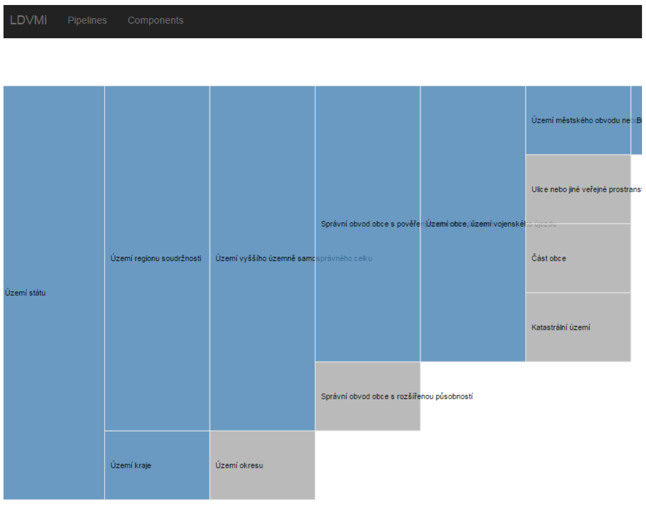
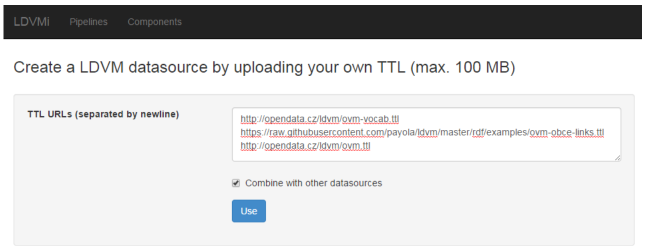


Figure 9: Treemap visualization of a simple hierarchy

a set of LDVM components, we can easily check whether a given dataset contains usable data and see some initial results quickly. This is thanks to the static data samples and SPARQL ASK based descriptors. As part of our future work we will do rigorous measurements to see the response times according to number of components and number and complexity of descriptors.

6.2 What Can I Combine My Data With To See More

We assume that we have the RUIAN data source and Maps visualizer registered in our LDVM instance. In addition, we will have a RUIAN Towns geocoder analyzer registered, which takes a list of towns from RUIAN (reference dataset) on one input and the dataset linked to RUIAN (linked dataset) on the other input. It outputs the linked dataset enhanced with GPS geocoordinates of the entities from the reference dataset. For this use case, we will use our dataset of Institutions



Create a LDVM datasource by uploading your own TTL (max. 100 MB)

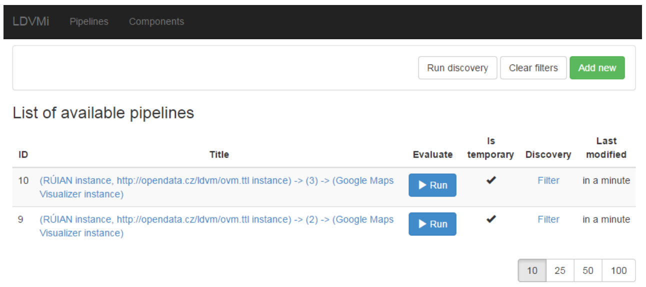
TTL URLs (separated by newline)

http://opendata.cz/ldvm/ovm-vocab.ttl
https://raw.githubusercontent.com/payola/ldvm/master/rdf/examples/ovm-obce-links.ttl
http://opendata.cz/ldvm/ovm.ttl

[✓] Combine with other datasources

Figure 10: File upload

of Public Power from `DataHub.io`. This could also be an internal dataset of a company. Note that we will also add the schema of the data for better filtering in the visualizer, which would, however, typically be in the second iteration after we found out that without it, we cannot filter properly in the visualizer, but we would still see the towns on the map. The dump and schema are in TriG serialization, which is not yet supported, however it is easy to convert it to Turtle. We upload the schema[7], the links[8] to the RUIAN dataset and the data in Turtle[9] as in Figure 10. After the file upload is finished, we see the possible pipelines as in Figure 11. Note



List of available pipelines

ID	Title	Evaluate	Is temporary	Discovery	Last modified
10	(RÚIAN instance, http://opendata.cz/ldvm/ovm.ttl instance) -> (3) -> (Google Maps Visualizer instance)	▶ Run	✓	Filter	in a minute
9	(RÚIAN instance, http://opendata.cz/ldvm/ovm.ttl instance) -> (2) -> (Google Maps Visualizer instance)	▶ Run	✓	Filter	in a minute

Figure 11: Possible pipelines for dataset combination

that this pipeline discovery is the same as in the example in 4.8 with one difference. There, the algorithm searched for all pipelines that could be created from the two datasets, which included a direct visualization of RUIAN on a map. Here, the discovery algorithm does not return this pipeline because it searches for pipelines that visualize the linked dataset in combination with other data sources. Therefore, we have two possibilities of how to see our newly linked dataset on a map. One is applying the RUIAN Towns geocoder to the linked dataset and takes the whole RUIAN data source as the other input. This one, while theoretically possible, is not usable in our current implementation because the whole RUIAN data source is large (600M triples) and contains tens of thousands of entities of various types. This is why we will choose the other possible pipeline, which, in addition, runs the RUIAN data through RUIAN Towns extractor analyzer, which filters out data about other RUIAN entities. The chosen pipeline can be seen in Figure 12. All that is left is to evaluate the pipeline (press the Run button) and display the resulting visualization that can be seen in Figure 13. The filtering of

[7] `http://opendata.cz/ldvm/ovm-vocab.ttl`
[8] `https://raw.githubusercontent.com/payola/ldvm/master/rdf/examples/ovm-obce-links.ttl`
[9] `http://opendata.cz/ldvm/ovm.ttl`

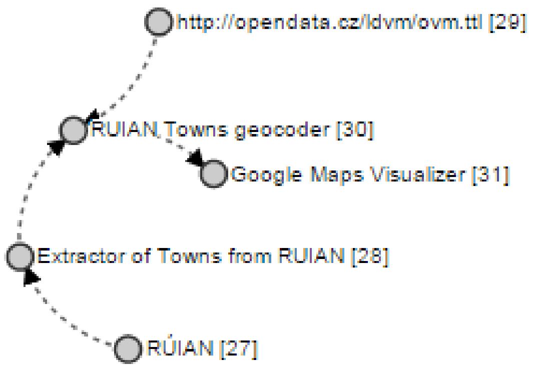

http://opendata.cz/ldvm/ovm.ttl [29]
RUIAN Towns geocoder [30]
Google Maps Visualizer [31]
Extractor of Towns from RUIAN [28]
RÚIAN [27]

Figure 12: The chosen pipeline combining datasets

displayed institution of public power is possible thanks to the schema that we included in the beginning. Note that the compatibility checks so far have a form of a query that checks for a presence of certain class and property instances in a dataset. E.g. in this use case, we determine the presence of links to RUIAN by presence of properties which we created for linking to RUIAN objects in the RUIAN vocabulary and we rely on creators of other datasets that they will use these properties when linking their data to RUIAN. What we do not check for at this time is whether the links in one dataset lead to existing or valid objects in the second dataset, because that would require non–trivial querying.

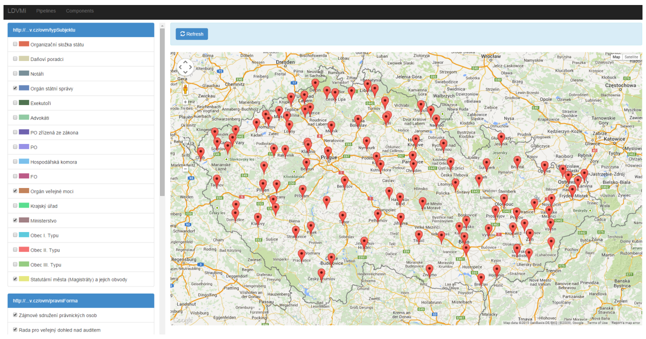
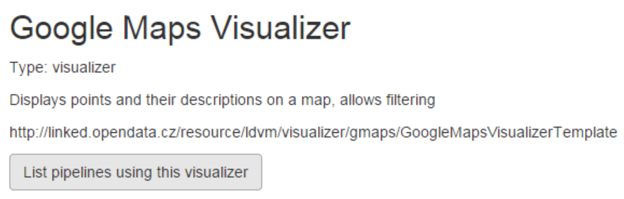


Figure 13: Maps visualization of linked dataset with filtering

This means that if someone connected a dataset of German towns represented using our RUIAN vocabulary to the RUIAN geocoder analyzer together with the Czech Institutions of Public Power, he would get a compatible pipeline. However, this pipeline would not produce any usable data on evaluation as the two input datasets simply do not have matching contents. We will look into possibilities of checking for these situations in our future work.

6.3 What Data Can I Visualize Like This

In this use case we will find datasets that are visualizable by a specific visualizer. It is in fact a simple filter of all known possible pipelines that contain this visualizer. For this use case we go to the list of available components in our LDVM instance. In this list, we will choose the desired visualizer such as the Google Map visualizer. There we click



Google Maps Visualizer

Type: visualizer

Displays points and their descriptions on a map, allows filtering

http://linked.opendata.cz/resource/ldvm/visualizer/gmaps/GoogleMapsVisualizerTemplate

List pipelines using this visualizer

Figure 14: All pipelines using this visualizer

the *list pipelines using this visualizer* button (see Figure 14) and we see the list of pipelines that contain it. This tells us the data sources and their possible transformations using analyzers and transformers that result in data that can be visualized by the chosen visualizer.

7. RELATED WORK

More and more projects are focused on analyzing, exploring and visualizing Linked Data. For a more complete survey of various Linked Data visualization tools see our previous paper [8]. Here, we will focus on the most recent approaches. With the LDVM vocabulary and our new implementation we aim at an open web-services like environment that is independent of the specific implementation of the LDVM components. This of course requires proper definition of interfaces and the LDVM vocabulary is the base for that. However, the other approaches so far usually aim at a closed browser environment. Those are similar to our Payola [7] in their ability to analyze and visualize parts of the Linked Data cloud. They do not provide configuration and description using a reusable vocabulary and they do not aim at a more open environment with their implementation that would allow other applications to reuse their parts. Recent approaches include *Hide the stack* [5], where the authors describe a browser meant for end-users which is based on templates based on SPARQL queries. Also recent is *LDVizWiz* [1], which is a very LDVM-like approach to detecting categories of data in SPARQL endpoints and extracting basic information about entities in those categories. An lightweight application of LDVM in enterprise is described in LinDa [10]. Yet another similar approach that analyzes SPARQL endpoints to generate faceted browsers is *rdf:SynopsViz* [3]. In [2] the authors use their *LODeX* tool to summarize LOD datasets according to the vocabularies used.

The most relevant related work to the specific topic of a vocabulary supporting Linked Data visualization is Fresnel - Display Vocabulary for RDF [9]. Fresnel specifies how a resource should be visually represented by Fresnel-compliant tools like LENA [10] and Longwell [11]. Therefore, Fresnel vocabulary could be perceived as a vocabulary for describing LDVM visualization abstraction. This is partly because the vocabulary was created before the Linked Data era and therefore focuses on visualizing RDF data without considering vocabularies and multiple sources.

8. CONCLUSIONS AND FUTURE WORK

[10]https://code.google.com/p/lena/

[11]http://simile.mit.edu/issues/browse/LONGWELL

In this paper we defined use cases that aid Linked Data experts in various stages of their work and showed how we can realize them using our implementation of the Linked Data Visualization Model (LDVM). The first use case was to easily show contents of a given dataset using LDVM components and mainly visualizers. The second use case was to show for a given dataset with which other known datasets it can be combined to achieve a visualization. The third use case was to show which known datasets can be visualized using a selected visualizer so that the expert can adjust his data accordingly. Then we briefly described LDVM and its vocabulary and implementation and our vision of LDVM components as independent web services. Finally, we showed that using the LDVM implementation populated by LDVM components we are able to execute the defined use cases.

During our work we have identified multiple directions we should investigate further. When we evolve our LDVM implementation into a distributed system with components as individual web services, many new opportunities will arise. We could be able to do load balancing, where we will have multiple implementations running on multiple machines able to process the same LDVM template and its instances. Also, the SPARQL implementations, while identical in principle, can be differentiated using various properties. One of those properties can be the actual SPARQL implementation used as, from our experience, every implementation supports SPARQL in a slightly different way or supports a slightly different subset of it. Also, the same SPARQL query can run substantially faster on one implementation and substantially slower on another one, etc. Another direction to investigate further is towards Linked Data Exploration – a process of searching the Linked Data Cloud for datasets that contain data that we can reuse. Our approach so far requires selecting the dataset to investigate. However, that alone can be a non–trivial effort and using Linked Data Exploration we could identify the datasets for LDVM processing based on some form of user requirements. Our closest goal of course is to make our new LDVM implementation more user friendly and to develop a more presentable library of visualizers, analyzers and transformers.

9. ACKNOWLEDGMENTS

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