Charles University in Prague
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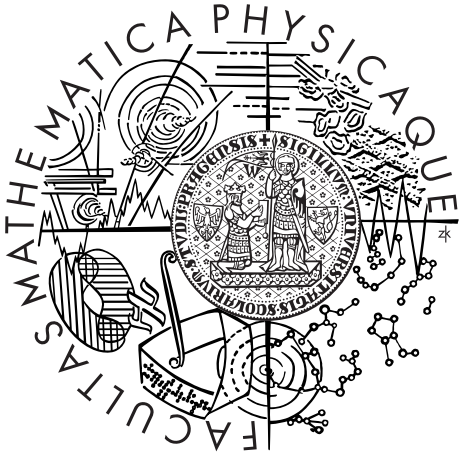
MASTER THESIS



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Analysing and Visualizing Statistical Linked Data

KSI

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I declare that I carried out this master thesis independently, and only with the cited sources, literature and other professional sources.

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Název práce: Analysing and Visualizing Statistical Linked Data

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Abstrakt: Práce popisuje způsoby zpracování statistických dat v prostředí Linked Data, především s využitím metaformátu Data Cube Vocabulary. Její součástí je popis nástrojů, které souvisí s analýzou a vizualizací RDF dat nejen ze statistického prostředí. Nedílnou součástí je také popis nástroje Payola, na jehož vývoji se autor i nadále podílí. Výsledkem práce je zejména návrh a implementace systému, který umožňuje konverzi RDF dat dle slovníků Data Cube Vocabulary. Navržený systém byl implementován a integrován do aplikace Payola. Dále autor implementoval několik dalších rozšíření tohoto systému. V rámci popisu implementace jsou zmíněna také omezení vyplývající z integrace se systémem Payola. V závěru práce autor popisuje několik experimentů, v jejichž rámci aplikoval implementovaný systém na vybrané datasety.

Klíčová slova: Linked Data, Data Cube, analýza, vizualizace, Payola

Title: Analysing and Visualizing Statistical Linked Data

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Abstract:

The thesis describes several means of processing statistical data in the ambience of Linked Data and is in particular focused on the utilization of Data Cube Vocabulary metaformat. Its content offers a description of tools related to analysis and visualization of RDF data not only from the statistical view. An indivisible part of this work is the depiction of the Payola tool on whose development is the author still working on. The outcome of this thesis is mainly proposal and consequential implementation of the system that enables a conversion of RDF data in compliance with the DCV vocabularies. The designed system was implemented and integrated to the Payola application. Several other extensions of the system were also implemented by the author. Within the scope of the implementation process there are mentioned also limitations arising from the integration with Payola. In the conclusion the writer describes a few experiments where some of the chosen datasets were applied to the implemented system.

Keywords: Linked Data, Data Cube, analysis, visualization, Payola

Contents

Introduction and motivation

Nowadays, there are many techniques of processing data. Unfortunately, there are many different data formats one can work with. It makes the processing a lot more difficult. The task becomes even harder when one wants to connect two different datasets in order to benefit from the connection. The connection allows us to get some additional information about entities from each of the standalone datasets. Therefore, a lot of computation time is spent on converting, formatting and transforming data into another form. But transforming datasets into a matching format is not enough. One needs to specify how the data should be linked together.

There are many ways of doing that. Starting with implementing the logic into a simple conversion script (according to a specific dataset) to introducing a more complex metadata description framework for purposes of generic data processing. Since one of the most attractive tasks in this area is to be able to connect any of the datasets available on the Internet, we are interested in the generic description frameworks. We would like to have a tool, which enables us to work with any data on the Internet (formatted according to some kind of rules). We would like to link them together, analyze them and visualize them.

One of the most used description frameworks is the Resource Description Framework [1]. It is a standard model for data interchange on the Web. It tells us how to describe resources on the Internet in order to allow other people, applications and tools to understand such a description. That gives us a potential to link any data on the Internet. Based on the framework, a new model named Linked Data [2] was introduced. The model has been brought up to make data interconnecting easier.

The result of interconnecting data while utilizing the principles of the Linked Data model and Resource Description Framework is a directed graph. Its vertices represent resources we have information about. The edges stand for relations between such entities. From this point on, it is up to us, how we look at the data. We can either explore them in a plain graph or apply some more semantics and make domain specific visualizations while using ontologies and other advanced techniques.

One of the specific domains are statistical data, which are one of the most interesting kind of data. They are produced and processed by many stakeholders. In the context of *Linked Open Data*, the most interesting are, of course, governments and scientific groups. But we would like to work with such data in the usual way — make tables, charts or more interesting visualizations. While speaking about Open Data, a specific user group — data journalists — would like to work with Linked Data, but they are probably missing some basic tools, which would enable them to interpret gathered results in the way readers would understand.

After applying the rules of the Linked Data model, the statistical data (even tabular data) get transformed into a generic graph. The only, but very important advantage, is that we have some additional metadata information available. Moreover, the data are still linked with related entities from all over the Internet. That brings us to another model, the Data Cube Vocabulary [3]. It is a model,

which tells us how to describe multi-dimensional (statistical) data with respect to Linked Data and RDF principles.

Goals of the thesis

The aim of this thesis is to describe these models, analyze the possibilities of working with multi–dimensional data in the environment of Linked Data. We will also propose a system which will enable its user to convert Linked Data into the Data Cube Vocabulary model. A prototype of such a system will be implemented. An exemplary visualisation of the statistical data will be implemented and presented. Moreover, some missing Payola user interface features will be implemented.

Structure of the text

In Chapter 1, we describe the aforementioned models and standards — RDF, Linked Data, Data Cube and Data Cube Vocabulary. Some examples are presented. Chapter 2 contains description of existing tools and applications. We compare those to our application, Payola [4]. We also examine some related papers, especially the LDVM proposal [5]. The Payola application is described in Chapter 3. Later on (Chapter 4), we propose a system for analyzing and visualizing data compliant with the Data Cube Vocabulary model. Implementation of a prototype is described in Chapter 5. In Chapter 6, we present capabilities of the implemented system and experiment with some statistical datasets.

1. Statistical data in the context of Linked Data

To understand the rest of the thesis, let us talk about the aforementioned models. We will take the description step by step, starting with a dataset stored in a plaintext file. After a while, we will get familiar with RDF, Linked Data and last, but not least, with the Data Cube Vocabulary.

Since we are discussing statistical data, we will use a simple real–life example. National statistical offices all over the world are well–known for periodic gathering of the statistics about the population of the country they are operating in. Moreover, those statistics are being regularly published and gathered by international organizations, e.g. the UN [6] which can make a comparison and build another statistics upon the national data. Also, other organizations, like Google [7] use those data to publish them and make some advanced statistics.

That is, in fact, why we would like to have the data in a pre–defined structure, wrapped with metadata to perfectly understand what the data in a given dataset mean. Moreover, we would take advantage of such a dataset to speed up and automate its processing. It would be great to be able to introduce a tool, which will take the national statistics immediately after its publishing and deliver a new version of the international dataset without the need of any user input.

1.1 From speech to structured data

We will introduce the reader to the problem by examining an example based on the total number of citizens living in the country. That is a very simple kind of information, but we will demonstrate how this could be put into the context of the models mentioned in the introduction.

Let us start with a dataset with only one entry:

```
The Czech Republic has 10 505 445 citizens.
```

That is a sentence a normal person would say but it holds a statistical information. If we wanted to keep this information in a simple structured text file, we would e.g. name it `number_of_citizens.txt` and it would have the following contents:

```
Czech Republic      10505445
```

Normally, we keep this kind of statistics to make a comparison, for instance, to compare the total number of citizens of all the countries in the world. We will, however, continue with just the two of them:

```
Czech Republic      10505445
Slovakia            5404555
```

That gives us a dataset with two entries. Each entry is consisted of two parts. Let us notice, that its semantics are kept in the reader's head. The document itself does not keep the information. To process the data, it is necessary to know what the information in the file represents. You could change the contents of the file into the following form:

```
Czech Republic      10505445
Slovakia            5404555
Meat                like
Fruit               orange
```

Such a dataset is technically correct (values are separated by tabulators), nevertheless semantically, it makes no sense. After reading the contents of the file, the reader is aware of the fact that in the given context the added lines do not fit in. Let us return to the meaningful example.

If we keep the meaning of the values, we know that in the first column we have the name of the country and in the second one, we have the total number of citizens. Those statements could be called *observations*, as it can be said that someone made an observation about there being over 10 million people living in the Czech Republic. We can also say that the dataset has got two *dimensions*. The first one is the place where the observation has taken place, the second one is the value being measured.

That would make a nice Excel table, simple chart or a nice map of central Europe with two labels. Those are the usual ways of processing such datasets.

Now, let us get back to the very first statement:

```
The Czech Republic has 10 505 445 citizens.
```

When transferring the statement into a more technical form, we forgot to extract one dimension. The sentence also carries information about time. This is quite an important part of the information since the count of citizens of the specific country evolves with time. People are dying as well as getting born. Since the sentence is presented while using the present tense, we can conclude that the observation is valid for the current year (2013).

That means the dataset stored in a plaintext file should look similar to this:

```
Czech Republic      10505445    2013
Slovakia            5404555     2013
```

The last column evidently holds the year of the observation being made. That gives us three dimensional dataset. We know the place, the total number of citizens and the time of the measured value being acquired.

Now, we may come to a decision of publishing such a document to the Web. We can transform it into a web page and publish it on a server.

Example of such a web page source code can be seen in Figure 1.1. We published the data not only in a more structured form but also provided an explanation of its meaning. Therefore, some additional data had to be added. In fact, we should speak of it as of metadata, since the meaning is rather descriptive instead of semantical.

```
<html>
    <head>
        <title>Number of citizens in a country</title>
    </head>
    <body>
        <table>
            <thead>
                <tr>
                    <th>Country name</th>
                    <th>Number of citizens</th>
                    <th>Year</th>
                </tr>
            </thead>
            <tbody>
                <tr>
                    <td>Czech Republic</td>
                    <td>10505445</td>
                    <td>2013</td>
                </tr>
                <tr>
                    <td>Slovakia</td>
                    <td>5404555</td>
                    <td>2013</td>
                </tr>
            </tbody>
        </table>
    </body>
</html>
```

Figure 1.1: An example of an HTML file with tabular data

With a specifically programmed script or a tool (so-called *scraper*) it is possible to convert such a web page into another format or make an eye–catching visualization. But one gets to learn the tool, the meaning of the data, its structures and the handling of each of the dimensions. Moreover, one is not able to gather more information, because there is not any in the document itself and there is no way of automatically linking the values in the document to other documents (unless, of course, one is developed).

This is where the Resource Description Framework [1] and the Linked Data [2] model come in. Those can help us introduce some semantical meaning to link entities in the document to other entities on the Internet. Let us provide more details about the RDF before getting back to this example.

1.2 Resource Description Framework

As stated before, the Resource Description Framework is one of the most used models for describing data with metadata. Its purpose is to give a common model for data interchange on the Internet in order to make all its users able to exchange data with semantics. It introduces a way of describing a schema of the interchanged data. It also offers features that help facing a situation when two datasets describe the same thing, but have different schemas.

The standard model of the web works on the principle of URIs. Each page, which is, in fact, an entity or resource, has a URI, which stands for its unique identifier. Nothing on the web should have the same identifier. What RDF adds to this model is that even relations between those resources have their URIs. An example of such a relation could be:

```
http://dbpedia.org/resource/Kenya  http://www.w3.org/1999/02/22-rdf-syntax-ns#type http://dbpedia.org/ontology/Country
```

This actually tells us that `Kenya is a country`. That statement could obviously be found on the Internet in a countless of different data sources; they are not usually presented in a machine–readable form, though. In order to work with that sentence we need a parser, which is able to get the information based on a bunch of linguistical rules. Moreso, the sentence might be more complicated, e.g. `Kenya, with Nairobi as its capital city, is a very beautiful country`. Ignoring the fact that the sentence brings another useful information, we should aim our focus on the fact that it is more of a complicated piece of language to parse.

The RDF notation gives a semantic meaning to the relation. The RDF model is based on making certain kinds of triples; such can be seen in the previous example. If we extend the set of triples with another, what we get is *a directed labeled graph*, where an edge represents *relation* between two resources. Those resources are represented by graph nodes. Based on the actual content of the triples, the graph may consist of two or more standalone connected components as well as of just a single one. Such a graph may potentially contain information about entities from all over the Internet, which would be very useful.

The main point is, that all the information published with respect to the RDF model may be automatically processed by a computer able to work with the semantics without needing the user to specify it (as somebody has already done that while publishing the dataset).

1.3 Linked Data

One implementation of the Resource Description Framework is the Linked Data model. It utillizes several technologies and principles to actually interconnect the data on the Internet. Both resources and relations are denoted with URIs. The HTTP protocol is used to make the resource public on the Internet. It may be found by dereferencing (accessing) the assigned URI. Both machines and people are therefore capable of looking the resource up.

When the URI is dereferenced, more useful information could be provided while utillizing the RDF and SPARQL standards. Since the model is called Linked Data, the most significant part of the concept is about knowing how the data could be connected when being published on the Web. It also brings some serialization formats, such as RDFa, RDF/XML, N3, Turtle and many others. One of the most significant projects involving Linked Data is the LOD2 project [8] (its visualization can bee seen) in Figure 1.5.

To make the idea about datasets more clear, let us mention some well–known data sources involving Linked Data:

- DBPedia — dataset made by transforming Wikipedia into the RDF model.
- FOAF — dataset describing persons, their properties and relationships.
- GeoNames — geographical LD database.
- CKAN — community–run catalogue of useful sets of data on the Internet.

Namespaces and prefixes

There is one rather technical note we should mention before taking further steps. The RDF also brings a way of expressing URI of a resource in a more compact form while utilizing so–called prefixes and namespaces. Let us look at an example:

```
http://dbpedia.org/ontology/populationTotal
http://dbpedia.org/ontology/populationAsOf
```

Those are URIs which reference specific properties with a semantic meaning as designed by the DBPedia [9]. At a closer look, one can see that there are some parts of the URI that are repeated in each of them. E.g. the scheme — http. Although that is a rather technical point of view. The most long common part of both URIs is `http://dbpedia.org/ontology/` which makes a namespace. It makes a logical sense that all the resources in the virtual folder `ontology` have something in common, therefore, they are grouped into the namespace.

Since one could remember easily the name of the specific resource in a namespace, e.g. `populationTotal`, it would be great if they had no need to look up the full URI of the namespace and express it with a short and easy–to–remember, but still unique, identifier. That is what prefixes are designed for. For instance, the `http://dbpedia.org/ontology/` was assigned the prefix `dbpedia-owl`. Since the scheme is then `prefix:localname`, one could write:

```
dbpedia-owl:populationTotal
dbpedia-owl:populationAsOf
```

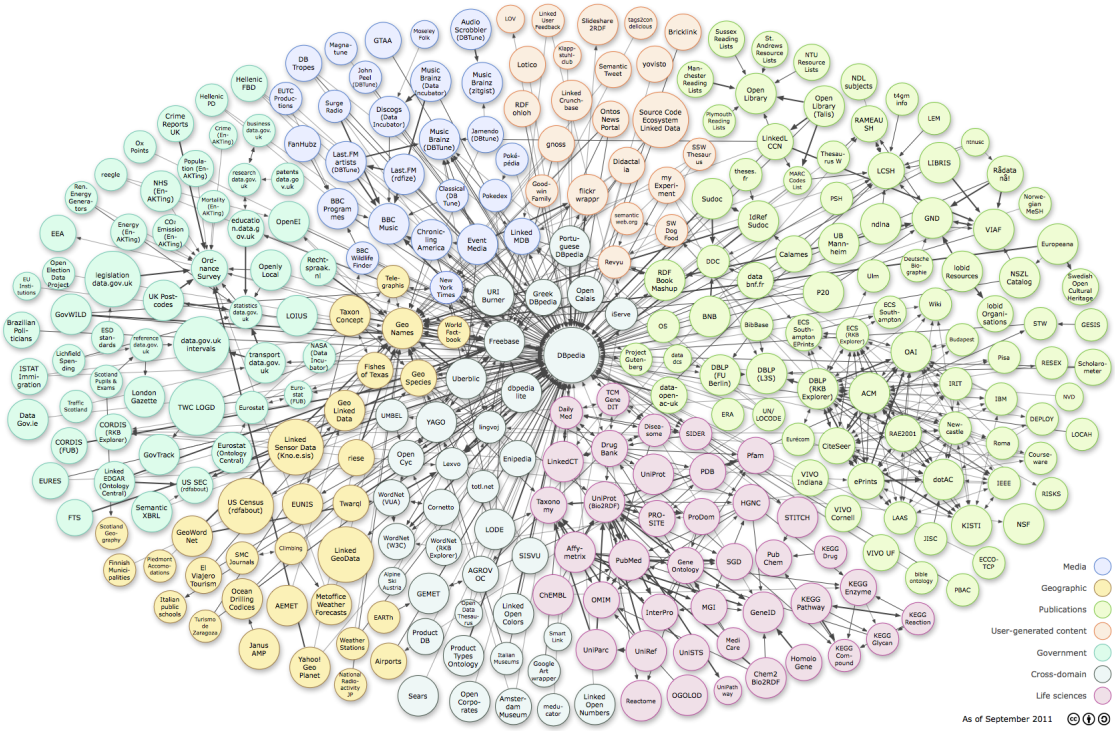


Figure 1.2: LOD cloud diagram by Anja Jentzsch [11] (situation as of 19. 9. 2011)

which is equivalent to the previous example. It is then a lot easier to write RDF documents for a human being, especially while using well–known prefixes. A kind of unofficial registry could be found on [10].

In order to get the processes in a country more transparent, governments also publish data related to the country (statistics, public spendings data, ...) to the Internet. Not many of them are published in the form of the Linked Data, so there are many initiatives interested in transforming the data into a machine-readable form.

It is definitely a great achievement to have such a dataset in a form of Linked Data, but what we need for understanding its contents is a suitable visualization of the data. Due to our knowledge of working with statistical multi–dimensional data we can apply our know–how to the aforementioned data as they are statistical datasets as well.

Our aim is to have a description model, which annotates a dataset with a semantically–specific notation. That would enable us to generalize the processes involving statistical Linked Data and prepare some universal types of visualizations, which are commonly used in the non-LD world.

Ontologies

Let us also introduce the concept of an ontology, which is a product of the RDF evolution. The Resource Description Framework is not very restrictive. One can build his own content of a RDF document, e.g.:

```
http://example.com/Czech_republic http://example.com/relation/hasCapital http://example.com/Prague
```

or

```
http://pedia.rdf/Czech_republic http://pedia.rdf/hasCapital http://pedia.rdf/Prague
http://pedia.rdf/Czech_republic http://pedia.rdf/language http://pedia.rf/Czech
```

By comparing the first lines from each of the documents, it might be apparent they hold the same information; that the capital city of the Czech Republic is Prague. At a closer look, a more observant reader can notice, that each of them uses different URIs to dereference the resources related to the Czech Republic and Prague (in fact, they use different namespaces to make the reference). They also use different URIs (and namespaces) to express the relation between a country and its capital.

Moreso, the second document holds more information as it tells us, that people of the Czech Republic speak Czech. Both documents are perfectly valid and could be published on the Web. That is why the concept of ontologies was introduced. With an ontology, one may specify the requested outline of the document.

When formalized as defined in [12]: *An ontology O is a triple (C, P, M) where C is a set of classes, P is a set of predicates and M is a set of RDF statements (mappings of the classes and properties to other ontologies). Both classes and predicates are specified using their unique URIs.*

Let us start with countries. Without a restriction, one may also include, let us say, planets. With an ontology, it can be specified what kind of resources could be included. It is needed to specify a URI describing the type `country`, for instance a rule can be set that a resource needs to be of the type `http://schema.org/Country`.

After that, another rule is added, which will define that the country may have its capital specified. Let us say one decides to go with the relation described by dereferencing the URI of `dbpprop:capital`.

It is clear, that none of the examples conform, since neither of them utilizes the relation `dbpprop:capital`.This is a very simple example of how ontologies could be used. What we did was that we utilized the possibility to constraint properties of a resource.

A new language, OWL (Web Ontology Language) [13], was developed based on the RDF in order to standardise the way of making restrictions. It gives us much stronger possibilities than just restricting the properties, which is, on the other side, the most commonly used technique.

Example with the usage of RDFa

Now, let us get back to the example related to the number of citizens in a country. At first, we will alter the HTML document to involve some semantics. To achieve that, we will utilize the RDFa model, as can be seen in Figure 1.3.

Since the original data were taken from Wikipedia [14], we decided to decorate the HTML document while using semantic definitions defined by DBPedia, the Linked Data version of Wikipedia. The DBPedia needed to come up with a series of ontologies to present the structure of documents extracted from Wikipedia. The ontology can be used not only to declare a publicly available definition of the document format, which is useful for those who query the DBPedia database; it can also be used by the team of the DBPedia in order

```
<html prefix="dbpedia-owl: http://dbpedia.org/ontology/">
    <head>
        <title>Number of citizens in a country</title>
    </head>
    <body>
        <table>
            <thead>
                <tr>
                    <th>Country name</th>
                    <th>Number of citizens</th>
                    <th>Year</th>
                </tr>
            </thead>
            <tbody>
                <tr about="http://dbpedia.org/page/Czech_Republic">
                    <td property="rdfs:label">Czech Republic</td>
                    <td property="dbpedia-owl:populationTotal">10505445</td>
                    <td property="dbpedia-owl:populationAsOf">2013</td>
                </tr>
                <tr>
                    <td property="rdfs:label">Slovakia</td>
                    <td property="dbpedia-owl:populationTotal">5404555</td>
                    <td property="dbpedia-owl:populationAsOf">2013</td>
                </tr>
            </tbody>
        </table>
    </body>
</html>
```

Figure 1.3: RDFa document example

to unify internal rules of a document which is created by scraping a Wikipedia page into RDF.

As can be seen, we have utilized the RDF Schema and DBPedia Ontology to describe the document and give it some semantic meaning. While this is a relatively simple process, it has dramatically increased the possibilities of the document processing by expressing the resource URI. By dereferencing the URI, one can get more related information and link his data with the rest of the Internet.

RDF example

When such a page is analyzed by a RDF–aware tool, it may be extracted into a more concise form:

```
http://dbpedia.org/page/Czech_Republic dbpedia-owl:populationTotal 10505445 ;
                                       dbpedia-owl:populationAsOf 2013 .

http://dbpedia.org/page/Slovakia       dbpedia-owl:populationTotal 5404555 ;
                                       dbpedia-owl:populationAsOf 2013 .
```

The document may naturally contain much more information about the resources, but for the purposes of our interest in the statistical values related to the population size we do not need anything more. In fact, the DBPedia database contains many more data related to the entity, e.g. the capital city, the name of the president, etc.

But all we need to start with statistical data in combination with the Linked Data concept is held by those RDF triples. In fact, the main goal of this thesis is to implement a prototype of a system, which will be able to convert such triples (and more complicated statistical structures) into slightly another, but still RDF–complaint, format.

1.4 Data Cube

Before proceeding with the example, let us stop for a while and talk about Data Cube outside of RDF and Linked Data scope. Generally speaking, a data cube is a *multi-dimensional* array of values describing some kind of data. In the data–mining context, it is often referenced as an *OLAP cube*, where OLAP stands for OnLine Analytical Processing.

One may think about it as a generalization of a well–known concept — spreadsheets. A spreadsheet (known e.g. from the *Excel*) is a two dimensional table, which can be made dynamic while using formulas and other techniques available in the software. What OLAP cube brings up is a higher count of dimensions. It holds a set of measures or, if you want, observations. Those are organised in a special data structure (star schema, snowflake schema, ...) and point to so–called facts table consisted of the actual measured values.

While involving some facts from the database theory, we could say that an OLAP cube is a form of a projection of an *RDBMS relation*. If we think about a standard two–dimensional table, we can formalize the relation between key and value in the following way:

$$R = f : K \ \rightarrow V$$

We have a single value (denoted `V`) that we get after dereferencing the key (denoted `K`). If we add one dimension, e.g. let us go back to the population count example, we would write:

$$R = f : (Y, C) \rightarrow V$$

where `Y` stands for a year and `C` stands for a country. `V` is the total number of citizens in the country `C` in the year `Y`. But as we presented before, the OLAP cube represents a concept of multi–dimensional statistical data. That is why we should generalize the formula a lot more. Let us think about a cube which has n dimensions. That could be expressed with the following formula:

$$R = f : (X_1, X_2, \ldots, X_{n-1}) \rightarrow X_n$$

But, of course, the X_n could be also a set of facts.

The Data Cube Vocabulary is a concept based on the previously mentioned Data Cube and OLAP cube theory. As we are interested in the ways of representing statistical data in the Linked Data model, the reader would not be surprised, that the Data Cube Vocabulary [3] concept is tightly connected to the Linked Data model.

Since the Data Cube Vocabulary is the starting point for reaching the goal of this thesis, we will pay a special attention to its description. It combines the advantages of the RDF model and Data Cube concept in order to make it easier to interlink resources involved in the published statistics. As the Data Cube Vocabulary model is based on the model defined by Statistical Data and Metadata eXchange standard [16], let us discuss the standard a bit more.

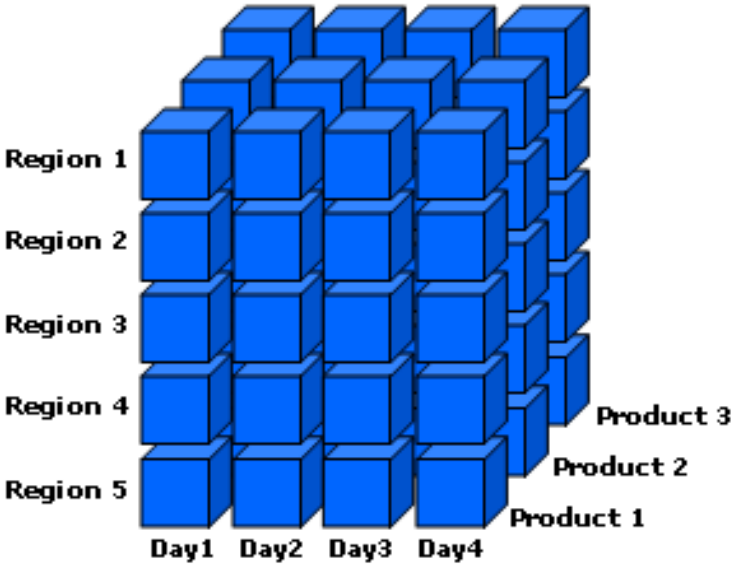


Figure 1.4: An example of data cube by Microsoft [15]

1.5 Statistical Data and Metadata eXchange

The SDMX Initiative [16] was introduced by seven organizations in order to make an effective standard to interchange statistical data. All those organizations, e.g. OECD, UN or Eurostat, have, without any doubt, an access to a large amount of statistical data, even more, they produce them. Some examples of such data could be found on [7]. In 2005, the Initiative has introduced a version 1.0 of a technical specification, which was approved by the International Organization for Standardization [17] as `ISO:TS 17369`. Later on, in May 2011, it was updated to version 2.1 (changes in web services guidelines, revised data messages, partial code lists and new metadata management). In January 2013 the specification has evolved into an International Standard, `ISO/IS 17369` [18].

The Initiative has also published a User Guide to cover major SDMX use cases [19]. It is focused on maintaining and handling statistical data and its metadata. It shows how to manage reporting, storage, retrieval and extending. As a natural side–effect, every organization, which follows the guide not only solves its problems with handling the data, but is also able to interchange those with any other company following the guide.

That corresponds with the idea of the RDF and Linked Data models. We have a large amount of datasets we want to interchange or even interlink. Actually, it comes out of needs of the founding organizations, which cooperate on the data they gather. Each of the companies creates a report, which is then processed or often even extended by one of the others. To make the chain of the data processing more efficient, they agreed on the original technical specification. They focused especially on the following issues detected in the statistical data exchange:

- Time consumption of the whole processing (data collection, transformations, exchange).
- Different approaches introduced by different organizations.

- Different approaches in how to utilize new technologies (like XML or web services).

While discussing the standard, several subprojects were introduced. One of them was to come up with a standardized vocabulary for statistical metadata (metadata common vocabulary). It was decided to use new technologies, such as web services or XML, but many of the subprojects were based on existing concepts, which were utilizing existing technologies. In the case of metadata common vocabulary, it was *Eurostat's Concept* and *Definitions Database (CODED)* and the *OECD Glossary of Terms*.

The important result of the process is *SDMX Content-Oriented Guidelines*. They were separated from the technical specification since they help to introduce some approaches to statisticians for their work. The technical specification was focused on developing applications conforming with the SDMX model. One could think that it is the technical specification which enabled us to make the transition between common statistical data and Linked Data, but it were the SDMX Content–Oriented Guidelines. On top of other products, it introduces the following:

- Cross–Domain Concepts.
- Cross–Domain Codelists.
- Statistical Subject–Matter Domains.
- Metadata Common Vocabulary.
- SDMX–ML for the Content-Oriented Guidelines (Concepts, Code Lists, Category Scheme).

These are products that the Data Cube Vocabulary works with and builds upon. More important features were added in the revision 2.0. The SDMX model was extended with reference metadata concept which tells us how to format and structure metadata with respect to data quality frameworks. Corresponding XML formats were introduced. Furthermore, a set of standard XML interfaces was added to enable SDMX Registry manipulation. The registry was introduced to enable data location catalogization and metadata cross–referencing over the Internet. Also, structured metadata manipulation was introduced.

Since the SDMX Content–Oriented Guidelines are focused on SDMX use cases, we will present one of them to the reader, since the same use case could be applied in the derived Data Cube Vocabulary in the environment of Linked Data.

In fact, the primary use case designed by the Initiative is called "web data dissemination" and is tightly related to the Linked Data world. It comes with a standardized process of retrieving data from the web periodically and keeping them up–to–date. It resembles a bit a process of scraping data into a Linked Data datastore, which was, perhaps, derived just from the web data dissemination process.

The next SDMX fundamental connected to the Linked Data model is defining concepts. That is very similar to the LD ontologies. A concept is a source of data semantics. It:

- Provides a detailed definition of the component, which describes the structure of the data or metadata.
- Can allow data and metadata for different structures to be comparable when concepts are reused.

The goal of SDMX is to reuse existing concepts introduced by any community related to the given dataset, not to enforce its own proprietary format. It is enforced by a rule which states that a new concept can be introduced only if no existing concept suffices. The reason is that those concepts are already used and implemented by a certain spectrum of applications, therefore it will lead to a greater interoperability. Similar concepts are then grouped into schemes which are versioned. When a concept changes, a new version of the whole scheme needs to be introduced.

Also the list of three main components of SDMX concept goes well with the Linked Data model

- Its identification, which must be unique within the scheme.
- Its name.
- Its description.

One is also able to include all those properties into a RDF–compliant resource definition, furthermore, the first one is also mandatory and represented by a URI.

Hand in hand with concepts goes defining code lists. It is a way of determining possible values. In fact, those code lists are enumerations. They also have the three basic components (identification, name and description) as concepts do. Code lists could be organized into hierarchies to reflect a certain kind of relations between members of the list. The hierarchy is meant to represent a children–parent relationship, but no additional properties are specified. Let us mention *Nomenclature des Unites Territoriales Statistiques (NUTS)* as an example of such a hierarchy.

The data definition reflects exactly what we need. It consists of a collection of components, which define what is being measured together with additional metadata.

1.6 Data Cube Vocabulary

This model could be relatively easily decorated with syntactic sugar taken from the RDF/LD world. This is exactly how the Data Cube Vocabulary was introduced based on the model shown earlier. The most significant rule of the model is that each dimension is needed to reference a concept to determine its semantic meaning.

But this is only a definition of a data structure, a set of rules of how a specific kind of information should be published. Based on that, a dataset is published in a way to respect such a set of rules. Therefore, every dataset represents a collection of data structures. Each data structure is consisted of a set of components. One of them needs to be a measure, so–called *primary measure*. The primary

measure is marked with a special flag to be found easily to enable more efficient processing.

Besides measures, there are *dimensions*. A data structure needs to have at least one. Each dimension references its concept and has a unique identification. The combination of all the dimensions (except the measure) defines a key, which allows it to point to the primary measure.

There are some kinds of specialized dimensions, which can be defined only once for a data structure:

- Time (point in time, when the observation was made).
- Measure (but could be a collection).

There are some preferred formats, which tell us how to publish the time of capturing the observation — a period, a duration or a timestamp. More details about that could be found in the SDMX User Guide [19].

Moreover, a data structure can hold some metadata, e.g. the unit of the measurement or a starting day of the week (in case of periodic time format).

As stated before, the SDMX 2.0 Information Model was used to build up the RDF Data Cube Vocabulary, especially the Content–Oriented Guidelines (COGs). The Data Cube vocabulary specification itself does not cover mechanics of transforming other formats into the Data Cube Vocabulary, including the SDMX mostly used SDMX-ML. It presents the final product, a model which builds upon the RDF and SDMX models.

In the section dedicated to the brief description of the RDF, we have discussed that resources are identified by a unique identifier — a URI. We have also mentioned that it is used to express them in a compact form while utilizing prefixes and namespaces. Before going further with the description of the Data Cube Vocabulary, let us present a short list of significant prefixes (presented in the Table 1.1), since some of them could appear in the text.

Table 1.1: Prefixes used frequently with Data Cube Vocabulary

Prefix	Namespace	Brief description
qb	`http://purl.org/linked-data/cube#`	Data Cube vocabulary
skos	`http://www.w3.org/2004/02/skos/core#`	Knowledge Organization Systems dictionary
scovo	`http://purl.org/NET/scovo#`	Statistical Core Vocabulary
void	`http://rdfs.org/ns/void#`	Vocabulary of Interlinked Datasets
foaf	`http://xmlns.com/foaf/0.1/`	People-related schemes
org	`http://www.w3.org/ns/org#`	Organizations dictionary
dcterms	`http://purl.org/dc/terms`	Dublin Core common properties dictionary
owl	`http://www.w3.org/2002/07/owl#`	Ontologies
rdf	`http://www.w3.org/1999/02/22-rdf-syntax-ns#`	RDF concepts
rdfs	`http://www.w3.org/2000/01/rdf-schema#`	RDF schema
eg	`http://example.org/ns#`	for examples only
pc	`http://purl.org/procurement/public-contracts#`	Public contracts

The Data Cube Vocabulary reuses the concept of a data structure as presented in the section dedicated to the SDMX description. Therefore, a data cube is also consisted of a set of dimensions, attributes and measures — components, speaking generally. As in the cases of OLAP cube and SDMX, dimensions are used to uniquely identify observed measures (remember the formal mapping marking mentioned in the section about RDBMS representation of OLAP cube). The outline of Data Cube Vocabulary can bee seen in Figure 1.5.

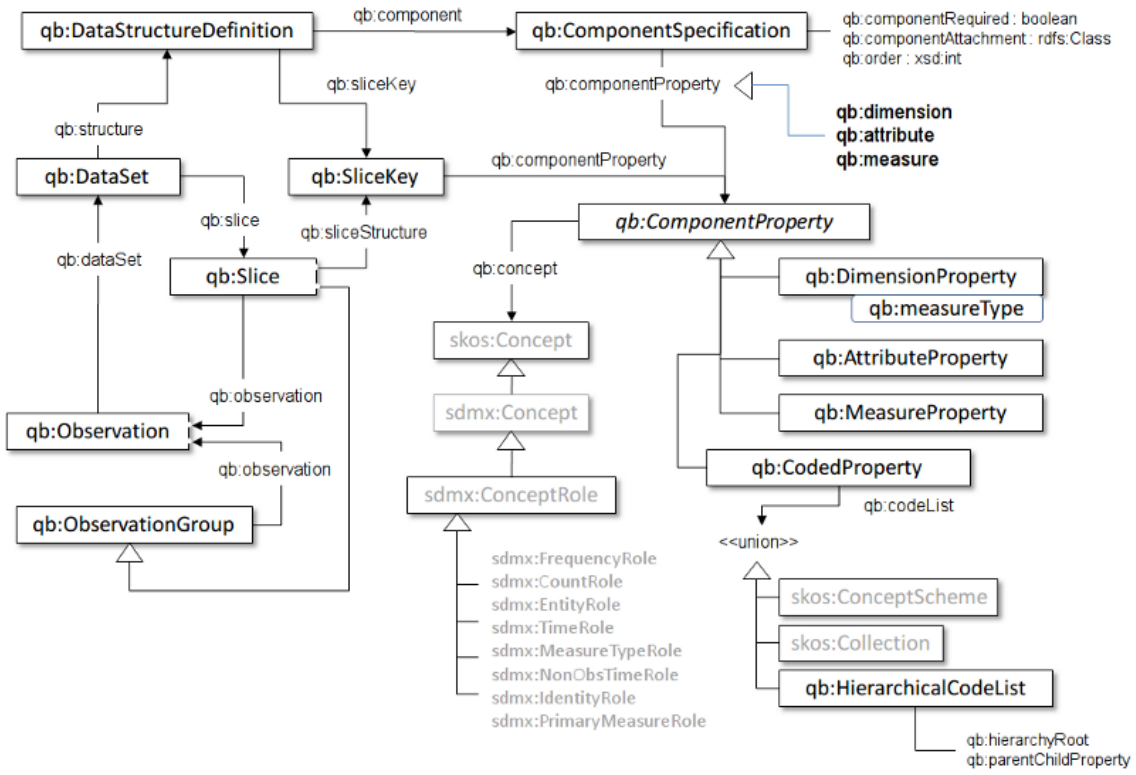


Figure 1.5: Data Cube Vocabulary Outline [3]

As a result, we are perfectly able to describe the measurement process - e.g., place, time and other significant conditions, combined with the measured value itself. The whole information is supplemented with additional attributes, which may make the measurement more accurate - units, multipliers but also other, not so important, notes.

As we have discussed in the section dedicated to the SDMX model, each data set should be published according to a specific data structure. Let us have a look on how the data structures are modified by including Linked Data and let us try to create a data structure definition according to our demography example.

A data structure definition is represented by `qb:DataStructureDefinition` resource. It defines how the data set should be formed in order to comply with Data Cube Vocabulary. It defines dimensions, attributes and measures, which may appear in the data set. Alongside with the definition, optional and required attributes are defined, as well as their ordering. This kind of information can be extracted easily from a well–formed document and needs to not be explicitly declared. But the explicit declaration enables you to:

- Verify the data set structure easily.
- Determine what dimensions are available for a given data set.
- Exchange structure definition.

Since the data structure defines attributes, measures and dimensions, other resources need to be involved. That is why `qb:ComponentProperty` class was introduced. It has a few derived classes, `qb:DimensionProperty`,

`qb:AttributeProperty` and `qb:MeasureProperty`. Those carry multiple pieces of information. Firstly, the concept, which is represented (e.g. time, place, nation, currency, chemical substance, etc.) is followed by the type of the component (dimension, attribute, measure). Last but not least, it carries the information about which code list (see section 1.5) is used to represent the value.

Since the goal of the SDMX model and Data Cube Vocabulary is to reuse community–proposed taxonomies, `qb:concept` property was introduced to make it possible to link `qb:ComponentProperty` with an existing concept. *SKOS vocabulary* is used to represent such concepts. SKOS does not define any specific concepts. It just defines a vocabulary for concept interlinking.

One could specify the range of the concept while defining a value of the `rdfs:range` property. Also, the concepts may be used repeatedly in a data set in different roles. For example, time could be used as a dimension (in the meaning that something was measured in the year 2012) as well as a measured value (something took 203 seconds).

It is of a great help, if the value is a part of an enumeration defined in a code list. Due to the existence of the qb:codeList property, an automatic validation and range checking can be performed. Moreover, tools can easily retrieve the complete list of possible values. To enable range checking on non–coded values, rdfs:range can be used.

Before getting back to our example, we need to point out a bridge between the SDMX and Data Cube Vocabulary models. A community group has introduced some RDF encodings of SDMX COGs. These are `sdmx-concept`, `sdmx-code`, `sdmx-dimension`, `sdmx-attribute` and `sdmx-measure`. That is a simple way of interlinking the Data Cube Vocabulary with the SDMX model.

Let us get back to the demography example. We will continue with the prepared RDF document and transform it into a Data Cube Vocabulary model. Since we know that each observation should conform to a specified data structure, we should at first define such a structure. To define a structure, we need to define all components first. We will use slightly modified examples presented in the Data Cube vocabulary definition since it fits our use case:

1. Time definition [dimension]:

   ```
   eg:refPeriod a rdf:Property, qb:DimensionProperty ;
       rdfs:label "reference period"@en ;
       rdfs:subPropertyOf sdmx-dimension:refPeriod ;
       rdfs:range interval:Interval ;
       qb:concept sdmx-concept:refPeriod .
   ```

   We define the `eg:refPeriod` and we state, that it is a `rdf:Property` and Data Cube dimension. The rest of the statements are metadata, which are not really necessary, textual description (label) and interlinking with existing concepts (relations to sdmx-dimension). To enable range cheking, `rdfs:range` is defined.

2. Place definiton [dimension]:

```
SELECT ?v WHERE {
  ?v a ?x .
  ?x rdfs:subPropertyOf sdmx-measure:obsValue .
}
```

Figure 1.6: A SPARQL query, which retrieves all observation values from a dataset

```
eg:refArea a rdf:Property, qb:DimensionProperty ;
    rdfs:label "reference area"@en ;
    rdfs:subPropertyOf sdmx-dimension:refArea ;
    rdfs:range admingeo:UnitaryAuthority ;
    qb:concept sdmx-concept:refArea .
```

3. Population count definiton [measure]:

```
eg:finalPopulation a rdf:Property, qb:MeasureProperty ;
      rdfs:label "the total number of citizens"@en ;
      rdfs:subPropertyOf sdmx-measure:obsValue ;
      rdfs:range xsd:decimal .
```

It is important to notice the link to the `sdmx-measure:obsValue`, which is the special flag mentioned in the section dedicated to description of SDMX values. With the power of SPARQL it is very easy to query a triple store for all the values, which are the observation values to get all values in a given graph. In fact, it should be sufficient to query all instances of `qb:MeasureProperty`, the relation to `sdmx-measure:obsValue` just makes the definition more precise. An example of such a SPARQL query can be seen in Figure 1.6.

It is natural that while performing a measurement, you can retrieve multiple values within a single observation. A good example of such an observation could be weather information sampling. One can measure many physical values (e.g. temperature, air pressure, humidity, ...) in a specific timeframe on a specific place. One can store those values separately, each in a standalone observation. But since the observation has been made at the same moment and the dimensions are exactly the same, it is only natural to add those value components into the same observation. One will end up with a 5–dimensional observation where 2 components are dimension properties (place and time) and 3 components are measure properties (temperature, pressure, humidity). Without grouping, one would make 3 related observations, each with a single measure property (3 dimensions overall).

Regardless of whether you group those observations into a single one or not, one is able to select the related observations from the data cube dataset relatively easily since they are all determined by exactly the same dimension properties. That is called *slicing*. If you take a cube and select all the related observations you make a slice. The slice is exactly the same as the 5–dimensional observation mentioned before.

Based on the data structure, we can publish a specific dataset. The dataset could be formalized as a collection of four data types:

- Observations — values, measured numbers.
- Organizational structure — dimensions of the measured value (could be in the form of slices)
- Internal metadata — additional data description used to interpret observations (units, estimation, etc.).
- External metadata — interlink to an author, dataset categorization, etc. (linked data principle).

An example of such a dataset can be seen in Figure 1.7.

In this chapter, we have introduced a long process of transforming a simple statement into a form, which is compliant with the Data Cube Vocabulary standard. The original statement was processed while applying a set of a simple transformation steps, at least from the point of view of a human brain. The goal of this thesis is to make one of these steps as automatic as possible in order to come up with a prototype of a system, which is able to transform an arbitrary set of RDF data into a Data Cube Vocabulary form, if possible. Also, a user input (a set of transformation rules) is needed to get such a task done.

Since Payola was designed to provide a platform for analyzing and visualizing Linked Data and its main goal is to lower the knowledge barrier, which one needs to overcome in order to analyze Linked Data, we also want all the newly–introduced components to fit into the concept of the whole platform — to be reusable. We will also demonstrate the benefits of such transformations while implementing a visualization, which will take advantage of the Data Cube Vocabulary.

```
@prefix rdf:     <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs:    <http://www.w3.org/2000/01/rdf-schema#> .
@prefix owl:     <http://www.w3.org/2002/07/owl#> .
@prefix skos:    <http://www.w3.org/2004/02/skos/core#> .
@prefix foaf:    <http://xmlns.com/foaf/0.1/> .
@prefix scovo:   <http://purl.org/NET/scovo#> .
@prefix void:    <http://rdfs.org/ns/void#> .
@prefix vcard:   <http://www.w3.org/2006/vcard/ns#> .
@prefix xsd:     <http://www.w3.org/2001/XMLSchema#> .
@prefix dcterms: <http://purl.org/dc/terms/>.

@prefix qb:              <http://purl.org/linked-data/cube#> .
@prefix sdmx:            <http://purl.org/linked-data/sdmx#> .
@prefix sdmx-concept:    <http://purl.org/linked-data/sdmx/2009/concept#> .
@prefix sdmx-dimension:  <http://purl.org/linked-data/sdmx/2009/dimension#> .
@prefix sdmx-attribute:  <http://purl.org/linked-data/sdmx/2009/attribute#> .
@prefix sdmx-measure:    <http://purl.org/linked-data/sdmx/2009/measure#> .
@prefix sdmx-metadata:   <http://purl.org/linked-data/sdmx/2009/metadata#> .
@prefix sdmx-code:       <http://purl.org/linked-data/sdmx/2009/code#> .
@prefix sdmx-subject:    <http://purl.org/linked-data/sdmx/2009/subject#> .

@prefix eugeo: <http://ec.europa.eu/eurostat/ramon/ontologies/geographic.rdf#> .

@prefix czso-teritorries:  <http://purl.org/cszo/teritorries#> .
@prefix czso-ds-dem-pop:   <http://linked.opendata.cz/resource/czso.cz/dataset/demography/final-population#> .
@prefix czso-ds-dem-bir:   <http://linked.opendata.cz/resource/czso.cz/dataset/demography/births#> .
@prefix czso-ds-dem-dea:   <http://linked.opendata.cz/resource/czso.cz/dataset/demography/deaths#> .
@prefix czso-ds-dem-imm:   <http://linked.opendata.cz/resource/czso.cz/dataset/demography/immigrants#> .
@prefix czso-ds-dem-emm:   <http://linked.opendata.cz/resource/czso.cz/dataset/demography/emmigrants#> .
@prefix czso-ds-def:       <http://linked.opendata.cz/resource/czso.cz/dataset-definitions#> .

czso-ds-dem-pop: a sdmx:DataSet ;
  dcterms:subject <http://eulersharp.sourceforge.net/2003/03swap/countries#cz>, <http://dbpedia.org/resource/Czech_Republic> ;
  dcterms:publisher <http://opendata.cz/me#> ;
  sdmx:maintainer <http://linked.opendata.cz/resource/business-entity/00025593> ;
  dcterms:date "2012-09-05"^^xsd:date ;
  qb:structure czso-ds-def:DemographyFinalPopulationDefinition .

czso-ds-dem-bir: a sdmx:DataSet ;
  dcterms:subject <http://eulersharp.sourceforge.net/2003/03swap/countries#cz>, <http://dbpedia.org/resource/Czech_Republic> ;
  dcterms:publisher <http://opendata.cz/me#> ;
  sdmx:maintainer <http://linked.opendata.cz/resource/business-entity/00025593> ;
  dcterms:date "2012-09-05"^^xsd:date ;
  qb:structure czso-ds-def:DemographyBirthsDefinition .

czso-ds-dem-dea: a sdmx:DataSet ;
  dcterms:subject <http://eulersharp.sourceforge.net/2003/03swap/countries#cz>, <http://dbpedia.org/resource/Czech_Republic> ;
  dcterms:publisher <http://opendata.cz/me#> ;
  sdmx:maintainer <http://linked.opendata.cz/resource/business-entity/00025593> ;
  dcterms:date "2012-09-05"^^xsd:date ;
  qb:structure czso-ds-def:DemographyDeathsDefinition .

czso-ds-dem-imm: a sdmx:DataSet ;
  dcterms:subject <http://eulersharp.sourceforge.net/2003/03swap/countries#cz>, <http://dbpedia.org/resource/Czech_Republic> ;
  dcterms:publisher <http://opendata.cz/me#> ;
  sdmx:maintainer <http://linked.opendata.cz/resource/business-entity/00025593> ;
  dcterms:date "2012-09-05"^^xsd:date ;
  qb:structure czso-ds-def:DemographyImmigrantsDefinition .

czso-ds-dem-emm: a sdmx:DataSet ;
  dcterms:subject <http://eulersharp.sourceforge.net/2003/03swap/countries#cz>, <http://dbpedia.org/resource/Czech_Republic> ;
  dcterms:publisher <http://opendata.cz/me#> ;
  sdmx:maintainer <http://linked.opendata.cz/resource/business-entity/00025593> ;
  dcterms:date "2012-09-05"^^xsd:date ;
  qb:structure czso-ds-def:DemographyEmmigrantsDefinition .

<http://linked.opendata.cz/resource/czso.cz/dataset/demography/final-population/554782-2011> a qb:Observation ;
    qb:dataSet <http://linked.opendata.cz/resource/czso.cz/dataset/demography/final-population#> ;
    czso-ds-def:refArea <http://linked.opendata.cz/resource/region/554782> ;
    czso-ds-def:refPeriod "2011"^^xsd:gYear ;
    czso-ds-def:finalPopulation "1241664"^^xsd:nonNegativeInteger .

<http://linked.opendata.cz/resource/czso.cz/dataset/demography/births/554782-2011> a qb:Observation ;
    qb:dataSet <http://linked.opendata.cz/resource/czso.cz/dataset/demography/births#> ;
    czso-ds-def:refArea <http://linked.opendata.cz/resource/region/554782> ;
    czso-ds-def:refPeriod "2011"^^xsd:gYear ;
    czso-ds-def:births "13968"^^xsd:nonNegativeInteger .
```

Figure 1.7: An example of a DCV dataset by OpenData.cz

2. Related Work

In this chapter, we would like to get the reader familiar with the variety of tools, which one can use to analyze and visualize Linked Data. We will naturally compare these tools with Payola, since in the past we participated on the proposal and development of this system. Since the goal of this thesis is to propose and implement a system based on the Data Cube Vocabulary standard we will, at first, focus on tools with the data cube support.

We will provide a well–arranged table in order to present a quick overview of what related tools are available at the time of writing this thesis and what are those tools capable of. Before we come up with the table let us mention, which features are examined and why.

The main goal of this thesis is to deliver a prototype of a system, which will map arbitrary RDF data to a form compliant with the Data cube Vocabulary. Based on this fact, one of the criteria is an ability to *convert arbitrary data into a form of cubes*. A difference lies in a format of *input data* of the mapping process. There are tools working with relational (R), Linked Data (LD) or arbitrary format (A).

The main benefit of implementing such a feature into Payola is that it becomes a part of the ecosystem. First of all, we have the user make an analysis over an arbitrary dataset (or, while using more than one data source even more than one dataset) and then map it into the Data Cube Vocabulary standard. That also means that one is able to analyze the data, interconnect them, filter them and enrich entities with more properties while utilizing the principles of Linked Data before the mapping is made. Moreover, the statistical dataset could be the result of an analysis. A new statistical dataset may originate from performing such an analysis. On the other hand, many of the existing tools provide a way of converting a rather static dataset. Let us imagine a situation when a user has a database of statistical facts. While using a tool, they can convert the database into a set of triples according to the Data Cube Vocabulary format. When it is done they are able to apply Linked Data principles on such a dataset. It might be a bit cumbersome to make the same analysis similar to the previous case after the mapping is done. As the two use cases are dissimilar in process we will learn whether the existing tools make the user able to analyze datasets or *create new ones*.

A part of the Payola ecosystem is also based on a fact that Payola is a web application with a *sharing option*. A user is able to make an analysis (an analytical algorithm or an analytical pipeline) and share it with other users. This applies also to analytical plugins, ontologies, etc. That is why we will differentiate between the following application types — desktop (D) and web (W). We will also want to know if it is possible to share *within the application*.

There are also tools, which make the user capable of *developing a custom vocabulary definition* (DCV data structure definition) based on the metadata of the input data. This feature will be also covered in the overview.

While Payola is a platform for analysing and visualising data, we will also focus on the latter. First of all, it interests us whether an examined tool allows the user to *prepare a visualization*. While keeping in mind the main principles of *Visual*

Information–Seeking Mantra [20] we will also discover which of these tools provide *faceted browsing*.

What is also important to know is how a tool behaves while converting a rather *large dataset*. We will not benchmark the tools but we will make a conclusion based on information available in corresponding papers since the authors usually make this very clear.

Table 2.1: Features of related tools

Tool	Cube support	Cube mapping	Mapping input	Analysing	Create datasets	Application type	Sharing	Custom vocabulary	Visualize	Faceted browsing	Large datasets
Payola	Y	Y	LD	Y	Y	W	Y	N	Y	N	N
OLAP2DataCube	Y	Y	R	N	N	W	N	Y	Y	Y	Y
Tabels	Y	Y	A	N	Y	W	N	Y	Y	Y	Y
CubeViz	Y	N	-	N	N	W	Y	-	Y	Y	Y
Geo Globe	N	-	-	N	-	W	N	-	Y	Y	N
Visualbox	N	-	-	N	-	W	Y	-	Y	N	Y
ViDaX	N	-	-	N	-	D	N	-	Y	Y	Y
LodVis	N	-	-	Y	-	W	N	-	Y	Y	Y
Rhizomer	N	-	-	N	-	W	N	-	N	Y	N
Sgvizler	N	-	-	N	-	W	Y	-	Y	N	N
Exhibit	N	-	-	N	-	W	Y	-	Y	Y	*
Explorator	N	-	-	N	-	W	N	-	Y	Y	Y
Tabulator	N	-	-	Y	-	W	N	-	Y	N	Y

2.1 OLAP2DataCube

While comparing this tool we also rely on information presented by its authors in [21]. The OLAP2DataCube tool is in fact a plugin for a well–known platform, the OntoWiki, which serves as an ontological knowledge base enabling the user to visualize and edit facts in the knowledge base in a specific way while utilizing the principles of Linked Data.

The idea behind this tool is the closest to what we aim to achieve in this thesis. In spite of this, it does something a bit different. It is designed to convert a whole relational database containing statistical data into a form of Data Cube Vocabulary. This also presents one of the biggest dissimilarities between the OLAP2DataCube and what we are about to propose — the source is not in the RDF format.

The reason why this plugin was introduced was the need to convert a large dataset of statistical Brazilian government data into the Linked Data standard. While doing that the authors wanted to build up on existing metadata standards,

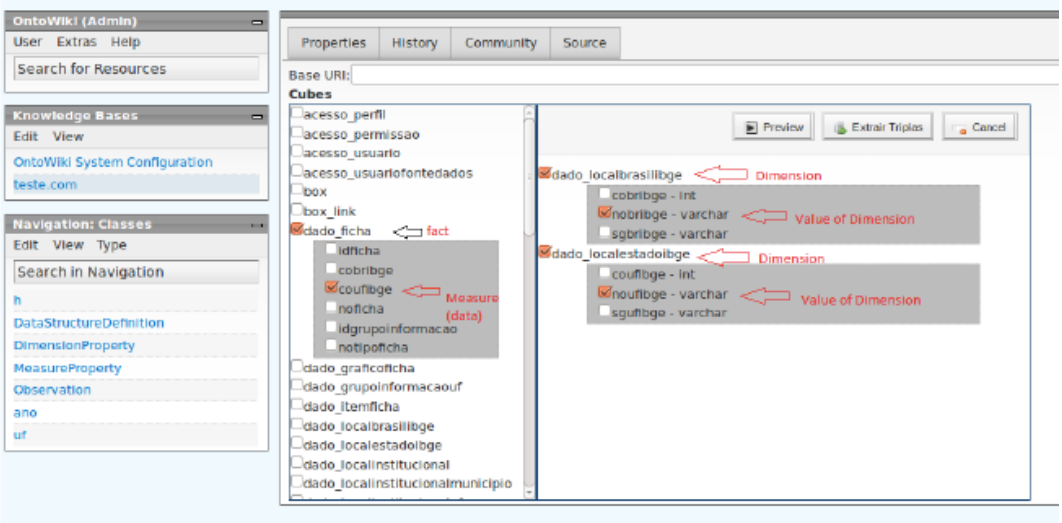


Figure 2.1: OLAP2DataCube mapping specification example (taken from [21])

such as SDMX and therefore on Data Cube Vocabulary. This could provide the idea of what this tool does. It takes a dataset from a relational database and produces another dataset compliant with the Data Cube Vocabulary.

It could be advantageous to borrow principles of the relational databases world and have them fit perfectly into the world of Linked Data. Tables in the relational database are organized into a shape of a star or a snowflake as described in Section 1.4. Moreover, they are interconnected through defined foreign keys, which can have the same semantics as edges in the directed RDF graph. On the other hand, what is completely missing is any kind of structured metadata. That is what the plugin needs to obtain from the user while the user is required to give the data a precise meaning.

That is why the authors introduced some steps where the user is asked to do the following:

- Select the fact table.
- Select dimensions tables.
- Enter additional metadata — units, description, etc. or point to a special dimension table containing the metadata.

The whole process of dataset conversion from relational database into Data Cube Vocabulary (the authors call it triplification) is then divided into the following steps:

- *Metadata extraction and Table categorization* (PKs and FKs analysis). The tables are precategorized as dimension or fact tables based on the number and direction of FKs.
- *Cube definition* done by the user as described in the previous paragraph.
- *Mapping.* The relational database is converted into a Data Cube Vocabulary compliant dataset while executing a set of SQL queries assembled based on the previous steps.

As a matter of fact, this process has two different outcomes. A converted dataset itself and a definition of dimensions. This varies a lot from what we would like to achieve. We are about to propose a system, which will convert a dataset in order to comply with an already existing datastructure definition.

The authors have proven the system qualities by converting a dataset of Brasilian government data into more than 31M triples, which is quite a large dataset. The faceted browsing capability fully depends on the OntoWiki platform features.

2.2 Tabels

Tabels [22] is quite an interesting tool, which enables the user to convert arbitrary data into the Data Cube Vocabulary compliant format. Moreover, it allows the user to interconnect the data with its existing RDF representation, if available.

The most interesting feature of the tool is that it supports a large variety of input types. The user can pass a URL of an arbitrary website or upload a file in many supported formats. The application then generates an automated script, which converts the source document from the input format into the RDF while utilizing the Data Cube Vocabulary standard.

Let us imagine a case of converting a webpage. The tool parses the source code of the webpage and finds tables contained in the body of the page. Those are converted into a simple RDF dataset. The same is done not only in the case of a webpage, but also in a case of other specific supported file formats. To achieve that a specific algorithm is used to extract the data from the file into a RDF graph. After this step is complete, the tool generates a DCV datastructure definition with respect to the kind of data found in the input dataset. Also, an automatic conversion script, which the user can later execute in order to triplificate the input data, is generated.

The script is written in a custom DSL (an example in Figure 2.2) which, with its structure, resembles the well–known transformation language XQuery. Although the script makes its job, the user may need to edit the script to improve the behaviour. That is one of the most problematic features of this tool. The user needs to have a heavy programmatic background in order to be able to use the advantages of all of the offered features. Even when binding the data in the input dataset with entities in an existing RDF dataset, the user needs to alter the generated script and specify, which field to bind and, of course, how.

On the other hand, the tool provides a unique form of making the user's own Data Cube Vocabulary dataset based on their statistical data in common file formats such as CSV, XLS, PX, KML and formats published by rather large institutions like Eurostat. The application is therefore able to visualize data in charts as well as on map in case of geospatial data.

Moreover, the tool also supports RDF as an input format, which makes it a competitor of the system we are about to propose. That is why we wanted to examine this tool a bit more in the manner of processing different RDF datasets. Despite the fact that the tool should be able to process RDF datasets, it produced an empty conversion script even on DCV datasets downloaded from the tool itself. Therefore, the only form of converting the input file into the DCV compliant dataset was to write the whole script manually, while specifying a set

```
PREFIX project: <http://idi.fundacionctic.org/tabels/project/gijon/>
PREFIX my: <http://idi.fundacionctic.org/tabels/project/gijon/resource/>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX dcat: <http://www.w3.org/ns/dcat#>
PREFIX dct: <http://purl.org/dc/terms/>
PREFIX foaf: <http://xmlns.com/foaf/0.1/#>
PREFIX neogeospatial: <http://geovocab.org/spatial#>
PREFIX neogeogeometry: <http://geovocab.org/geometry#>
PREFIX skos: <http://www.w3.org/2004/02/skos/core#>
PREFIX emergel: <http://purl.org/emergel#>

SET ?shapeFile IN files "Parroquias.shp.zip"{
        SET sheets "dbf"
            FOR ?feature IN rows FILTER get-row(?feature)
                LET ?featureResource = resource(?feature,<http://idi.fundacionctic.org/tabels/project/gijon/resource/>)
                MATCH [?oBJECTID,?pARROQUIA,?dATOS,?xMAX,?yMAX,?xMIN,?yMIN,?shapeLeng,?shapeLel,?shapeArea,?geometry,?xml] IN horizontal
                LET ?styleConcept = resource(replace(?pARROQUIA,"[^a-zA-Z0-9]",""),<http://idi.fundacionctic.org/tabels/project/gijon/resource/style/>)
                LET ?geometryResource = resource(?xml,<>)
                LET ?geometryType = resource(?geometry,<>) ;
        SET sheets "sld"
            FOR ?feature IN rows
                MATCH [?col,?style,?json] IN horizontal
                LET ?styleConcept = resource(replace(?style,"[^a-zA-Z0-9]",""),<http://idi.fundacionctic.org/tabels/project/gijon/resource/style/>)
                LET ?styleResource = resource(?json,<>)
                LET ?shapefileConcept = resource(?shapeFile,<http://idi.fundacionctic.org/tabels/project/gijon/resource/>)    }

CONSTRUCT {
    ?featureResource a neogeospatial:Feature .
    ?featureResource my:oBJECTID ?oBJECTID .
    ?featureResource my:pARROQUIA ?pARROQUIA .
    ?featureResource my:dATOS ?dATOS .
    ?featureResource my:xMAX ?xMAX .
    ?featureResource my:yMAX ?yMAX .
    ?featureResource my:xMIN ?xMIN .
    ?featureResource my:yMIN ?yMIN .
    ?featureResource my:shapeLeng ?shapeLeng .
    ?featureResource my:shapeLel ?shapeLel .
    ?featureResource my:shapeArea ?shapeArea .
    ?featureResource neogeogeometry:geometry ?geometryResource .
    ?geometryResource a ?geometryType .
    ?featureResource dct:subject ?styleConcept
}

CONSTRUCT {
    ?styleConcept a skos:Concept .
    ?styleConcept skos:prefLabel ?style .
    ?styleConcept emergel:prefStyle ?styleResource .
    ?styleConcept skos:inScheme my:collection .
    ?shapefileConcept skos:prefLabel ?shapeFile
}

CONSTRUCT {
    ?shapefileConcept a skos:Concept .
    ?shapefileConcept skos:narrower ?styleConcept
}
```

Figure 2.2: Tabels DSL example (script taken from examples repository [22])

of SPARQL construct statements. That is, in fact, a default behaviour of any available SPARQL endpoint, which enables it to execute a SPARQL query on datasets.

2.3 CubeViz

The CubeViz [23] tool has been developed by the AKSW [24] group in the scope of the LOD2, a large–scale project co–funded by European Commission that is focused on integrating and syndicating Linked Data with existing applications.

The motivation behind this tool was to bring a better user–experience into a large–scale application, developed by this group, called the *Open Data Portal of European Commision*. While utilizing the Data Cube Vocabulary standard, they prepared a library of 5700 visualized statistical datasets.

As well as the OLAP2DataCube tool, the CubeViz is also based on the OntoWiki [25] application. In fact, it adds another layer to the technology stack and provides a way of exploring and discovering statistical data in a faceted browser. The GUI is made with common technologies like PHP, HTML and JavaScript. They used the HighCharts [26] library in order to provide data visualization (an example can be seen in Figure 2.3).

While utilizing the principles of Linked Data and Data Cube Vocabulary standard, the authors were able to come up with a really sophisticated faceted browser, which makes the user capable of filtering data in detail based on the statistical semantics (DCV). The user is able to filter data based on each dimension, or to use the proper term, to slice the cube as needed. That gives us a generic tool, which compares any statistical data with the ability to learn more information while taking advantage of the entities Linked Data interconnection.

At the time of writing this thesis, the tool was limited [27], [28] to basic chart types such as line, bar and pie chart (for datasets with one dimension). Those types were available also for the 2–dimensional datasets for which the polar

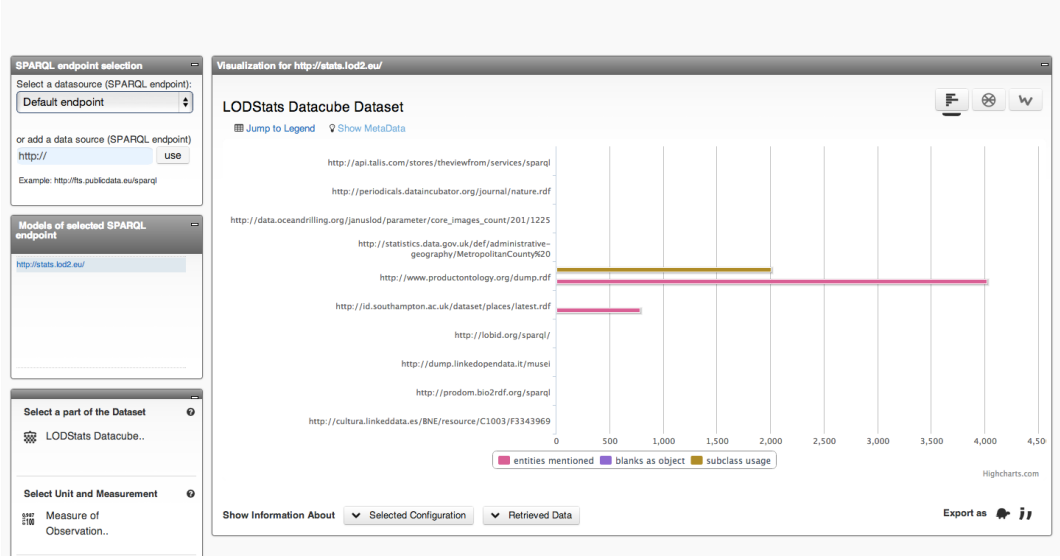


Figure 2.3: CubeViz visualization example

chart is offered as well. More than two dimensions were not supported at all. In order to visualize multidimensional datasets one needs to slice it into a 2–or–less–dimensional one. The tool also makes it able to publish dataset metadata.

An interesting feature of the faceted browser is that the user can generate a permalink in order to obtain a reference to the current visualization state. That makes it very easy for the user to share their visualization with the community.

2.4 Visualbox

Based on LODSPeaKr [29], a tool, which makes it easier to create Linked Data Websites and to publish RDF datasets, a visualization tool named Visualbox [30] has been introduced. The motivation behind this was very similiar to those behind OLAP2DataCube, ViDaX or CubeViz. The author wanted to present a visual tool, which would make it easy for the user to understand results of a data analysis.

The main argument is e.g. that a line chart is much more expressive and much easier to understand than a table of data or some even more complicated data representation. Therefore, the author wanted to utilize existing visualization techniques people are used to intercept.

As a result of this effort, he presented [31] a developer tool, which enables an easier preparation of a visualization. One needs to know basic web development technologies in order to be able to use the tool. Specifically, the HTML language, the handlebars templating syntax and a concept of filters, which resembles the concept used in the JavaScript MVC framework AngularJS [32]. One is however required to posses the knowledge of the SPARQL in order to select data and prepare them for the visualization. An example of a SPARQL query and a visualization embed into a webpage can be seen in Figure 2.4.

On the other side, for those, who have this technological background the tool is really easy to use. By using a simple snippet, the developer is able to embed

```
PREFIX conversion: <http://purl.org/twc/vocab/conversion/>
SELECT ?g sum( ?triples ) as ?estimated_triples
WHERE {
  GRAPH ?g  {
   ?g void:subset ?subdataset .
   ?subdataset conversion:num_triples ?triples .
  }
}
GROUP BY ?g

{{models.logd.triples|GoogleVizColumnChart:"g,estimated_triples,width=1200"}}
```

Figure 2.4: Visualbox scripting examples

a chart visualization on the web.

The main benefit of this tool is that it brings a unified approach to visualising tabular data. Furthermore, it comes up with an informal standard of processing such data and visualising them. Based on the Google Charts visualization API, it allows the developer to visualize their data in basic charts as well as in a map if geospatial data are present. Although the features of the tool are mainly shown while visualising statistical data, the tool has no support for Data Cube Vocabulary.

2.5 GeoGlobe

The GeoGlobe mashup [33] is an example of a faceted browser for statistical data related to all the countries in the world. As the SPARQL query, visualization rules and more are hardcoded in this single–file demonstration, it serves us only as a great example of what could be the result of a Data Cube Vocabulary dataset visualization.

The tool fires a XHR to the server, which contains a SPARQL query. The query is executed in order to obtain data from a remote SPARQL endpoint. In fact, it uses some Data Cube Vocabulary constructs to filter the data. The data are sent back to the client in a form of a JSON string. The mashup then uses the D3 [34] visualization library in order to present the user with a D3 Geo visualization of the obtained data.

Simple GUI of the faceted browser changes the contents of the exectued SPARQL query. It decides how the original data cube is sliced to be visualized as the user wanted.

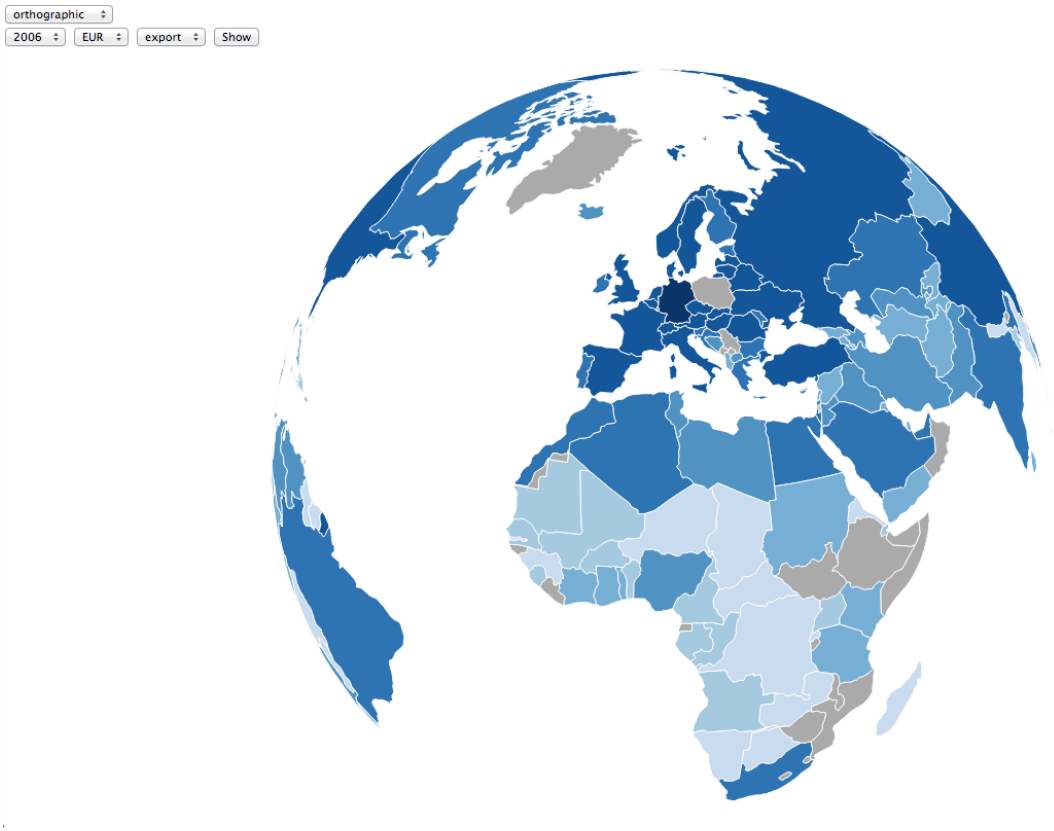


Figure 2.5: GeoGlobe visualization example

2.6 ViDaX

ViDaX [35] is a desktop application written in the Java programming language. Based on the features of the underlying visualization toolkit Prefuse [36], it manages to visualize RDF data in many ways. The toolkit is perfectly capable of visualising statistical data, but the application does not take advantage of the Data Cube Vocabulary standard.

Despite this, the application has some features related to statistical data. The visualization type is selected automatically based on the semantics of the visualized data. The application analyzes and normalizes the data selected by the user and extracts the types of the different properties. Those are consequently mapped to some basic supertypes such as Time, Location, etc. Based on the mapping, the tool offers a visualization template to the user.

As a result, the authors implemented a tool capable of visualizing statistical data with appropriate visualization type without the need of using the Data Cube Vocabulary standard. On the other hand, if the tool followed the standard, the results could be even more reliable.

2.7 Tabulator

Tabulator is a generic RDF browser and editor. The motivation behind this tool is to provide a generic semantic browser with serendipitous re–use. The authors want to provide a form of finding more relevant datasets while exploring or pub-

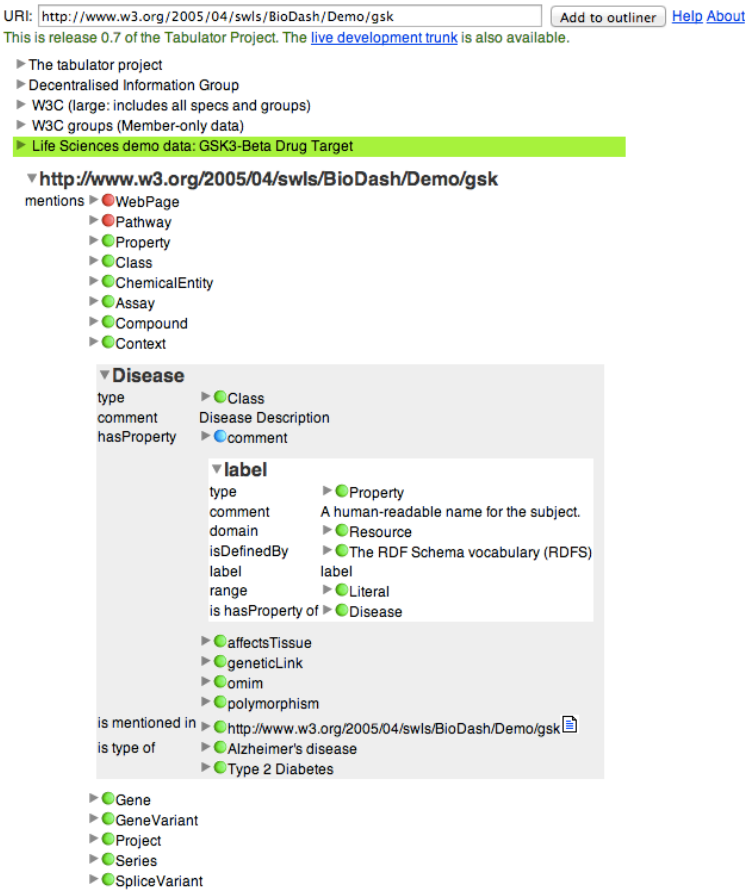


Figure 2.6: Tabulator browsing mode example

lishing another datasets.

The experimental version of the tool was, according to [37], developed completely as a client–side application for a web browser. Therefore, technologies like JavaScript, AJAX, XML, RDF and SPARQL were utilized.

The tool offers two basic modes, exploration and analysis. In the exploration mode, the user starts to explore the Semantic Web by entering a URI of a resource. They are then presented with a tree view where each node represents a resource. By clicking the node, the user expands a subtree to obtain more information. The tool implicitly follows links that may contain more relevant nodes.

In order to switch to the analysis mode, the user selects fields to define a pattern, which is then matched against the original graph. The tool executes a specific SPARQL query to find all occurrences of the selected pattern. The projection of this kind of analysis could be visualized in many different views such as a table, a timeline, a calendar and a map. The user can switch back to the exploration mode by double–clicking on an instance in the analysis view.

The most important feature of this tool is an implementation of a *query–by–example* principle. By highlighting the properties in a tree view, the user unknowingly constructs a SPARQL query. As a result of such a process, the user may create a SPARQL query, which selects e.g., latitude and longitude. Dataset containing such properties (geospatial data) is then visualized on a map. Although the tool is able to visualize statistical data, the Data Cube Vocabulary standard is not used.

2.8 Explorator

The authors of the Explorator application had the same motivation as the authors of the Tabulator — to come up with a tool that simplifies a dataset exploration. One can browse RDF datasets without a deep knowledge of the RDF standard. In order to offer the exploratory search [38] feature, the authors also utilized the query–by–example principle. Only simple so–called *SPO SPARQL queries* (`SELECT { ?s ?p ?o } WHERE { ?s ?p ?o }`) are supported. Generally, the tool enables the user to specify a much simpler pattern than the Tabulator application. On the other hand, it offers a faceted browser, which generates those queries.

Unlike the Tabulator project, based on information presented in [39], the Explorator is not able to offer any advanced visualizations, such as a map or a chart. To speed up the application, the authors integrated a local SESAME [40] repository where dereferenced URIs are stored.

2.9 Exhibit

The MIT Simile project [41] has spent a more than a decade developing and experimenting with software tools for Web–based data publishing. As a result of the whole process a new tool, Exhibit, was introduced.

Exhibit is a JavaScript library, which produces embeddable widgets. A developer can easily embed a visualization of a RDF dataset in an arbitrary web page. The idea behind the tool is very similar to the idea behind the Visualbox project. After a quick examination, the use of the tool is no more complicated compared to the Visualbox despite the fact that the manual suggests so. As an example of a visualization, we can mention timeline, lenses and maps. Again, the tool is able to visualize data, which could be considered statistical, but it lacks the support of the Data Cube Vocabulary standard.

The tool became very popular for its rather easy–to–use approach of publishing visualizations. The very first version of the software was introduced while completely ignoring the problem of large datasets. Since it runs in a web browser, it needs to have the visualized data fitted into the memory of the client computer. That is why U.S. Library of Congress initially funded the project to make its authors solve the scaling problem.

According to the information in [42] the last version of the software supports 1000 times more items in the dataset (100000 vs. 1000) and up to 20000 properties in the faceted browser. The user is able to share views on the data after applying filters of the faceted browser.

2.10 Sgvizler

The Sgvizler project is, as the name suggests, focused on data visualization. It is a JavaScript library, which parses an HTML source and finds specific element attributes. It fills matched elements with a data visualization based on the rules specified in the element attributes.

The developer is required to specify a SPARQL query as one of those attributes. The query is executed against a defined SPARQL endpoint. By setting an attribute of the placeholder element, the user also specifies the type of visualization, which should be applied on results of the SPARQL query execution.

As well as the aforementioned tools, Sgvizler is also capable of visualising statistical data, but the Data Cube Vocabulary standard is not used in any way. For instance, in the case of a map visualization, the library expects the query to return a table with a location name in the first column and a measurement value in the second one. It does not really take advantage of the semantical properties in the dataset.

2.11 Rhizomer

Another tool focused on faceted browsing is Rhizomer. It is a web application offering quite an interesting feature, which partially fits into the LDVM concept. Based on data filtered by the faceted browser, the user is hinted about which visualizers are available. Moreover, it indicates how many entities of the current view will be displayed after switching to the more advanced browsing mode.

As usually, those advanced modes are a timeline, a map and a chart visualization. As in the previous cases, the tool also works with datasets that could be classified as statistical, but it does not comply with the DCV standard. On the other hand, it relies on semantics of the data and autodetects properties, which can have a dimensional meaning, e.g. latitude and longitude for geospatial data.

2.12 LODStats

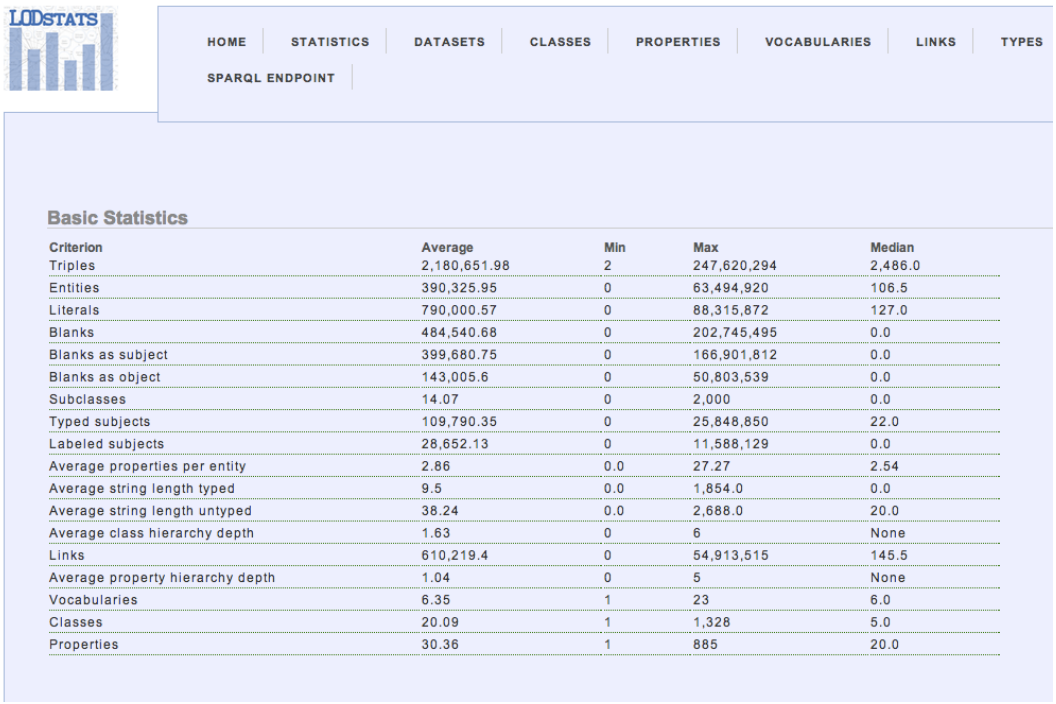
The authors of the LODStats project suggested that a major problem while working with data on the Web is to get a clear picture of the structure of a dataset. They also introduced a term *external coherence*, which explaines how well the resources of the examined dataset are connected with other resources, generally speaking, how the dataset is interconnected with other datasets.

In order to solve the problem, they have introduced the LODStats project, an extensible framework optimized to work on a rather large datasets. Its purpose is to compute statistics on the given datasets. The tool is integrated with the CKAN [43] dataset metadata registry (The Data Hub [44]) in order to cover the most known and most used datasets, therefore to offer statistics for a great part of the Data Web.

Since one can overview rather small datasets without any significant problem, the biggest advantage of the LODStats tool lies in the ability to work fast with datasets containing millions of RDF triples. The authors took advantage of the presence of a SPARQL endpoint, which allows them to work with the datasets dynamically, without the need to load all those millions of triples into the memory.

The way of processing a dataset with a large amount of triples is an approach which Payola should definitely adopt in the future.

The authors of the tool implemented statistics that were defined by VoID [45]. Which means that 32 different statistics are computed while utilizing the following



Criterion	Average	Min	Max	Median
Triples	2,180,651.98	2	247,620,294	2,486.0
Entities	390,325.95	0	63,494,920	106.5
Literals	790,000.57	0	88,315,872	127.0
Blanks	484,540.68	0	202,745,495	0.0
Blanks as subject	399,680.75	0	166,901,812	0.0
Blanks as object	143,005.6	0	50,803,539	0.0
Subclasses	14.07	0	2,000	0.0
Typed subjects	109,790.35	0	25,848,850	22.0
Labeled subjects	28,652.13	0	11,588,129	0.0
Average properties per entity	2.86	0.0	27.27	2.54
Average string length typed	9.5	0.0	1,854.0	0.0
Average string length untyped	38.24	0.0	2,688.0	20.0
Average class hierarchy depth	1.63	0	6	None
Links	610,219.4	0	54,913,515	145.5
Average property hierarchy depth	1.04	0	5	None
Vocabularies	6.35	1	23	6.0
Classes	20.09	1	1,328	5.0
Properties	30.36	1	885	20.0

Figure 2.7: LodStats statistics example

approaches:

- *Quality analysis* — The problem of a dataset quality is tightly connected to the form of the eventual data use. Therefore, a static analysis should give us a general purpose measure (similar to Google's Page Rank) to determine the quality very briefly, e.g. based on the number of outgoing and incoming edges.

- *Coverage analysis* — The authors present two subtypes of coverage - *vertical* and *horizontal*. While the horizontal is introduced to determine the size of the domain (how many resources are described), the vertical deals with the scale of details (how deeply the description goes).

- *Privacy analysis* — While analyzing what classes and properties are used, the authors of the project try to determine if a dataset might contain any personal information.

- *Link target identification* — According to the authors, less than 10 % of entities on the Data Web are interlinked. This technique should help the user determine what dataset should the examined one be connected with.

Since the authors have focused on performance and declared to develop a tool with a smaller memory footprint and better scalability, it would be really useful to integrate such a tool with the Payola tool. The integration would give the Payola user the opportunity to get familiar with the chosen dataset before analyzing it. In fact, as a circumstantial goal of this thesis, we will integrate the tool (on HTTP communication basis) with the previously mentioned LODvisualization application, the illustration of the concept introduced in [5]. Integrating

Payola with the LODStats analyzer should be also possible since the source code of both tools is available on GitHub [46] [47], but that is not a part of this thesis.

The authors made the tool to examine a given dataset in two ways, to examine the *schema-level characteristics* and *data–level characteristics*. The former describes the characteristics of an entity in the context of the used schema fragments (e.g. depth in a tree where hierarchical ontologies are used). The latter then describes the characteristics related directly to the values appearing in the dataset (such as minimum, maximum values, average values, entities equality, etc.). An example of computed statistics can be seen in Figure 2.7.

One will learn very quickly that Payola and LODStats are focused each on something completely different, but can complement each other very well. The Payola tool should definitely learn from the statement–stream–based approach in order to handle larger datasets better. The authors of the tool also published some statistics [48] gathered while integrating with the CKAN database, which is a great source of information when trying to get the idea of how an average dataset could look like.

2.13 Yahoo Pipes, DERI pipes

There are many analytical tools for processing RDF data. We would like to compare the Payola tool with the most important of them and provide the most significant differences. When deciding how the Payola tool should work, we came across an existing tool — Yahoo Pipes [49]. Providing an interactive editor, it allows the user to construct his own analytical *pipe*, which, in fact, corresponds with the term *analyser* (as defined in LDVM [5]). The only exception is that the various offered data sources are providing plain XML data (they are not in the RDF format). The tool does not offer the same level of analyzing data. It would be very hard to simulate SPARQL with tools like XPath.

That is how we came up with the idea of *analysis* concept for Payola. We offered a basic editor, which enables the user to build his own analysis (also called an *analytical pipeline*).

On purpose we made the editor with a rather restrictive behavior in order to avoid creating invalid or incomplete analyses. The user is able to insert new plugins into an existing analysis (analytical pipeline) only by connecting it to an output of another one. Since we are analyzing RDF data, the basic set of plugins is strongly related to the capabilities of the SPARQL.

After a while, we came across the DERI Pipes project [50], which is also inspired by the Yahoo Pipes project and is focused on processing RDF data. The editor is distributed in a form of a Java JAR package, therefore, one should be able to integrate it in another Java–based software rather easily.

Unlike Payola, it contains some basic text operators, which even enable the user to construct the URL that is used as a parameter of the RDF data fetcher. This is also the biggest difference between DERI Pipes and Payola: Payola lets you work only with RDF data which is the reason why plugin parameters (with basic data types string, boolean, integer and float) could not be computed in the process and are statically given by the user when defining an analytical pipeline.

The DERI Pipes tool offers some of the operators provided also by Payola. Some of them require the user to know the SPARQL in order to fill in the pa-

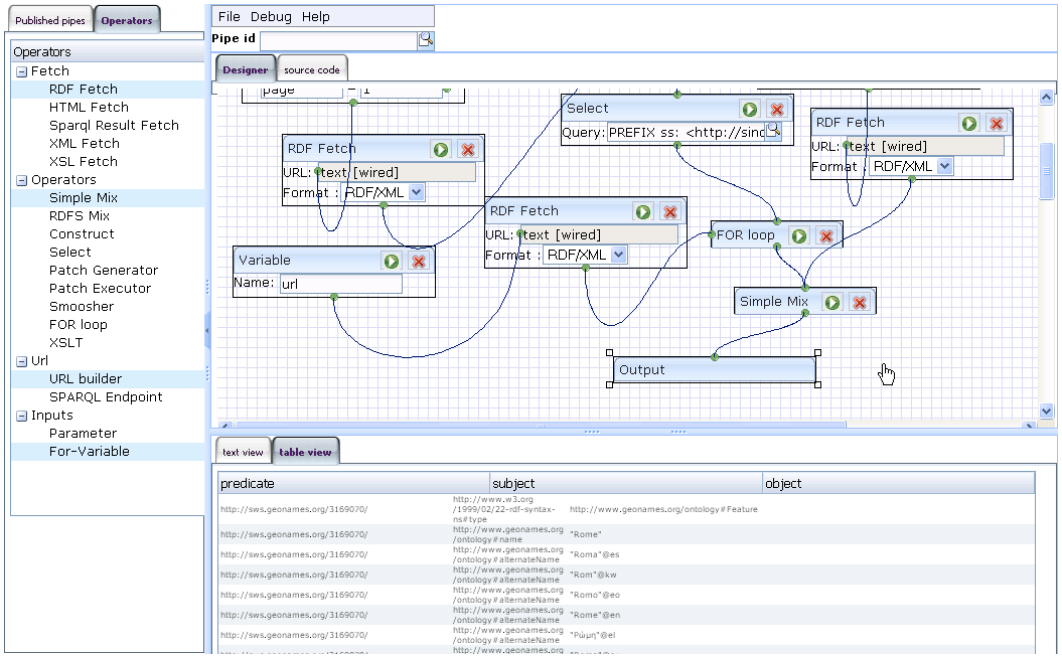


Figure 2.8: Deri Pipes example as shown in an instruction videocast [51]

rameters, e.g. the `SELECT` operator. One may also apply XSLT transformation operators and use `FOR` loops. It also enables the user to use more datatypes as an input of a pipe, for instance a classic HTML document.

2.14 Payola visualization model vs. LDVM

The primal reason of the Payola tool implementation was to prove some basic concepts:

- Generic Linked Data analysis with a web application.
- Generic visualization of analysis results.
- All–in–one (read, share, analyze, visualize) Linked Data tool.

As the original intent of the tool was not to implement any specific existing visualization model, the system has been created with its own internal visualization pipeline architecture. Let us compare such an architecture with the model proposed in [5]. For an easier orientation, let us name the Payola visualization model as *Payola model*. The model proposed in [5] is named *LDVM*. We will describe the Payola model while utilizing the terms used in [5]. Moreover, we will also explain the differences between the LDVM and the Payola model.

The Payola system is able to visualize all kinds of RDF data. It retrieves them from different types of RDF storages. Since it is not currently important, suffice it to say that it just fetches arbitrary RDF raw data. It uses SPARQL `CONSTRUCT` queries to retrieve those data from the given sources in order to work with graphs.

After the dataset is fetched, it is processed by an *analyzer*. This could be a set of any kind of transformations or operations. The most common case is running

a SPARQL query on the input graph. The only invariant is that the analyzer retrieves a RDF graph representation and its output is also a RDF graph representation (regardless of a concrete implementation). This is the phase described in [5] as *Data transformation*. Naturally, the product of such an operation is a result of the analysis, which is called an *Analytical abstraction* in [5].

Since Payola is a web application, which delegates rendering the view to the client–side of the application, the result of an analysis is transformed into a simplified format for a *visualizer*. At first, the result, which is an RDF format representation, is serialized to a custom `JSON` string that is transferred to the client–side. The string is then deserialized to an internal visualizer representation. In fact, this procedure is similar to one called *visualization transformation* in [5]. The product is the *visual abstraction* [5].

When the visualizer has all the data it needs, it maps the visualization abstraction to a visual representation, or, as described in [5], to a View. Actually, the process of mapping in [5] described as Visual mapping transformation is just traversing the retrieved data and interpreting them in a visual form (regardless of the concrete form).

As one can see, the Payola model and the LDVM are very similar. In fact, the Payola pipeline architecture corresponds with the proposed LDVM with some minor exceptions. Some of them originate from the fact that the Payola model is the result of an implementation based on concrete technologies. That is why some additional constraints (especially the graph invariant) are added.

Another exceptions issue from the modularity of the Payola system. The system was designed to provide a platform, which also means that the developer is able to build his own visualization plugins. This suggests as well that while serializing data into the JSON, the platform cannot perform any data optimizations in order to preserve all available information. Let us remind the reader of a part of visualization transformation definition from [5]:

The goal of this transformation is to condense the data into a displayable size and create a suitable data structure for particular visualizations.

This operation may be repeated *on–the–fly* in the visualization mapping transformation phase by the concrete visualization plugin chosen by the application user. In fact, one can say that the visualization transformation phase is duplicated and the pipeline contains two stages of *visual abstraction*. One can see an overview of the Payola visualization model in the fig. 2.9.

LOD visualization

To prove the concept of LDVM, one of the authors decided to come up with a tool based on the concept. The LOD visualization tool [52] is oriented to perform well on rather big datasets and provide their main characteristics in a reasonable time. Its main purpose is to enable to orient quickly in a given dataset. It provides several visualization types that help the user to understand the structure of the dataset.

That is also the most significant difference between the Payola tool and LOD visualization. The basic Payola analyzer and visualizer implementation provides deep details. It shows the whole dataset in the most possible detail. In fact, the performance could become an issue on a rather larger dataset.

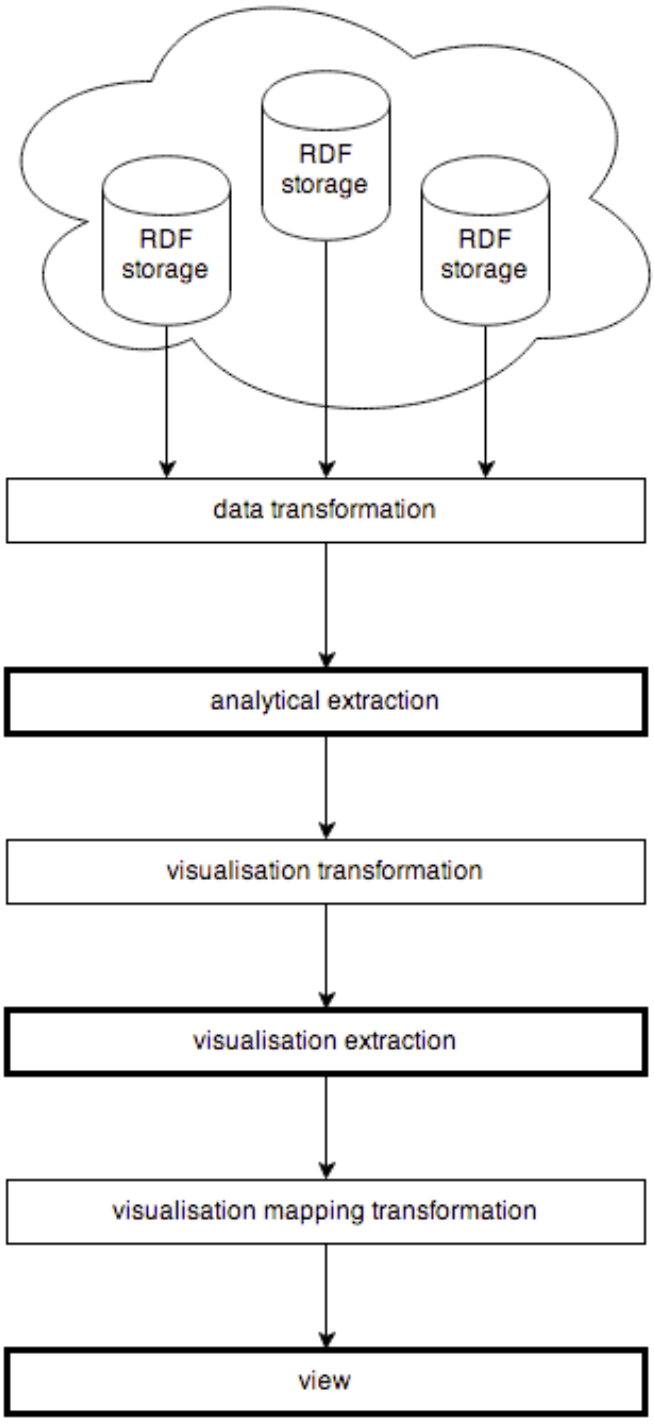


Figure 2.9: Payola visualization model

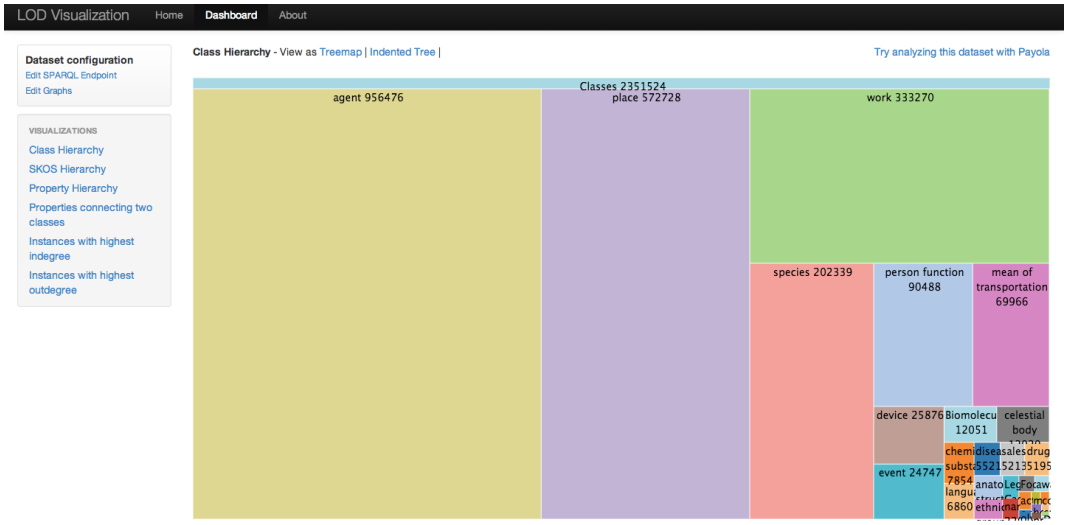


Figure 2.10: LodVis visualization of DBPedia class hierarchy

Those two tools are actually complementing each other. While working with a dataset one could start with the LOD visualization tool to get the overall picture of the dataset — the *data coherence*. It will also help to get the idea of what is included in the dataset without making a specific query.

Payola comes in when one is familiar with the structure of the dataset. The user is now able to perform specific queries, analayze the dataset and attempt to make a visualization of the analysis result. Therefore, one of the minor tasks of this thesis will be a simple integration of the LODvisualization tool into Payola.

The user of the LOD visualization tool is able to utilize the following visualizations:

- Class hierarchy.
- SKOS hierarchy.
- Property hierarchy.
- Properties connecting two classes.
- Instances with the highest indegree.
- Instances with the highest outdegree.

In a form of an interactive treemap or tree view, one can traverse through the tree that expresses the hierarchy of RDF classes used in the given dataset. One can also do the very same thing with properties. The user is also able to list all of the properties that are somehow (in both directions) connecting any two classes from the dataset. When given a class, the tool is able to quickly find an instance of such a class, which is the most referenced instance. It is also able to determine what instances have the largest amount of references — they have the highest amount of outgoing edges.

The extended version of LDVM

Since the original paper was published on ISWC 2012 as a demo and a work–in–progress, the model is being developed even while writing the text of this thesis. We will operate with the latest available version [12] and look at the new features of the proposed model. In fact, the latest version of the paper also covers an evaluation of RDF data visualization tools including Payola.

The most significant change came with introducing the concept of a *visualisator reusability*. The authors talk about so–called *GVDTs* (Generic Visualization Data Types). That forces us to think about what types of visualizators we could need. That applies also to one of the core products of this thesis — visualizators for multi–dimensional data. One will probably repeatedly use a limited count of visualizers.

While Payola makes it possible to reuse a visualizer, it does not satisfy the requirements set down in the proposal [12]. The idea goes a little bit further, beyond the borders of a single application. Being integrated with the LOD cloud, it should be possible to query it with the characteristics of the data we would like to visualize and get a list of visualizers available in the cloud and suitable for the task.

By reusing this concept, the same could be applied to analyzers and so–called *transformers* designed to transform the results of an analysis into another form more suitable for a certain class of visualizers. That could include a process of gathering more useful data (e.g. to visualize some data on a map it is needed to enrich the dataset with a GPS locations).

The result is a dynamic pipeline architecture (*LDVM Pipeline Instance*), starting with an arbitrary dataset passed to some analyzer followed by a chosen transformer ending up with visualising the result with one of the visualizers. As a result of applying the concept, we would obtain something similar to dynamic registry of analyzers, visualizers and transformers.

To make the Payola tool compliant with this concept, we would need to introduce a module, which allows the user to describe the analyzer (user–made analyses) and make the analyses more reusable. Currently, each analysis is tightly connected to the data sources it utilizes and those cannot be easily switched. That would, in fact, require massive changes in the analyses editor, which is not very user–friendly when it comes to editing an existing analysis.

The concept of transformers is completely missing in Payola since, as stated before, it is up to each visualizer to transform the passed data into a more suitable form, even enrich them with necessary information.

All the visualizers currently implemented in the Payola stack are fully reusable. But the tool lacks the feature to receive data from an external source and apply a visualizer on them. Or, from another point of view, there is no way of invoking the visualizer itself and specify where the data is and execute a visualization process.

All those missing features have one thing in common. Payola is missing an API, which would be able to tell, which analyzers, transformers and visualizers are present in the current installation of the tool and provide a machine–readable description of such components. Moreover, it is missing a mechanism that will allow the user to run those components separately out of the context of the Payola tool.

The authors call the above a *compatibility* in [12] and introduce a formalization that involves defining an *input signature*. In case of the basic Payola components, with an exception of one visualizer, the signatures would be empty. This would effectively express the fact that they are designed to visualize every dataset. The only exception is the *Chart visualization*, which requires the data to have a specific pattern so it would be sufficient to sign it just with a SPARQL query. While speaking about analyses made by the user or more advanced visualizers, ontologies would also come in.

2.15 Payola visualisator framework features

Since there are generally many publications focused on data visualization (with no connection to Linked Data), we would like to compare the recommended approaches to the implementation of visualizers embedded in Payola.

Ben Shneiderman introduces in [20] a term *Visual lnformation–Seeking Mantra*. He tries to define what a good visualizer should provide to satisfy its user. He also puts those definitions into a context with some specific data formats, more particularly with multi–dimensional data, which are related to the topic of Linked Data, moreover the Data Cubes metaformat. We try to compare the specified list of features with those provided by Payola. We also want to explain, why some of those features are missing or provided in another form.

The author states that every visualizer should have the following features:

- Overview.
- Zoom.
- Filter.
- Details-on-demand.
- Relationship view.
- User actions history.
- Sub-collections extractions.

Let us go through the list of the features and comment them gradually. All the visual plugins embedded within Payola provides the *Overview*. It is important to state that it contains some limitations. Since Payola is a generic Linked Data visualization tool, the output of practically all of the plugins is a graph (network). It contains all of the vertices included in the visualized dataset. Those are placed by a given algorithm on the screen, but are not clustered. The result is that the user is (in most cases) able to see the whole dataset on his screen (Figure 2.11). But the visualization could be a bit confusing since all the vertices are present. The recommended adjustment would be to somehow simplify the initial view.

The visualized graph might be dense. Some of the used algorithms will create a graph, which will have virtual clusters of vertices with a very little distance between them. In fact, some of those vertices would be so close to one another that

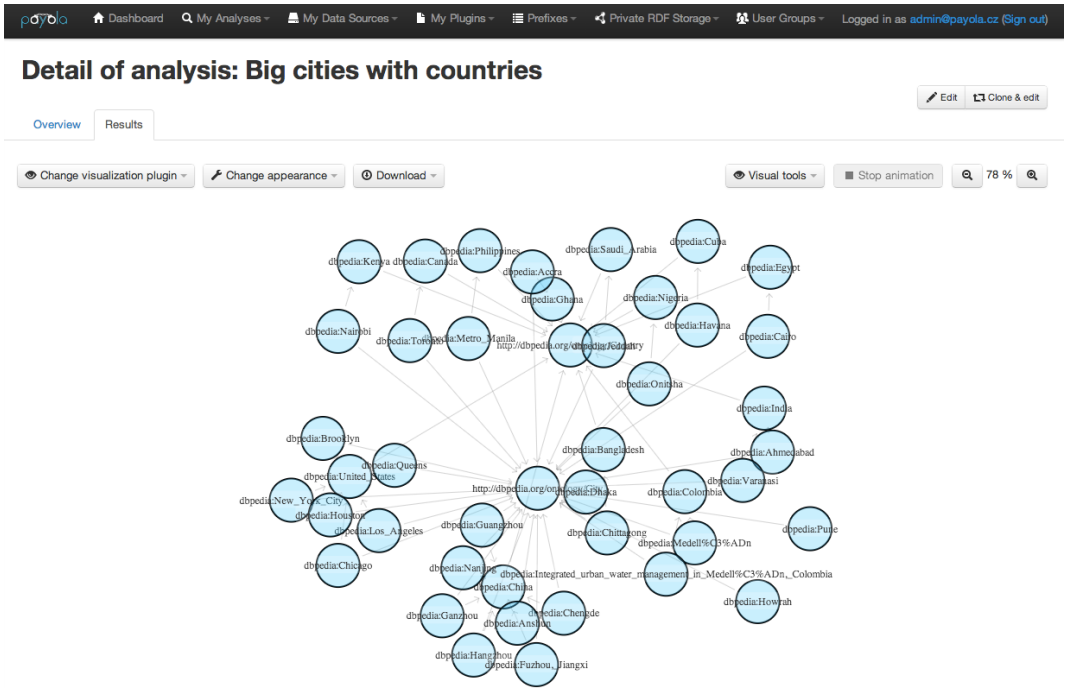


Figure 2.11: Payola analysis result visualization

they would overlap. Therefore Payola enables the user to *zoom* in and regulate the virtual distance between vertices.

When speaking about the *Details–on–demand* feature, we would like to distinguish between two different scenarios:

- Detailed information about a vertex.
- More detailed relationship information.

To make the view more synoptic many of the embedded plugins extract the related literal vertices and collapse them into a vertex meta information. E.g. the entity `http://dbpedia.org/resource/Dhaka` has some properties - `label`, `populationDensity`, `populationTotal`. Those are actually relations. Despite that fact, visualizers do not treat them that way. They store this information in the memory and display it if and only if the user interacts with the related vertex.

The most missing Payola feature is loading relationships on–demand. With the connection to the problem mentioned in the overview section of this chapter it would be more suitable, if the Payola system would enable the user to view only significant vertices at first and only load details when needed. This is also connected to the *Sub–collections* extractions feature, which is partially available in the analytical Payola module.

Since Payola visualizes Linked Data, it naturally visualizes the *relations between the entities*. The only feature, which is rather missing in comparison to the feature list from [20], is *User actions history*. There is only one component of Payola that enables a user to walk through history of actions and that is a SPARQL endpoint browser. It remembers the path that the user creates while clicking through the dataset. The other visualizers however are not equipped with such a feature.

Payola does not fulfill the basic thought stated in [20], since there is no visualization plugin that would enable the user to overview the examined data set via a specialized visualization such as a treemap in [52]. What one gets after visualizing the results of an analysis is a detailed view, which is (in the case of graph visualizations) however zoomed out to enable the user to see the whole dataset at once. Despite that fact, it contains representation of all the nodes in the data set and therefore breaks the visual information seeking mantra.

3. Payola

Quite some time ago, we decided to participate on a large–scale software project focused on analyzing and visualising Linked Data. As a result of the project a completely new tool, Payola, was introduced. Since we are proposing a system, which could fit into the technological stack of Payola, in this chapter, we will get the reader familiar with the tool. Even if we decide not to integrate the system we are about to propose, the Payola tool remains a related work tool and worth describing.

Payola is an HTML5 application oriented on a generic processing of Linked Data. The main goal was to come up with an application that will eventually reduce the software stack one needs to browse, analyze and visualize Linked Data. We wanted the tool to compile some existing approaches and bring a compact way for processing LD.

Upon a closer look at Section 2, it will become apparent that many of those tools are immensely capable. However at a more detailed look one will see that they might have to be chained in order to convert data into RDF, perform analysis over an RDF graph and visualize those results.

Payola, on the other hand, is a framework developed with keeping in mind that the user should have no need for another tool to process their data. However, as a large–scale project actively being developed, it still lacks many features and originally offers just a basic set of operations to enable a *generic* processing of an arbitrary dataset.

To understand the architecture of a possibly proposed plugin, we need to walk the reader through the architecture of the framework itself. But, to be able to understand the architecture of the system it is required to familiarize oneself with its features first.

3.1 Payola concepts

In order to fully understand the following text, let us explain some concepts implemented in Payola:

- *Data Source* — data storage with a defined interface like a SPARQL endpoint. If we talk about a data source, we almost always have in mind an RDF data source.

- *Analysis* — one can look at an analysis as an algorithm, which describes transformation of data from a data source in order to provide results. It is a way of specifying the data sources you want to fetch the data from, filtering them, combining them, constraining them on properties, applying ontologies, etc. Also known as an analytical pipeline or an analyser.

- *Plugin* — as Payola is a platform, it is reasonable to expect that some of the features might get to be extended by plugins. In Payola, we distinguish between two different types of plugins — *analytical plugins* and *visualisation plugins*. Whilst visualisation plugins are small components, which

take an RDF graph as an input, the analytical plugins are processing units, which generally transform one input graph (or more) into another one.

That includes anything from a simple forwarding of the graph from input to output, making union of two graphs, executing a SPARQL query on the graph to constructing a completely different graph. The new graph is created by applying in–memory operations defined by the source code of the plugin.

- *Data fetcher* — a component, which serves to fetch data from a data source. For example, while communicating with DBPedia [9], a data fetcher is needed to connect to a SPARQL Endpoint, execute a SPARQL query against it and return the results.

3.2 Payola features

Basically, we differentiate between two types of Payola users — anonymous and registered. While an anonymous user has a very limited accessibility as they can only view and explore publicly available resources a registered user is able to take a full advantage of the application.

One of the basic features offers the possibility of creating your own instances of a data source. Based on the available data fetcher types, the user is able to create his own instance. An instance is a mean where one specifies parameters of a concrete data fetcher. For example in the case of a SPARQL Endpoint data fetcher, the user fills in the URL of the SPARQL Endpoint and optionally a URI of the named graph containing the desired dataset. Having done this, the user is able to share such an instance with the other users of Payola. Moreover, the user can make it publicly available and share an URL of that instance, which allows any Internet user to browse through the data source equally as its owner.

3.2.1 Exploration mode

On the application dashboard is the user presented with a list of accessible resources, including data sources. After clicking on a data source the user is presented with a neighbourhood of an *initial vertex*. The choice of an initial vertex depends on the implementation of the underlying data fetcher. Those bundled with Payola choose a random entity from the data source and use it as a starting point of a data source exploration.

The user is also provided with his own data repository, which is created by Payola in the underlying installation of the Virtuoso [53] triplestore. Payola then eases the upload of an arbitrary dataset in the RDF/XML or TTL format into the private repository. The repository may be used as a data source in analyses.

In the exploration mode, one can choose from a couple of visualisation plugins. By default, the results are displayed in a form of a triple table, but the user can opt to more advanced modes — a graph visualisation and a chart visualisation (which currently requires a special pattern to be present in the data). By using those visualizers, the user is able to traverse from a node to a node, thus exploring the whole dataset.

3.2.2 Analytical mode

In the analytical mode, the user is able to build a custom data analysis. As stated before, an analysis could be presented as an algorithm, which decides how to process data. Moreso, in the analysis, one is expected to specify where the data have to be fetched from.

The analysis concept arises from ideas seen in projects like DERI Pipes [50], meaning, that the user is needed to assemble a pipeline, which processes the input data in a specified way. Therefore, to enable them to build an analysis, Payola is bundled with several basic plugins. Generally, the list of plugins contains as many plugins as needed in order to simulate basic SPARQL query behaviour.

- *Typed* — This plugin selects vertices of an RDF type that is filled in as a parameter called RDF Type URI from its input graph.
- *Property Selection* — the plugin takes property URIs separated by the newline character as a single parameter. It selects vertices connected to others using one of the listed URIs.
- *Filter* — the plugin lets the user select vertices with an attribute of a particular value or property.
- *Ontological Filter* — this plugin filters the input data so that the result contains only vertices and properties defined in an ontology specified by the given URI.
- *SPARQL Query* — a plugin for more advanced users who are capable of constructing a custom SPARQL query. Since plugins in the pipeline work solely with graphs, the SPARQL query should be of a CONSTRUCT type.
- *Union* — a plugin with more than one input. As the name suggests, it takes the input graphs and unifies them into a single one that is passed onto the output.
- *Join* — the behaviour of the Join plugin could be a bit tricky so it is advisible to take a closer look at it in the application's user guide [54]. The most common case simulates the behaviour of the join statement as we know it from the world of relational databases.

An example of an analysis can be seen in Figure 3.1. The goal of the analysis is to query against DBPedia SPARQL Endpoint and retrieve cities with a number of population higher than the specified parameter. Those cities are then connected to the country they belong to.

3.2.3 Visualisations

One would certainly like to visualize the results of an analysis. Therefore, Payola is bundled with some basic visualizer plugins. As described in Chapter 2, the Payola basic visualization plugins support some features suggested in the Visualisation mantra [20].

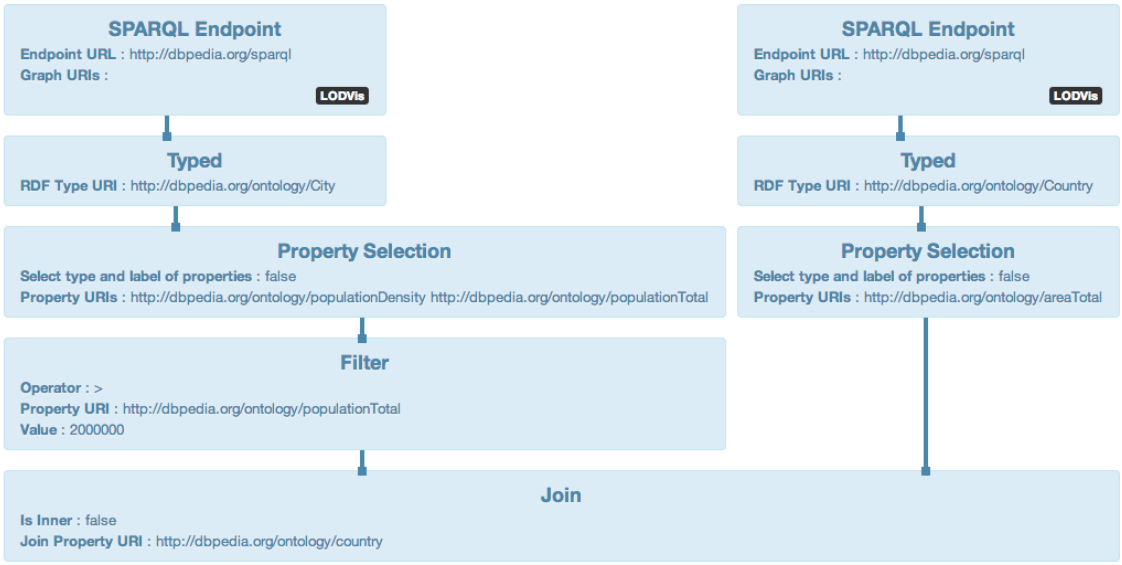


Figure 3.1: An example of Payola analysis

The bundled plugins enable the user to visualize the results of an analysis in a couple of different ways. The basic visualisation generates a triple table, while more advanced variants offer a generic graph visualisation with a support of OWL ontologies. The visualizer allows the user to customize the view based on an ontology. The user can customize colours and other graphical features of a rendered graph representation with respect to a URI type defined in an ontology.

3.2.4 Sharing

Since Payola was designed as a collaborative tool, it contains group management and a generic mechanism for sharing. Many types of content such as a data source, an analysis, a custom analytical plugin, an ontology customization for visualization, all can be shared with other users of the Payola application installation.

Since the description of the tool is not the main goal of this thesis, we will keep it brief and refer the reader to the Payola User's guide [55] to learn more.

3.3 Payola architecture

The application is divided into several parts, packages, in fact. That can be seen in Figure 3.2. Since this will be useful in an upcoming chapter about implementation, we will look at them more closely.

At first, there is the `common` package consisted of a code, which is shared with all of the other parts of the application. Every other packages can access it and use the declared code. Moreso, the classes and objects in this package are automatically compiled into the JavaScript language and are available also on the client–side. As an example of a class from the common package, we can name the `Graph` or `Vertex` classes, which serve as object representations of an RDF graph or a vertex (resource, entity). Moreover, there are traits for en-

tities that are consequentially independent on a concrete DAL implementation.

The domain package contains a code related to the business logic of the application. It solves mostly basic operations for entities, such as *add a user into a group* or *grant a certain privilege to a user*. It also contains components related to the analytical plugins compiler. The compiler is executed when a user submits their own analytical plugin via the user interface. It validates and compiles the code. If successful, the plugin is loaded into the application. Last, but not least, the *analysis evaluator* is present in this package. Since this is crucial, we will talk about the evaluator in more detail in this chapter.

The data package then wraps the entities from the previous packages with a concrete implementation of DAL (Data Access Layer), which in our case is the Squeryl ORM framework [56].

The model package builds up a wrapper, which encapsulates all the business and data access logic. The goal of the code in this package is to decouple any presentation layer from the application logic and data access. In fact, all of the existing presentation layers (web application controllers and RPC remote objects) are built on top of this package.

The web package contains all the code needed to build the web application — a server side, a client–side and everything in between. It contains the code of the MVC application as well as the code of the client–side subapplications. It also contains the code of visualizer plugins and an analysis editor. One of the most complex and interesting features from this package is the RPC mechanism.

The RPC mechanism was implemented in order to bridge the gap between the client side and the server side application and to hide the XHR request from the developer of the application and/or any extension. Since the application heavily uses the *Scala to JavaScript* component, we invested some effort into developing the RPC protocol. That enables a developer to transparently call a method on the server from the client–side.

To learn more about the architecture or the implementation details, please see the Payola Developer's Guide [57].

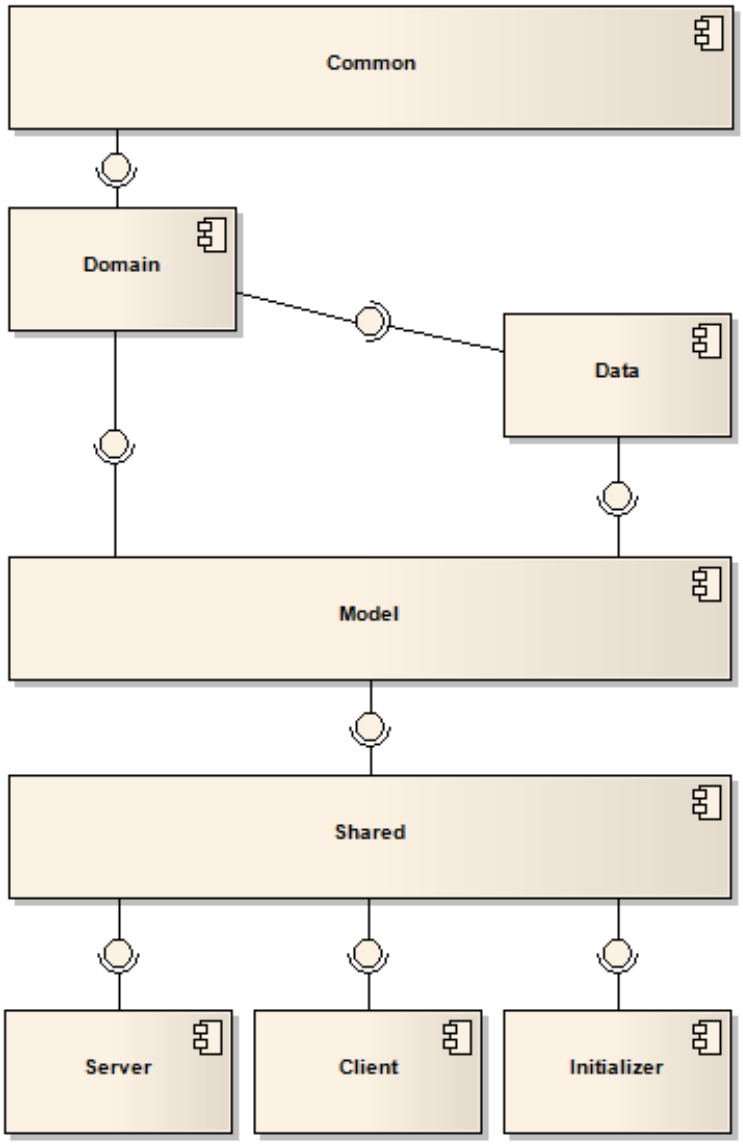


Figure 3.2: Packages structure

3.4 Analysis evaluation

When we are now familiar with the parts of the application, we may explain a bit more the processing and visualizing of an analytical pipeline. That is crucial to know before an implementation of any extension.

When an analysis evaluation is requested, the analysis gets *validated*. We need to make sure that the application meets some requirements, e.g. it has one *output*, all *inputs* and outputs of all the plugins in the analysis are *bound*, etc. If it does, the application tries to *optimize* it. Generally, executing a plugin means that it is provided with an input graph, it performs some operations and returns another graph. Since the project has integrated the Jena library [58], it is very easy to query an in–memory representation of a graph and return the results.

Let us imagine a situation where a user wants to select a rather small range of data from a data source. For instance, a list of cities from DBPedia, which includes those with a population count higher than 2000000 people. Without an optimization the evaluator would have selected all available entities from the DBPedia database (which is not possible anyway due to their SPARQL endpoint configuration). After transferring all of the data to the Payola server, it would have executed a simple SPARQL *typed&filter* query in the memory. However, this would be a far cry from an efficient solution. It would even bring many technical difficulties, e.g. the whole DBPedia dataset would require the Payola server to have a huge amount of RAM.

That is why an optimalization would take place in such a situation. The original query which would fetch all the data from DBPedia would be altered to include the constraints set by the presence of typed and filter plugins, so that the data fetcher would have to fetch as less data as possible. The optimizer can also handle unions or joins over the same data sources.

That gives us the idea of how the plugins work and how they can cooperate in the context of an optimized analysis. The evaluation itself is transformed into a problem, which is solved by the Scala Actors framework. For each plugin in the optimized analysis, there is an instance of an actor. The actor waits until all of the inputs of the corresponding plugin have been provided with the input data from its predecessor. When inputs are bound with input data, the executive part of the plugin is performed. That could be anything from executing a SPARQL query to finding the shortest path between two nodes in a specified graph. The only constraint is that the result of the plugin execution needs to be also a graph.

As the last plugin (with no bound successor on its output) gets evaluated, the analysis is done. The results are sent via RPC (while being serialized into JSON) to the client–side and visualized by the basic visualisation – the triple table. The user is then able to switch to another visualisation. The JSON representation of the resulting graph is stored in the memory of the user's web browser and every visualizer, which is activated by the user accesses the in–memory representation and renders whatever it needs into a given canvas.

That is a brief description of the evaluation process. It offers an insight to what happens of in the background. Later, we will learn how this affects the implementation of the proposed system.

3.5 Technological stack

In order to deliver an application, which is easy to use and does not require the user to install it on a client machine, Payola is being developed as a web application. Since it is assumed that Linked Data community is consisted of rather advanced computer users with modern web browsers installed, the application takes advantage of a variety of modern technologies, like HTML5 (specifically canvas element) and CSS3.

In order to bring a basic level of compatibility with existing applications from the LOD2 stack, it was decided that it has to run on the JVM platform. The Scala programming language was chosen as a main implementation language of the whole application. Since the team of the project wanted to avoid a code repetition while keeping in mind the DRY programming paradigm, one of the members introduced his own version of Scala to JavaScript compiler [59]. Therefore, even the client–side code of the application is written in the Scala programming language and many parts of the code are shared between the client–side and the server side.

There were many different advantages of choosing the Scala programming language, for example the presence of the Scala Actors framework, which fits into the analysis evaluation problem.

The application utilizes the following libraries and technologies:

- *Play Framework 2.0* — a web application MVC framework completely written in the Scala programming language.
- *SBT* — build tool for Scala projects.
- *jQuery* — JavaScript library used mainly for solving crossbrowser differences.
- *Squeryl* — Scala ORM framework used in DAL.
- *Apache Jena* — well known Java RDF library.
- *Twitter Bootstrap* — library for building an eye-catching user interface.
- *Ace* — JavaScript editor for programming languages.
- *Flot* — JavaScript chart library.

4. System proposal

Based on what we have presented in Chapter 2, we would like to propose a system, which will enable the user to map arbitrary RDF dataset into a form compliant with the Data Cube Vocabulary standard. Since this is quite an open definition, we have to dive into the problem a little bit deeper to find out what is possible and to propose a system that meets some real–world functional requirements.

We are about to propose a system that is in a specific way very similar to the implementation of OLAP2DataCube (Section 2.1) or Tabels (Section 2.2). On the other hand, both of them are focused on converting arbitrary statistical *non–RDF* data into a form compliant with the Data Cube Vocabulary. In Figure 4.1 we remind the reader how the transformation process is done in the case of OLAP2DataCube. The important fact is that the data source (RDBMS) already contains statistical data in an obvious form. Those are structured in tables connected via foreign keys and organized in a shape of a star or a snowflake. The system is designed to take advantage of those foreign keys. Based on them it categorizes tables (fact table, dimension tables) and hints the user within the cube definition step. The user is required to define relations semantics and select columns containing measures and dimensions. In the last step, a mapping is done based on the information gathered in the previous steps. Notice that a Data Cube Vocabulary definition is a part of the result.

Let us take a brief excursion back to the OLAP2DataCube described in Section 2.1. The tool was not designed just to convert a non–RDF dataset into the RDF standard with respect to the DCV metaformat. Executing the tool on a dataset has one important side–effect: there is a new QB data structure definition generated with bases on the structure of the input dataset. Therefore, the tool does not map the dataset to match an existing data structure definition, it creates a new one. That is definitely needed when one transforms a non–RDF dataset into RDF. But once this is done, it is probable that a company or an organzation will produce the same kind of data periodically, therefore, they will reuse the same data structure definition.

This is the reason why we will propose a system which fill focus on the task of mapping the input dataset to match an existing data structure definition. The authors of the LDVM [5] (see Section 2.14) propose to make standalone visualizers. Each of them will be able to visualize a specific kind of datasets. Its visualization abilities will be described with an *input signature*. A Data Cube

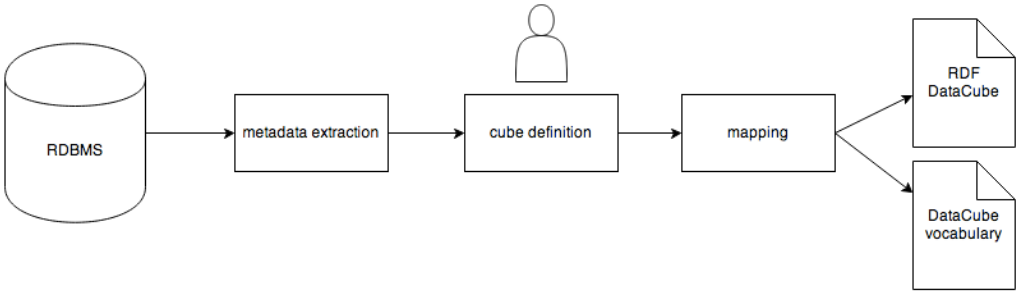


Figure 4.1: OLAP2DataCube mapping process

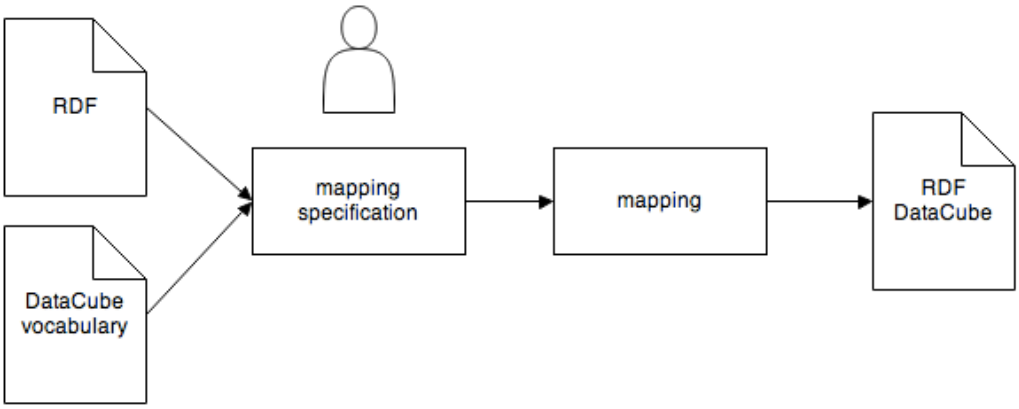


Figure 4.2: RDF to DataCube mapping in a generic system

data structure definition could be easily transformed into an example of such a signature. That is another reason why we want the tool to map the input dataset into an existing definition.

That means we would like to enable the user to take an existing RDF dataset and give it a statistical meaning. The initial thought was to implement a set of specialized mapping modules. We would have to implement a standalone mapping module for each existing Data Cube Vocabulary. Since this is rather impossible and surely inefficient, we made some experiments in order to ensure that we would be able to come up with a generic mapping component. That is why the process of the implemented system will be similar to what is shown in Figure 4.2. The process seen in the diagram represents a high–level view of the system. As we consider some additional criteria we will provide a more detailed schema of the proposed system.

The biggest difference is that the original dataset can contain the statistical data in a not–so–obvious form, as in the case of the relational DB. The user may need to apply an analytical extraction (a term introduced in [5]) in order to select the transformed data. We start with an arbitrary RDF document, specify the process of mapping and how the system transforms the data in order to comply with the Data Cube Vocabulary standard. We also require the user to provide a Data Cube Vocabulary definition. The proposed system will map the data to conform with such a definition.

We will now walk the reader through the decision process we have made in order to propose the system. As stated before, the input is an arbitrary RDF graph. To be able to map data from the graph to a form compliant with a Data Cube Vocabulary, the system also needs for a vocabulary to be a part of the input. As discovered in Section 1.6, the vocabulary is another RDF graph.

Based on that fact, we concur that the system needs to contain a mechanism, which parses an arbitrary RDF graph and searches for DCV data structure definitions. We need to extract those definitions and have the user select one. The selected definition will be used in the upcoming steps to obtain mapping specification from the user. What we need to obtain is presented in Figure 4.3. On the right side the reader can see a generic visualization of a DCV data structure definition. A random graph is placed on the left side of the illustration.

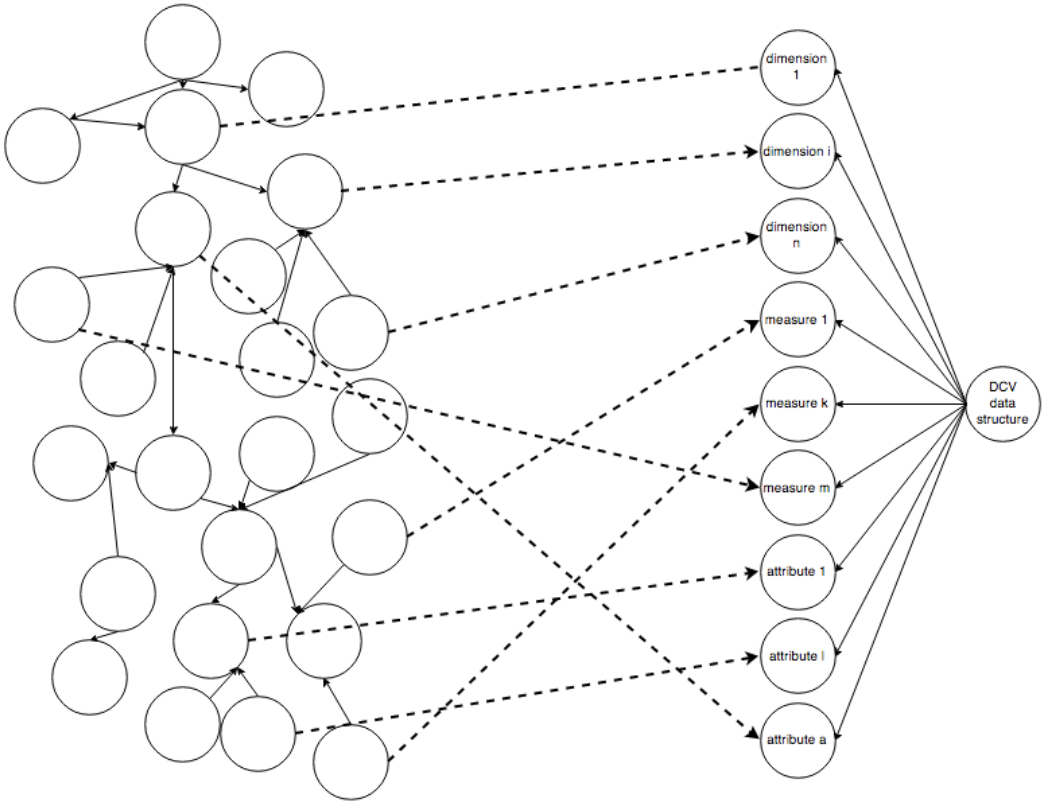


Figure 4.3: Mapping example. Original dataset on the left, DCV data structure definition on the right.

The dashed lines connect the resources from the original dataset with corresponding DCV components. Naturally, the figure represents an example of a mapping.

4.1 Pattern selection

We are lacking some rules telling the system how to do the mapping. Without such rules it is not possible to map the input graph properly. Let us imagine an input graph, for instance the whole DBPedia database. That represents a huge graph containing many facts and naturally, some of those are statistical data. But they are not referenced in such a context. For example the resource *Prague*, which is the capital city of the Czech Republic has properties `populationTotal` and `populationAsOf`. Together it creates a slice of a cube. This says that the city Prague (location dimension) had in a certain day (time dimension) a certain amount of citizens (measure).

Although this cube is originally based on a very simple pattern (a shape of a pair of cherries), it is not possible to map such a slice into a form compliant with a data structure definition since the relation between the definition and the dataset is not defined in the original data. For a well–defined data structure definition and a well–defined dataset, it could be possible to propose another system, which would try to detect the relation and create them automatically. For instance, the location dimension, which is usually named *reference area* could be connected to a generic type – a location. Also the resource *Prague* could

be connected with the location type. But that would mean introducing a system, which would process a lot of data trying to match each supertype of the dimension with the properties of every resource in the graph. It would have to use advanced heuristics and it would probably have to adopt some techniques from the machine–learning field. A fully–automated system would also introduce a lot of mistakes into the results since it would be a highly experimental approach. Therefore, implementing such a system would not be the goal of this thesis.

On the other hand, we would like to propose a system, which will be flexible enough to allow the user to take an arbitrary Data Cube Vocabulary data structure definition and map a reasonable part of this dataset into a compliant form.

Unfortunately, the phrase *reasonable part* is not very scientific. It comes from the data semantics and it is quite difficult to formalize. What the user should map to a given data structure definition should have a corresponding semantics. For instance, if we use the population size example, the user should probably not map the statistics of government debts to that definition. Even though a country is a location, the amount of the debt represents a number and was certainly calculated on a specific day, therefore, the data match the ranges of the data structure definition components, but it does not match the semantics.

On the other hand, we do not want to make the tool too restrictive in order to achieve better user experience. For instance, we have mentioned (Figure 1.7) a data structure for the population example that declares a dimension `czso-ds-def:refArea`. The range of that dimension is specified as `czso-reg:Municipality`. With a restrictive approach, the tool would not enable the user to map the data from the DBPedia database to match the data structure definition, since the DBPedia dataset does not contain the `czso-reg` namespace. Nonetheless, Prague is certainly a Czech municipality. Therefore, the tool will not check the range while performing the mapping. If it had, the user would need to involve other datasets so as to provide the range–related information.

What is still missing is the way of informing the tool about how to map the data. Obtaining such a specification can be implemented in many different ways. All of them are actually described in Chapter 2. Some of the tools used their native language – the SPARQL. That is beneficial for a developer due to its relatively easy implementation. But it is a bit cumbersome for a user who is required to know the SPARQL language. On the other hand, from all the approaches it restricts the possibilities of the system the least. It enables the user to specify a wide range of mappings.

OLAP2DataCube took an advantage of the database structure (Section 2.1) — especially of relational feature — foreign keys. Since the RDF format is based on expressing relations it would not present an issue. But what the OLAP2DataCube tool did, was that it transformed already existing statistical data from the star–shaped database structure into another format. But in the world of RDF data we would restrict the tool a lot if we relied only on star–shaped schemas, hence, we need to work with a generic graph.

Tabels introduced a custom DSL that should have made the situation easier for a user (Section 2.2). But as experienced while doing research for Chapter 2, we did not find it very user–friendly. There certainly was a pre–generated script

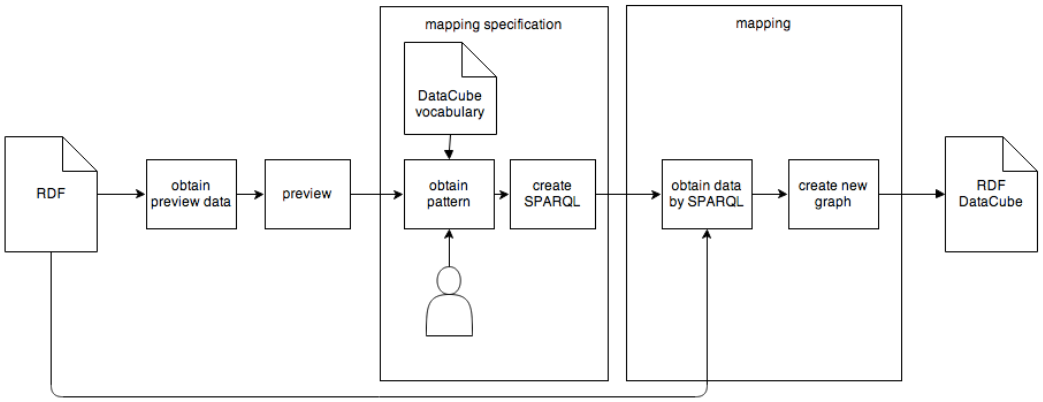


Figure 4.4: Detail of the proposed system.

based on the uploaded file but in most cases the user had to modify the script in order to achieve desired results. The user is required to learn a completely new language, but will probably not find any other use of such a skill elsewhere. Moreover, it is not an easy task to implement the custom DSL itself. Therefore, we consider this approach to be the worst.

The last approach we have noted is the *query–by–example* introduced in Tabulator (Section 2.7). It was used to let the user specify what type of data patterns they are interested in. In the exploration mode the user was able to *visually* specify the pattern and switch to the analytical mode. Such an approach enables us to construct a SPARQL query and come closer to the very first (and the least restrictive) approach. Nonetheless, it brings some new implementation issues.

The most obvious one is the transformation of the user's selection into a SPARQL query. We will also require the system to be capable of making a preview of the original dataset in order to offer the user a visualization. The visualization itself will interact with the user and provide them a way to specify the pattern.

Of course, the query–by–example does not need to be necessarily done visually. But obtaining an example with a non–visual approach leads to the involvement of a DSL. Even a simple DSL, for instance a variation of CSV format, is not as user–friendly as the visual approach. The visual approach also enables us to force some restrictions to avoid dealing with an arbitrary user input. We will obtain an input that is already valid.

After obtaining the pattern all the necessary information are gathered. We may proceed to the mapping process itself. The mapping module will query the data source for the data. It will use the pattern specified by the user. After fetching the data, it will construct a new graph containing a set of DCV observations. Based on what we have learnt so far, the system will appear in detail as shown in Figure 4.4.

4.2 Mockups

We will show the reader our idea of a user interface of the proposed system. We will refine some previously outlined features, especially the pattern selection.

In the first step (Figure 4.5), the user is required to specify the source of the da-

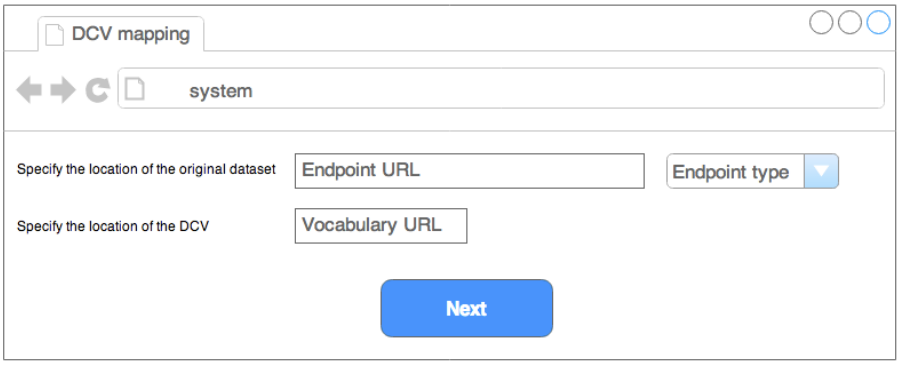


Figure 4.5: Step 1: data source and vocabulary specification

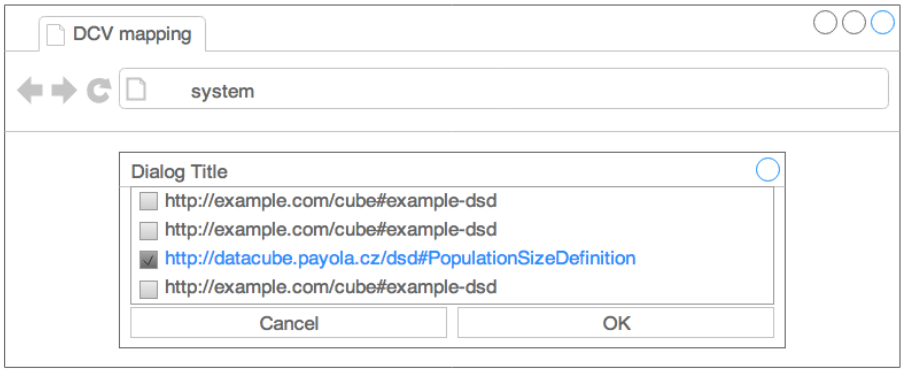


Figure 4.6: Step 2: DCV data structure selection

ta that will be transformed. They will probably supply a reference to a SPARQL Endpoint, e.g. `http://dbpedia.org/sparql`. The user also has to reference a graph, which contains the desired Data Cube Vocabulary data structure definition. That is a URL as well, e.g. `http://datacube.payola.cz/dsd/population.ttl`. The type of data source is needed in order to determine how to fetch the data.

After proceeding to the next step (Figure 4.6), the user will be asked to choose a DCV data structure definition. The definition list is prepared based on the vocabulary provided in the previous step. The system has already parsed the supplied graph and filtered all DCV data structure definitions. As an example, the user will select the `http://datacube.payola.cz/dsd#PopulationSizeDefinition` data structure definition.

The system now selects data for a preview. The retrieved dataset is visualized and shown in a dialog (Figure 4.7). The user is required to specify a pattern. The specification is done by clicking the vertices in the visualized graph (some progress is shown in Figure 4.8).

After the pattern is specified the system has all the information it needs. The user is able to start the mapping process. When done, the system offers the results (RDF graph).

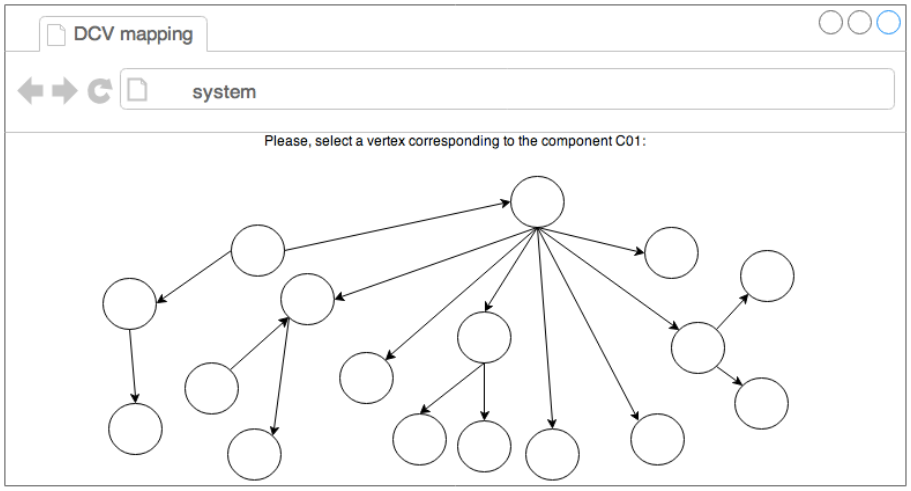


Figure 4.7: Step 3: Pattern selection

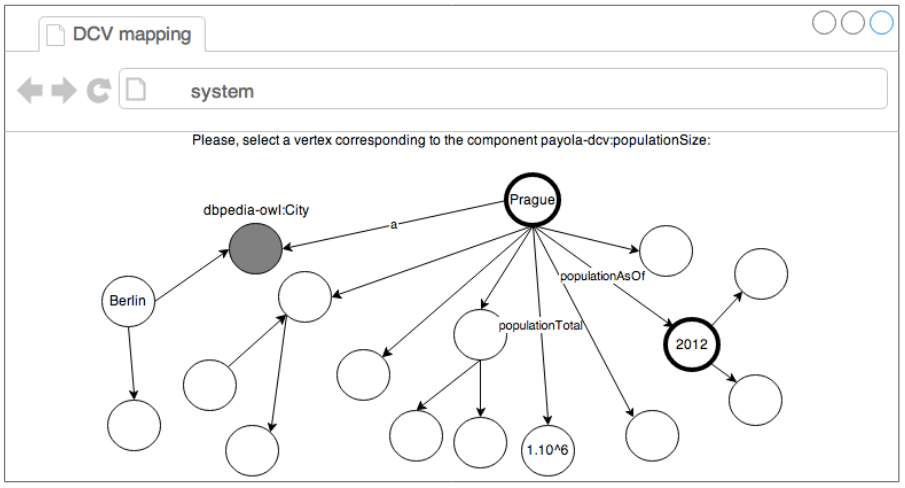


Figure 4.8: Step 3 (example): Pattern selection. The user has to provide an example for mapping the dataset to a population vocabulary. In the last step, the user is asked to select a vertex corresponding to the `payola-dcv:populationSize` property. They have already selected the vertices representing Prague and observation date in order to satisfy the other components. The `dbpedia-owl:City` vertex can be selected to refine the example, but it does not correspond with any component. The user is about to select the vertex connected via the `populationAsOf` relation. This represents an example of selecting a meaningful pattern, which is a connected graph.

4.3 Benefits of integration into Payola

Since we have participated on the implementation of the Payola RDF tool, we will now go through the pros and cons of integrating the proposed system into Payola. We will also decide if we proceed with the integration.

In Chapter 3 we familiarized the reader briefly with the main concepts of the Payola framework. The reader also knows how the analysis evaluation is done. Therefore we may demonstrate the benefits arising from the integration of the proposed system with the Payola framework.

The crucial feature of the Payola framework is the analysis subsystem. It enables a user to combine multiple data sources and benefit from their combination. Based on that, a completely new set of facts can be computed. (This could be optimized with SPARQL 1.1 and Federated queries [60].) Therefore, it could be handy to introduce a Data Cube Vocabulary analytical plugin, which would be able to convert the results of an analysis into the Data Cube Vocabulary format. Such a plugin could be connected directly to an output of a data fetcher plugin — this will cover the basic implementation shown in Figure 4.4.

But we can go a bit further. Since it would be an analytical plugin, the user would be able to use such a plugin in an arbitrary step of the analysis. Let us look back again at the DBPedia and the population statistics example. A plugin representing the proposed system would substitute multiple different plugins in order to obtain the same data. In this case it is the `Typed` plugin and the `Property selection` plugin. Those are covered based on the selected pattern. In addition, the result would be compliant with the Data Cube Vocabulary standard.

Another asset is considered to be the ability to transform multiple data sources in one step. The users might also further use the converted datasets — combine them (join, union) and analyze those datasets in a unified format (specified by the DCV).

The next benefit of the integration with the Payola analyzer is that the user can assemble an algorithm, which is applicable multiple times. The main advantage is that it reflects the current state of the data sources at the time of the execution. That means that if the data source contents get updated, the user just executes the analysis again and the mapping is instantly performed. There is no need to specify anything for the second time. This is useful especially in a case where the analysis is more complicated than the mapping process itself.

As stated before, the Payola application also offers the functionality of sharing. This feature is usable at least in a case of sharing the results of an analysis. The introduction of a Data Cube Vocabulary plugin does not change anything. The user will still be able to share the analysis. If the analysis contains just the data fetcher and the DCV plugins, the user shares only the mapping process.

Another aspect could be an effort needed to implement such a system. Since the goal of software engineering is not to implement the same systems over and over but to bring new systems, new features, speed up the computation process and bring better user experience, it makes no sense not to take advantage of an already existing platform. The same approach could be seen in the case of reviewed tools like Olap2DataCube (section 2.1) or CubeViz (section 2.3).

The Payola framework contains a variety of useful components. As an example of such components we might name data fetchers, RDF processing modules

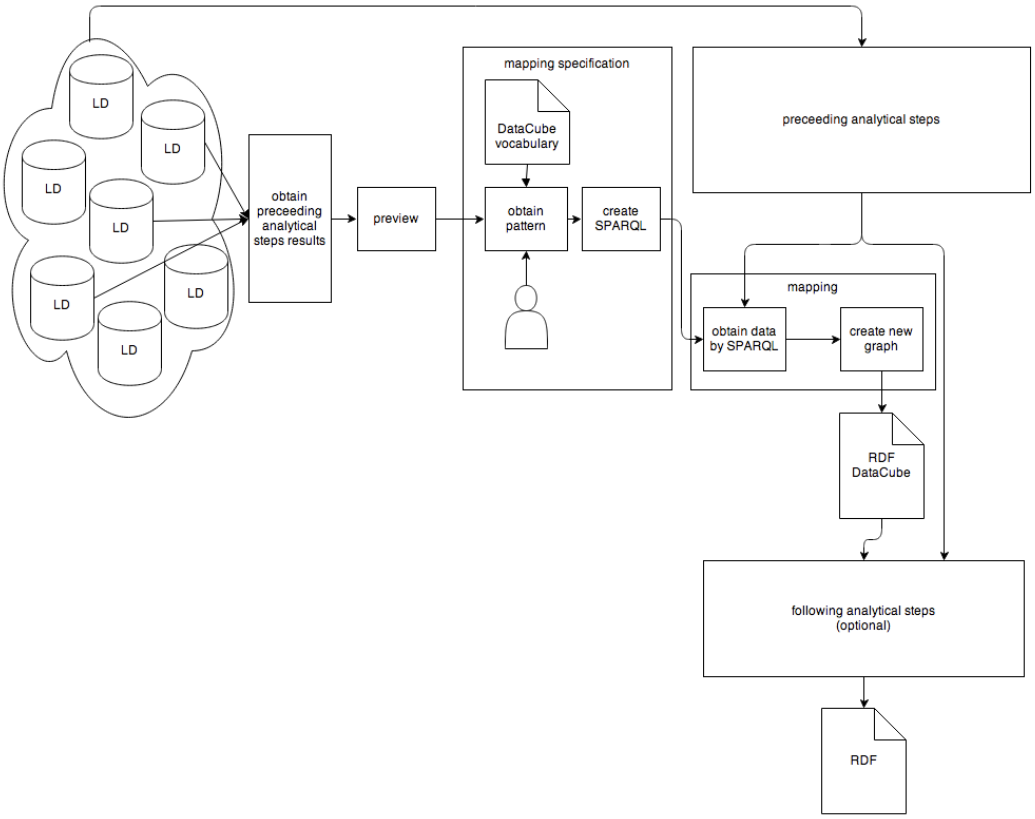


Figure 4.9: Mapping process integrated into the Payola analyzer.

or visualization API.

Since a part of the goal of this thesis is to implement an exemplary visualization that takes advantage of the Data Cube Vocabulary format, it will be very useful to stay focused on the task and implement just the visualizer, instead of a lot of supporting subsystems that are already implemented elsewhere.

Moreover, we can take advantage of the existing visualization plugins. The basic one, triple table plugin, offers a quick overview of the data. The user will also be able to download the results of the transformation into a static RDF file for further use or just for simple backup purposes.

We show a possible way of the integration of the mapping process into the Payola analytical extraction in Figure 4.9. It shows the proposed system in a context of an analytical pipeline. Such a pipeline is constructed by the user. The process starts with querying data sources in order to offer the user an overview. The amount of the sources depends on which sources are involved in the analytical pipeline. They are fully independent and spread throughout the whole Internet. The obtained data are visualized to the user who is required to select a pattern. Since we need to guide the user to select a proper one, we also need them to specify a Data Cube Vocabulary. We will need to parse the Vocabulary, extract the DCV datastructure definitions and offer the user a list of the available definitions. After they choose one, we will be able to determine how many mapping references we need the pattern to contain. The number is, of course, based on the amount of components within the datastructure definition. We will construct a SPARQL query based on the selected pattern.

The rest of the process is a common analytical pipeline execution. The Data Cube Vocabulary plugin can be interpreted as a standard plugin. Since the transformation is done by executing a SPARQL query, it corresponds with an execution of a SPARQL query plugin. During the evaluation of the analytical pipeline we reach a certain point of an undergoing mapping (thanks to a DCV plugin). On the output of this plugin, we will for certain find a dataset compliant with the DCV standard. But the dataset need not be the result of the analytical pipeline execution. It may be used as an input for the upcoming analytical steps.

Based on facts presented in the text above we find it reasonable to integrate the proposed system into Payola.

4.4 Formalization

In this section, we are going to formalize the aforementioned process a bit more. We need to specify the input of the system. We will also provide a definition of the mapping process. A description of the output will be also presented.

4.4.1 Input and output

The input of the system will be an arbitrary RDF graph G_{input} as shown in Figure 4.3. It will be mapped into a form compliant with the DCV standard. Since the DCV also takes advantage of the RDF standard, the result will likewise be a graph, let us say G_{output}.

As stated before, the system will have another input — a data structure definition. The Data Cube Vocabulary standards are built on top of the RDF as described in the section 1.6. That means, that a data structure is also a graph. We will denote the user–provided definition as D. But the user will probably not supply just a definition. They will provide an arbitrary graph, which contains the definition D (or even more definitions) as a subgraph (see Figure 4.10). We will denote a graph supplied by the user as G_{def}. The system has to extract a list of all the definitions (let us say $D_1, ..., D_d$) from the graph G_{def}. As shown in Figure 4.6, the user will select one of the offered definitions, for instance $D = D_x(1 \leq x \ \leq d)$. The graph may contain also other data, not only DCV definitions. It is true that:

$$D \subseteq G_{def}$$

But having the graphs G_{input} and D is not enough. We require the user to specify also an example pattern (based on the query–by–example principle). Since all the inputs and outputs are RDF graphs (G_{input}, G_{def}, D, G_{output}), we can take advantage of some existing approaches specialized on RDF transformation. A technically simple but powerful way, is to utilize the SPARQL language. Based on what we have introduced before, we are able to transform a user–selected pattern into a form of a SPARQL query. We will talk about such a query as of a *transformation query* and denote it Q_t.

What we have now is an information about what is needed on the input and what the result would be:

$$(G_{input}, G_{def}, Q_t) \rightarrow G_{output}$$

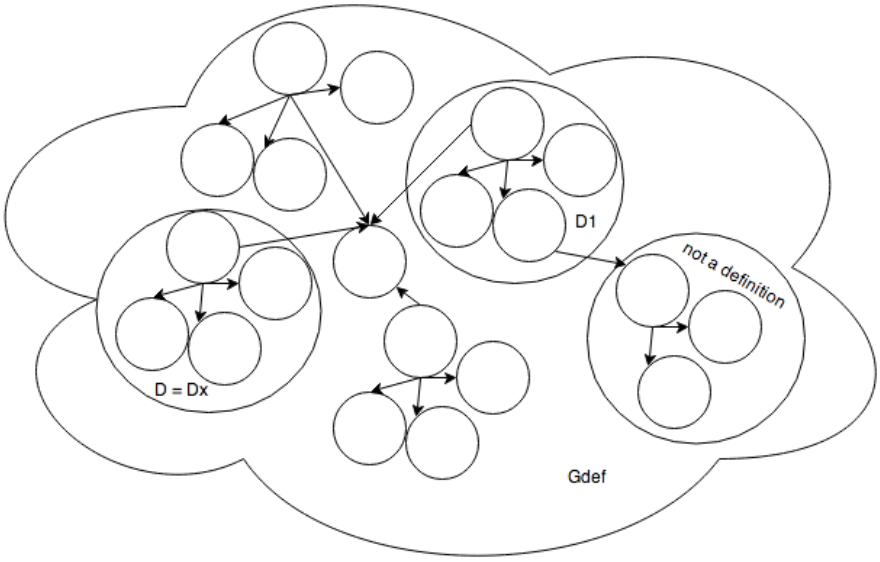


Figure 4.10: A user will provide an arbitrary RDF graph G_{def}, which may contain more than one definition. The user will select only one to work with, D.

In fact, the user will make the selection of the definition D before the mapping starts. Therefore, we can extract the definition D from the generic graph G_{def} and use it as a part of the input. That is possible because the system does not require an arbitrary RDF graph G_{def}. It requires the DCV data structure definition D. The rest is done in order to improve the user experience. Therefore:

$$(G_{input}, G_{def}, Q_t) \rightarrow (G_{input}, D, Q_t) \rightarrow G_{output}$$

What we still do not have is a description of the SPARQL query used to transform the data in order to obtain the output graph G_{output}. The form of the query is dependent on the definition D. To be more accurate, the definition D contains a set of components $(C_1, ..., C_n)$, which represent dimensions, measures and attributes. Let us say, that the structure defines n components, m measures, d dimensions and a attributes. It is true that

$$n = m + d + a$$

For each n–tuple matched in G_{input}, the output graph G_{output} will contain a node with $n + 2$ neighbours (+1 for `qb:Observation` and +1 for `qb:dataSet` — first two statements in Figure 4.11). A concrete example of an observation is shown in Figure 4.12.

The result will comply with the template shown in Figure 4.11. O_i denotes an identifier (URI) of the generated observation, S stands for an identifier of the input dataset, T_{Dim_1} ... T_{Dim_d} stands for the type of a corresponding dimensions from the given data structure definition, similarly for T_{Msr_1} ... T_{Msr_m} – measures and T_{Attr_1} ... T_{Attr_a} – attributes. $R_{i,1}$ ... $R_{i,n}$ stands for resources matched in the input graph G_{input}, moreover, it means that the value of the dimension T_{Dim_1} is $R_{i,1}$, etc.

O_i	a	qb:Observation ;
	qb:dataSet	S ;
	T_{Dim_1}	$R_{i,1}$;
	...	...
	T_{Dim_d}	$R_{i,k}$;
	T_{Msr_1}	$R_{i,l}$;
	...	...
	T_{Msr_m}	$R_{i,m}$;
	T_{Attr_1}	$R_{i,o}$;
	...	...
	T_{Attr_a}	$R_{i,n}$.

Figure 4.11: Description of an output graph node (turtle notation)

<http://ex.com/observed#1234>	a	qb:Observation ;
	qb:dataSet	<http://dbpedia.org/sparql> ;
	my-population:count	'10233222' ;
	my-population:location	<http://dbpedia.org/page/Prague> ;
	my-population:time	'2012-02-23' .

Figure 4.12: A concrete instance of the pattern shown in Figure 4.11

4.4.2 Transformation query

The last unanswered question is how the query Q_t should look like. It would certainly not be an arbitrary query. Let us analyze the situation and walk the reader through the process of coming up with a set of constraints for the query.

It should be obvious that the query Q_t will generate a new graph (in fact, it will generate the graph G_{output}) based on some specific rules (see Figure 4.3). Therefore, it would be a CONSTRUCT query. It is also very clear what kind of triples it will generate; the pattern is shown in Figure 4.11. The only thing we need to sort out is retrieving the resources $R_{i,1}, ...R_{i,n}$.

Pattern

The process of resolving those resources depends on the input graph G_{input}. We will demonstrate it on the most simple case — a 2–dimensional data structure definition. Such a definition requires us to specify how to select a 3–tuple of resources from the graph (2 dimensions, 1 measure). We will present some ideas while using the example of the population size.

The initial idea could be that we need a country, therefore, we map all the countries to the `refArea` dimension, all instances of time to the `refPeriod` dimension and all instances of *numbers* to the measure. But that is not sufficient. At first, we need to make sure that all instances of numbers really express an amount of citizens in a country. Moreover, we need to map the matching amount of citizens to a corresponding country. Therefore, all the selected resources need to be connected with the rest. We need to select a specific pattern, which will contain the relation between the resources.

We will use an example from DBPedia, the Czech Republic resource. The resource itself references a location, therefore, it should be mapped to the `refArea` dimension. It has got a `populationTotal` property, which should be mapped

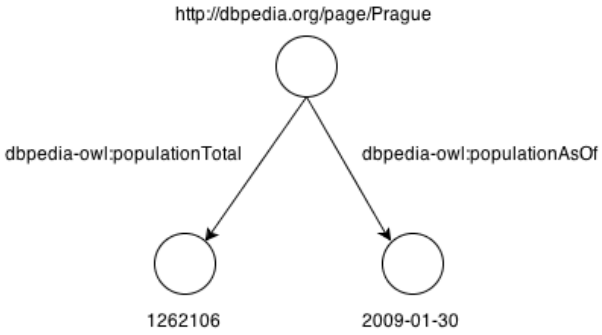


Figure 4.13: Cherry–shaped pattern example.

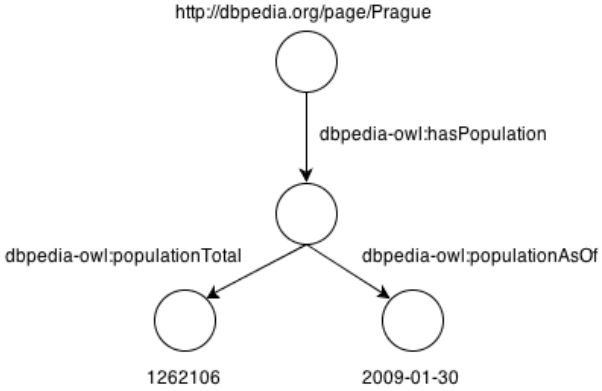


Figure 4.14: The example from Figure 4.13 extended with a blank node.

to the measure. Last, but not least, it has the `populationAsOf` property, which should be mapped to the `refPeriod` dimension.

That gives us a simple shape of a cherry–pair as shown in Figure 4.13. But what if the resource is connected to a blank node with an edge of type population and the blank node had two properties — size and time (see Figure 4.14)? It is clear now that there could be in the least a long oriented path between the participating vertices.

While keeping this fact in mind, we can accede to assembling a formula of a generic pattern used for an extraction of the resources from the original graph G_{input}. But there is one piece of the puzzle still missing. While analyzing all the possibilities, until now we assumed that the pattern *starts* (in the topological order) with a resource, which represents one of the data structure components. But that is not the case.

The most simple example is the observation pattern itself. The entities come together but their connection is dependent on a completely different resource. We reference such an entity as a *reference vertex*. Any pattern vertices corresponding to a component from the data structure definition could also match the *reference vertex*.

Later on, we have discovered that such a kind of patterns is not what the user wants to select. We have applied too much restrictions. Such a pattern represents only a subset of patterns the user may want to select. We have learnt that the most concrete designation of such a pattern is the well–known term: *connected graph*.

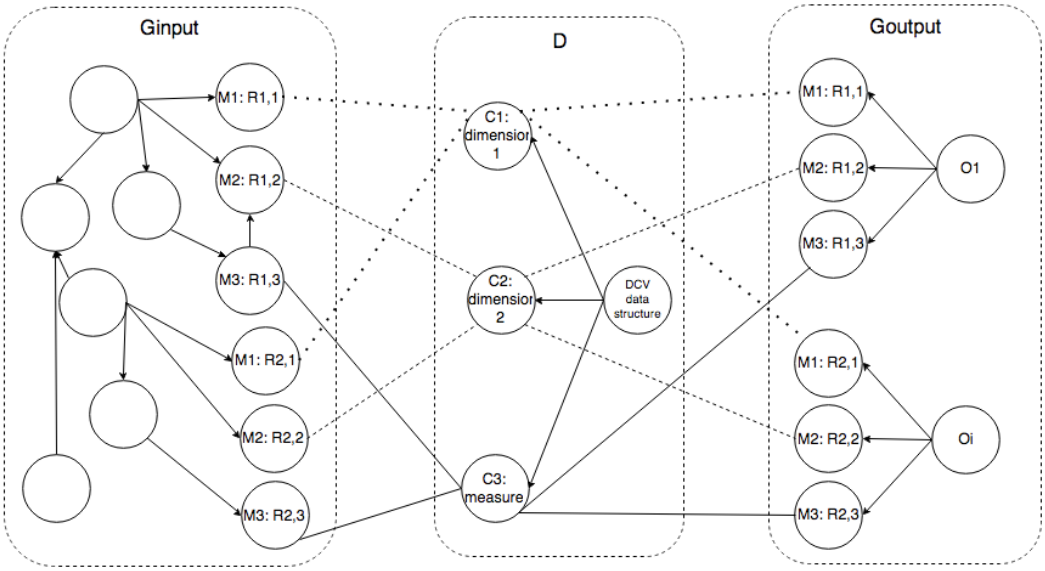


Figure 4.15: An example of mapping. G_{input} is an input graph, D a data structure definition, G_{output} an output graph. Lines between those graphs represent mapping. For each component $C_1, ..., C_n$ we need the user to give an example of a matching entity. That means one concrete instance $R_{i,1}$ for component C_1. Such a match is generally denoted as M_1.

We left out the term *oriented* on purpose. While experimenting with the system, we had discovered that for purposes of the pattern specification the orientation is not necessary. We need all the referenced vertices to have a relation between each other, but the orientation does not matter.

In order to get the reader familiar with some approaches we will utilize while implementing the system, we are about to point out some facts.

We are about to build a pattern P. The pattern reflects an example set by the user, an example that represents the user's proceedings of the data mapping to the components from a data structure definition. The pattern will be used later to construct the desired transformation query Q_t. As shown in Figure 4.3, we require the user to find an equivalent for each component ($\{C_1, ...C_n\}$) of the data structure definition D in the input graph G_{input}. The equivalent for C_1 is in Figure 4.11 denoted as $R_{i,1}$. But there are many other equivalents for the component in the input graph ($R_{i,1}$ is one of many instances). That is why we need to generalize the symbols used for matching resources. Therefore, we introduce a new set of symbols, $M_1, ..., M_n$ to express that such a resource is a vertex matched in the mapping process, M_1 for component C_1, etc. To understand this better, see Figure 4.15.

Please, keep in mind that we are about to construct a connected graph. Therefore, we define an invariant, which says that in every step of the pattern construction the pattern P needs to be a connected graph.

As shown in Figure 4.7 and Figure 4.8, the system iterates over data structure definition components and lets the user select an example of a vertex corresponding to the current component.

For each component we are about to extend the constructed pattern. We will take advantage of the notation from the graph theory, because the pattern is also

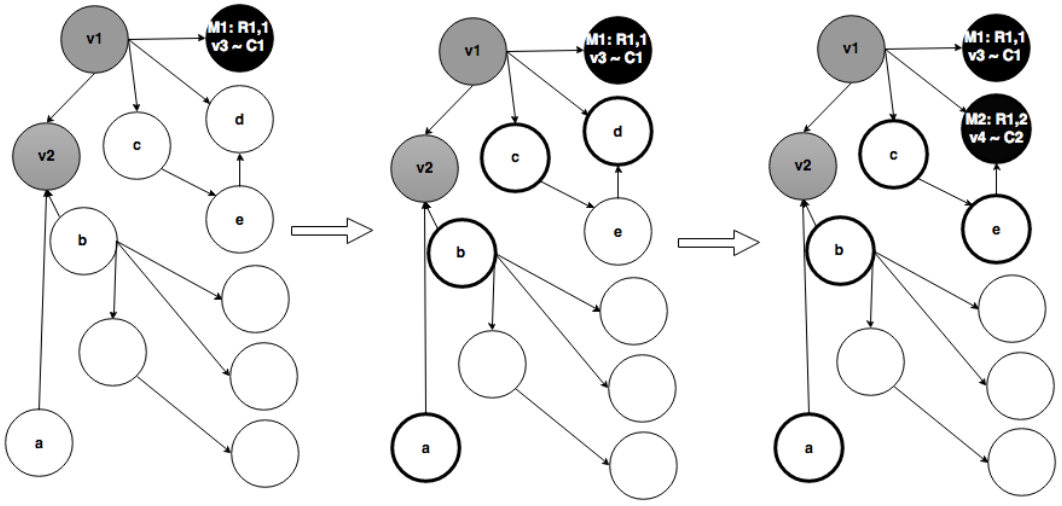


Figure 4.16: An example of pattern extension. We start with three selected vertices – v_1, v_2, v_3. Due to the invariant, we are able to extend the pattern only with the vertices a, b, c, d. We choose the vertex d.

a graph (let us remember the connected graph invariant). Therefore, in the beginning:

$$P = (V = \emptyset, E = \emptyset)$$

We will extend the pattern P for each component $C_1, ..., C_n$ of the definition D. We need the pattern to contain all the vertices from $\{M_1, ..., M_n\}$, because they represent examples of each component. An example of a pattern extension for a component is shown in Figure 4.16.

In order to maintain the invariant, we will enable the user to add only such vertices that are somehow related with an arbitrary vertex already contained in the pattern P (an element of set of vertices V — vertices a, b, c, d in Figure 4.16, step 1). To make it more formal, let us remind the reader that an edge is a tuple of vertices (e.g. (v_1, v_2)).

Therefore when adding an arbitrary vertex v_i, we demand that there exists an edge e for which it is true that:

$$e = ((v_i, v_x) \text{ or } e = (v_x, v_i)) \wedge \mathrm{v}_x \in V$$

Of course, this is not possible to apply in the first step since the graph P is empty. In order to make the pattern more accurate or more restrictive to obtain a more efficient transformation query, the user may want to reference some other vertices and not only the component equivalents. Because of that observation, for each component from $C_i \in \{C_1, ..., C_n\}$ the pattern is extended by adding a set of vertices $V_i = \{v_{i_1}, ..., v_{i_u}\}$ and set of corresponding edges E_i:

$$\forall \mathrm{C}_i \in \{C_1, ..., C_n\}\colon\ P = (V = V \cup V_i, E = E \cup E_i)$$

In Figure 4.16 we make two steps. In the first one, we can add vertices a, b, c, d and we choose to add d. That means that we extend the set of vertices V

```
CONSTRUCT {
  []    a   <http://purl.org/linked-data/cube#Observation> ;
        <http://purl.org/linked-data/cube#dataSet>   S ;
        C_1        M_1  ;
        ...
        C_i        M_i  ;
        ...
        C_n        M_n  .
} WHERE {
  {
    SELECT DISTINCT ?M_1 ... ?M_n
    {
        v_1        E_1        v_2
        v_2        E_2        v_3
        ...
        v_{i-1}    E_{i-1}    v_i
        v_i        E_i        v_{i+1}
        ...
        v_{v-1}    E_{v-1}    v_v
    }
  }
}
```

Figure 4.17: Pattern of the transformation SPARQL query

with the set $V_i = \{v_4 = d\}$ and the set of edges E with the set $E_i = \{(v_1, v_4 = d)\}$.

Because of the invariant:

$$\exists e \ \in E_i : e \ = (v_{in}, v_{out}) \wedge (v_{in} \in V \ \vee v_{out} \in V)$$

and of course:

$$M_i \in V_i \subseteq V$$

— the example equivalent M_i for component C_i was also selected. One of the added vertices from $V_i = \{v_{i_1}, ..., v_{i_u}\}$ is equal to M_i (v_3 is equal to M_1 in Figure 4.16).

By applying the described approach, we get a connected graph, where:

$$\{M_1, ..., M_n\} \subset V \ .$$

That means, that the pattern covers our needs. Now, we are about to present a generic form of the pattern, which will come out from such an approach. The pattern is shown in Figure 4.17. n of the vertices from the $\{v_1, ..., v_v\}$ matches vertices $M_1, ..., M_n$.

4.5 Visualizers

In the beginning, we promised to implement an exemplary visualization. Unfortunately, the Data Cube Vocabulary standard covers a wide variety of data domains, therefore it is hard to make a decision and choose, which visualization should be offered.

Based on what we have seen while exploring tools described in Chapter 2 and keeping in mind the rules of a so–called *visualisation mantra* (Section 2.15), we decided to implement two visualizers, TimeHeatmap and Universal DCV.

4.5.1 TimeHeatmap

The decision to implement this visualizer was based on the example of the population size data presented in Chapter 1. A table or a bar chart is definitely a reliable way of presenting this kind of data. But while getting familiar with Data Cube Vocabulary, we found out that it is very popular to visualize geospatial data. A visualization on a map is easy to understand and is very popular among the non–technical people. It helps to popularize Data Cube Vocabulary. This is also the correct type of visualization for data journalists we have mentioned before.

As the name suggests, this visualizer is able to handle datasets with two kinds of dimensions. The first one will express the time of the measurement, the second one will cover its location. It will support one measure that has to be a number.

We will place a heatmap layer over a standard map layer. The layer will express the intensity of the measured value with respect to the others. The scale will go from green to red where the latter represents the largest value measured.

4.5.2 Universal DCV

Implementing a domain–complete library of visualizers is a long–term project. Despite the fact, we would like to offer a visualizer, which would enable the user to visualize a large amount of datasets in a comfortable way. While experimenting we have experienced on our own some discomfort in reading triple tables.

That is why we have decided to implement a visualizer, which takes advantage of the idea behind faceted browsers. We presented some of those in Chapter 2. Therefore we would like to implement a visualizer that will enable the user to slice visualized datasets and prepare usual visualizations of the slices. A mockup of such a visualizer is shown in Figure 4.18. It should contain a pie chart and a bar chart visualization.

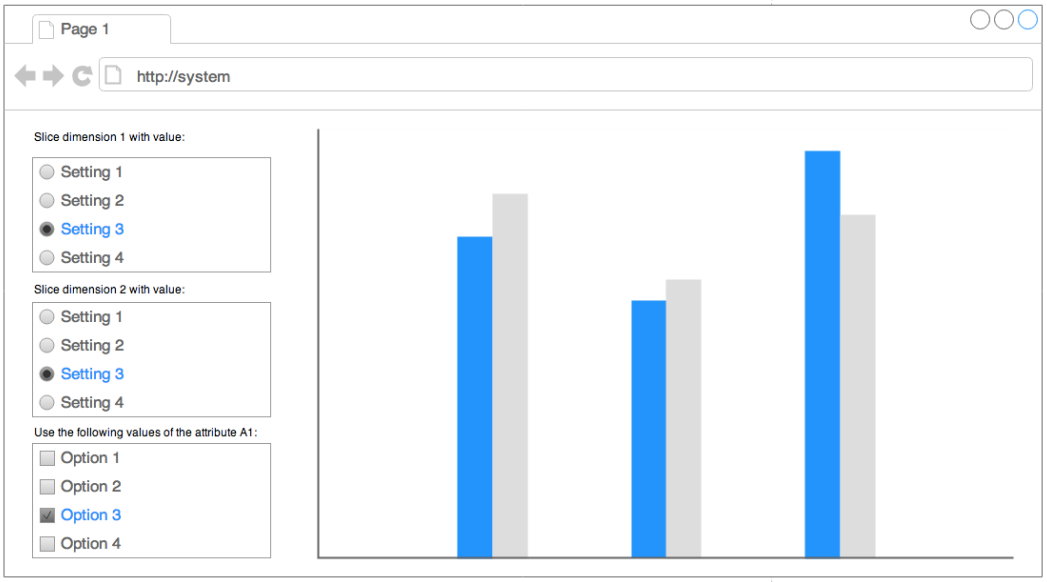


Figure 4.18: Data Cube Vocabulary universal visualizer. The user is presented with a chart visualization and a set of controls. Those controls make them able to change parameters of the visualization, especially slice the data.

5. Implementation

In this chapter we would like to walk the reader through the process of implementing the proposed system. Naturally, one of the possibilities was to implement a completely new system, which would comply with our requirements. But since we participate on a development of a large RDF application – Payola; and based on the facts from Section 4.3, we had decided to implement the proposed system as a plugin for Payola. This will affect the implementation by fetching into specifications a few non–functional requirements.

Before we start, let us mention again some tools whose authors decided to do the same — to integrate them into a larger project. We are talking specifically about OLAP2DataCube(Section 2.1) and CubeViz (Section 2.3), which are based on the OntoWiki platform developed by the AKSW [24] group at the University of Leipzig [61].

We would now like to describe in detail the process of integration of our proposed system with Payola. However at first, we need to provide a description of Payola internals, thus presenting all the facts that we deem necessary, in order to make the implementation fully understandable to the reader.

5.1 Integration of the proposed system

We will build up on the brief description from Chapter 3 and familiarize the reader more with the architecture of Payola. We will especially focus on those parts that were important to the integration of the proposed system.

Payola is a web application. It is built on top of a Scala MVC framework (Play! 2.1 [62]). Payola takes advantage of some modern web technologies like HTML5 (especially the canvas element). Therefore, we will implement the system as a component of a web application. We could have implemented the tool as a standalone application (e.g. a console or web a service) with a certain kind of API, but that would have meant less than full advantage of some of the Payola framework features. It would not allow us to profit from all the benefits described in Section 4.3.

We are used to talk about Payola as either an application or a tool or a framework. To distinguish those terms we consider Payola to be an application (or a tool) from the user's point of view whereas we are looking at it as a framework from the developer's side.

As described in Section 4.3, the most beneficial way of implementing the proposed system into Payola is as an analytical plugin. In Chapter 3 we have got the reader acquinted with the general principles of how the analyses and plugins work. We have also provided some examples of already existing plugins. We are about to widen the variety of plugins and introduce a new one.

5.2 Analytical plugins

Before moving forward, one needs to understand the technical details behind the analytical plugins. We have already stated that such a plugin is a compu-

tation unit. Its task is to transform the input graph(s) into one output graph. The transformation fully depends on the implementation of such a plugin. Each plugin has always exactly one output but may have more than one input. It might also have no input at all. For instance, all the data source plugins that fetch data from some kind of storage, are generally considered to be graph generators. That is why they have no inputs. The Filter plugin filters the input graph by applying a specified constraint. That is why it has one input (the constraint is applied on a single graph). An example of a plugin with more than one input is known as the Union plugin, which takes two graphs and combines them together.

One can see that this is perfectly suitable for completing our task — we are about to implement a system that will transform an input graph into a different one.

In the case of the `Filter` plugin, we spoke about *specifying a constraint*. The plugin has parameters that enable its reuse in multiple–case scenarios. For instance, the Data Fetcher plugin has a parameter, which tells the plugin where to fetch the data from. It would be to no avail had we implemented a plugin enabling the user to fetch the data solely from DBPedia (the fact that it is one of the largest data sources notwithstanding). The original implementation of Payola recognized 4 different types of plugin parameters — `string`, `float`, `int` and `boolean`.

If the reader were to remember Chapter 4, they would recall that we determined that the system would need the following input:

- An arbitrary RDF graph.
- A graph containing the DCV data structure definition.
- A transformation pattern.

At this point we should decide, which of them would become parameters and which of them inputs of the plugin. It may seem to be a good idea to supply the graphs as inputs and the transformation pattern as a parameter. At least, it is consistent with the idea that a graph is an input type of an analytical plugin. But if we think about it just a bit longer we realize that once we have the transformation SPARQL query, we do not need the data structure definition for processing anymore. We just need the plugin to receive the input data and transform them while applying the transformation query.

We need from the data structure definition to only inform the user as to what kind of data are they are working with. We require them to select a valid and meaningful pattern. Therefore, we need for the plugin to have one input (the arbitrary RDF dataset) and one parameter (the transformation pattern). Under normal circumstances that would be sufficient, but we need to find a way of storing the data structure definition metadata in order to present them to the user if necessary.

When we started experimenting with the system, the idea of specifying the transformation pattern was a little bit different. Initially, we thought that it would be possible to specify a pattern for each DCV component separately. After a while, we had learnt that it makes the task harder for the user. It is more complicated to select a valid pattern, especially when the pattern

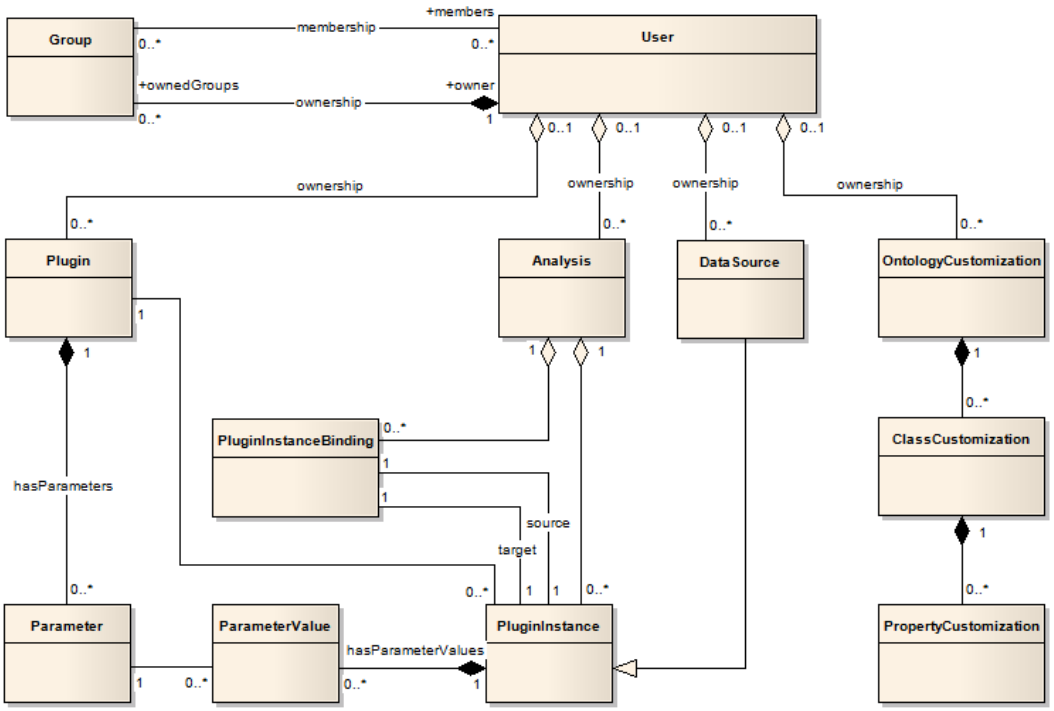


Figure 5.1: Payola entities schema containing a schema of the parameters subsystem of the Payola framework. [57]

needs to be a connected graph for a conclusive expression of the relations between matched entities.

In the process of experimenting, we came up with a new way of storing the data structure definition within an analytical plugin. We made each component to be a parameter in order to enable the user to select a pattern for each of them. Such an approach was an unexplored territory in the scope of the Payola framework.

The architecture of the parameters subsystem can be deduced from a schema in Figure 5.1. We distinguish between two different basic types of entities – `Plugin` and `PluginInstance`. The first one represents a template for each plugin type. An instance of the second one is created for each occurrence of the plugin in an analytical pipeline. Whilst an instance of the `Plugin` class defines the number of parameters, an instance of the `PluginInstance` defines their values.

For instance, the Filter plugin implementation is coded in the class `Filter`. That class is derived from the `Plugin` abstract class. There is a single record in the database table `plugins`, which represents the information about the Filter plugin existence. Among others, it contains the FQDN of the `Filter` class. This course will inform the analytical pipeline evaluator which class is responsible for handling a specific type of plugin. The class also defines that the Filter plugin has 3 parameters. It even defines their data types. One single instance of such a class is sufficient. On the other hand, we need multiple instances of the `PluginInstance` class in order to handle parameters values. Each occurrence of the Filter plugin will be probably used with a completely different set of parameters (while having the same count).

The aforementioned features enabled us to implement what is shown in Fig-

Figure 5.2: A user is able to create a new DCV plugin or to connect an existing one.

Figure 5.3: To create a new one, the user is required to supply an URL of a graph containing a chosen vocabulary.

ure 5.2. When adding a new connection into the analytical pipeline the user is able to create a new DCV plugin or connect an existing one. To create a new one, the user is required to supply an URL of a graph containing a chosen vocabulary (see Figure 5.3). After processing the supplied graph, the user is required to choose a desired definition as shown in Figure 5.4.

5.2.1 Data Cube Vocabulary analytical plugin

In the case of the implemented plugin, we take advantage of the fact that the `Plugin` abstract class allows us to pass a variable count of parameters to the plugin implementation. See Figure 5.5 to learn how the abstract class header looks like. That is beneficial mostly due to every vocabulary being consisted of a different count of components. But we need to create an instance of the `Plugin` entity for each vocabulary in order to store the components metadata.

Until now, there was usually just one entity derived from the type `Plugin` associated with a codebase of a plugin. The concept of plugins was not formerly designed to have a variable count of parameters for each plugin instance.

That is why we have decided to acquire a new approach. By adding a plugin into the analytical pipeline we will give the user an opportunity to create a new instance of the `Plugin` class. This instance is based on a specified data structure definition with an appropriate count of parameters. Each parameter represents a component of the data structure definition. Moreover, a `Plugin instance` is instantly created based on the formed `Plugin` template. A representation

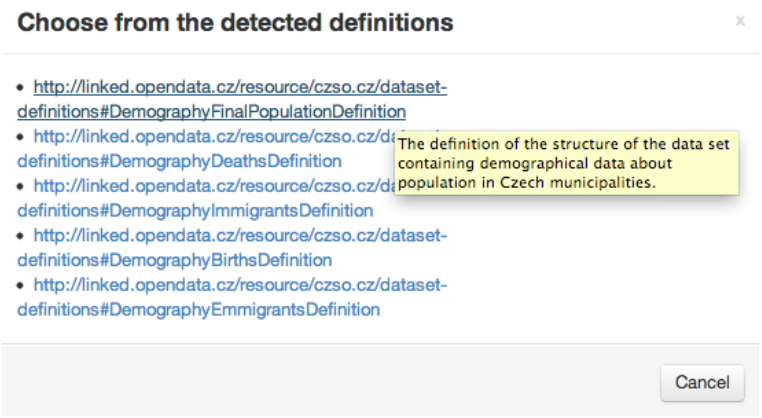


Figure 5.4: A list of detected DCV definitions is shown to the user.

```
/**
  * @param _name Name of the plugin.
  * @param _inputCount Count of the plugin inputs.
  * @param _parameters The plugin parameters.
  * @param id ID of the plugin.
  */
abstract class Plugin(
    protected var _name: String,
    protected val _inputCount: Int,
    protected val _parameters: immutable.Seq[Plugin#ParameterType],
    override val id: String = IDGenerator.newId) ...
```

Figure 5.5: The header of the `cz.payola.domain.entities.Plugin` class. It does not restrict the count of the passed parameters, it receives a generic sequence.

of that instance is consequently rendered into the pipeline editor and the instance itself bound into the analytical pipeline.

Let us present a short example and consider an exemplary data structure definition `example:population` consisted of 3 components; let us say dimensions `example:refArea`, `example:populationAsOf` and measure `example:populationCount`. Such a data structure leads us to the creation of a new plugin of type Data Cube Vocabulary named `example:population`. It would have 3 parameters named in the same way the components are, all of type `string`.

Such an implementation fits into the Payola architecture. Moreover, as a side–effect, it brings an added value — based on the data structure definition, a plugin is created. That means that there will be a specific plugin for each DCV data structure definition. That plugin can be owned by the user who initiated its creation. From that point onward, the plugin will be available to the user and they will not need the data structure definition anymore. What we got is a component, which is reusable on the level of an analyzer. Since the user is able to share their custom plugins with other Payola users, they are naturally able to share the created Data Cube Vocabulary plugin, too.

An important fact is that regardless of the amount of the parameters, it is sufficient to have a single codebase. We will implement a single Scala class that represents the behaviour of the plugin. That is because the `Plugin` abstract class (Figure 5.5) from the Payola framework API does not constrain the count of parameters supplied to the class.

This however causes a different kind of a problem. As we have stated before, the approach of selecting a pattern per each component does not align well with what we need. Only a few lines above we also discovered that all that is needed is a single parameter — a transformation pattern. Therefore, we need to modify a bit the behaviour of the analytical pipeline editor in order to render the `Plugin instance` in a non–generic way. We will also coerce the plugin to always store the transformation query within the first parameter.

We realize that this approach is not quite clean nor nice but we need to accept it for several reasons. The first being a simultaneous research based on the original Payola done by various people where at the time of writing this thesis and experimenting with the proposed system, some of the researchers would not be able to overcome the major architectural change and thus not finish their project. But such a change would have been required since it would have been necessary to introduce a new parameter into the `Plugin` trait. It would demand something general enough to carry metadata that are not determined for computational purposes (and distributed together with the plugin throughout the whole system). It would have also been extremely difficult to coordinate such a change at that time, that is why it will be more suitable to refactor the implementation in the future when the concept of the proposed system is proved.

The second reason is that the Payola data access layer is consisted of three different sublayers (Figure 5.6) and due to the utilization of the Squeryl ORM framework [56] it would be a very difficult task to try and modify the existing database structure. In the list of the future changes of the Payola framework there is a thought for a replacement of the underlying ORM framework and respectively for a heavy refactoring of the data access layer.

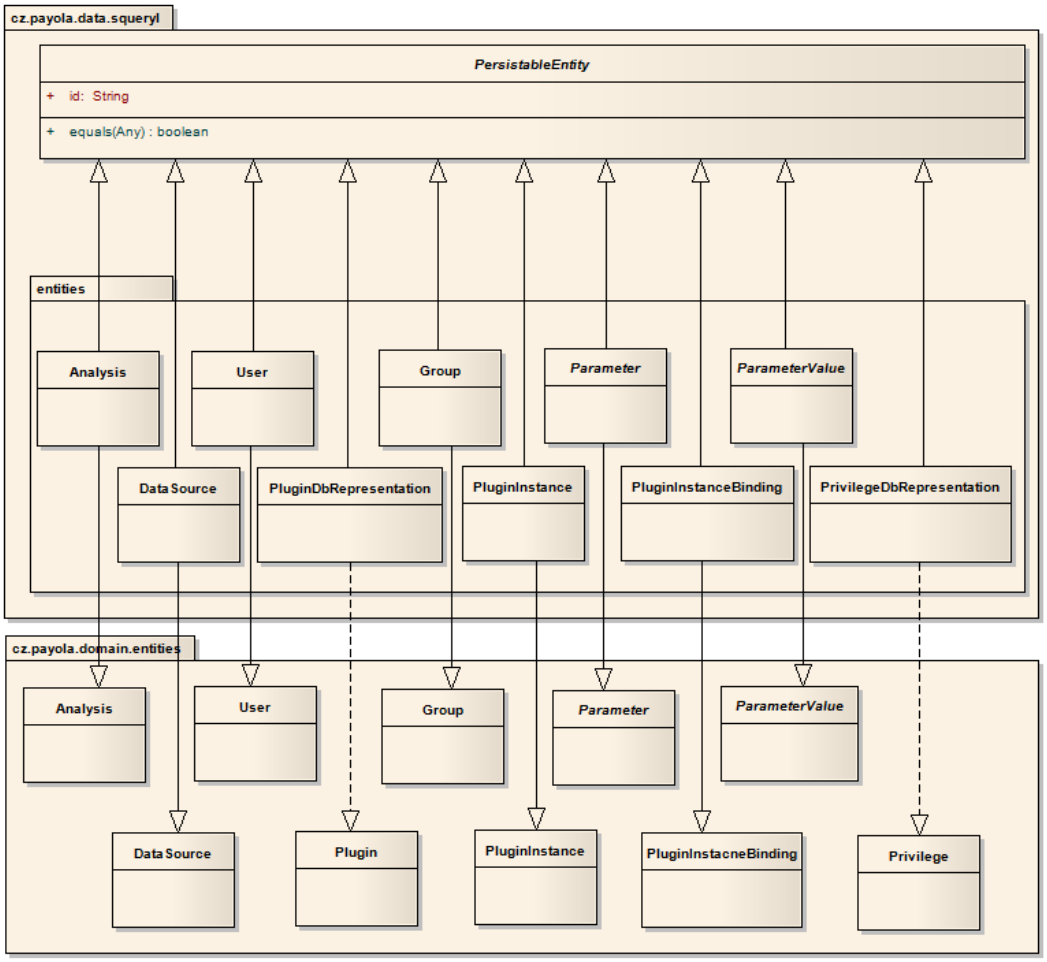


Figure 5.6: The data access is divided into 3 layers. The first one, which is a part of the common package defines entities and relations between them (not in the figure — see Figure 3.2). The second one is a part of the domain package. It defines basic business logic. The last one has its own package — data. It binds the others with a concrete DAL implementation, in this case with the Squeryl ORM. [57]

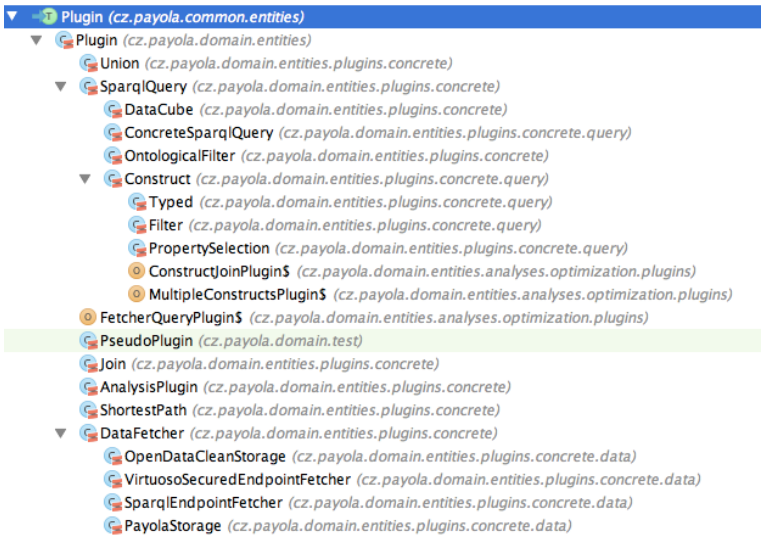


Figure 5.7: Payola plugin hierarchy. Notice the SparqlQuery class.

Therefore, we have decided to focus on the task and implement the feature with as little modifications to the Payola framework as possible. In fact, the used adjustment is kept in the socpe of the newly added features and does not blemish the rest of the framework.

The implementation of the plugin is pretty straightforward since we are taking advantage of the Payola framework. The Payola framework recognizes a special subtype of a `Plugin`, a `SparqlQuery`. See Figure 5.7 to see the whole plugins' hierarchy. There is a special reason for this as a SPARQL query could be executed on a remote data source, e.g. a SPARQL endpoint. A series of SPARQL queries could be optimized into a single, more efficient query. Without such a mechanism, the framework would have to fetch all the data from the data source, transfer them to the server where Payola is running on, store them in the memory (wrapped with the Payola internal object representation) and pass it to a plugin. After that, the graph would be processed inefficiently within the memory of the Payola server with the JENA RDF toolkit consuming uselessly a lot of probably unnecessary computation time.

Moreover, the Payola framework restricts the use of a non–SPARQL–query in the analytical pipeline right after the data fetcher plugin. That is done in order to avoid the aforementioned performance difficulties. There is one restriction regarding our plugin if we were to derive it from the `SparqlQuery` class. The complete behaviour of the plugin needs to be expressed by a single SPARQL query. Fortunately, such a constraint does comply with what we need in order to implement the proposed system. That also means that the existing Payola query optimizer will engage and will make the plugin execution faster. Therefore, the system will again benefit from the integration with the Payola framework.

The plugin will load the stored query from the database and pass it to the evaluation framework, which will handle the rest.

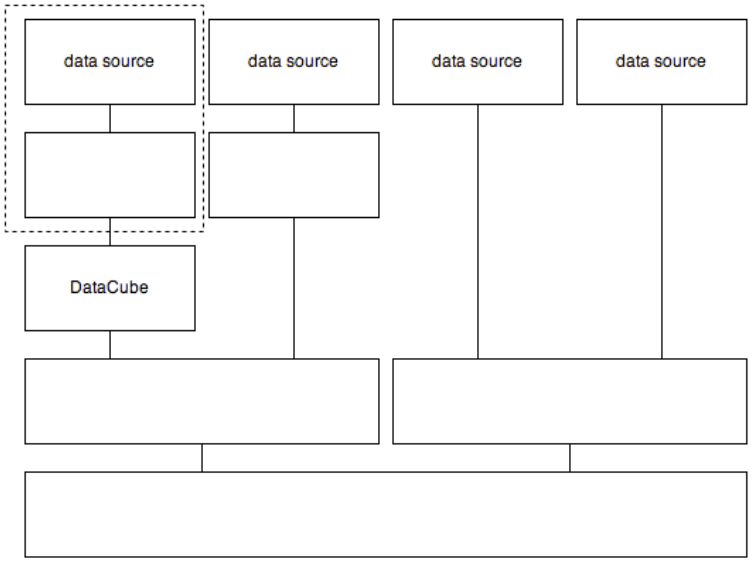


Figure 5.8: Making a preview for the Data Cube Vocabulary plugin. Only the plugins in the dashed box are relevant. The rest of the analytical pipeline is not.

5.2.2 Obtaining the transformation pattern

The more complicated task still awaits us. We need to implement an interface, which will obtain the transformation pattern from the user. The implementation builds up on what we have learnt of the pattern in Chapter 4. The best way is to simulate the approach we used for getting the formal expression of the transformation pattern (see Section 4.4.2).

We have already stated that we are about to implement a user interface, which will allow the user to select the pattern based on the Tabulator's (Section 2.7) query–by–example principle. But to do that, we need to introduce a lot of new features into the Payola framework.

Analysis preview

In order to enable the user to choose a pattern by an example, we need to offer them a preview of the given dataset. The dataset serves as an input graph of the mapping process. We have decided to make the proposed system a part of the analytical pipeline, which brings on some interesting and unexpected complications.

Mainly, the dataset may come from any point of the analytical pipeline execution. In fact, we need the evaluation framework to give us a partial result. We need the analyzer to process the pipeline and at some point, to take an input of the inserted Data Cube Vocabulary Plugin instance and send it to us as a result. Moreover, only a part of the pipeline could be used to make a preview. For instance, if we had an analysis based on extracting the data from several different data sources, let us say 4, those 4 fetching processes would run collaterally regardless of the fact that the DCV plugin is a part of one of them. We will throw away the results of the rest. It is shown in Figure 5.8.

It brings on not only a technical complication, it also rises a performance question. The analytical pipeline may take a lot of time to be processed.

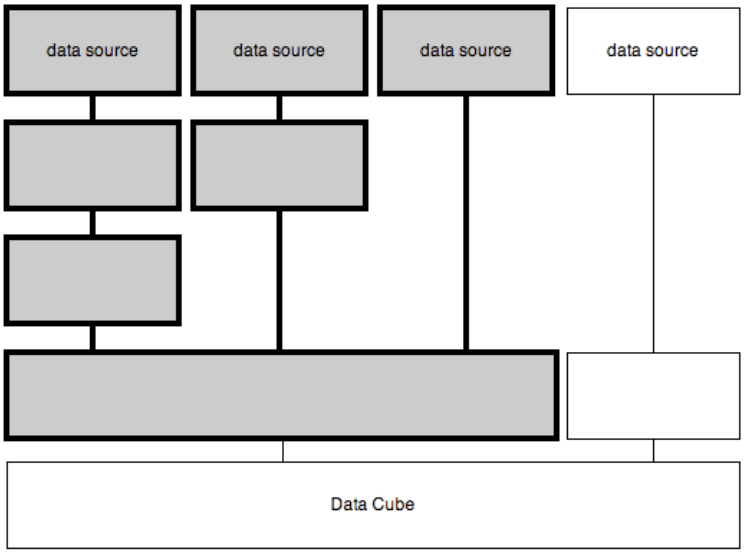


Figure 5.9: Making a preview for the Data Cube Vocabulary plugin. The highlighted plugins are required to be evaluated and become a part of a sub–pipeline created in the background.

That is why we had to introduce a mechanism, which, in the right moment, extracts a proper sub–pipeline. If the reader looks closer on Figure 3.1 they learn that the pipeline is, in the reverse topological order, a tree (as known from the graph theory). Every instance has one output. Every output is connected to an input of a successor (if present, if not it is an output of the whole pipeline). Therefore, it is easy to traverse the tree and select a subtree, which precedes the Data Cube Vocabulary plugin instance.

Such a tree is then used in the background without the knowledge of the user to create a completely new analytical pipeline. When this step is complete, such a pipeline can be executed by a standard pipeline evaluator. That is because the result of the whole newly created pipeline is the dataset we make the preview from. See an example of such a pipeline in Figure 5.9.

Nonetheless, what remains is a potential performance problem, which is partially given by features provided by the Payola framework. The result of executing an analytical pipeline could become eventually a very huge dataset. A dataset so large that it may not fit into the memory of the user's computer. That is a limiting factor, since the visualisation is performed fully on the client–side. It makes no difference whether it is a table or a graph rendered into the canvas HTML element.

In order to solve this problem in the Payola framework, a larger milestone is planned. The results need to be cached on the server hosting Payola. Such an approach could be seen in the case of the project Explorator (section 2.8) project, which implemented a local cache while utilizing the tool SESAME [40]. It is planned to introduce a new subtype of the `Graph` trait, `PersistentGraph`, which would be cached on the Payola server in order to enable techniques like pagination, exploration in the analytical mode, etc. Since this requires also a huge modification to the existing visualizers but is not a goal of this thesis, we will not realize this plan. However we will implement the preview in a way that will

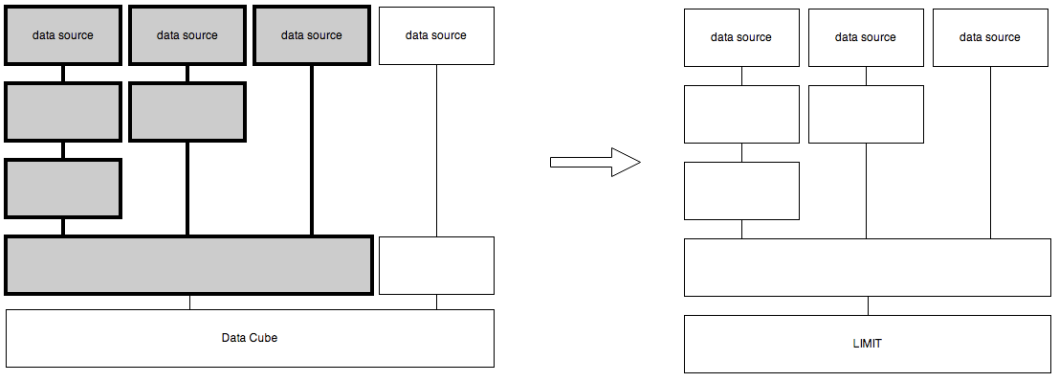


Figure 5.10: Making a preview for the Data Cube Vocabulary plugin. An instance of SparqlQuery plugin representing a LIMIT statement is added.

automatically take advantage of the modifications when they are done.

This still leaves us with the problem of a huge results dataset. Therefore, we decided to make use of the `LIMIT` SPARQL query statement, which will enforce the results to be reasonably large. This could be done by extending the previously extracted sub–pipeline with appending a plugin that will limit the number of the results of the analytical pipeline evaluation (see Figure 5.10). Therefore, we introduced another completely new plugin – `Limit`.

Unfortunately, that brings a completely new problem. By limiting the size of the result, it is possible that some important vertices might get excluded from the preview. And there is no way of telling, which vertices could be important to the user. Therefore, we made the size of the preview to be a variable that could be changed before making the preview and selecting the transformation pattern. Of course, the better approach would be to insert the plugin into such an execution point of the pipeline that it would work with data as small as possible. In other words, we should use an analysis to compensate a large size of the original dataset, if possible.

Obtaining the pattern

Hopefully, it is now fully understood what is required to be done before a preview is made so we can move onto the description of the process of obtaining the pattern from the user. Moreover, we will describe, which components have been modified or newly implemented and why.

We take advantage of the previously presented approach (the query–by–example), which we consider to be the best for the user. Firstly, the user is asked to mark a vertex that represents the first component of the associated Data Cube Vocabulary data structure definition. Since the only criteria we set is that the pattern needs to be a connected graph at any time, it is sufficient to select only a single vertex. Of course, the user might consider selecting a more complicated pattern with keeping in mind the *reference vertex* concept mentioned in the proposal (Chapter 4).

If we enable the user to extend the pattern not only by adding a vertex, which has an incoming edge from one of the already added vertices, but also by adding a vertex, which has an outgoing edge into one of the already added

vertices, the user is capable of building a complicated pattern in a way compatible with a natural thinking process. They will select the important vertex *accidentally* while extending the pattern in order to select another. Therefore, the only restriction applied in the vertex selection mode is that we prevent the user from selecting a non–related vertex (more accurately a vertex, which would break the connected graph invariant).

The selection process is made to be as simple as possible. We will describe the user interface in the following text more deeply.

5.2.3 User interface

The basics of the user interface come out of the architecture of the Payola framework. We need to make the plugin as simple as possible for the user. But we also need to keep it aligned with the design of the Payola framework. In order to make the reader understand the following text, we need to dive a bit into the architecture of the Payola application.

As stated before, Payola is a web application. Its implementation is based on the MVC design pattern. Nowadays, that is a usual approach to a web application. However, it is not that usual to acquire a stance to the utilization of a design pattern on the client–side. The Payola team has decided to use the MVP pattern there and due to the presence of the Scala to JavaScript compiler, the client–side is also being developed in the Scala programming language.

Therefore a majority of pages produced by the Payola application is delivered in two different parts. The layout of a page and a placeholder for the client side application is rendered on the server while utilizing the subsystems of the Play Framework 2.x. The placeholder is then provided to a JavaScript application, which is referenced from the rendered layout. The utilization of the s2js compiler and the custom RPC gateway (which translates JSON calls into method invocation and serializes its results back to the client), prevents code duplication and makes the development process more transparent.

Therefore, every client–side application can avoid becoming a confusing piece of a spaghetti code and utilize the MVC pattern. A crucial feature is the RPC mechanism that, hand in hand with the Scala to JavaScript compiler brings a way of transparent client–server communication.

The analytical pipeline editor is one of those client–side MVC applications. We are interested specifically in this one since we require for it to be able to work with our newly introduced Data Cube Vocabulary analytical plugin.

Until now, the pipeline editor applied a unified approach for rendering the layout of the pipeline. Every plugin was rendered while using a generic renderer, which determined the appearance of the plugin based on its metadata. An example of such a rendered pipeline could be seen in Figure 5.11. The reader can see a rendered title, based on the name of the plugin and a parameter form. The form is based on the type of the corresponding parameters. A `string` parameter gets rendered as an input or a textarea based on an additional flag `isMultiline`, which determines whether the value can be spread into multiple lines. An `int` or `float` parameter is also rendered as an input field. A `boolean` parameter is rendered as a checkbox.

Since we would like to provide the ability to select a pattern, we need to intro-

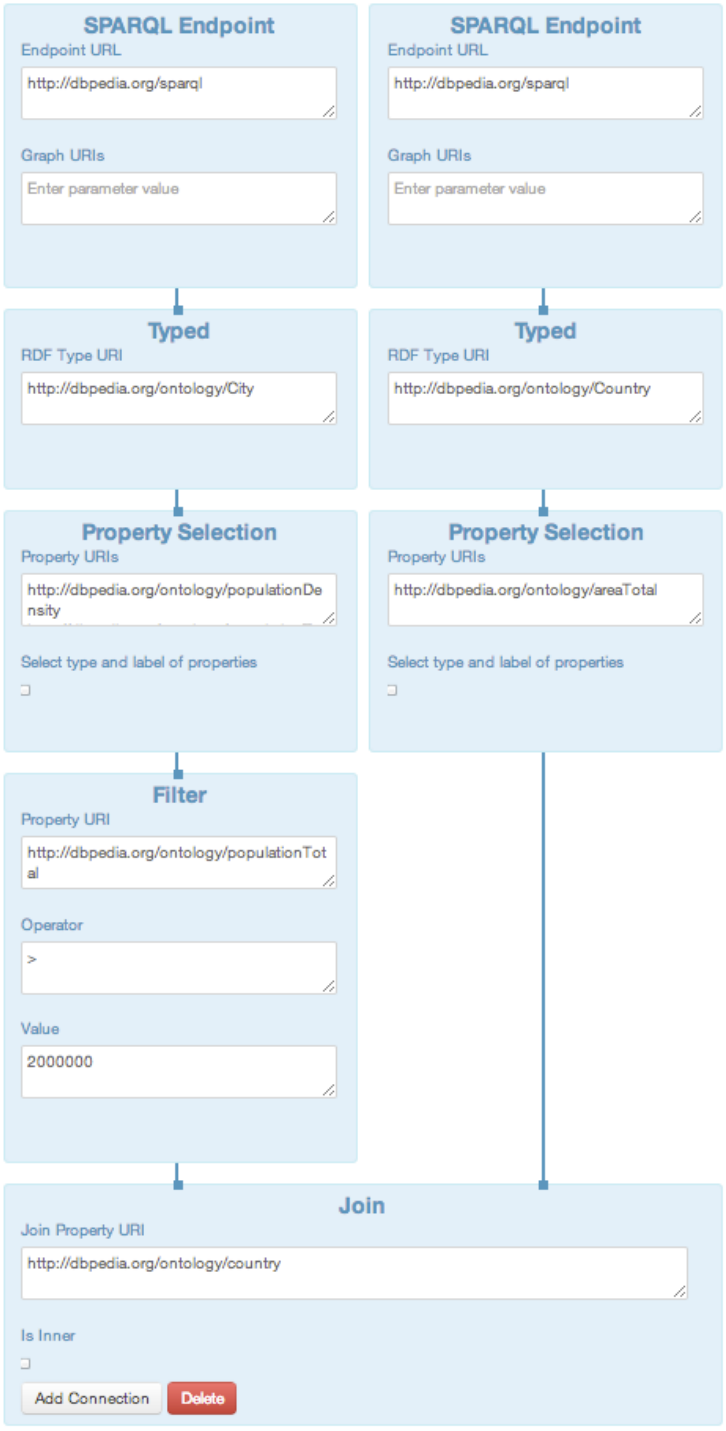


Figure 5.11: An example of an editable analysis (retrieving a list of cities with a certain population size).

duce a completely new approach. To keep it generic, we start with the modification of the parameters subsystem. We would like to introduce a new type of parameter, a `pattern`. Since the data access layer of Payola is very difficult to modify, we use a less obtrusive approach. A pattern results in a SPARQL query, which is a string. Therefore, we add a flag to the string parameter, called `isPattern`, which the system will take advantage of. It is based on the same unobtrusive principle as the `isMultiline` flag.

Another problem comes out of the fact that a plugin has as many parameters as the data structure definition has components and we utilize just the first one to store the query. That also means that we need to render the representation of the plugin in a slightly different way. At the time of implementing this thesis, the same requirement came up from two other developers who integrate their tools with Payola. Therefore, we introduced a mechanism, which solves the problem of loading custom plugin renderers.

We introduce a dynamic loader of plugin instance renderers for an analysis editor. Based on the plugin classname, it tries to load a custom override of the default renderer. It enhances the extensibility of Payola. Until now, it was not possible to override the visualization of a plugin instance within the editor. The user was able to upload a custom analytical plugin, but they were not capable of affecting its appearance in the editor.

With our loader, the user is able to define a custom renderer derived from one of the `ReadOnlyPluginInstanceView` and `EditablePluginInstanceView` classes. The name of the override is precisely given. It is required to match one of the following patterns: `classnamePluginInstanceView`, `classnameEditablePluginInstanceView`. The implementation is required to be declared within the `cz.payola.web.client.views.entity.plugins.custom` package.

The editor was altered so that it does not create renderer instances itself. It uses a newly introduced `PluginInstanceViewFactory`. This factory is responsible for creating a proper instance. Based on the given plugin classname it calls a dependency manager. The manager is a part of the s2js compiler and it provides a JavaScript implementation of the required class with all the necessary dependencies. Therefore the factory calls the manager and requests an implementation of a specified override. If it exists, the manager returns its implementation. If it does not, it returns an empty string. After that, the factory tries to make an instance of the override. If it succeeds, an instance of the override renderer is created. If it fails, it returns an instance of a generic renderer.

Our custom implementation of the Data Cube Vocabulary plugin renderer results in a form shown in Figure 5.12. First of all, it enables the user to select the pattern. Clicking the Preview button starts the process of making a sub–pipeline, evaluating it and rendering a preview. It also opens a pattern–selection dialog, which we introduce later. The second provided field enables the user to specify how large should the pattern–selection preview be. We have already presented the reason behind this a few paragraphs above.

The last part of the UI is the pattern selection dialog. After the user clicks on the button of the rendered plugin, the application extracts a sub–pipeline, which is relevant to the preview. Such a pipeline is executed automatically. When the pipeline evaluation is done, the application opens a new dialog, which gives

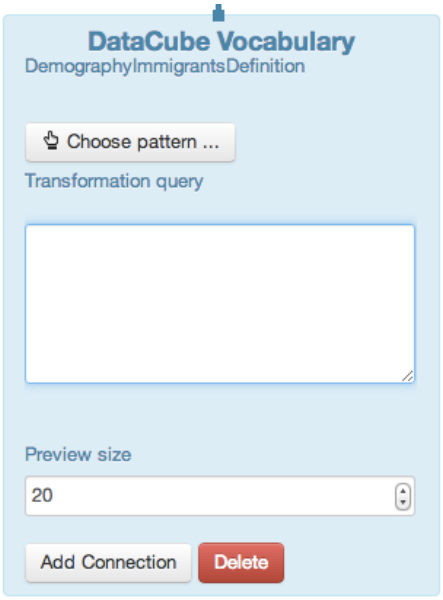


Figure 5.12: Data Cube Vocabulary plugin instance custom view.

the user the opportunity to select the transformation pattern. With every step, the user is presented with a label and/or a URI of the matching DCV component based on what is available. An example of a pattern selection is shown in Figure 5.13 (some additional details are provided in Section 4.4.2 and in figures 5.13 and 4.16). With a single click the user includes a vertex into the constructed pattern. A double–click has it representing a currently processed component. We also had to modify the visualization algorithm to avoid collapsing literal vertices into an info table. We need the literals to remain visualized in order to be selectable.

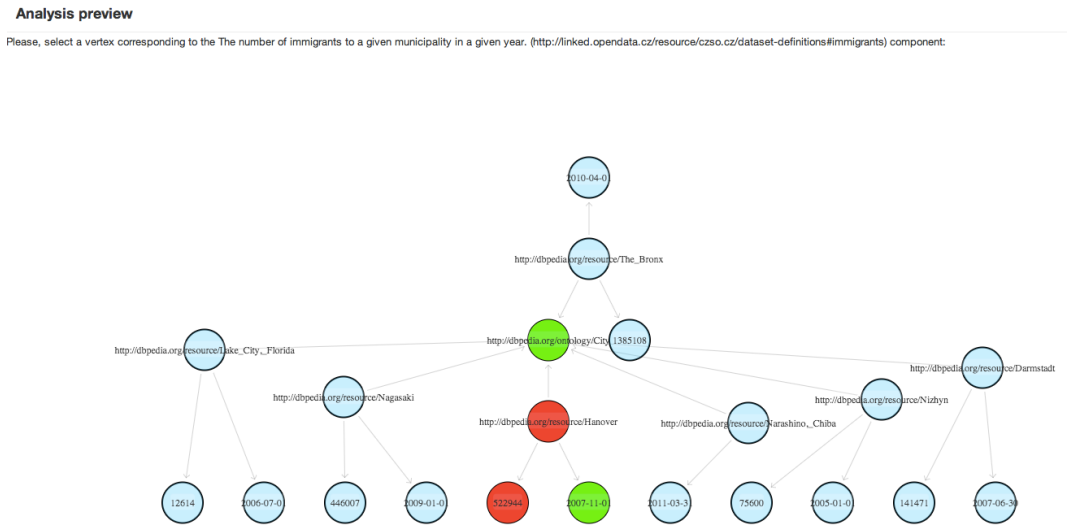


Figure 5.13: An example of a pattern selection.

5.3 Visualisers

As stated in Chapter 4, we have decided to implement two different visualization plugins for Payola. All the presented visualizers are configurable by specifying a Data Cube Vocabulary. As in the case of the rest of the system, the implementation of the visualization plugins will be influenced by the architecture and features of the Payola framework as well.

The feature that is lacking the most is a sophisticated faceted browsing. All the presented plugins implement offered filters only on the client–side, therefore all the data needs to be loaded within the memory of the user's computer. As described before, Payola needs a series of modifications in order to work effectively with larger datasets, hence a client–side–only visualization is the only one currently making sense.

To make them able to work with the Data Cube vocabularies, we had to append definitions of those vocabularies into the result of the mapping process. The visualizer is then able to acquire them and take advantage of them, for instance while building a user interface.

5.3.1 TimeHeatmap

In order to deliver the TimeHeatmap visualizer, we took advantage of an existing map library. We chose to integrate a visualization based on Google Maps API. We decided to do so for several reasons. One of them is an easy use of the API and that it allows us to create an eye–catching visualization in a short time. Google is known for its high–quality map imagery and due to its infrastructure also for a reliable delivery. The API also offers the ability to create a heatmap layer.

But the heatmap layer itself is not enough. In order to support the time dimension, we had to come up with a way of visualizing time entries. The interface is built with the following idea in mind. Let us imagine an example of population size data (see Figure 5.1).

City	Population size	Year
Prague	1000000	2010
Prague	1100000	2011
Prague	1200000	2011
Liberec	100000	2010
Liberec	110000	2011
Liberec	112000	2012

Table 5.1: Population size example

It is more constructive to visualize such a dataset year–by–year. Grouped values are not very attractive no matter what aggregation is applied. The most useful approach is to enable the user to make a slice based on the year and visualize a heatmap for the selected year.

Therefore, we wrap the map with a custom control. It contains a list of years detected in the dataset. The user is able to select an arbitrary subset of years. The visualizer shows and hides a corresponding layer based on what is selected.

In order to deliver an easy–to–use visualizer, we decided to ignore GPS data and employ places names. With the integration of the Geocoder library of a colleague of ours, Matej Snoha, the visualizer is now able to translate the names of the places to GPS coordinates and place them into the map. The library takes advantage of a locally installed application Gisgraphy. The installation is maintained by the author of the used library.

We tried to make the visualization as easy as possible, therefore we decided to exert the URI resource itself. It usually contains the name of the place in a way, which is convertible into a form recognized by the Gisgraphy application. For instance, `http://dbpedia.org/page/Brasserie_Du_Bocq` can be converted into Brasserie du Bocq very easily.

An example of such a visualisation will be presented in Chapter 6.

5.3.2 Universal Data Cube Vocabulary

We decided to offer a basic set of usual statistical visualisations. As stated in Chapter 4, we achieve that by giving the user the ability to slice the dataset. We need them to fix values of $n-1$ dimensions in order to transform the dataset into a two–dimensional one (1 dimension + 1 measure).

We took advantage of the chart library Flot [63] and prepared a visualizer, which allows the user to create bar or pie charts. It comes out from the proposal shown in Figure 4.18. By applying filters, the user slices the dataset.

It supports multiple dimensions, attributes and even measures. It is configurable by a Data Cube Vocabulary. We require the user to specify a dimension that gets to be used on x–axis of a bar chart (or defined groups in a pie chart). Based on filters, the visualizer groups DCV measures by the specified dimension (aggregated by applying sum function). In case of a bar chart, multiple measures are displayed as groups of columns.

We present an example of a visualization made by this plugin in Chapter 6.

Figure 5.14: LodVis integration link in a visualization of an analytical pipeline.

5.4 Payola improvements

In order to make the added value of the Payola application integrated with the proposed system even higher, we decided to implement also some other improvements. Mostly in order to enhance the user experience. Some of the changes had also brought completely new features and possibilities. We will mention these modifications briefly. Since they are of a rather technical character than scientific, we will make the corresponding analyses a part of the implementation reports in order to make the text consistent for the reader.

5.4.1 LodVis integration

While writing the review of the tool LodVis (see Section 2.14), we have discovered, that the provided features are very conducive though completely missing in Payola. The application does not offer an overview of a dataset in order to help discover the most used concepts.

Since we want the user to know their dataset before choosing the pattern in the preview, we find this tool very interesting. It may help the user to locate the statistical subset of the data. Therefore, we discovered a simple way of implementing a plain kind of interaction between Payola and LodVis.

Visualising Payola data sources in LodVis

The first part is introducing a way of allowing the user to visualize a dataset in the scope of the LodVis application. That is done by utilizing a simple REST API. We only create a link, which is inserted wherever we consider it relevant. The user can click on the link in order to switch to LodVis, which handles the rest. We utilize a simple URL pattern:

```
http://lodvisualization.appspot.com/?graphUri={graph-uri}&endpointUri={endpoint-uri}
```

The pattern has only two parameters. The first one, the `graph-uri` designates the URI of the graph we want LodVis to visualise. This parameter is not mandatory. The second parameter, `endpoint-uri` is required and it tells the LodVis application, where to fetch the data from. It is not possible to visualize results of an analysis in LodVis. An example of this could be seen in Figure 5.14.

Visualising Payola data sources in LodVis

In cooperation with the LodVis team, we have also implemented a reverse mechanism — an API, which allows the user of the LodVis application to browse a dataset in the scope of the Payola application. To make it easy for the LodVis team to integrate a link to the Payola application, we prepared an API very similar to theirs. The URL pattern is very similar:

```
http://live.payola.cz/visualize?endpointUri={endpoint-uri}&graphUri={graph-uri}
```

In addition, we support referencing a list of graph URIs separated by a comma. Since we wanted to avoid any difficulties arising from passing a URI in an URL, we decided to have the parameters encoded with the Base64 algorithm.

The only problem was, that Payola was not able to visualize a dataset not registered within its database. Therefore, when somebody accesses the URL, the application takes the parameters and creates an anonymous analyzer pipeline. The only plugin in the pipeline is a data source specified by the passed parameters. By evaluating such a pipeline, the user is able to visualize the neighbourhood of the vertex in the given dataset. The vertex is chosen by the SPARQL endpoint backend, e.g. OpenLink Virutoso [53].

To allow an anonymous user to modify the pipeline, we also set a cookie with an authorization token to their browser. When logged into Payola a user having such a token can overtake the ownership of the pipeline and fully modify it.

5.4.2 Secured endpoints

What was also lacking was the support for password–guarded SPARQL endpoints. It is a natural matter, that a company would like to keep its statistics non–public, but they might wish to analyze and visualize them. Therefore, we have decided to introduce a support for secured endpoints.

Since every SPARQL endpoint may have different possible solutions, we have introduced a support for only one specific engine. We chose the most used OpenLink Virutoso [53]. It takes advantage of the Digest HTTP authentication as introduced in the RFC 2617 [64]. Therefore, we had to include the Apache HTTP commons library [65]. It was also necessary to introduce a new subtype of `string` parameter — `password`. That was done as before (remember the `isMultiline` or the `isPattern` flag) by adding a new flag.

One can see a visualization of the described plugin in Figure 5.15.

5.4.3 Analytical pipeline reuse

During the period of writing this thesis Payola has undertaken a user test. One of the significant results of the test was that the users wished to modify the analyses of others. At least, they would like to reference an analysis of another user within their own. That also fits into analyzing statistical data — a company provides an analysis and presents its statistics while somebody else wishes to process them and apply DCV. That is why two different features were added.

Clone and edit

The first one is less powerful. It enables the user to clone an analysis of another user. After doing that, they get a newly created analysis owned by them. Therefore, they are in a full control of the analysis and may modify it in any way they want.

We were required to enhance the capabilities of the application in order to support a plugin instance cloning. We also had to clone bindings from an existing

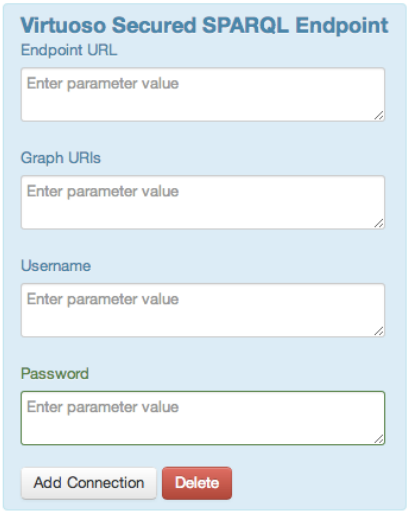


Figure 5.15: One may simply include an instance of Virtuoso Secured SPARQL Endpoint plugin instead of an instance of the generic SPARQL Endpoint plugin.

Figure 5.16: A clone button.

analytical pipeline and translate the identifiers of the cloned plugin instances in order to keep the bindings working.

The most difficult part was, unfortunately, to find a way of storing the cloned analysis, because the data access layer was not prepared for that. That is why the persistence of the cloned analysis had to be split into several steps and may take a bit longer than expected.

As a result the user is presented with a inconspicuous button as shown in Figure 5.16.

Inner analyses

Much powerful feature is enabling the user to reference an existing analysis in another one. We introduced a fake analytical plugin with no implementation at all. It allows the user to insert a reference to an existing analysis instead of specifying a data source. As the inserted analysis generates a graph, it is hence a graph generator and might be considered a data source.

Of course, we had to find a way of implementing such a feature without making huge modifications of the evaluation framework. That is why the plugin has no implementation at all. The trick is that before starting an analysis evaluation we walk through the analysis and make some changes. The idea is very simple. We examine the analysis and replace each instance of the fake plugin with all the plugins from the referenced analysis. We call such a process an *analysis expansion*.

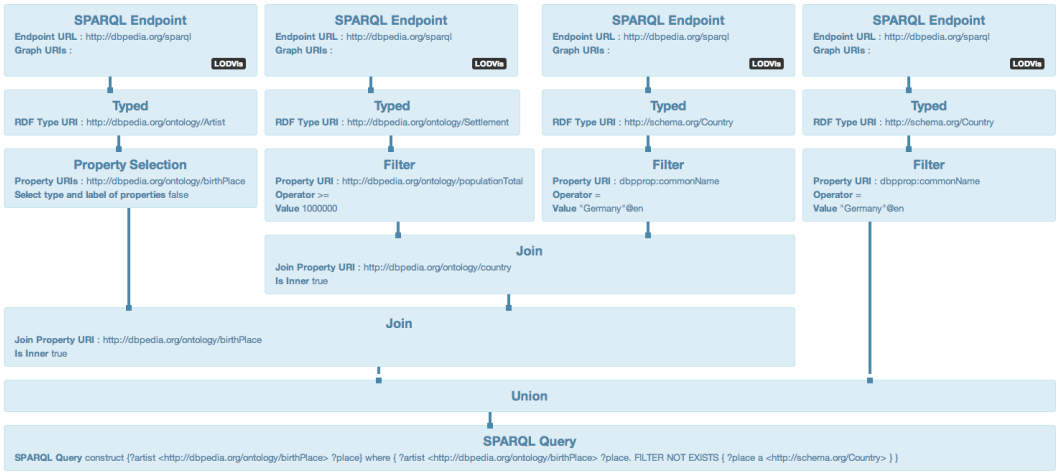


Figure 5.17: A great example of an analysis that can benefit from inner analyses. Notice the two rightmost branches of the analytical pipeline. They are the same. By making an inner analysis we can at least convert the analysis into a pipeline shown in Figure 5.18

.

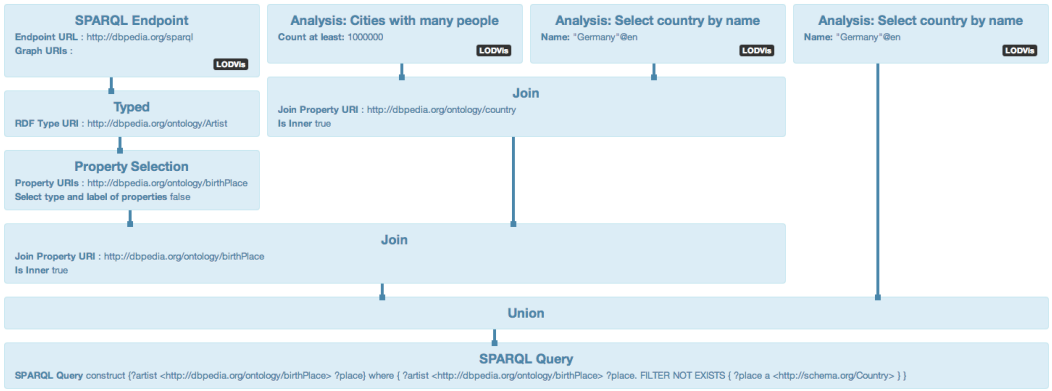


Figure 5.18: An example of simplifying an analysis while utilizing inner analyses.

.

To make the feature even more sophisticated we made a special user interface to enable them to parametrize an inner analysis. When inserting an analysis into another, the user is able to click the names of parameters of plugin instances in the inner analysis in order to promote them to *analysis parameters*.

That is why we took an advantage of what we have learnt while implementing the core of this thesis and created a special plugin for each inner analysis. That makes it possible for the plugin to have a variable parameters count. As a result the user creates a new shareable plugin. Such a plugin is also promoted to be a new data source available at any time in the future.

Moreover, we gave the user a tool for a simple parametrization of an existing analysis. They do not need to extend the analysis with other steps. They may simply take advantage of the new feature to ease their work.

5.4.4 Data Source browser permalinks

Another minor change was done within the scope of the data source browser. We introduced a mechanism, which enables the user to send a link to a current state of the triple table data source browser. It detects the specified URI in the URL and fetches an initial vertex based on that. The original behaviour delegates the decision on an underlying engine of the queried data source. We simply add a location hash to the URL that makes the permalink available in the address bar of the user's browser. The implementation was extended with an onload event handler, which looks for the location hash and reacts to it.

5.4.5 Limit plugin

In order to bring a better performance and user experience to the DataCube plug-in preview mechanism, we had to implement a completely new plugin. It is derived from the `ConstructQuery` class in order to allow some optimalizations. We needed to modify the `DataFetcher` plugin and introduce new optimalization phases to increase the speed of the most common cases of dataset preview. For instance, we merge a `DataFetcher` plugin followed by `Typed` and `Filter`, terminated with the `Limit` plugin into a single SPARQL query. We have also implemented a phase which optimizes the query in the case we combine a common SPARQL query with the `Limit` plugin.

6. Experiments

In this chapter, we would like to demonstrate the abilities of the implemented system. We experimented with a variety of datasets and will use some of them to show how the system works. We will also present how the implemented visualizers work on an example of real–world data.

6.1 DBPedia demography

We used the example of the DBPedia demography throughout the whole thesis. Now it is time to show how the implemented system deals with such a dataset. In order to start the conversion, we need to have a dataset (DBPedia) and a vocabulary containing a data structure definition. We made a custom vocabulary with a definition as shown in Figure 6.1.

DBPedia is based on a very large dataset (about 400 million facts). Therefore we need to narrow down the dataset a lot in order to make a meaningful data preview for the pattern selection. We briefly examined the resource `http://dbpedia.org/Prague` and learnt that it is of a type `dbpedia-owl:City` and has two important properties – `dbpedia-owl:populationTotal` and `dbpedia-owl:populationAsOf`. Hence, we prepared an analytical pipeline as shown in Figure 6.2.

With the preview size set to 20, the preview is shown as pictured in Figure 6.3. In this case, the transformation pattern is very simple, as shown in Figure 6.4. As a result, the system will apply the following query to transform the data into the Data Cube Vocabulary standard:

```
CONSTRUCT {
   []  a  <http://purl.org/linked-data/cube#Observation> ;
       <http://purl.org/linked-data/cube#dataSet> <http://live.payola.cz/analysis/...> ;
       <http://datacube.payola.cz/dataset-definitions#location> ?v1 ;
       <http://datacube.payola.cz/dataset-definitions#period> ?v3 ;
       <http://datacube.payola.cz/dataset-definitions#populationSize> ?v4 .
   } where {
       {
           SELECT DISTINCT ?v1 ?v3 ?v4 {
              ?v1 <http://www.w3.org/1999/02/22-rdf-syntax-ns#type> ?v2 .
              ?v1 <http://dbpedia.org/ontology/populationAsOf> ?v3 .
              ?v1 <http://dbpedia.org/ontology/populationTotal> ?v4 .
           }
     }
}
```

The transformation is made in another step of the analytical pipeline. The whole evaluation is done in seconds. An exact measurement would not be conclusive since it depends on the actual load of the DBPedia. The endpoint returns in about 150 entities no matter what we do because that is the final count of entities with the required properties.

As a result, we get a dataset compliant with the Data Cube Vocabulary standard. We made a visualization of the dataset in both new visualizers. The results are shown in Figure 6.5 and Figure 6.6.

In this experiment, we proved that the system is capable of converting an arbitrary RDF dataset to a format compliant with the Data Cube Vocalbulary

```
@prefix rdf:     <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs:    <http://www.w3.org/2000/01/rdf-schema#> .
@prefix xsd:     <http://www.w3.org/2001/XMLSchema#> .

@prefix qb:              <http://purl.org/linked-data/cube#> .
@prefix sdmx:            <http://purl.org/linked-data/sdmx#> .
@prefix sdmx-concept:    <http://purl.org/linked-data/sdmx/2009/concept#> .
@prefix sdmx-dimension:  <http://purl.org/linked-data/sdmx/2009/dimension#> .
@prefix sdmx-measure:    <http://purl.org/linked-data/sdmx/2009/measure#> .


@prefix payola-dcv:   <http://datacube.payola.cz/dataset-definitions#> .

payola-dcv:PopulationSizeDefinition a qb:DataStructureDefinition ;
  rdfs:label "The definition of the DS of a dataset containing information about population size."@en ;
  # Dimensions
  qb:component [
    qb:dimension payola-dcv:location;
    qb:order 1 ;
    rdfs:label "The dimension representing populated location."
  ] ;
  qb:component [
    qb:dimension payola-dcv:period;
    qb:order 2 ;
    rdfs:label "The dimension representing the time of the measurement."
  ] ;
  # Measure
  qb:component [
    qb:measure payola-dcv:populationSize;
    rdfs:label "The measure representing the total count of citizens."@en
  ] .
  # Attributes

payola-dcv:location a rdf:Property, qb:DimensionProperty ;
  rdfs:label "reference location"@en ;
  qb:concept sdmx-concept:refArea .

payola-dcv:period a rdf:Property, qb:DimensionProperty ;
  rdfs:label "reference period"@en ;
  qb:concept sdmx-concept:refPeriod .

payola-dcv:populationSize a rdf:Property, qb:MeasureProperty ;
  rdfs:label "population at the end of the measured period"@en ;
  rdfs:subPropertyOf sdmx-measure:obsValue ;
  rdfs:range xsd:nonNegativeInteger ;
  qb:concept sdmx-concept:statPop .
```

Figure 6.1: A custom Data Cube vocabulary containing a data structure definition for population size.

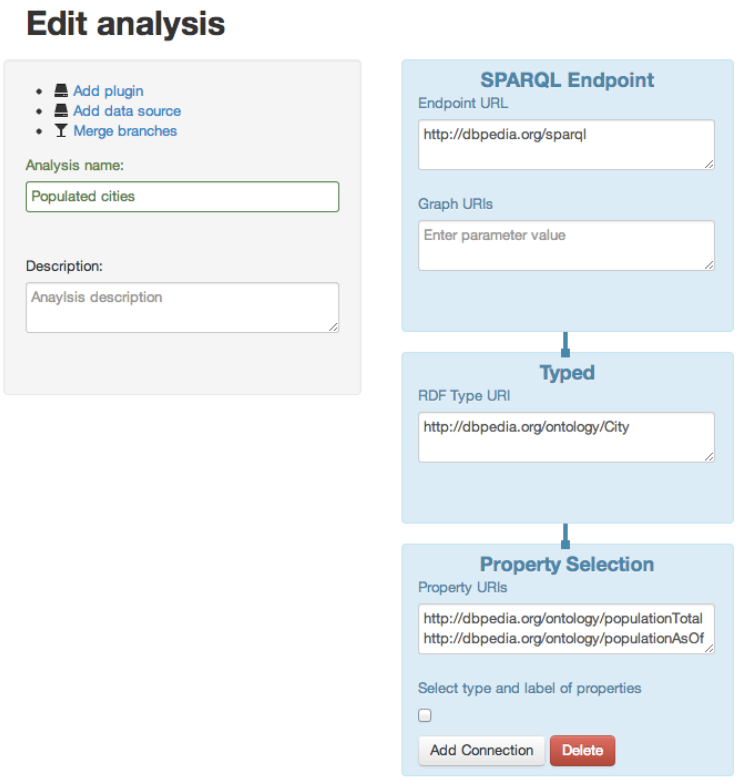


Figure 6.2: An analytical pipeline made to extract population data from the DBPedia.

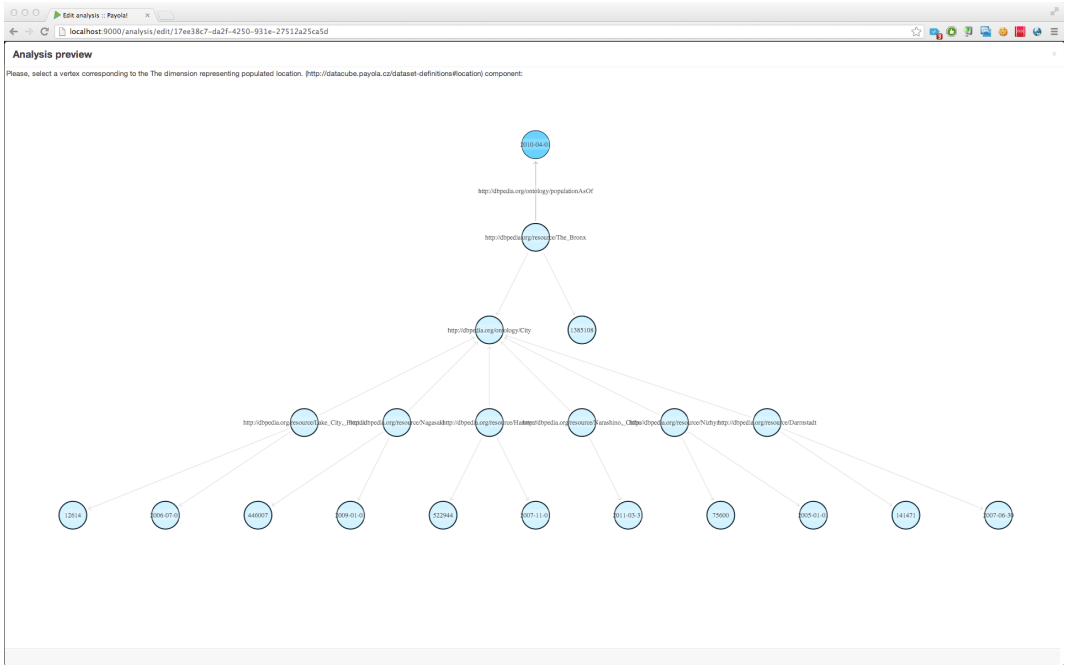


Figure 6.3: An analytical pipeline preview used for a pattern selection.

Figure 6.4: An example provided by the user in a form of a pattern.

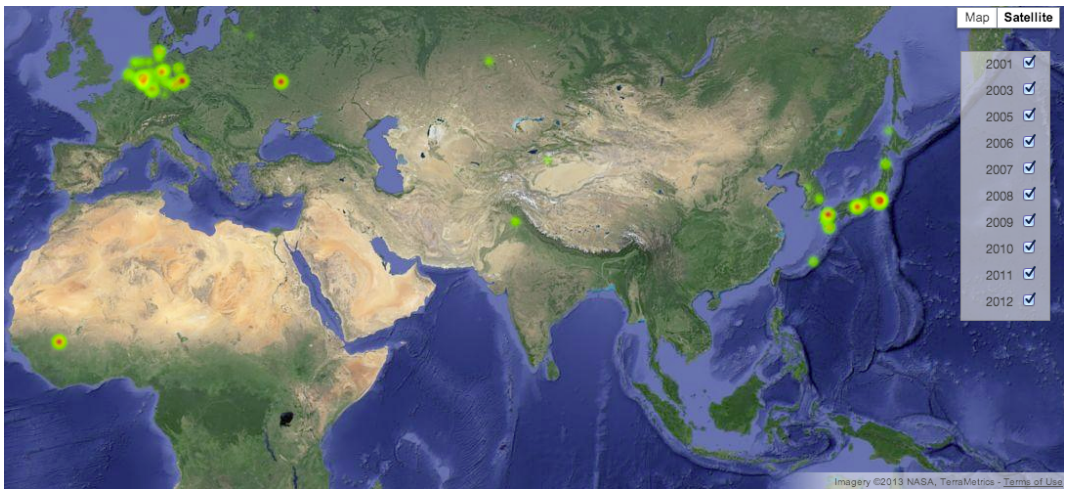


Figure 6.5: Experiment 1: visualization with the TimeHeatmap plugin.

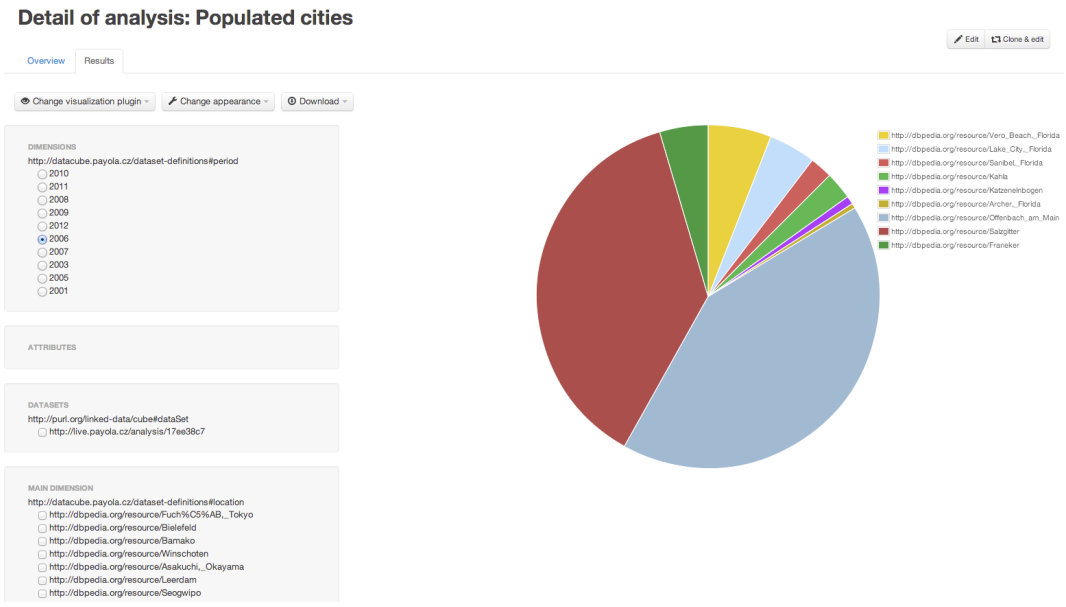


Figure 6.6: Experiment 1: visualization with the Universal DataCube plugin.

standard. We took advantage of the integration with the Payola application in order to obtain a meaningful preview.

The system performed well on the dataset provided by the DBPedia endpoint, but it is important to remember that the endpoint returned a small amount of resources. The quality of the DBPedia datasets differs a lot and many statistical data are present in a non–user–friendly form, e.g. while using the property `2000pop`. It might be interesting to use Payola to discover all those properties and build an analytical pipeline, which will unify all the approaches. When unified, the implemented system can be used in order to transform the data into the form of DCV and/or visualize those.

We have also shown that our visualizers work with real–life data. Based on what we have experienced, we will propose some future user experience improvements in Chapter 7. One of those is optimizing a longer running geocoding process, which transforms the city names into GPS coordinates.

6.2 COINS – UK government spending

Many organizations including governments produce a lot of statistical datasets focused on spendings. Therefore, we wanted to examine the behaviour of the system when applied on such a dataset. We chose to use a dataset named COINS [66]. It is the database for UK Government expenditure.

The `data.gov.uk` project also made the dataset available in a form of Linked Data. Moreover, it is published in a form compliant with Data Cube Vocabulary. Therefore, it is not necessary to do a transformation of the dataset. But we tried to use the implemented system to extract the data from the original dataset.

It is possible to use only the universal visualizer to visualize the data contained in the dataset, but we would need to extract them manually. In fact, we tried to do that and we had to construct a SPARQL query, which is shown in Figure 6.10. It allows us to extract the data for a specific data structure definition and visualize them. The result of such a visualization is shown in Figure 6.7.

As stated before, we tried to use the implemented system in order to obtain similar results. Since the original dataset is very large, we had to prepare an analysis in order to get a reasonable preview for a pattern selection. The analysis contained only one step. We added a SPARQL query plugin. The query is presented in Figure 6.11.

By executing such a query, we obtained all triples from the endpoint related to the specified dataset. We made a strong constraint for bringing down the volume of returned entries. By using the `qb:dataSet` property, we automatically filtered the observations.

Despite the narrowed dataset, the preview was still too large for the resulting visualization to be well–arranged. A screenshot of the preview can be seen in Figure 6.8. After a while, we managed to select the desired pattern. The SPARQL query shown in Figure 6.12 was constructed.

As one can see, the query differs from the one we were about to simulate. We did not select available labels. On the other hand, we obtained a more general query, which does not fix a value of the `dataType` dimension. That means that the user is able to slice the results of such an analysis with the universal visualizer

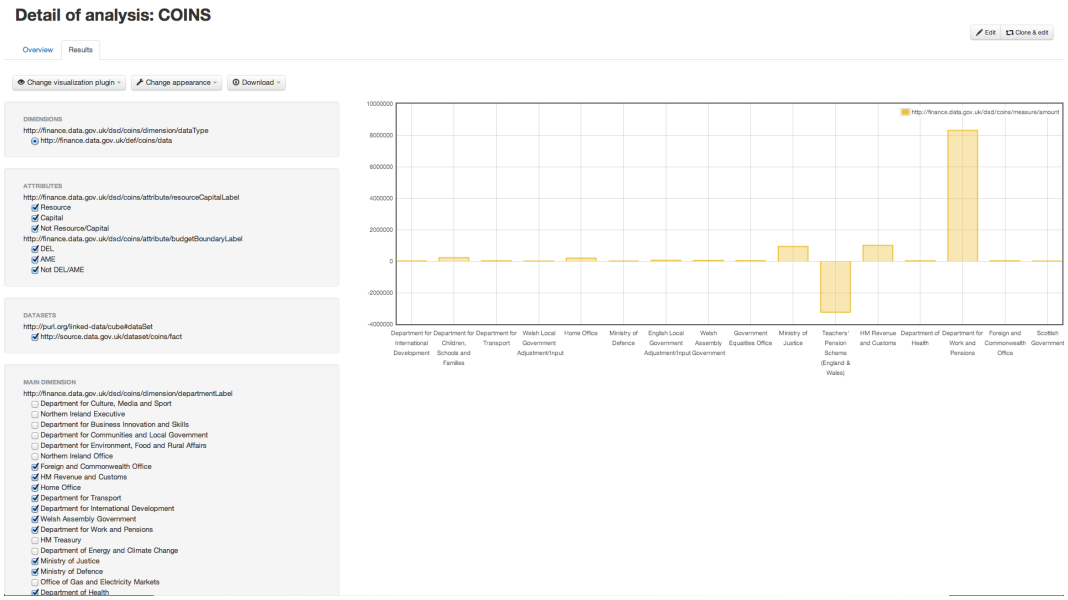


Figure 6.7: Experiment 2: visualization of a custom query with the Universal DataCube plugin.

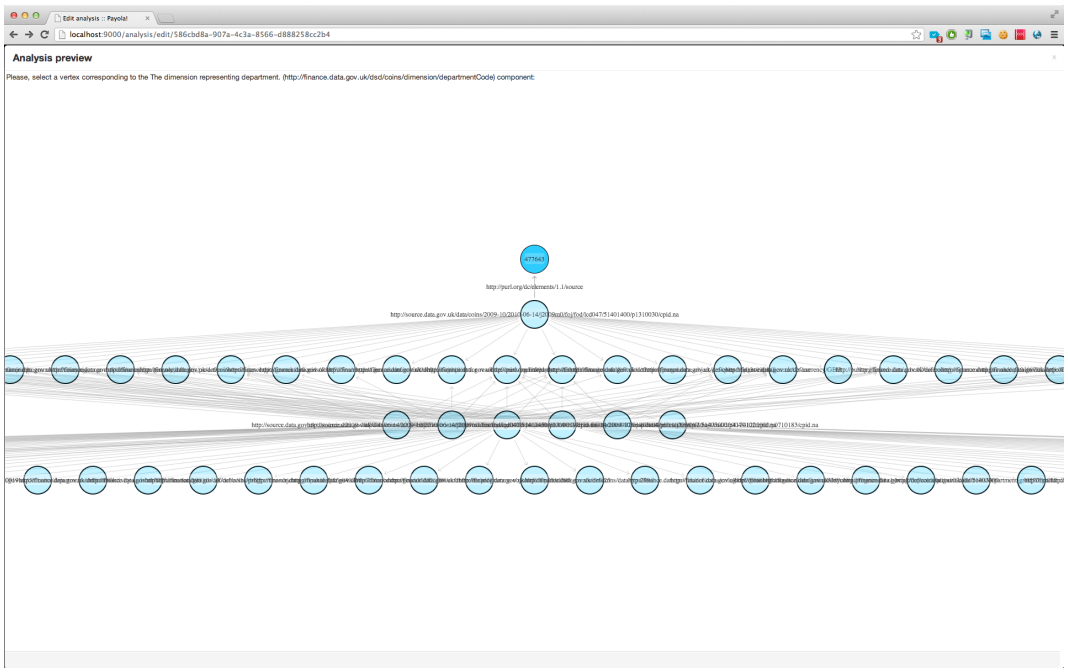


Figure 6.8: Experiment 2: Selecting an exemplary pattern in a complex graph might be difficult, yet possible.

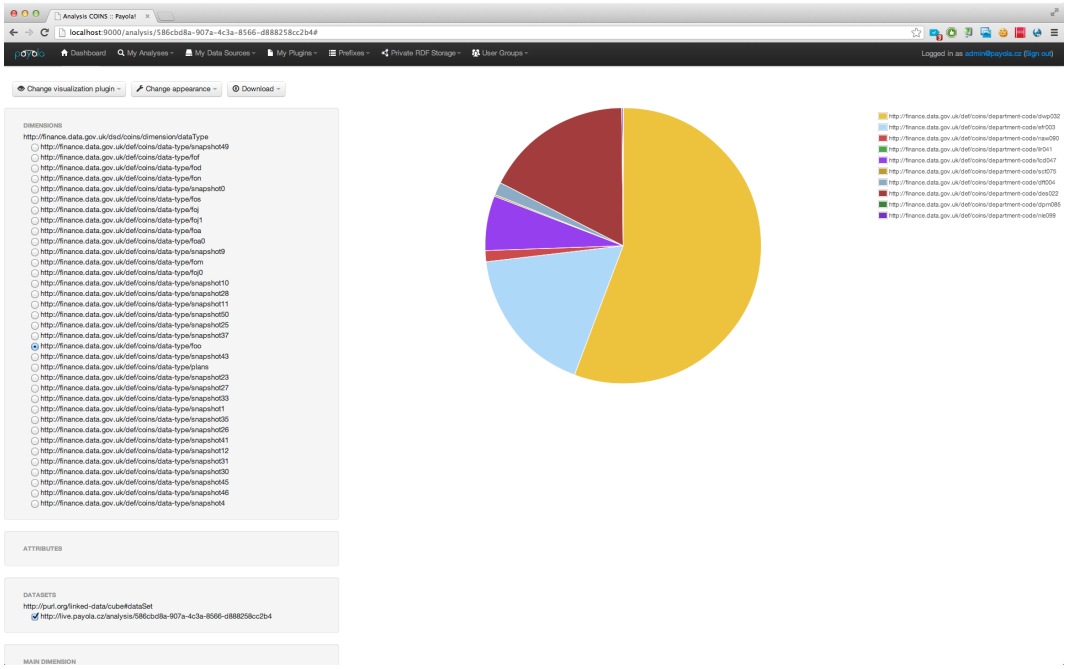


Figure 6.9: Experiment 2: Visualization of the extracted dataset.

```
PREFIX  coins-dimension: <http://finance.data.gov.uk/dsd/coins/dimension/>
PREFIX  coins-measure: <http://finance.data.gov.uk/dsd/coins/measure/>
PREFIX  source: <http://source.data.gov.uk/>
PREFIX  coins-attribute: <http://finance.data.gov.uk/dsd/coins/attribute/>
PREFIX  qb:   <http://purl.org/linked-data/cube#>

CONSTRUCT
  { ?obs qb:dataSet ?ds .
    ?obs a qb:Observation .
    ?obs coins-dimension:dataType <http://finance.data.gov.uk/def/coins/data-type/outturn> .
    ?obs coins-measure:amount ?amount .
    ?obs coins-dimension:departmentLabel ?deptLongName .
    ?obs coins-attribute:budgetBoundaryLabel ?boundaryLabel .
    ?obs coins-attribute:resourceCapitalLabel ?rcLabel . }

WHERE
  { ?obs qb:dataSet ?ds .
    ?obs coins-dimension:departmentCode ?dept .
    ?obs coins-dimension:dataType <http://finance.data.gov.uk/def/coins/data-type/outturn> .
    ?obs coins-measure:amount ?amount .
    ?obs coins-attribute:budgetBoundary ?boundary .
    ?obs coins-attribute:resourceCapital ?rc
    GRAPH <http://source.data.gov.uk/finance/coins/2010-06-14/schema>
      { ?boundary <http://www.w3.org/2000/01/rdf-schema#label> ?boundaryLabel .
        ?rc <http://www.w3.org/2000/01/rdf-schema#label> ?rcLabel .
        ?dept <http://www.w3.org/2000/01/rdf-schema#comment> ?deptLongName
      }
  }
```

Figure 6.10: A custom SPARQL query used to extract DCV from the COINS dataset.

```
CONSTRUCT { ?o ?p ?x }
WHERE
{ ?o qb:dataSet <http://source.data.gov.uk/dataset/coins/fact-table-extract-2009-10> ;
      ?p ?x .
}
```

Figure 6.11: A custom SPARQL query used for narrowing the original dataset.

```
  CONSTRUCT {
    [] a <http://purl.org/linked-data/cube#Observation> ;
    <http://purl.org/linked-data/cube#dataSet> <http://live.payola.cz/analysis/...> ;
    <http://finance.data.gov.uk/dsd/coins/dimension/departmentCode> ?v2 ;
    <http://finance.data.gov.uk/dsd/coins/dimension/dataType> ?v3 ;
    <http://finance.data.gov.uk/dsd/coins/measure/amount> ?v4 .
} WHERE {
    {
        SELECT DISTINCT ?v2 ?v3 ?v4 {
            ?v1 <http://finance.data.gov.uk/dsd/coins/dimension/departmentCode> ?v2 .
            ?v1 <http://finance.data.gov.uk/dsd/coins/dimension/dataType> ?v3 .
            ?v1 <http://finance.data.gov.uk/dsd/coins/measure/amount> ?v4 .
        }
    }
}
```

Figure 6.12: A SPARQL query constructed based on the pattern selection dialog.

in order to obtain the same visualization as was in the case of the custom query. Moreover, they are able to explore a much wider range of data.

Unfortunately, as the original dataset is way too large it was not possible to fetch all the related data. The SPARQL endpoint `http://openuplabs.tso.co.uk/` is placed behind an Apache proxy, which monitors the load of the underlying triplestore caused by executing a query. After a while we hit the limit and had a restricted access to the endpoint for a few minutes. Therefore, we had to limit the size of the extracted dataset. We managed to get 10000 in the Payola's default limit (30 seconds). Most of the time was spent on obtaining all the data from the endpoint, the extraction to DCV was completed in a matter of seconds. Also, the universal visualizer performed well on a dataset that large. We made a screenshot of the visualization that was prepared during this experiment. It can be seen in Figure 6.9.

We learnt that the system is capable of mapping larger datasets in a reasonable time. But we also found out that the preview mechanism will need further modifications in order to handle larger previews in a more user–friendly way. Performance of the universal visualizer was acceptable for the user interface responded continuously without any lags. However, we hit the limit of the endpoint and were not able to obtain the complete dataset.

The proper way of working with this dataset would require a fully faceted browser connected directly to the original SPARQL endpoint. Since it contains DCV data, the system would be able to automatically discover used vocabularies and offer them to the user. On the other hand, the vocabularies are not published separately, which made our task a bit harder. Implementing an advanced browser with an exploration mode will definitely become the next step in the future work. It would be very useful to give the user a tool, which will help them discover vocabularies and related data in datasets, which are already compliant with Data Cube Vocabulary.

The recommended way of solving the large dataset problem with the current state of the system is to place the DCV plugin into a more suitable point. The preceding operations should narrow the dataset more naturally by setting semantical constraints.

In this experiment, we tried to use the implemented system in a slightly different use case. We used it in order to extract a dataset which is already

in a form of Data Cube Vocabulary. Despite the fact that the tool was not originally meant for this, we managed to fulfill our goal. On the other hand, we discovered some user experience flaws, which will be eliminated in the future development of the whole Payola framework.

6.3 Czech public contracts

As we are able to access the data related to public contracts realized in the Czech Republic, we want to demonstrate on them the possibilities of the implemented system. The dataset was created by scraping website produced by an online system focused on publishing details about public contracts. Therefore, the form of the data is natural and does not come out from a statistical source.

At first, we wanted to extract the data by using a very simple analysis containing a sole plugin, an *ontological filter*. Unfortunately, the length of the generated SPARQL query exceeds the limit of the queried SPARQL endpoint. We extracted the generated query and tried to shorten it by applying prefixes and removing whitespace characters. However, after overcoming this challenge, we hit another limit — the underlying Virtuoso endpoint refused to run the query due to a large estimated time of transaction execution.

That is why we had to construct a custom query in order to obtain the required data for making a preview and a transformation. We designed the query to gather as much data as possible while keeping the important statistical facts in all of the returned entries. The query is shown in Figure 6.13. It returns the details of about 40000 public contracts.

We also had to construct a custom Data Cube vocabulary with a data structure definition. We present the vocabulary in Figure 6.14.

After we had prepared all the prerequisities, we proceeded with transforming the original dataset to the form compliant with Data Cube Vocabulary. Based on the data structure definition, we created a corresponding plugin, which was then inserted into an analysis. The preview contained one of the selected entries, therefore it was an easy task to select a mapping pattern. One step of the pattern selection process is pictured in Figure 6.15. As a result, the system gave us the SPARQL query show in Figure 6.16.

The conversion of all the resources in the source lasted around 300 seconds. We have noticed that it took about 200 seconds to make the mapping itself, the rest was spent on fetching the data.

We tried to visualize the dataset in both implemented Data Cube visualizers. At first, we experimented with the TimeHeatmap visualizer. While working with the large dataset, we experienced some user discomfort. The UI was unresponsive for a short period of time (that is caused by the single–threaded JavaScript processing concept and would require involving Web Workers to avoid such behaviour). In order to geocode the locations from the result, we had to increase the maximum size of a POST request allowed in the application. We present samples of created visualizations in Figure 6.17 and Figure 6.18.

The geocoding process was done in an acceptable time, but the size of the dataset caused that the Google Maps visualization had troubles with zooming. It had to recompute all the 40000 of locations with every zoom.

```
PREFIX contract: <http://purl.org/procurement/public-contracts#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX dcterms: <http://purl.org/dc/terms/>
prefix vcard: <http://www.w3.org/2006/vcard/ns#>
prefix gr: <http://purl.org/goodrelations/v1#>
prefix ns4: <http://purl.org/procurement/public-contracts-eu#>

CONSTRUCT
{
   ?v1 a contract:Contract .
   ?v1 contract:location ?vloc .
   ?vloc rdfs:label ?locLabel .
   ?vloc ns4:hasParentRegion ?reg .
   ?v1 contract:startDate ?v17 .
   ?v1 contract:estimatedPrice ?ep .
   ?ep gr:hasCurrencyValue ?epv.
}
WHERE
{
   ?v1 a contract:Contract .
   ?v1 contract:location ?vloc .
   ?vloc rdfs:label ?locLabel .
   ?vloc ns4:hasParentRegion ?reg .
   ?v1 contract:startDate ?v17 .
   ?v1 contract:estimatedPrice ?ep .
   ?ep gr:hasCurrencyValue ?epv.
}
```

Figure 6.13: A query constructed to obtain a dataset containing desired data.

The size of the dataset caused a performance drop also in the case of the Universal Data Cube visualizer. Despite the fact, we are able to slice it and take advantage of the Data Cube Vocabulary format. An example of a visualization made by the Universal Data Cube visualizer is shown in Figure 6.19.

In this experiment, we confirmed that the implemented system is capable of transforming an arbitrary RDF dataset into a form compliant with a selected Data Cube vocabulary. We also examined the system while working with a larger dataset. We confirmed some aforementioned assumptions about the performance of the system. Therefore, we confirmed that we have correctly identified all the bottlenecks predicted while preparing the proposal of integrating the system with Payola. We will account them in the future improvements.

```
@prefix rdf:     <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs:    <http://www.w3.org/2000/01/rdf-schema#> .
@prefix xsd:     <http://www.w3.org/2001/XMLSchema#> .
@prefix payola-dcv:   <http://datacube.payola.cz/dataset-definitions#> .
@prefix qb:              <http://purl.org/linked-data/cube#> .
@prefix sdmx:            <http://purl.org/linked-data/sdmx#> .
@prefix sdmx-concept:    <http://purl.org/linked-data/sdmx/2009/concept#> .
@prefix sdmx-dimension:  <http://purl.org/linked-data/sdmx/2009/dimension#> .
@prefix sdmx-measure:    <http://purl.org/linked-data/sdmx/2009/measure#> .
@prefix pc: <http://purl.org/procurement/public-contracts#> .
@prefix ns4: <http://purl.org/procurement/public-contracts-eu#> .
@prefix nuts:     <http://ec.europa.eu/eurostat/ramon/ontologies/geographic.rdf#> .

payola-dcv:ContractsDatastructureDefinition a qb:DataStructureDefinition ;
  rdfs:label "The definition of the DS of a dataset containing information about public contracts."@en ;
  # Dimensions
  qb:component [
    qb:dimension payola-dcv:location;
    qb:order 1 ;
    rdfs:label "The dimension representing location, where the money was spent."
  ] ;
  qb:component [
    qb:dimension payola-dcv:period;
    qb:order 2 ;
    rdfs:label "The dimension representing the time of realizing the contract."
  ] ;
  # Measure
  qb:component [
    qb:measure payola-dcv:price;
    rdfs:label "The measure representing the price spent on realizing the contract."@en
  ] ;
  qb:component [
    qb:attribute payola-dcv:contract;
    rdfs:label "The attribute linking the observation with a corresponing contract."@en
  ] ;
  qb:component [
    qb:attribute payola-dcv:region;
    rdfs:label "The attribute specifying the region, where the contract was realized."@en
  ] ;
  qb:component [
    qb:attribute payola-dcv:currency;
    rdfs:label "Currency of the price."@en
  ] .

payola-dcv:location a rdf:Property, qb:DimensionProperty ;
  rdfs:label "reference location"@en ;
  qb:concept sdmx-concept:refArea .

payola-dcv:period a rdf:Property, qb:DimensionProperty ;
  rdfs:label "reference period"@en ;
  qb:concept sdmx-concept:refPeriod .

payola-dcv:price a rdf:Property, qb:MeasureProperty ;
  rdfs:label "price"@en ;
  rdfs:subPropertyOf sdmx-measure:obsValue ;
  rdfs:range xsd:nonNegativeInteger ;
  qb:concept sdmx-concept:valuation .

payola-dcv:contract a rdf:Property, qb:AttributeProperty ;
  rdfs:label "corresponding public contract"@en ;
  rdfs:range pc:Contract ;
  qb:concept sdmx-concept:comment .

payola-dcv:region a rdf:Property, qb:AttributeProperty ;
  rdfs:label "Parent NUTS region."@en ;
  rdfs:range nuts:NUTSRegion;
  qb:concept sdmx-concept:refArea .
```

Figure 6.14: Public contracts data structure definition.

Figure 6.15: Experiment 3: Pattern selection.

```
CONSTRUCT {
    [] a <http://purl.org/linked-data/cube#Observation> ;
       qb:dataSet <http://live.payola.cz/analysis/...> ;
       <http://datacube.payola.cz/dataset-definitions#location> ?v2 ;
       <http://datacube.payola.cz/dataset-definitions#period> ?v4 ;
       <http://datacube.payola.cz/dataset-definitions#price> ?v6 ;
       <http://datacube.payola.cz/dataset-definitions#contract> ?v3 ;
       <http://datacube.payola.cz/dataset-definitions#region> ?v7 ;
} where {
   {
      SELECT DISTINCT ?v2 ?v4 ?v6 ?v3 ?v7 {
         ?v1 <http://www.w3.org/2000/01/rdf-schema#label> ?v2 .
         ?v3 <http://purl.org/procurement/public-contracts#location> ?v1 .
         ?v3 <http://purl.org/procurement/public-contracts#startDate> ?v4 .
         ?v3 <http://purl.org/procurement/public-contracts#estimatedPrice> ?v5 .
         ?v5 <http://purl.org/goodrelations/v1#hasCurrencyValue> ?v6 .
         ?v2 <http://purl.org/procurement/public-contracts-eu#hasParentRegion> ?v7 .
      }
   }
}
```

Figure 6.16: Experiment 3: Transformation query.

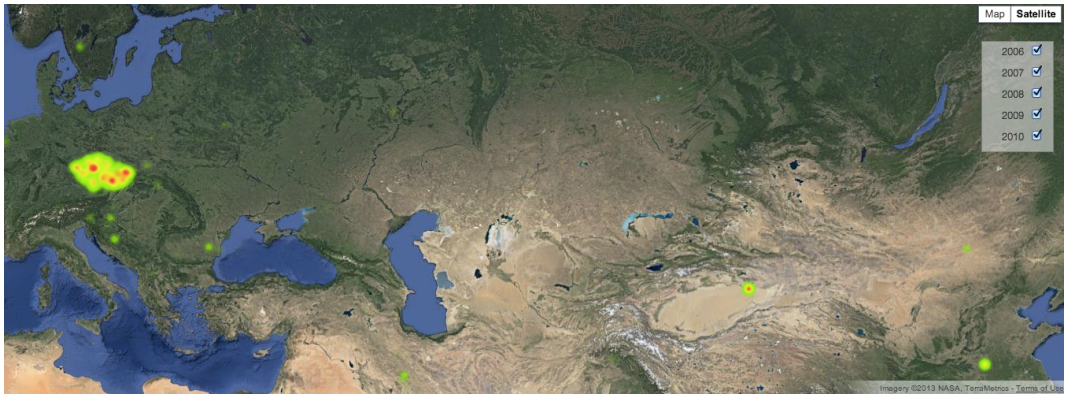


Figure 6.17: Experiment 3: Map expressing the amount of money spent by the Czech Republic in the world.

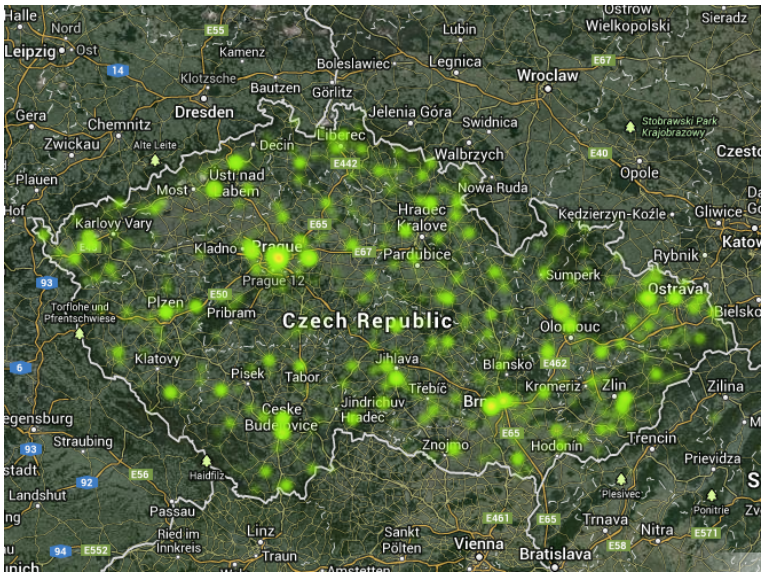


Figure 6.18: Experiment 3: Map from Figure 6.17 zoomed to the level of the Czech Republic.

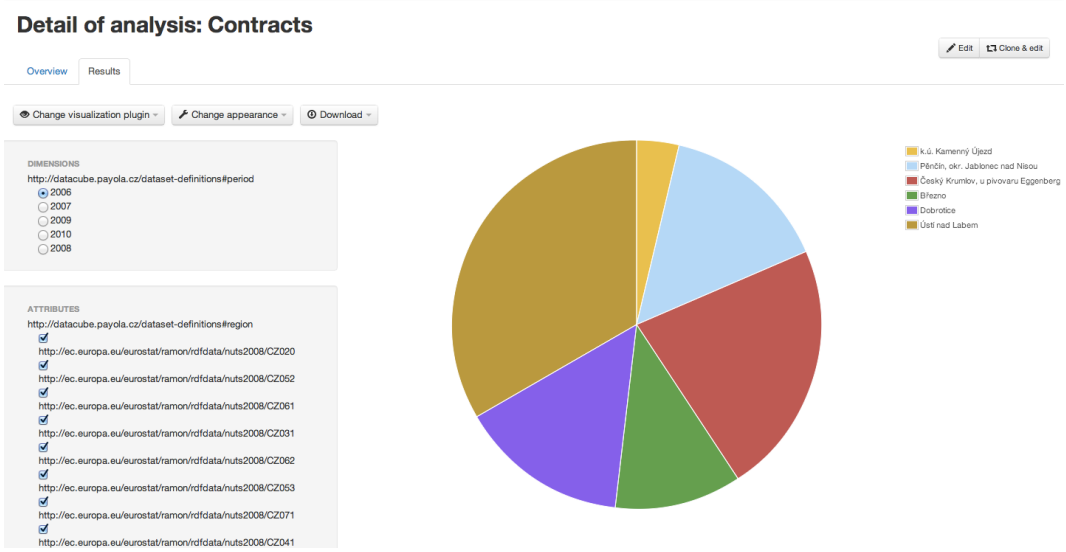


Figure 6.19: Experiment 3: Universal Data Cube visualizer.

7. Future work

Based on the restrictions of the Payola framwork mentioned in Chapter 5 and based on experiments with the implemented system (some of them are described in Chapter 6), we learnt what needs to be done in the future in order to improve the qualities of the implemented system.

The most crucial lacking feature is a fully faceted browser. We had to adopt the design flaw of Payola, which is not capable of caching the results of an analysis. Therefore, the user is forced to work with all the results at once, which may cause poor performance of the system. We need the Payola framework to adopt some existing approaches in order to deliver such a feature. One of them was mentioned before — the integration of a caching mechanism (SESAME, Virtuoso, etc.).

That will dramatically increase the capabilities of the implemented system, because it will be possible to work with a proper portion of the data. The user will be potentially able to preview the whole dataset while selecting a pattern. A really important fact is that the visualizers will be able to query the data based on the current state of the visualization, which will significantly help to increase the performance of the whole system. One of the features that could be done immediately is an improvement to the listings of the detected values of the Universal DCV visualizer — also more sophisticated component than a list of checkboxes should be used.

In order to improve the user experience of the preview, we can use some advanced techniques described in [67], for instance an ordering by `IRI:RANK`.

Another task will be to undergo a user evaluation in order to reveal other missing features and imperfections. Not only based on that, we should continue improving the existing visualizers and introduce others for domain–specific visualisations. The list of requested visualizers will form on–the–fly, while exploring other datasets. Such a process will also suggest other modifications to the existing visualizers. One comes to mind instantly — we should be able to take advantage of more metadata, for instance measure and dimension datatypes, ranges, etc. It is also possible to integrate other types of charts.

It would be also possible to propose some procedures, which will examine a given dataset and try to convert it to Data Cube Vocabulary automatically. It will almost certainly require a more sophisticated integration with the LodVis project.

We will also continue to improve Payola features, which are not related to Data Cube Vocabulary. Based on the feedback from the ESWC 2013 conference, where the Inner analysis feature was presented, people found these modifications and features interesting and would like to use them.

Some of those improvements will require Payola to undergo a heavy refactoring, where the most adjusted subsystems would be the data access layer and the analytical pipeline evaluator.

Conclusion

We have implemented the proposed system. We have thusly introduced a tool which is, with a user input, able to convert an arbitrary RDF dataset into a form compliant with Data Cube Vocabulary. As a part of our long–term research, we decided to integrate it into a larger system (Payola) in order to benefit from such an integration. For example, the user is able to make the conversion as a part of a larger analytical process. It enables the user to work with the statistical data in a usual way. Moreover, they are able to work with data from multiple datasets at once.

We have also examined several already existing tools but did not find any that would enable the user to perform such a conversion. There were some related tools focused on a very similar task and we used the knowledge gained from examining them. Especially, we used the query–by–example principle in order to deliver our system to our advantage.

During the process of implementation, we have managed to extend Payola, our RDF application. We not only added the Data Cube Vocabulary related features but also included some other useful user experience improvements. Moreso, we integrated a completely new approach (in the scope of Payola) a construction of a SPARQL query, which can be reused in other scenarios in order to deliver some new features.

Based on our experience and our research, we have also determined those parts of Payola, which are in need of an improvement or redesign for providing a more efficient behaviour. That is also crucial in order to improve the reliability, the performance and the usability of the implemented system while working on this thesis.

Last, but not least, we delivered two new visualizer plugins, which enable the user to explore the Data Cube Vocabulary related datasets. Whilst the first one tends to be universal, the second one is focused on visualizing geospatial data. Improving the user experience of those visualizers should become the core of the future work, including an implementation of a fully faceted browser. To offer a visualizer, which may probably be considered a basis for a sophisticated faceted browser for cube data, represents a significant achievement.

We fulfilled the goal of this thesis. In spite of the fact that the system will be eventually improved as it happens with every other new system, we find the implementation satisfactory to the current state of the Payola framework. We consider the provided feature to be of a great benefit to the Payola users.

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List of Tables

List of Abbreviations

- *AKSW*: Agile Knowledge Engineering and Semantic Web
- *API*: Application Programming Interface
- *COG*: Content-Oriented Guidelines
- *CSS*: Cascading Style Sheets
- *CSV*: Comma Separated Values
- *DAL*: Data Access Layer
- *DB*: Database
- *DC*: Data Cube
- *DCV*: Data Cube Vocabulary
- *DRY*: Do-not Repeat Yourself
- *DSL*: Domain Specific Language
- *ESWC*: Extended Semantic Web Conference
- *FOAF*: Friend-of-a-friend
- *FQDN*: Fully-qualified Domain Name
- *GPS*: Global Positioning System
- *GUI*: Graphical user interface
- *GVDT*: Generic visual- ization Data Types
- *HTML*: HyperText Markup Language
- *HTTP*: HyperText Transfer Protocol
- *ID*: Identifier
- *IRI*: Internationalized Resource Identifier
- *ISO*: International Organization for Standardization
- *ISWC*: International Standard Musical Work Code
- *JAR*: Java Archive
- *JS*: JavaScript
- *JSON*: JavaScript Object Notation
- *JVM*: Java Virtual Machine

- *LD*: Linked Data
- *LDVM*: Linked Data Visualisation Model
- *LOD*: Linked Open Data
- *MIT*: Massachusetts Institute of Technology
- *MVC*: Model-View-Controller
- *NUTS*: Nomenclature of Territorial Units for Statistics
- *OECD*: Organisation for Economic Co-operation and Development
- *OLAP*: Online Analytical Processing
- *ORM*: Object-relational mapping
- *OWL*: Ontology Web Language
- *PHP*: PHP: Hypertext Preprocessor
- *QB*: Data Cube
- *RAM*: Random-access memory
- *RDBMS*: Relational database management system
- *RDF*: Resource Description Framework
- *REST*: Representational State Transfer
- *RFC*: Request For Comment
- *RPC*: Remote procedure call
- *SBT*: Simple Build Tool
- *SDMX*: Statistical Data and Metadata eXchange
- *SKOS*: Simple Knowledge Organization System
- *SPARQL*: SPARQL Protocol and RDF Query Language
- *SPO*: Subject-Predicate-Object
- *SQL*: Structured Query Language
- *TTL*: Turtle - Terse RDF Triple Language
- *UI*: User Interface
- *UK*: United Kingdom
- *UN*: United Nations
- *URI*: Uniform Resource Identifier

- *URL*: Uniform Resource Locator
- *XHR*: XMLHttpRequest
- *XML*: eXtensible Markup Language
- *XSLT*: eXtensible Stylesheet Language Transformations

A. CD Contents

A.1 Files and directories

- directory: git-repo: the latest snapshot of the git repository.
- directory: text: LaTex sources of this text.
- file: user-guide.html: User Guide
- file: developer-guide.html: Developer Guide
- file: thesis.pdf: This text

To generate API documentation, use the ‘doc‘ SBT task on the root project. Each project has its own API documentation which can be found in the ‘target/scala-2.9.1/api‘ subdirectory of the project.

B. Online sources

- `http://datacube.payola.cz` — a list of DCV analysis examples and DCV DSDs.
- `http://live.payola.cz` — a live instance of the current Payola version.
- `https://github.com/payola/Payola.git` — the latest version of the code.
- `http://payola.cz` — the latest documentation.
- `https://github.com/teuzz/master-thesis` — sources of the text of this thesis are available on GitHub.
- `http://helmich.cz/master-thesis` — PDF version of this text and CD contents.

C. List of commits related to this thesis

```
Repository: http://github.com/payola/Payola
> git log --after={2012-09-10} --shortstat --oneline --pretty=format:"%cd  %an  %h  %s" --date=short
    --author='Jiri Helmich'

2013-07-31  Jiri Helmich  affdfde  http prefixes should not be in the db
 1 file changed, 1 deletion(-)

2013-07-31  Jiri Helmich  8277387  docs
 1 file changed, 55 insertions(+), 63 deletions(-)

2013-07-30  Jiri Helmich  9e117f1  inner analyses bugfix, a parameter was missing in the definition
 1 file changed, 1 insertion(+), 1 deletion(-)

2013-07-29  Jiri Helmich  69434e9  beautify blocking dialog
 2 files changed, 11 insertions(+), 13 deletions(-)

2013-07-29  Jiri Helmich  981462d  Limit constructor
 1 file changed, 4 insertions(+), 2 deletions(-)

2013-07-29  Jiri Helmich  540b85d  initializer repair
 1 file changed, 5 deletions(-)

2013-07-29  Jiri Helmich  ba6f3af  dev guide update
 3 files changed, 113 insertions(+), 16 deletions(-)

2013-07-28  Jiri Helmich  4248ee4  images were in a wrong order
 1 file changed, 2 insertions(+), 2 deletions(-)

2013-07-28  Jiri Helmich  72e3888  move images to a proper folder and add them
 3 files changed, 0 insertions(+), 0 deletions(-)

2013-07-28  Jiri Helmich  75a902a  move images to a proper folder
 3 files changed, 0 insertions(+), 0 deletions(-)

2013-07-28  Jiri Helmich  bce587f  datacube user guide, part 3
 4 files changed, 7 insertions(+), 5 deletions(-)

2013-07-28  Jiri Helmich  c4d3f43  datacube user guide, part 2
 5 files changed, 97 insertions(+), 69 deletions(-)

2013-07-28  Jiri Helmich  79f4719  datacube user guide, images
 11 files changed, 0 insertions(+), 0 deletions(-)

2013-07-28  Jiri Helmich  9ceb087  datacube user guide, part 1
 1 file changed, 71 insertions(+), 1 deletion(-)

2013-07-28  Jiri Helmich  58ad7ec  Merge branch 'master' of github.com:payola/Payola
2013-07-28  Jiri Helmich  3c53e9f  datacube docs
 30 files changed, 286 insertions(+), 16 deletions(-)

2013-07-28  Jiri Helmich  8038c8d  datacube docs
 19 files changed, 189 insertions(+), 5 deletions(-)

2013-07-23  Jiri Helmich  512d910  initializer update
 1 file changed, 7 insertions(+), 1 deletion(-)

2013-07-23  Jiri Helmich  7f567b5  DCV - improved pattern selection
 1 file changed, 23 insertions(+), 41 deletions(-)

2013-07-22  Jiri Helmich  d9c70d0  DCV ROPIV beautify
 1 file changed, 4 insertions(+), 2 deletions(-)

2013-07-22  Jiri Helmich  8ef4c8c  TimeHeatmap settings and beautify
 8 files changed, 209 insertions(+), 64 deletions(-)
```

```
2013-07-21  Jiri Helmich  0971213  DataCube progress, plugin changes, new Limit plugin,
 Uni DC parametrized, DCV forwarding
 26 files changed, 565 insertions(+), 46 deletions(-)

2013-07-03  Jiri Helmich  f38d79e  touch
 1 file changed, 1 insertion(+)

2013-07-02  Jiri Helmich  c59ba4a  DCV + param ordering
 9 files changed, 17 insertions(+), 10 deletions(-)

2013-07-02  Jiri Helmich  e47ba5f  Merge branch 'master' of github.com:payola/Payola
2013-07-02  Jiri Helmich  5c074bb  parameter ordering
 24 files changed, 68 insertions(+), 48 deletions(-)

2013-07-01  Jiri Helmich  1320f00  data cube - mapview improvement
 3 files changed, 60 insertions(+), 23 deletions(-)

2013-07-01  Jiri Helmich  ccfde40  MF
2013-07-01  Jiri Helmich  caa004e  data cube improvements
 16 files changed, 210 insertions(+), 63 deletions(-)

2013-05-21  Jiri Helmich  471f7ae  name parameters when selecting substitute
 4 files changed, 50 insertions(+), 14 deletions(-)

2013-05-13  Jiri Helmich  5c9e077  expandable analysis need to be mapped based on parameter value,
 not on parameter itself
 7 files changed, 28 insertions(+), 18 deletions(-)

2013-05-10  Jiri Helmich  71b35c3  analysis plugin fixes - CSS bugs, minor UI changes, inputcount: 0
 6 files changed, 30 insertions(+), 6 deletions(-)

2013-05-08  Jiri Helmich  e641b10  Merge branch 'master' of github.com:payola/Payola
2013-05-08  Jiri Helmich  48b5a31  analysis in analysis, completed.
 24 files changed, 384 insertions(+), 94 deletions(-)

2013-05-03  Jiri Helmich  678338a  dynamic custom PluginInstanceView loading - Editable
 13 files changed, 265 insertions(+), 207 deletions(-)

2013-04-27  Jiri Helmich  3863a7e  Virtuoso Secured Endpoint now with Digest Auth support
 3 files changed, 46 insertions(+), 21 deletions(-)

2013-04-26  Jiri Helmich  b2ab1ea  String param init
 1 file changed, 1 insertion(+), 1 deletion(-)

2013-04-26  Jiri Helmich  039390c  isPassword constructors
 1 file changed, 3 insertions(+), 3 deletions(-)

2013-04-26  Jiri Helmich  68f7afa  typo
 1 file changed, 2 insertions(+)

2013-04-26  Jiri Helmich  d68b1e3  typo
 1 file changed, 1 insertion(+), 1 deletion(-)

2013-04-26  Jiri Helmich  1befc9d  secured virtuoso imports
 1 file changed, 1 insertion(+)

2013-04-26  Jiri Helmich  9ada606  secured virtuoso imports
 1 file changed, 2 insertions(+)

2013-04-26  Jiri Helmich  69c0420  Merge branch 'master' of github.com:payola/Payola
2013-04-26  Jiri Helmich  0358c4e  secured virtuoso endpoint plugin
 6 files changed, 121 insertions(+), 4 deletions(-)

2013-03-09  Jiri Helmich  2d22c48  time heatmap - rc1
 18 files changed, 966 insertions(+), 178 deletions(-)

2013-03-02  Jiri Helmich  fe9f312  timeheatmap
 1 file changed, 2 insertions(+), 2 deletions(-)

2013-02-28  Jiri Helmich  e5503de  data cubes RC1
 57 files changed, 2189 insertions(+), 1123 deletions(-)

2012-12-27  Jiri Helmich  b626245  multiple ontologies takes effect
```

```
 13 files changed, 45 insertions(+), 46 deletions(-)

2012-12-03  Jiri Helmich  1685eb7  select proper plugin while editing datasource
 1 file changed, 1 insertion(+), 1 deletion(-)

2012-11-22  Jiri Helmich  901488d  analysis owner verification fixed in accessible analysis list
 1 file changed, 1 insertion(+), 1 deletion(-)

2012-11-20  Jiri Helmich  280679e  LodVis link
 4 files changed, 25 insertions(+), 4 deletions(-)

2012-11-19  Jiri Helmich  24bc6b3  clone & edit, accessible analyses instead of owned
 1 file changed, 1 insertion(+), 1 deletion(-)

2012-11-18  Jiri Helmich  b638220  count of items on a page increased to 30
 1 file changed, 1 insertion(+), 1 deletion(-)

2012-11-18  Jiri Helmich  eab9879  clone and edit feature
 5 files changed, 47 insertions(+), 4 deletions(-)

2012-11-11  Jiri Helmich  fa25d7f  solution for https://github.com/payola/Payola/issues/6
 1 file changed, 1 insertion(+), 1 deletion(-)

2012-11-11  Jiri Helmich  5e5c004  jena
 3 files changed, 0 insertions(+), 0 deletions(-)

2012-11-11  Jiri Helmich  c115a1c  scala library 2.9.2
 1 file changed, 0 insertions(+), 0 deletions(-)

2012-11-11  Jiri Helmich  c3063c9  upgrade play to 2.1-SNAPSHOT, scala 2.9.2, SBT 0.12.1, graphUri
 in LOD API is now an array
 11 files changed, 12 insertions(+), 11 deletions(-)

2012-11-04  Jiri Helmich  7ee760b  lodvisualisation integration (setup analysis via URL)
 14 files changed, 165 insertions(+), 42 deletions(-)

2012-10-20  Jiri Helmich  4eb3bde  LODVisualisation link added to dashboard
 1 file changed, 2 insertions(+)
```