

Towards Linked Statistical Data Analysis

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Abstract. Linked Data principles are increasingly employed to publish high-fidelity, heterogeneous statistical datasets in a distributed way. Currently, there exists no simple way for researchers, journalists and interested people to compare statistical data retrieved from different data stores on the Web. Given that the RDF Data Cube vocabulary is used to describe statistical data, its use makes it possible to discover and identify statistical data artifacts in a uniform way. In this article, the design and implementation of an application and service is presented, which utilizes federated SPARQL queries to gather statistical data from distributed data stores. The R language for statistical computing is employed to perform statistical analyses and visualizations. The Shiny application and server bridges the front-end Web user interface with R on the server-side in order to compare statistical macrodata, and stores analyses results in RDF for future research. As a result, distributed linked statistical data can be more easily explored and analysed.

Keywords: Linked Data, SDMX, Statistics, Statistical database, Data integration, Regression analysis, User interface

1 Introduction

Statistical data artifacts and the analyses conducted on the data are fundamental to testing scientific theories about our societies and the universe(s) we live in. As statistics are often used to add credibility to an argument or advice, they influence the decisions we make. The decisions are, however, complex beings on their own with multiple variables based on facts, cognitive processes, social demands, and maybe even factors that are unknown to us. Regardless of uncontrollable forces, in order for the society to tract and learn from its own vast knowledge about events and things, it needs to be able to gather statistical information from heterogeneous and distributed sources. This is to uncover insights, make predictions, or build smarter systems that the society needs to progress. This brings us to the core of our research challenge; how do we reliably acquire statistical data in a uniform way and conduct well-formed analyses that is accessible to different types of data consumers and users?

This article presents an approach - Statistical Linked Data Analyses - towards this challenge with its contributions. In a nutshell, it takes advantage of Linked Data design principles that are widely accepted as a way to publish and consume data without central coordination on the Web. The work herein offers a Web based user-interface for researchers, journalists, or interested people to compare statistical data from different sources against each other without having any knowledge of the technology underneath or the expertise to develop themselves. The service, which we built, proceeds with running decentralized (federated) structured queries to retrieve data from various endpoints, runs an analysis on the data, and provides the analysis back to the user. For future research, analysis is stored so that it can be searched for and reused.

2 Background

As pointed out in Statistical Linked Dataspaces [1], what linked statistics provide, and in fact enable, are queries across datasets: Given that the dimension concepts are interlinked, one can learn from a certain observation's dimension value, and enable the automation of cross-dataset queries.

The RDF Data Cube vocabulary [2] is used to describe multi-dimensional statistical data, and SDMX-RDF as one of the statistical information models. It makes it possible to represent significant amounts of heterogeneous statistical data as Linked Data where they can be discovered and identified in a uniform way. The statistical artifacts that are produced, and which use this vocabulary, are invaluable for statisticians, researchers, and developers.

Linked SDMX Data [3] provided templates and tooling to transform SDMX-ML data from statistical agencies to RDF/XML, resulting in linked statistical datasets at 270a.info [4] using the RDF Data Cube vocabulary. In addition to semantically uplifting the original data, information pertaining provenance was kept track using the PROV Ontology [5] at transformation time, while incorporating retrieval time provenance data.

3 Related Work

Performing Statistical Methods on Linked Data [6] investigated simple statistical calculations, such as linear regression and presented the results using R [7] and SPARQL queries. It highlighted the importance of a wide range of typical issues on data integration for heterogeneous statistical data. The other technical issues raised are SPARQL query performance, and the use of a central SPARQL endpoint, which contained multiple data sources. For future work, the work pointed out a friendly user-interface that allows dataset selection, statistical method and a visualization of the results.

Defining and Executing Assessment Tests on Linked Data for Statistical Analysis [8] explains: identification of data items, analysis of data characteristics, and data matching as key requirements to conduct statistical analysis on integrated Linked Data.

Linked Open Piracy: A story about e-Science, Linked Data, and statistics [9] investigated analysis and visualization of piracy reports to answer domain questions through a SPARQL client for R [10].

Towards Next Generation Health Data Exploration: A Data Cube-based Investigation into Population Statistics for Tobacco [11], presents the qb.js [12] tool to explore data that is expressed as RDF Data Cubes. It is designed to formulate and explore hypotheses. Under the hood, it makes a SPARQL query to an endpoint which contains the data that it analyzes.

Publishing Statistical Data on the Web [13] explains CubeViz [14], which was developed to visualize the multidimensional statistical data. It is a faceted browser, which utilizes the RDF Data Cube vocabulary, with a chart visualization component. The inspection and results are for a single dataset.

Google Public Data Explorer [15], derived from the Gapminder [16] tool, displays statistical data as line graphs, bar graphs, cross sectional plots or on maps. The process to display the data requires the data to be uploaded in CSV format, and accompanying Dataset Publishing Language (DSPL) [17] in XML to describe the data and metadata of the datasets. Its visualizations and comparisons are based on one dataset at a time.

Generating Possible Interpretations for Statistics from Linked Open Data [18] talks about Explain-a-LOD [19] tool which focuses on generating hypotheses that explain statistics. It has a configuration to compare two variables, and then provides possible interpretations of the correlation analysis for users to review.

Looking at this state of the art, we can see a common pattern which is that the analysis is conducted on central repositories. As statistical Linked Data is published by different parties independently from one another, it is only reasonable to work towards a solution that can gather, integrate and analyze the data without having to resort to centralism.

4 Analysis platform for Linked Statistical Data

The analysis platform is focused on two goals: 1) a Web user interface for researchers to compare macrodata observations and to view plots and analysis results, 2) caching and storage of that analysis for future research and reuse. Here, we describe the platform at stats.270a.info [20].

4.1 Functional Requirements

The requirements for functionality and performance are that Linked Data design principles are employed behind the scenes to pull in the statistical data that are needed to conduct analysis, and to make the results of the analysis available using the same methods for both, humans and machines. While achieving this workflow includes many steps, the front-end interface for humans should aim for minimum interactivity that is required to accomplish this. Finally, the performance of the system should be reasonable for a Web user interface, as it needs to display a visualization and present analysis. Additionally, essential parts of the analysis should be cached and stored for future use both, for application responsiveness and data discovery.

4.2 User interface

A web application was created to provide users with a simple interface to conduct regression analysis and display of scatter plot(s). The interface presents

three drop-down selection areas for the user: an independent variable, a dependent variable, and a time series. Both, the independent and dependent variables are composed of a list of datasets with observations, and time series are composed of reference periods of those observations. Upon selecting and submitting datasets to compare, the interface then presents a scatter plot with the best line of best fit from a list of linear models that is tested. The points in the scatter plot represent locations, in this case, countries, which happen to have a measure value for both variables, as well as the reference period that was selected by the user. Below the scatter-plot, a table of analysis results is presented. Figure [1] is a screenshot of the user interface.

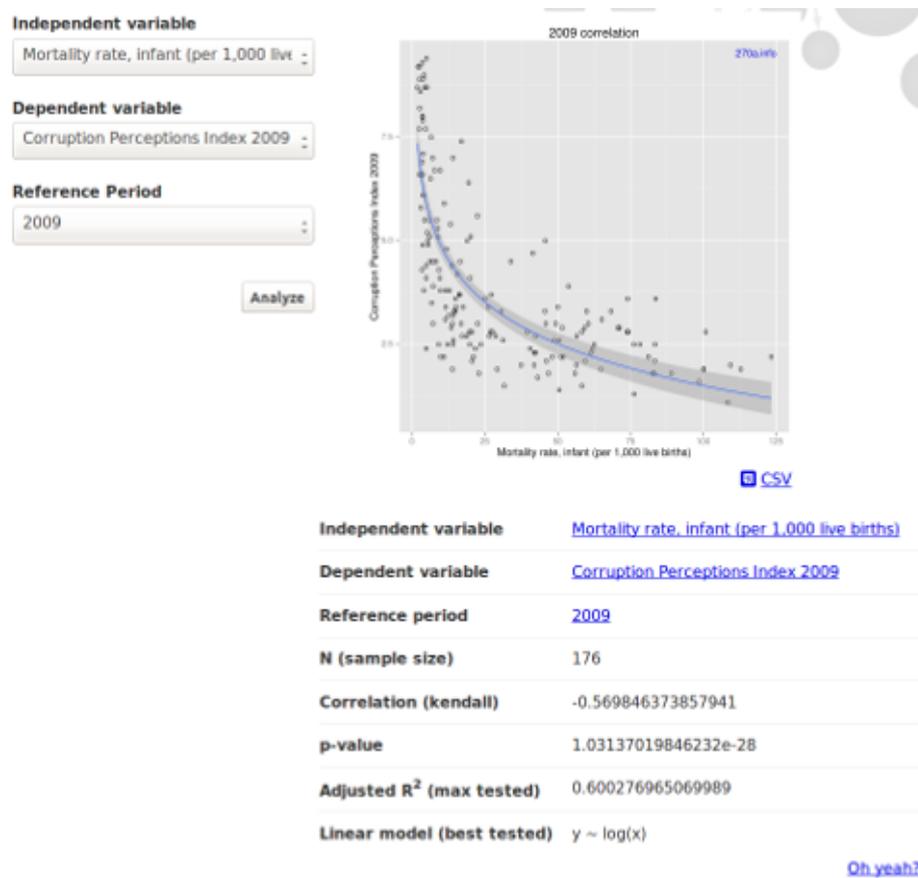


Figure 1: stats.270a.info analysis user interface

The datasets are compiled by gathering `qb:DataSets` (an RDF Data Cube class for datasets) from each statistical dataspace at 270a.info. Similarly, the reference periods are derived from calendar intervals e.g., YYYY, YYYY-MM-DD, YYYY-QQ.

4.3 Data Requirements

Our expectation from the data is that it is modeled using the RDF Data Cube

vocabulary and is well-formed. Specifically, it needs to pass some of the integrity constraints as outlined by the vocabulary specification. For our application, some of the essential checks are that: a unique data structure definition (DSD) is used for a dataset, DSD includes measure (value of each observation), Concept dimensions have code lists, Codes from code list.

In addition to well-formed adherence, to compare variables from two datasets, there needs to be an agreement on the concepts that are being matched for in respective observations. Here, the primary concern is about reference areas (locations), and making sure that the comparison made for the observations from dataset_x (independent variable) and dataset_y (dependent variable) are using concepts that are interlinked (using the property `skos:exactMatch`). Practically, a concept e.g. Switzerland, from at least one of the dataset's code lists should have an arc to the other. It ensures that there is a reliable degree of confidence that the particular concept is interchangeable. Hence, the measure corresponding to the phenomenon being observed, is about the same location in both datasets. Concepts in the datasets were interlinked using LInk discovery framework for MEtric Spaces (LIMES) [21]. Figure [2] shows available outbound interlinks for the datasets at <http://270a.info/>.

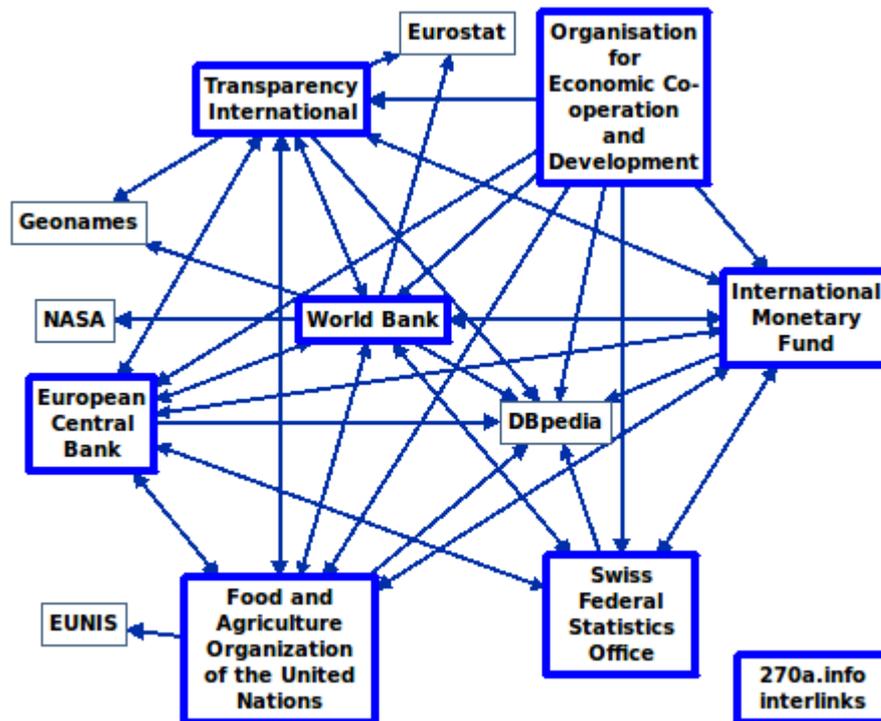


Figure 2: Outbound interlinks for 270a.info datasets

The limitations of the interlinks are that reference areas (concepts) are interlinked based on their notations and labels, excluding their temporality and changes in their space. The shortcoming is that the machine-readable metadata

is unavailable from many sources. Feature plans to accommodate this will provide a richer concept assignment system, and incorporate provenance.

One additional requirement from the datasets is that the RDF Data Cube component properties (e.g., dimensions, measures) either use `sdmx-dimension:refArea`, `sdmx-dimension:refPeriod`, `sdmx-measure:obsValue` directly or are `rdfs:subPropertyOf`s. Given decentralized mappings of the statistical datasets (published as SDMX-ML), their commonality is expected to be the use, or a reference to SDMX-RDF properties in order to achieve generalized federated queries without having complete knowledge of the structures of the datasets, but rather only the essential bits.

In order to proceed with the analysis, we use the selections made by the user: `datasetx` and `datasety`, reference period, and then gather all observations with corresponding reference areas, and measures (observation values). Only the observations whose values for the reference areas with interlinked concepts are retained in the final result.

4.4 Application

Shiny [22], an R package, along with Shiny server [23] is used to build an interactive web application. A Shiny application was built to essentially allow an interaction between the front-end Web application and R. User inputs are set to trigger an event which is sent to the Shiny server and handled by the application written in R. While the application uses R for statistical analysis and visualizations, to achieve the goals of this research, other statistical computing software can be used. The motivation to use R is due to it being an open source software and it being a requirement of Shiny server's

The application assembles a SPARQL query using the input values and then sends them to `stats.270a.info/sparql` endpoint which dispatches federated queries to two SPARQL endpoints where the datasets are located. The SPARQL query request is handled by the SPARQL client for R. The query results are retrieved and given to R for statistical data analysis. R generates a scatter plot containing the (in)dependent variables, where each point in the chart is a reference area (e.g., country) for that particular reference period selection. Regression analysis is done where correlation, p-value, and the line of best fit is determined after testing several linear models, and shown in the user interface.

4.5 Federated Queries

During this research, establishing a correct and reasonably performing federated query was one of the most demanding steps. This was due in part by ensuring dataset integrity, finding a balance between processing and filtering applicable observations at remote endpoints and at the originating endpoint. The challenge was compromising between what should be processed remotely and sent over the wire versus handling some of that workload by the parent endpoint. Since one of the requirements was to ensure that the concepts are interlinked at either one of the endpoints (in which case, it is optional per endpoint), each endpoint had to include each observation's reference area as well as its interlinked concept. The result from both endpoints was first joined and then filtered in order to avoid

false negatives. That is, either concept_x has a `skos:exactMatch` relationship to concept_y, or vice versa, or concept_x and concept_y are the same. One quick and simple way to minimize the number of results was to filter out exact matches at each endpoint which did not contain the other dataset's domain name. Hence, minimizing the number of *join* operations which had to be handled by the parent endpoint.

In order to put the cost of queries briefly into perspective i.e., the conducted tests and sample sizes of the dataspace that were used; the total number of triples (including observations and metadata) per endpoint are: 50 thousand (Transparency International [24]), 54 million (Food and Agriculture Organization of the United Nations [FAO] [25]), 225 million (Organisation for Economic Co-operation and Development [OECD] [26]), 221 million (World Bank [27]), 242 million (European Central Bank [ECB] [28]), 36 million (International Monetary Fund [IMF] [29]).

The anatomy of the query is shown in Figure [3]. Essentially, the SPARQL Endpoint URI and the dataset URI are the only requirements. The structure of the statements and operations are particular to getting the most out of Apache Jena's [30] TDB storage system [31], TDB Optimizer [32] and Fuseki [33] SPARQL endpoints. Better performing queries can be achieved by knowing the frequencies of the predicates upfront, and choosing better orders for a given dataset to avoid processing of false negatives.

```

SELECT ?refAreaY ?x ?y ?identityX ?identityY
WHERE {
  SERVICE <http://example.org/sparql> {
    SELECT DISTINCT ?identityX ?refAreaX ?refAreaXExactMatch ?measureX
    WHERE {
      ?observationX qb:dataSet <http://example.org/dataset/X> .
      ?observationX ?propertyRefPeriodX exampleRefPeriod:1234 .
      ?propertyRefAreaX rdfs:subPropertyOf* sdmx-dimension:refArea .
      ?observationX ?propertyRefAreaX ?refAreaX .
      ?propertyMeasureX rdfs:subPropertyOf* sdmx-measure:obsValue .
      ?observationX ?propertyMeasureX ?x .
      <http://example.org/dataset/X>
        qb:structure/stats:identityDimension ?propertyIdentityX .
      ?observationX ?propertyIdentityX ?identityX .
      OPTIONAL {
        ?refAreaX skos:exactMatch ?refAreaXExactMatch .
        FILTER (REGEX(STR(?refAreaXExactMatch), "^http://example.net/"))
      }
    }
  }
  SERVICE <http://example.net/sparql> {
    SELECT DISTINCT ?identityY ?refAreaY ?refAreaYExactMatch ?measureY
    WHERE {
      ?observationY qb:dataSet <http://example.net/dataset/Y> .
      ?observationY ?propertyRefPeriodY exampleRefPeriod:1234 .
      ?propertyRefAreaY rdfs:subPropertyOf* sdmx-dimension:refArea .
      ?observationY ?propertyRefAreaY ?refAreaY .
      ?propertyMeasureY rdfs:subPropertyOf* sdmx-measure:obsValue .
      ?observationY ?propertyMeasureY ?y .
    }
  }
}

```

```

<http://example.net/dataset/Y>
  qb:structure/stats:identityDimension ?propertyIdentityY .
  ?observationY ?propertyIdentityY ?identityY .
  OPTIONAL {
    ?refAreaY skos:exactMatch ?refAreaYExactMatch .
    FILTER (REGEX(STR(?refAreaYExactMatch), "^http://example.org/"))
  }
}
}
FILTER (?refAreaYExactMatch = ?refAreaX
        || ?refAreaXExactMatch = ?refAreaY
        || ?refAreaY = ?refAreaX)
}
ORDER BY ?identityY ?identityX ?x ?y

```

Figure 3: Federated SPARQL Query

For the time being, the use of NAMED GRAPHS in the SPARQL queries were excluded for a good reason. For federated queries to work with the goal of minimal knowledge about store organization, the queries had to work without including graph names. However, by employing Vocabulary of Interlinked Datasets (VoID) [34], it is possible to extract both, the location of the SPARQL endpoint, as well as the the graph names within. This is left as a future enhancement.

As statistical datasets are multi-dimensional, slicing the datasets with only reference area and reference period are insufficient. It is likely that there would be duplicate results if we leave the column order to reference area, $measure_x$, $measure_y$. For this reason, there is an additional expectation from the datasets indicating one other dimension to group the observations with. This grouping is also used to display faceted scatter-plots.

Recommendations from On the Formulation of Performant SPARQL Queries [35] and Querying over Federated SPARQL Endpoints — A State of the Art Survey [36] were applied where applicable.

4.6 Analysis caching and storing

In order to optimize application reactivity for all users, previously user selected options for analysis are cached in the Shiny server session. That is, the service is able to provide cached results which were triggered by different users.

In addition to a cache that is closest to the user, results from the federated queries as well as the R analysis, which was previously conducted, is stored back into the RDF store with a SPARQL Update. This serves multiple purposes. In the event that the Shiny server is restarted and the cache is no longer available, previously calculated results in the store can be reused, which is still more cost efficient than making new federated queries.

Another reason for storing the results back in the RDF store is to offer them over the stats.270a.info SPARQL endpoint for additional discovery and reuse of analysis for researchers. Interesting use cases from this approach emerge immediately. For instance, a researcher or journalist can investigate analysis that meets their criteria. Some examples are as follows:

- analysis which is statistically significant, and has to do with Gross Domestic Product (GDP) and health subjects
- a list of indicator pairs with strong correlations
- using the line of best fit of a regression analysis to predict or forecast possible outcomes
- countries which have less mortality rate than average with high corruption

4.7 URI patterns

The design pattern for the analysis URIs which refer to the data and the analysis is aimed to keep the length as minimal as possible, while leaving a trace to encourage self exploration and reuse. The general URI pattern with base <http://stats.270a.info/analysis/> is as follows:

```
{independentVariable}/{dependentVariable}/{referencePeriod}
```

As URIs for both independent and dependent variable are based on datasets, and the reference period is codified, their prefixed names are used instead in the analysis URI to keep them short and friendly:

```
{prefix}:{dataset}/{prefix}:{dataset}/{prefix}:{refPeriod}
```

For example, the URI <http://stats.270a.info/analysis/worldbank:SP.DYN.IMRT.IN/transparency:CPI2009/year:2009> refers to an analysis which entails the infant mortality rate from the World Bank dataset as the independent variable, 2009 corruption perceptions index from the Transparency International dataset as the dependent variable, for the reference interval **year:2009**. The variable values are prefixed names, which correspond to their respective datasets, i.e., **worldbank:SP.DYN.IMRT.IN** becomes <http://worldbank.270a.info/dataset/SP.DYN.IMRT.IN>, and **transparency:CPI2009** becomes <http://transparency.270a.info/dataset/CPI2009> when processed.

4.8 Vocabularies

Besides the common vocabularies: RDF, RDFS, XSD, OWL, the RDF Data Cube vocabulary is used to describe multi-dimensional statistical data, and SDMX-RDF for the statistical information model. PROV-O is used for provenance coverage.

A statistical vocabulary (<http://stats.270a.info/vocab>) [37] is created to describe analyses. It contains classes for analyses, summaries and each data row that is retrieved. Some of the properties include: graph (e.g., scatter plot), independent and dependent variables, reference period, sample size, p-value, correlation value, correlation method that is used, adjusted R-squared, best model that is tested, reference area, measure values for both variables, and the identity concept for both variables.

Future plans for this vocabulary is to reflect back on the experience, and to consider alignment with SemanticScience Integrated Ontology (SIO) [38]. While SIO is richer, queries are more complex than necessary for simple analysis reuse at stats.270a.info.

5 Results

Putting it all together: following the Linked Data design principles, the platform for linked statistical data analyses is now available for different types of users. Human users with a Web browser can interact with the application with a few clicks. This is arguably the simplest approach for researchers and journalists without having to go down the development road. Additionally, humans as well as machines can consume the same analysis as an RDF or JSON serialization. In the case of JSON, the analyses can be used as part of a widget on a webpage. The Scalar Vector Graphics (SVG) format of the scatter plot can be used in articles on the Web. Storing the analyses permanently and having it accessible over a SPARQL endpoint opens up the possibility for researchers to discover interesting statistics. Finally, with the help of Apache Rewrites, Linked Data Pages [39] handles the direction of these requests and provides dereferenceable URIs for a *follow your nose* type of exploration. The source code [40] is available at a public repository.

6 Conclusions

We believe that the presented work here and the prior Linked SDMX Data effort contributed towards strengthening the relationship between Semantic Web / Linked Data and statistical communities. The stats.270a.info service is intended to allow humans and machines explore statistical analyses.

Some research and application areas that are planned as future work:

Making the query optimization file from Jena TDB available in RDF and at SPARQL endpoints can help to devise better performing federated queries, or placed in VoID along with LODStats [41].

With the availability of more interlinks across datasets, we can investigate analysis that is not dependent on reference areas. For instance, interlinking currencies, health matters, policies, or concepts on comparability can contribute towards various analyses.

Enriching the datasets with information on comparability can lead to achieving more coherent results. This is particularly important given that the European Statistics Code of Practice [42] from the European Commission lists *Coherence and Comparability* as one of the principles that national and community statistical authorities should adhere to. While the research at hand is not obligated to follow those guidelines, they are highly relevant for providing quality statistical analyses.

The availability of the analysis in JSON serialization, and the cached scatter plot in SVG format, makes it possible for webpage widget to use them. For instance, they can be dynamically used in articles or wiki pages with all references intact. As the Linked Data approach allows one to explore resources from one item to another, consumers of the article can follow the trace all the way back to the source. This is arguably an ideal scenario to show provenance and references for fact-checking in online or journal articles. Moreover, since the analysis is stored, and the queried data can also be exported in different formats, it can be reused to reproduce the results.

This brings us to an outlook for Linked Statistical Data Analyses. The reuse

of Linked analyses artifacts as well as the approach to collect data from different sources can help us build smarter systems. It can be employed in fact-checking scenarios as well as uncovering decision-making processes, where knowledge from different sources is put to their potential use when combined.

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References

1. Capadisli, S.: Statistical Linked Dataspaces. Master's thesis, National University of Ireland (2012), <http://csarven.ca/statistical-linked-dataspaces>
2. The RDF Data Cube vocabulary, <http://www.w3.org/TR/vocab-data-cube/>
3. Capadisli, S., Auer, S. Ngonga Ngomo, A.-C., Linked SDMX Data, Semantic Web Journal (2013), <http://csarven.ca/linked-sdmx-data>
4. 270a.info, <http://270a.info/>
5. The PROV Ontology, <http://www.w3.org/TR/prov-o/>
6. Zopilko, B., Mathiak, B.: Performing Statistical Methods on Linked Data, Proc. Int'l Conf. on Dublin Core and Metadata Applications (2011), <http://dcevents.dublincore.org/IntConf/dc-2011/paper/download/27/16>
7. The R Project for Statistical Computing, <http://www.r-project.org/>">
8. Zopilko, B., Mathiak, B.: Defining and Executing Assessment Tests on Linked Data for Statistical Analysis, COLD, ISWC (2011), http://iswc2011.semanticweb.org/fileadmin/iswc/Papers/Workshops/COLD/cold2011_submission_13.pdf
9. Hage, W. R. v., Marieke v., Malaisé., V.: Linked Open Piracy: A story about e-Science, Linked Data, and statistics (2012), http://www.few.vu.nl/~wrvhage/papers/LOP_JoDS_2012.pdf
10. SPARQL client for R, <http://cran.r-project.org/web/packages/SPARQL/index.html>
11. McCusker, J. P., McGuinness, D. L., Lee, J., Thomas, C., Courtney, P., Tatalovich, Z., Contractor, N., Morgan, G., Shaikh, A.: Towards Next Generation Health Data Exploration: A Data Cube-based Investigation into Population Statistics for Tobacco, Hawaii International Conference on System Sciences (2012), http://www.hicss.hawaii.edu/hicss_46/bp46/hc6.pdf
12. qb.js, <http://orion.tw.rpi.edu/~jimmccusker/qb.js/>
13. Percy E. Rivera Salas, P. E. R., Mota, F. M. D., Martin, M., Auer, S., Breitman, K., Casanova, M. A.: Publishing Statistical Data on the Web, ISWC (2012), http://svn.aksw.org/papers/2012/ESWC_PublishingStatisticData

- /public.pdf
14. CubeViz, <http://aksw.org/Projects/CubeViz>
 15. Google Public Data Explorer, <http://www.google.com/publicdata/>
 16. Gapminder, <http://www.gapminder.org/>
 17. Dataset Publishing Language, <https://developers.google.com/public-data/>
 18. Paulheim, H.: Generating Possible Interpretations for Statistics from Linked Open Data, ESWC (2012), <http://www.ke.tu-darmstadt.de/bibtex/attachments/single/310>
 19. Explain-a-LOD, <http://www.ke.tu-darmstadt.de/resources/explain-a-lod>
 20. stats.270a.info, <http://stats.270a.info/>
 21. Ngonga Ngomo, A.-C.: LInk discovery framework for MEtric Spaces (LIMES): A Time-Efficient Hybrid Approach to Link Discovery (2011), <http://aksw.org/Projects/limes>
 22. Shiny, <http://www.rstudio.com/shiny/>
 23. Shiny server, <https://github.com/rstudio/shiny-server>
 24. Transparency International, <http://transparency.270a.info/>
 25. Food and Agriculture Organization of the United Nations, <http://fao.270a.info/>
 26. Organisation for Economic Co-operation and Development, <http://oecd.270a.info/>
 27. World Bank, <http://worldbank.270a.info/>
 28. European Central Bank, <http://ecb.270a.info/>
 29. International Monetary Fund, <http://imf.270a.info/>
 30. Apache Jena, <http://jena.apache.org/>
 31. Jena TDB, <http://jena.apache.org/documentation/tdb/index.html>
 32. Jena TDB Optimizer, <http://jena.apache.org/documentation/tdb/optimizer.html>
 33. Jena Fuseki, https://jena.apache.org/documentation/serving_data/
 34. Vocabulary of Interlinked Datasets, <http://www.w3.org/TR/void/>
 35. Loizou, A., Groth, P.: On the Formulation of Performant SPARQL Queries, arXiv:1304.0567 (2013) <http://arxiv.org/abs/1304.0567>
 36. Rakhmawati, N.R., Umbrich, J., Karnstedt, M., Hasnain, A., Hausenblas, M.: Querying over Federated SPARQL Endpoints — A State of the Art Survey, arXiv:1306.1723 (2013) <http://arxiv.org/abs/1306.1723>
 37. Stats Vocab, <http://stats.270a.info/vocab>
 38. SemanticScience Integrated Ontology, <http://semanticscience.org/ontology/sio.owl>
 39. Linked Data Pages, <http://csarven.ca/statistical-linked-dataspaces#linked-data-pages>
 40. LSD Analysis code at GitHub, <https://github.com/csarven/lzd-analysis>
 41. Demter, J., Auer, S., Martin, M., Lehmann, J.: LODStats – An Extensible Framework for High-performance Dataset Analytics, EKAW (2012), <http://svn.aksw.org/papers/2011/RDFStats/public.pdf>
 42. European Statistics Code of Practice, http://epp.eurostat.ec.europa.eu/portal/page/portal/quality/code_of_practice