DataGraft: One-Stop-Shop for Open Data Management¹

Editor(s): Rinke Hoekstra, Vrije Universiteit Amsterdam, The Netherlands Solicited review(s): Christophe Guéret, BBC, UK; Wouter Beek, Vrije Universiteit Amsterdam, The Netherlands; One anonymous reviewer

Dumitru Roman^{a,*}, Nikolay Nikolov^a, Antoine Putlier^a, Dina Sukhobok^a, Brian Elvesæter^a, Arne Berre^a, Xianglin Ye^a, Marin Dimitrov^b, Alex Simov^b, Momchill Zarev^c, Rick Moynihan^d, Bill Roberts^d, Ivan Berlocher^e, Seonho Kim^e, Tony Lee^e, Amanda Smith^f, and Tom Heath^f ^aSINTEF, Forskningsveien 1a, 0373 Oslo, Norway ^bOntotext AD, Tsarigradsko Shosse, 1784 Sofia, Bulgaria ^cSirma Mobile, Bulgaria ^dSwirrl IT LTD, Springbank Road, Macfarlane Gray House, Stirling, FK7 7WT, Stirlingshire, United Kingdom ^eSaltlux Inc., 6F Deok-il Building,967 Daechi-Dong, Guaugnam-Gu, 135-848 Seoul, Republic of Korea ^fOpen Data Institute, St. James Square, St. James House, GL50 3PR Cheltenham, United Kingdom

Abstract. This paper introduces DataGraft (https://datagraft.net/) – a cloud-based platform for data transformation and publishing. DataGraft was developed to provide better and easier to use tools for data workers and developers (e.g., open data publishers, linked data developers, data scientists) who consider existing approaches to data transformation, hosting, and access too costly and technically complex. DataGraft offers an integrated, flexible, and reliable cloud-based solution for hosted open data management. Key features include flexible management of data transformations (e.g., interactive creation, execution, sharing, and reuse) and reliable data hosting services. This paper provides an overview of DataGraft focusing on the rationale, key features and components, and evaluation.

Keywords: data transformation, data publication, data hosting, data-as-a-service, open data, linked data

1. Introduction and Motivation

For the past five years, government and nongovernment institutions in the EU and around the globe have increasingly made data accessible under open licenses and often in reusable formats [1]. Recent statistics clearly display the achievements of these efforts. According to the EU-funded project OpenDataMonitor, 28 European countries have published more than 237,500 datasets through more than 160 catalogues [2]. Compared to the Zettabytes of data that the Internet is estimated to host, 1.25 Terabyte of open data spread across Europe may still appear like a modest result. But given the limitations and difficulties which data publishers and consumers face so far, it is not. A large portion of the data openly available online consists of unstructured or semi-structured information [3], which often makes data consumption difficult and expensive [4]. Furthermore, removing barriers from open data publication and consumption processes remains a primary concern.

DataGraft started with the mission to alleviate some of these obstacles through new tools and ap-

¹ DataGraft is accessible at <u>https://datagraft.net/</u>. This paper presents the capabilities of DataGraft as of January 2016.

Corresponding author. E-mail: <u>dumitru.roman@sintef.no</u>.

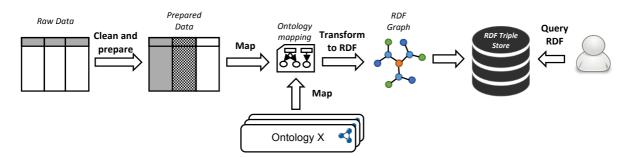


Figure 1. Typical data transformation/publication and access process: from tabular data to a queriable semantic graph.

proaches that support a faster and lower-cost publication and reuse of open data.

Open data is increasingly showing effects in solving problems for the public and private sectors, as well as addressing issues related to the environment and society. Figure 1 displays a typical process for the creation and provisioning of linked open data. Raw data, most often tabular data [5], need to be cleaned, prepared, and transformed to RDF. The data cleaning phase of the process consists of steps related to removing data anomalies. Steps during the cleaning phase may relate to normalising the data (e.g., splitting data values, transposing the dataset, extracting information from the headers, etc.), correcting the data (e.g., filling missing fields, correcting word spelling, replacing special characters, etc.), removing duplicate values, or any other dataset-specific cleaning operations. The preparation phase consists of any additional operations that are specifically needed for the process of RDF transformation (e.g., annotation of data with URIs). Once data are prepared, they are transformed through a mapping, into an RDF graph conforming to the user's chosen ontology and data model. The resulting RDF is then stored in a semantic graph database, or triple store, where data users can easily access and query the data. Conceptually, this process is rather straightforward, however, to date, such an integrated workflow is not commonly implemented. Instead, publishing and consuming (linked) open data remains an intricate, tedious task due to a combination of the following three reasons:

1. The technical complexity of cleaning and preparing open data for publication is high. The technical complexity typically includes a steep learning curve, the need for a lot of configuration and customisation, the lack of scalability with increasing volumes of data, and poor support for developers or end users. Furthermore, toolkits are typically poorly integrated and require expert knowledge. Such expertise includes knowledge of linked data technologies and tools, database and system administration (for maintaining the necessary infrastructure for the proprietary tooling). This is especially true when it comes to more advanced publications of linked data that require consistent, manually curated metadata.

- 2. Even when the data cleaning and preparation process is supported, organisations still face considerable costs to expose their data and provide reliable and scalable access to them. Especially in the absence of direct monetisation or other cost recovery incentives, the relative investment costs can easily become excessively high for many organisations. This might result in open data publishing initiatives being postponed, or executed in a way that makes data access and reuse difficult.
- 3. A poorly maintained and fragmented supply of open data also causes problems for those who want to reuse this resource. Firstly, in many cases, datasets are provided through a number of disconnected outlets. Additionally, even sequential releases of the same dataset are often formatted and structured in different ways. For example, column orders might have changed from one release to the next. Such basic errors make even very simple projects hard to sustain, e.g., running a web application, which relies on a single, continuously updated dataset.

Furthermore, there are a number of interesting problems that require smart solutions in order to assist data publishers and developers in the process depicted in Figure 1:

- Interactive design of data transformations: Designing transformations that provide instant feedback to users on how data changes can speed-up the process and provide users with mechanisms to ensure that the individual clean-up and preparation steps result in the desired outcome.
- *Repeatable data transformations*: Very often a data transformation/publication process needs to be repeated as new data arrives (e.g., monthly budget reports are published through

the exact same process each month). Executable and repeatable transformations are a key requirement for a scalable and lower-cost data publication process.

- *Reusable and shareable data transformations:* Capabilities to reuse and extend existing data transformations created and shared by other developers further improve the speed and lowers the cost of the data publication process.
- Distributed deployment of data transformations: Transforming data necessitates a varying resource utilization due to the varied load requirements with different inputs. Thus, having mechanisms to dynamically deploy and execute transformations in a distributed environment results in a more reliable, scalable and faster data publication process.
- *Reliable data access*: Once data are generated following a data transformation process, provisioning it reliably is another key aspect to ensure access to the data from third party applications and services.

What is therefore needed is an integrated solution that enables a *self-serviced* effective and efficient data transformation/publication and access process. At the very core, this means automating the open data publication process to a significant extent – in order to increase the speed and lower its cost. What this will eventually lead to is that both data publishers and data consumers can focus on their goals:

- *Data consumers* can focus on utilising open data for data-driven decision making, or for creating new applications and services (rather than being data "hunters" and "gatherers");
- Data publishers can focus on providing high quality data in a timely manner, and finding monetization channels for their data (rather than spending time and resources on developing their own data publication & hosting platforms).

DataGraft was developed as a cloud-based platform for data workers to manage their data in a simple, effective, and efficient way, supporting the data transformation/publication and access process discussed above, through powerful data transformation and reliable data access capabilities.

The remainder of this paper provides an overview of DataGraft's key features and core components

(Section 2), evaluation (Section 3), discussion on related systems (Section 4), ending with a summary and outlook (Section 5).

2. DataGraft: Key Features and Components

DataGraft was designed and developed to support two core capabilities: data transformations and reliable data access.

For *data transformations*, DataGraft provides the following features:

- 1. Interactively build data transformations;
- 2. Deploy executable transformations to repeatedly clean, prepare, and transform spreadsheet data;
- 3. Share transformations publicly;
- Fork, reuse and extend transformations built by third parties from DataGraft's transformations catalogue;
- 5. Programmatically access transformations and the transformation catalogue.

Related to *reliable data access*, DataGraft provides the following features:

- 1. Data hosting on DataGraft's reliable, cloudbased semantic graph database;
- Query data through generated SPARQL endpoints or access data via linked data APIs;
- 3. Share data publically;
- 4. Programmatically access the data catalogue;
- 5. Operations and maintenance performed on behalf of users.

DataGraft realizes these capabilities through four core technical components, as shown in Figure 2.

Grafter is a software library for data cleaning, preparation and transformation to RDF. This is supplemented by **Grafterizer**, the front-end framework and interface for the underlying Grafter library in DataGraft. The **Semantic Graph Database-as-a-Service (DBaaS)**, establishes DataGraft's data warehouse for RDF data. Finally, the **DataGraft portal** ties together these service offers through a userfriendly, one-stop front-end. In the following we describe these components in further detail and end with a summary of additional backend services and APIs.

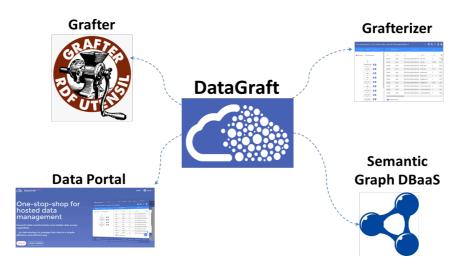


Figure 2. Core components of DataGraft.

2.1. Grafter

Grafter² is a library of reusable components designed to support complex and reliable data transformations, which are exposed to DataGraft through the Graftwerk service. At the heart of Grafter is a domain-specific language (DSL), which allows the specification of pipelines that convert tabular data (e.g., for the purpose of cleaning it up), or transform it to produce linked data graphs.

It is implemented using Clojure, a functional programming language that runs on the Java Virtual Machine (JVM). A functional approach is well suited to the idea of a transformation pipeline and by using a JVM-based implementation it becomes straightforward to exploit the large collection of useful libraries already available for the ecosystem of JVM-based programming languages.

Grafter benefits additionally include:

 Clean-up, preparations and transformations to RDF are free from side effects and implemented as pure functions on immutable data. This is important in supporting transformation previews as data is not changed in place, and transformations can be run without causing potentially destructive effects. Additionally reasoning about pure functions is simpler than reasoning in imperative model, as functions only take values and return them, whereas procedures can do this and cause unrestrained side effects.

- Grafter supports large data transformations efficiently. Unlike other tools it takes a streaming approach to processing data, which means the maximum size of the dataset that can be processed is not limited by the available memory. The streaming approach leverages Clojure's lazy sequences to represent the sequence of rows in the data. Clojure's lazy sequence abstraction allows to treat unrealized data as if they were realized, which is achieved through in-memory sequences. As values are required from the sequence, they are realized and cached in memory within the sequence abstraction.
- It supports an easy way to convert tabular data into linked data, via graph templates, which specify how a row of tabular data maps to a set of RDF triples. In Grafter, graph templates are defined as part of the functions, which can be called when the tabular data needs to be transformed to RDF.
- It has an efficient streaming implementation of a normalising melt [6] operation (going from a 'wide' table format to a 'long' table format), that lets you easily change crosstabulations featuring arbitrary numbers of categories (frequently used to summarise data), back into a normalised representation suited for machine processing. A common use case is in converting pivot tables [7].

² <u>http://grafter.org/</u>

	Grafterizer							
grafter.tabular	grafter.rdf.templater grafter.rdf.io g	rafter.rdf.repository						
grafter.sequences	grafter.tabular	grafter.url						
grafter.pipeline								

Figure 3. Grafter architecture stack.

- It provides APIs for serialising linked data in almost all of its standard serialisations.
- It provides integration with semantic graph databases (triple stores) via standard interfaces.
- It has a highly modular and extensible design.

Grafter is composed of a number of modules to cleanly demarcate functionality, as illustrated in Figure 3. These modules broadly fall into two categories identified by the namespaces grafter.tabular and grafter.rdf. These two primary divisions represent the two sides of the Extract-Transform-Load (ETL) problem Grafter is addressing:

- The cleaning and preparation of tabular data.
- The transformation and loading of that data into linked data (RDF).

The grafter.tabular namespace contains a wide variety of data processing functions for filtering data (by row, column or cell contents) and applying userspecified transformation functions to cells through functions like derive-column, which adds a new column to the dataset derived by applying a function to every cell in one or more source columns. Additionally, it includes more complex and powerful functions for normalising data into a more uniform form such as fill-when, which can be used to copy omitted values down a column, and melt, which is similar to melt from the reshape2 package in R.

Functionality is also being added to help materialise errors and ensure they can be displayed in the appropriate cell or context where they occur. Tabular Grafter transformations are typically expressed as a sequence of step-wise operations on whole tables of data. All tabular operations are simply pure functions that take a *dataset* (a table) as input, and produce a *dataset* as output.

This can be seen in the example Grafter code in Figure 4(a). This tabular dataset transformation processes a spreadsheet where each line represents a function call that receives a *dataset* (table) and returns a new one that has been changed. Sequences of tabular operations such as those, where a table is received as input and returned as output, are called *pipes*.

Pipes are simply a set of pure functions, composed together with the restriction that they receive a *dataset* as their first argument, and must return a *dataset* as their return value. The interesting property about *pipes* is that they can be composed together arbitrarily, and always result in a valid *pipe*. Additionally because the inputs, outputs and intermediate steps to pipes are always tables, they are very intuitive for users to manipulate and use.

In order to publish linked data, a final step must take place to transform the input data and produce the graph structure used by RDF. This final step is referred to as a *graft*. A *graft* maps each row of the source data into a graph. That graph is made up of a sequence of 'quads' as used in the RDF approach, each consisting of a subject, predicate, object and context.

```
(-> (read-dataset data-file)
    (make-dataset move-first-row-to-header)
    (drop-rows 1)
    (derive-column :permeab-en [:idPermeab]
                                            map permeability code to definition en)
                               [:idPermeab]
    (derive-column :permeab-es
                                            map_permeability_code_to_definition_es)
    (derive-column
                   :permeab-pt
                                 idPermeab]
                                            map_permeability_code_to_definition_pt)
                                                                                                   (a)
                               [:IdAcidity]
                                            map_acidity_code_to_definition_en)
    derive-column
                   :acidity-en
    derive-column
                   :acidity-es
                                :IdAcidity]
                                            map_acidity_code_to_definition_es)
    (derive-column :acidity-pt [:IdAcidity]
                                            map_acidity_code_to_definition_pt))
(def make-graph
 (graph-fn [{:keys [permeab-en permeab-es permeab-pt acidity-en
                     acidity-es acidity-pt idLitholo]}]
    (graph "http://data.smartopendata.eu/sp-pt-pilot/
      [(base-soil idLitholo) [rdf:a smod:Soil]
                             [smod:soilPermeabilityRate
                               (datatypes/convert-literal permeab-en "string" :lang-tag "en")]
                                                                                                   (b)
                             [smod:soilPermeabilitvRate
                               (datatypes/convert-literal permeab-es "string" :lang-tag "es")]
                             [smod:soilPermeabilityRate
                               (datatypes/convert-literal permeab-pt "string" :lang-tag "pt")]
                             [smod:soilAcidity
                               (datatypes/convert-literal acidity-en "string" :lang-tag "en")]
                             [smod:soilAcidity
                               (datatypes/convert-literal acidity-es "string" :lang-tag "es")]
                             [smod:soilAcidity
                               (datatypes/convert-literal acidity-pt "string" :lang-tag "pt")]
                             1)))
```

Figure 4. Grafter sample code of data transformation (a) and creation of RDF triples (b).

Because a *graft* takes as input a table and returns a lazy sequence of quads representing the linked data graph as its output, it doesn't have the composition property that pipes do. However, additional filtering steps can be added to the stream of quads if necessary.

Typically the bulk of clean-up and preparations are best performed whilst the data is in the table, though post processing can be performed by filters.

Grafter supports a simple graph template to express the conversion of each row of an input tabular dataset into a graph. That template makes use of a simple sub-DSL to specify commonly-used RDF generation, combined with selections from the input data and literal values.

The code in Figure 4(b) is used to express the mapping of columns in a tabular *dataset* into its position in a linked data graph.

Generating RDF from tabular data with the help of Grafter is compliant with the W3C recommendation defined in [8], although doesn't follow it precisely. The conversion procedure described in the W3C recommendation operates on an annotated tabular data model and provides an exact algorithm for data conversion. In contrast, Grafter provides more flexibility by allowing users to add necessary annotations to the table just before the conversion to RDF and to define proprietary algorithms for generating it. In DataGraft, Grafter comes together with **Graftwerk** – a back-end service (accessed through a RESTful API) for executing transformations. Graftwerk provides a sandboxed Platform-as-a-Service (PaaS) execution environment for Grafter transformations and supports two primary platform features:

- 1. The ability to execute a given Grafter transformation on the entirety of a supplied tabular dataset. The results of the whole transformation are returned.
- The ability to specify a page of data in the tabular data to apply the supplied Grafter transformation to, and to return a preview of the results of the transformation on that subset.

The first of these features ensures that transformations hosted on DataGraft can be applied to arbitrary datasets, generating results for download or hosting. The second feature for generating live previews of the transformation is critical to providing a high quality interactive user experience via the interface. Graftwerk supports both of these features on both kinds of transformations: *pipes* and *grafts*.

Further information about Grafter and Graftwerk can be found in [9] and [10].

	PIPELINE	RDF MAPPING	CLOJURE			/ED DATA	/ 1140343	soilAcidity s		NALDATA	- "	Û
Sh Edit prefixes			î	idLitholo 🗸	idPermeab,	IdAcidity 🗸	permeab-en 🗸	permeab-es 🗸	permeab-pt 🗸	acidity-en	√ acidit	v =
2	÷,,		- 1	101	3	2	High	Alta	Alta	Neutral	Neutro	
	9		- 1	102	3	2	High	Alta	Alta	Neutral	Neutro	0
	make-dat aset		- 1	10	1	3	Low	Baja	Baixa	Acid	Ácido	
	drop-rows			11	1	3	Low	Baja	Baixa	Acid	Ácido	
	derive-column		- 1	12	1	3	Low	Baja	Baixa	Acid	Ácido	
	derive-column	1		13	1	1	Low	Baja	Baixa	Basic	Básic	0
	-			15	1	1	Low	Baja	Baixa	Basic	Básic	0
	derive-column			16	1	3	Low	Baja	Baixa	Acid	Ácido	
	derive-column			210	1	1	Low	Baja	Baixa	Basic	Básic	0
	derive-column		- 1	4								
	derive-column		- 1	Automa	atic preview						C C	Э

V M V 🖉 Stem API - Obscience v X 🖓 Material Design - Kei: X 🗋 DB 2 SUM X V V server (synthetice Y unit: X V Dialard Rotes) Ten: X V Dialarotes) Ten

VIETADATA PI	ELINE ROF MAPPIN	۱.	CLOJURE		PI	IEVIEWED DATA				ORIGINAL	DATA	
🛑 Map the tabular da	a to RDF			idLitholo ~	idPermeab~	IdAcidity v	permeab-en v	permeab-es \sim	permeab-pt ~	acidity-en ~	acidity-es v	acidity-p
				101	3	2	High	Alta	Alta	Neutral	Neutro	Neutral
Edit RDF mapping prefixe	5			102	3	2	High	Alta	Alta	Neutral	Neutro	Neutral
				10	1	3	Low	Beja	Baixa	Acid	Ácido	Acid
raph URI				11	1	3	Low	Baja	Baixa	Acid	Ácido	Acid
ittp://data.smartopenda	ta.eu/sp-pt-pilot/			12	1	3	Low	Baja	Baixa	Acid	Ácido	Acid
				13	1	1	Low	Baja	Baixa	Basic	Básico	Basic
(Lase soil)	0.074	0	(arred)	15	1	1	Low	Baja	Baixa	Basic	Básico	Basic
- idLibiolo		0	Soll	16	1	3	Low	Beje	Baixa	Acid	Ácido	Acid
	Sancd soilPermeab.	0	permeab-en	210	1	1	Low	Baja	Baixa	Basic	Básico	Basic
	O shod sorterness.	0	permeases	21	1	1	Low	Baja	Baixa	Basic	Básico	Basic
				22	2	2	Medium	Media	Média	Neutral	Neutro	Neutral
	🔿 snod soiPerneab	0	permeab-es	2310	1	0	Low	Baja	Baixa	No data	No data	No data
				23	1	0	Low	Baja	Baixa	No data	No data	No data
	🔘 smod soiPerneab	0	permeab-pt	310	1	3	Low	Baja	Batxa	Acid	Acido	Acid
				33	2	3	Medium	Media	Média	Acid	Ácido	Acid
	nod soilAcidity	0	acidity-en	34	1	2	Low	Baja	Baixa	Neutral	Neutro	Neutral
	<u> </u>	- C		35	3	3	High	Alta	Alta	Acid	Ácido	Acid
	0	0	acidity-ea	36	2	2	Medium	Media	Média	Neutral	Neutro	Neutral
	🔘 smod soilAcidity	0	anniy-ea	37	1	2	Low	Beja	Batxa	Neutral	Neutro	Neutral

Figure 5. Grafterizer transformation pipeline and preview (a) and RDF mapping (b).

2.2. Grafterizer

Grafterizer [11] is the web-based framework for data cleaning, preparation and transformation based on Grafter. It provides an interactive user interface with end-to-end support for data cleaning, preparation (Figure 5(a)) and RDF transformation (Figure 5(b)):

• Live preview – Grafterizer interactively displays the results of the tabular clean-up or preparation steps in a side-panel. It also retains a view of the original version of the uploaded tabular dataset. Additionally, in case errors in the transformation or RDF mapping are present, it is equipped with an integrated error reporting capability.

- Forking of existing transformations the user interface allows users to create copies of transformations by a single click of a button.
- Specifying and editing data cleaning (pipeline) steps – the clean-up and preparations performed on tabular data can be added, edited,

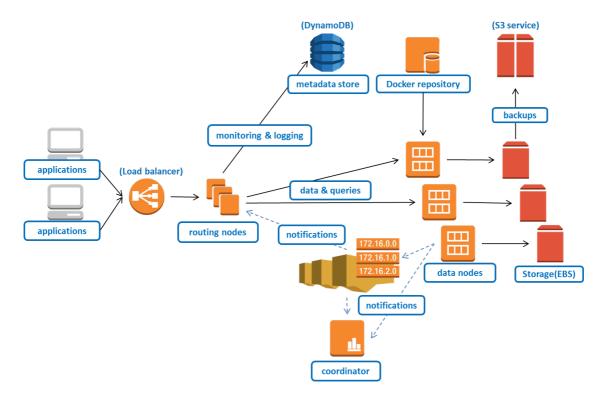


Figure 6. Architecture of the RDF DBaaS.

reordered or deleted. All functions are parameterised and editing allows users to change each of these parameters within the function with immediate feedback.

- Data page generation based on the specified RDF mappings, users are able to directly produce and publish data pages where their data will be available for access through an endpoint.
- Direct download of resulting data the cleaned-up/transformed data from Grafterizer (both CSV and mapped RDF) can be directly accessed and downloaded locally.
- Customisation data clean-up and preparation, are fully customisable through embedding custom code, both as individual cleanup/preparation steps, or part of certain steps. In addition, developers can directly edit the resulting Clojure code and see the result in interactive mode.

Grafterizer implements a web-based wrapper over the Grafter library and Graftwerk service. The interface allows users to specify Grafter transformations in a much easier and more intuitive manner, compared to directly coding in Clojure. It also provides instant feedback alongside the other features described in the previous section.

The Grafterizer interface works by submitting the transformation that is being specified to the Graftwerk service along with the data that needs to be cleaned, prepared and/or transformed. Depending on the type of the request, Graftwerk will then either generate a preview of the data that the UI can display, or return the output data (linked or tabular).

In order to produce linked data, RDF mappings are (typically) executed over well-formed CSV files, whereby each row contains one entity and each column represents an attribute of the entity. Nevertheless, Grafterizer is meant to operate with any form of CSV input, whereby any malformed CSV can be normalised into a well-formed one-record-per-row/one-fieldper-column structure using the data transformation functions provided in the UI. The result of a transformation can be either a set of RDF triples that can be hosted on DataGraft in its semantic graph (RDF) store (described in the next subsection), or a tabular dataset that can be downloaded or accessed from the platform's file storage.

Further information about Grafterizer and its integration with DataGraft can be found in [12].

2.3. Semantic Graph Database-as-a-Service

DataGraft's database-as-a-service is a fully managed, cloud-based version of GraphDB[™] semantic graph database (triple store), which provides an enterprise-grade RDF database as-a-service. Users therefore do not have to deal with typical administrative tasks such as installation and upgrades, provisioning and deployment of hardware, back-up and restore procedures, etc. The utilization of cloud resources by the DBaaS depends on the load of the system itself, whereby they can be elastically provisioned and released to match the current usage load.

From a user standpoint, the DBaaS supports an API for linked data access, querying, and management. These functionalities are based on a complex architecture, which ensures components scalability, extensibility and availability on large scale (see Figure 6).

The DBaaS implementation follows the principles of micro-service architectures, i.e., it is composed of a number of relatively small and independent components. The data management architecture is based on the Amazon Web Services (AWS) cloud platform and consists of the following components:

- Load balancer the entry point to the database services is the load balancer provided by the AWS platform, which routes incoming data requests to one of the available routing nodes. It can distribute requests even between instances in different datacentres.
- *Routing nodes* host various micro-services such as: user authentication, access control, usage, metering, and quota enforcement for the RDF database-as-service layer. The frontend layer is automatically scaled up or down (new instances added or removed) based on the current system load.
- Data nodes this layer contains nodes running multiple instances of the GraphDB[™] database (packaged as Docker³ containers). Each data publisher has its own database instance (container), which cannot interfere with the database instance or with the data of other users of the platform. The data are hosted on network-attached storage volumes (EBS)⁴ and each user/database has its own private EBS volume. Additional OS-level security ensures appropriate data isolation and access control.

- Integration services (denoted by dashed arrows in Figure 6) a distributed queue and push messaging service enable loose coupling between the various front-end and database nodes on the platform. All components use a publish-subscribe communication model to be aware of the current state of the system. This allows the front-end and the backend layers to be scaled up or down independently as they are not aware of their size and topology.
- Distributed storage all user data are stored on the reliable and redundant networkattached storage (EBS), whereas static backups and exports remain on the S3 distributed storage. Logging data, user data as well as various configuration metadata are stored in a distributed NoSQL database (DynamoDB).
- Monitoring services the AWS cloud provides various metrics for monitoring the service performance. The DBaaS utilises these metrics in order to provide optimal performance and scalability of the platform. The different layers of the platform can be automatically scaled up (to increase system performance) or down (to decrease operational costs) in response to the current system load and utilisation.

Further information about semantic graph database used in DataGraft can be found in [13].

2.4. DataGraft Portal

The DataGraft portal integrates the previously discussed components together in a modern, userfriendly web-based interface designed to ensure a natural flow of the supported data processing and publication workflow. Accordingly, four main aspects have been considered and addressed throughout the development of DataGraft's portal front-end:

- 1. Design and implement a highly intuitive UI, which facilitates user interaction with large, complex sets of linked open data.
- 2. Simplify the data publishing process by implementing a fast-track for publishing data, e.g., using simple drag and drop operations.
- 3. Create basic data exploration tools, which help users with limited technical skills to explore data hosted on the DataGraft platform.

³ <u>https://www.docker.com/</u>

⁴ http://aws.amazon.com/de/ebs/



edFemalesVestby - EmployedFemalesSki

- Figure 7. Configuring widgets (a) and visualizing data (b) in DataGraft.
- Deploy data visualization components that can 4. be easily used by non-specialists to build data driven portals.

5000

4500 4000

'alues 3500

300

2500

2000

Two complementary modules have been implemented to create the DataGraft portal. Firstly, a dragand-drop interface, which allows users to easily publish and annotate data. The entire process of publishing data is thus reduced to a simple wizard-like interface, where publishers can simply drop their data and enter some basic metadata. All data that are published on the platform are accessible via data pages. Users who publish on DataGraft can specify whether the data is made publically available or not (i.e., if the

data page is public or private) and the license under which the data is made available. Finally, the DataGraft portal provides a module that helps visualize data from the semantic graph database (triple store). Publishing data on the web usually implies specific programming skills in order to create web pages or portals. Thereby, the programming process has been all but eliminated through the deployment of visualization widgets that can serve as reusable components for data publishing. These widgets can access and use data in the repository and expose it through a data page. Currently, the platform provides a number of visualization widgets, including tables, line charts, bar charts, pie charts, scatter charts, bubble charts and

-			C 1	beta
Da	tac	ira	FF.	
 Du	cu v	Jiu		

Explore

Dashboard

Publish

Public transformations

Search

Public data pages

Data page 🔶	User 🖨	Published 🖨	Transformation 🔶	
AGSA ForestryTile Plant Species	smod	28 Sep	TRAGSA Chemical characteristics - soil acidity soil	S
AGSA3_sorted_idWorkUnit_located_idParcel	smod	27 Sep	permeability	
AGSA3_sorted_parcels-processed	smod	27 Sep	London demo - TRAGSA Chemical characteristics - soil acidity soil permeability	tes
AGSA ChemicalCharacteristics SoilAcidity ilPermeability	smod	22 Sep	TRAGSA WorkUnitEcosystem AnimalSpecies-fork	sm
AGSA WorkUnitLocation Municipality	smod	22 Sep	TRAGSA Climatology IdPluvio	sn
AGSA WorkUnitLocation IdDistrict IdNuts	smod	22 Sep	TRAGSA WorkUnitEcosystem AnimalSpecies-fork-fork	no
AGSA3_sorted_idLandSp_code	smod	22 Sep	TRAGSA ForestryTile Plant Species-fork	sn
AGSA3_aux_020400_InvTerresAnimalSp	smod	22 Sep	TRAGSA WorkUnitEcosystem InvTerresAnimalSp	sm
AGSA3_sorted_idWorkUnit_idLitholo	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit idLandSp	sm
AGSA WorkUnitLocation Neighborhood	smod	22 Sep	TRAGSA ChemicalCharacteristics SoilAcidity SoilPermeability	sm
AGSA WorkUnitLocation Districts	smod	22 Sep	TRAGSA WorkUnitLocation IdDistrict IdNuts	sm
AGSA3_fixed_sorted_idWorkUnit_located_idNeighbor	smod	22 Sep	TRAGSA WorkUnitLocation IdDistrict Idivitis	sm
AGSA WorkUnitLocation IdMuni IdDistrict	smod	22 Sep	TRAGSA WorkUnitLocation IdNeighbor IdMuni	sm
AGSA WorkUnitLocation IdNeighbor IdMuni	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit	sn
AGSA3_sorted_idWorkUnit1	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit	sm
AGSA3_sorted_idWorkUnit2	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit IdCLC06	sm
AGSA3_sorted_idWorkUnit_idCLC00	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit IdCLC90	sm
AGSA3_sorted_idWorkUnit_idCLC06	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit IdeLess	sm
AGSA3_sorted_idWorkUnit_idCLC90	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit IdEalidSp	sm
AGSA3_sorted_idWorkUnit_IdLandSp	smod	22 Sep	TRAGSA WorkUnitLocation IdWorkUnit IdParcel	sm
			TRAGGA WORKOHILLOCATION IG WORKOHIL IGT GIVEN	3111

Figure 8. Data pages catalogue (left) and data transformations catalogue (right).

maps (using the Google Maps widget). All widgets are populated with data through the use of specific SPARQL queries on RDF databases.

Figure 7(a) depicts the configuration of a line chart widget using SPARQL for comparing statistical data on employment in two municipalities in Norway, and the result of the visualization on a data page is shown in Figure 7(b).

Further information about the DataGraft portal can be found in [14].

2.5. DataGraft Backend Services and APIs

In addition to the core components described above, DataGraft comes with a set of services (that can be accessed through RESTful APIs) for managing data and transformations, user management, security and authentication.

DataGraft provides capabilities to search the data pages and data transformation catalogues. Figure 8

depicts the data transformations and data pages catalogues as seen by a DataGraft user.

Examples of back-end services for data transformations include CRUD operations on transformations catalogue (create, retrieve, update, or remove data transformations), as well as distribution of transformations code and services supporting the interactive preview of transformations.

Examples of back-end services for data include: CRUD operations on data pages catalogue (create, retrieve, update, or remove data pages); distribution of data (DCAT⁵ compliant); services for managing DBaaS instances; and services for querying of the linked data graphs using the OpenRDF API.

Further information about the DataGraft backend services can be found in [12] and [13].

ıblished 🗲

Next -

⁵ http://www.w3.org/TR/vocab-dcat/

Table 1 summarizes the technical components of DataGraft and Figure 9 provides an architectural overview and how components are interdependent.

Grafter	Clojure-based DSL for data cleaning, preparation and transformation
Graftwerk	Grafter/Clojure execution engine
Grafterizer	Front-end framework for data clean- ing, preparation and transformation
Portal UI	Dashboard, exploration, user data, API keys, upload of files, data pages, transformation pages
Back-end services	User management, cataloguing, trans- formation management, data publish- ing
Semantic graph DBaaS	Cloud-based data-as-a-service com- ponent

Table 1. Summary of DataGraft components and their capabilities

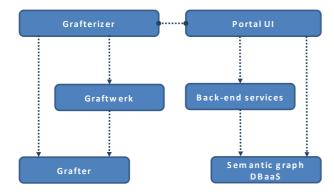


Figure 9. DataGraft high level components interactions.

3. Evaluation

The DataGraft platform was launched in public beta in September 2015. Early usage figures show that the platform, by beginning of December 2015, has:

- 495 (91 public) registered data transformations
- 1520 uploaded files
- 181 registered users
- 183 public data pages

DataGraft has been used in various domains to transform and publish data. In general, the following

positive aspects resulted from the use of DataGraft in practice:

- Simplified data publishing process;
- Time-efficient data transformation and publishing process;
- Repeatable and sharable data transformation process;
- Data hosting and querying support, with possibility to visualize data;
- Support for integration of transformed RDF data with external data sources using established web standards.

In the following we provide examples of how DataGraft was used in practice, the positive aspects and limitations identified in those examples.

3.1. PLUQI

Saltlux,⁶ a South Korean company operating in the domain of knowledge management, developed a Web application called the *Personalised Localised Urban Quality Index* (PLUQI). PLUQI implements a customizable index model that can be used to represent and visualize the level of well-being and sustainability for given cities based on individual preferences.

Aside from building an attractive and engaging end-user interface, the main challenges associated with PLUQI were to integrate and/or merge data from various sources, e.g., open data portals, social sensor systems, etc. This index model takes into account data from various domains such as daily life satisfaction (weather, transportation, community, etc.), healthcare level (number of doctors, hospitals, suicide statistics, etc.), safety and security (number of police stations, fire stations, crimes per capita, etc.), financial satisfaction (prices, income, housing, savings, debt, insurance, pension, etc.), level of opportunity (jobs, unemployment, education, re-education, economic dynamics, etc.), and environmental needs and efficiency (green space, air quality, etc.).

PLUQI was implemented in two iterative versions. The first implementation used Korean data, providing a semantic integration of heterogeneous open data from the Korean Statistical Information Service (KOSIS). This included nine files processed in DataGraft with the help of five reusable transformations. Four of them were created via the forking (copying) capabilities of DataGraft. The transfor-

⁶ <u>http://saltlux.com/</u>

mations for the Korean data processing included 15 special utility functions with custom code, 10 of which were reused across different transformations. The second implementation has been developed based on similar data about Scotland (from the statistics office of the Scottish Government, and other open data), and it compares the PLUQI index between Edinburgh and other council areas.

A typical process for implementing an application such as PLUQI requires four main steps: (1) data gathering (identifying relevant data sources); (2) data transformation (cleaning, preparation, harmonization, integration); (3) data provisioning (making integrated data reliably available); and finally (4) implementing the application (e.g., web application, visualizing and accessing the provisioned data). DataGraft was used for steps (2) and (3) for transforming/integrating data, and reliably provisioning the data. Saltlux reported reduction of cost for implementing these steps of approximately 23% compared to traditional approaches (i.e., use of spreadsheets for data transformation and data publication, proprietary tooling, or technologies, such as relational databases and manual coding/scripting) for integrating and provisioning data. This enabled Saltlux to focus on steps (1) and (4) while outsourcing the other two steps to DataGraft.

DataGraft was perceived as a convenient platform to integrate various datasets into one repository based on the linked data approach. It supports transformation features for raw datasets, which are not written in RDF format so that they can be retrieved using SPARQL queries, linking them to other datasets. This functionality was recognised as very powerful for services such as PLUQI that need to use various datasets. Data are also expected to be retrievable from one repository, enabling a reasonable response time against the user's requests. PLUQI illustrates the capability of DataGraft to support a wide variety of data integration and analysis applications.

The capability of DataGraft to allow users to share data transformations was considered as a really useful feature when transforming datasets with related structure. For example, when transforming air quality data for different cities – one transformation pipeline for one city was reused with small modifications to transform air quality data from other cities. In addition, most of the input files for PLUQI contained the same quality issues (e.g., not normalized headers, malformed column header labels, etc.) and required similar transformation operations for transposing data, reformulating column header labels and bringing data into a normalized form. However, these operations were not exactly the same for every input file because of their structure. DataGraft allowed formulating complex transformation operations as parameterized utility functions and forking the entire transformation with all the utility functions within the transformation. Creating the transformations via the forking capability of DataGraft made it possible to avoid the tasks related to creating normalization functions from scratch. Instead, it allowed reusing them with different parameters, which significantly reduced the time and effort needed to transform the data.

When it comes to limitations, PLUQI revealed the need for DataGraft to export or share visualization widgets that can be used by third party services or applications: currently, the data pages in DataGraft provide capabilities to visualize datasets in various widgets, but it was pointed out by PLUQI developers that it would be useful to implement exporting and sharing features for widgets, in order to raise the usability of the portal. In addition, DataGraft did not provide capabilities for ontology editing, and therefore the PLUQI developers had to use third party ontology editing tools such as Protégé to create the ontologies against which that data was annotated in the RDF publication process.

Further information about the PLUQI application can be found in [15] and [16].

3.2. Transforming and Publishing Environmental Data

As part of the SmartOpenData project⁷, DataGraft was used to transform and publish data as open data in the biodiversity and environment protection domain from two organizations: TRAGSA, a Spanish company, and ARPA, the environmental protection in Italy. In the case of TRAGSA, 42 transformations were created, out of which 25 were created via the reuse/forking capability of Grafterizer. For the purposes of ARPA, five transformations were created, out of which two were created via the reuse/forking capability. The following aspects were noted during the data transformation/publication process:

• The ability to 'fork' (copy, then adapt) existing transformations allowed users to easily reuse existing transformations and thus save time in the process of creating a new transformation.

⁷ <u>http://www.smartopendata.eu/</u>

• The ability to edit the parameters of each transformation step interactively, and to change the order of steps, helped them to: create transformations in general, detect and correct mistakes, experiment with different parameters for clean-up and preparation steps, specify proprietary transformation designs (through the ability to add utility functions with custom code) and reuse proprietary functions.

The users identified some features not currently available in Grafterizer that would have made the tools more useful for them, notably the ability to join more than one input dataset and the ability to sort datasets. To overcome these limitations, it was necessary to carry out some pre-processing of the input files (e.g., for one transformation, 27 of the 43 files tested required some pre-processing). It is possible to perform joins and to sort inside a Grafter pipeline, but at the time of the writing of this paper, the Graftwerk back-end did not yet provide explicit support for these operations.

3.3. Other Examples

Statsbygg⁸ – the Norwegian government's key advisor in construction and property affairs - has experimented with DataGraft for the purpose of publishing their data about public buildings in Norway and integrating it with external information about accessibility in buildings (e.g., types of facilities for the disabled). This was done in order to provide better information about public buildings in Norway, and enable a more efficient mechanism to share data about public buildings. In this context, DataGraft was used for a wide range of tasks, including cleaning and preparation of tabular data about buildings, data transformation, generation and hosting of RDF data, integration with external data sources, querying the integrated data (e.g., which public buildings are located in Oslo and don't have handicapped entrances), and visualization of public buildings and associated data on a map.

Noted benefits for use of DataGraft in this context included the possibility to create a "live" services (vs. storing and managing information about public buildings using spreadsheets) that can be easily updated as new data becomes available, efficient sharing of data, and simplified integration with external datasets. On the other hand, lack of selective data sharing in DataGraft was pointed out – it is often the case that some buildings such as prisons or King's properties are not to be shared in an open fashion. This is not necessarily a technical deficiency of DataGraft but it is rather expensive to enforce it in practice. Group- or role-based access control of DataGraft assets (which as of the writing of the paper is not supported in DataGraft), could be a potential solution to share data selectively.

Another example where DataGraft has been applied is in publishing statistical data as RDF, querying and visualization. For instance, DataGraft was applied for cleaning, preparation, and transformation statistical data from StatBank Norway⁹. StatBank contains detailed tables with various time series data. Users can create custom selections and serialise them in different file formats. An interesting observation here was the ease of use of repeatable and reusable transformations provided by DataGraft, which allowed users to repeatedly apply and adjust transformations on the tables generated from StatBank Norway. Figure 7 depicts an example of configuring a widget and visualizing the RDF data transformed from StatBank Norway. In this context, users pointed out the limitation of DataGraft of currently allowing only CSV files as input for data transformations. The limitation is related to the capabilities of Graftwerk (the transformation execution service), and not of Grafter. As a matter of fact, Grafter, as a standalone library, has been applied by Swirrl¹⁰, a UK SME working in data publishing, to generate a large number of linked data datasets for local government organisations in the UK (including Glasgow, Hampshire, Surrey and Manchester councils) whose source data covered a range of file formats, including CSV, Excel, PostGIS (relational database with GIS extensions), and ESRI Shapefiles (a common GIS format).

DataGraft has been used in other contexts for transforming and publishing data, such as air quality sensor data from the CITI-SENSE project¹¹, data about transportation infrastructure (e.g., the road network, bridges, etc.) and the impact of natural hazards in transportation infrastructure as part of the InfraRisk project¹², or investigating crime data in small geographies¹³. Furthermore, DataGraft components are being taken up in various other contexts. For ex-

¹² http://www.infrarisk-fp7.eu/

⁸ <u>http://www.statsbygg.no/</u>

⁹ https://www.ssb.no/en/statistikkbanken

¹⁰ <u>http://www.swirrl.com/</u>

¹¹ <u>http://www.citi-sense.eu/</u>

¹³ <u>http://benproctor.co.uk/investigating-crime-data-at-small-geographies/</u>

ample, typical open source project metrics show that Grafter currently has 87 stars on Github, external contributors, and receives typical email & bug reports from external users. The semantic graph DBaaS component is also deployed as part of Ontotext's S4¹⁴ product which has commercial customers.

Currently DataGraft is offered as a free service with some imposed limitations per account as follows:

- Data upload: Users can upload CSV files of up to 10MB each, and RDF files of up to 100MB each;
- Data pages: Users can have up to 10 RDF data pages;
- Persistent storage: Users can host up to 2 GB of CSV data, and 10 Million RDF triples for RDF data.

The number of databases that are hosted on a single virtual machine (data node) varies depending on the amount of available hardware resources. The currently deployed (the default free offering) data nodes on DataGraft host eight RDF databases per node with up to 10 repos per database of up to 10 million triples. Each RDF database has around 2GB of reserved memory for performing queries. The amount of reserved memory can be re-configured on request (or based on the needs of the platform) – it can be set to 1, 2, 4, 8 or 16GB based on the size of the database and performance requirements. As of now, the limitations for data upload, number of data pages and persistent storage are enforced in order to maintain DataGraft as a free offering to its users. Nevertheless, DataGraft does allow for the hosting and transformation of much larger quantities of data. The largest deployed database in DataGraft (not supported as a free offering) can host up to 1 billion triples in up to 50 repositories. Transforming large quantities of data is implemented through taking advantage of the Clojure (Grafter) compatibility with the JVM. This means that all transformations specified in DataGraft can be bundled into executable Java Archives (JAR files). These JARs are available through a DataGraft service and can be downloaded and executed locally to process arbitrarily large inputs.

4. Related Work

DataGraft offers an integrated, flexible, and reliable cloud-based service, whereby maintenance of resources and infrastructure are transparent to the user. This frees data experts from having to deal with systems engineering aspects and enables them to focus on their domains of expertise related to the actual data tasks. Furthermore, its unique combination of features provides out-of-the-box and integrated tools, which reduces the effort to quickly implement a process of data transformation and publication. The combination includes features such as interactivity in data transformations, the provided DSL to implement them, reliability, seamless data provisioning, scalable cloud-based triple store, and other user-oriented features (e.g., the catalogues, data visualizations, and programmatic APIs to its capabilities) - all provisioned out-of-the-box for the user. This combination of features and functionalities sets DataGraft apart from other approaches, which, although in some cases can be hosted on the cloud, typically lay the burden of provisioning of resources and maintenance on the users

Related systems fall under the types of systems for linked data and open data publication/hosting and ETL tools. In the following we outline the most relevant systems and discuss the differences.

The Linked Data Stack [17] is a software stack consisting of a number of loosely coupled tools, each capable of performing certain sets of operations on linked data, such as data extraction, storage, querying, linking, classification, search, etc. The various tools are bundled in a Debian package and a web application can be deployed to offer central access to all the tools via a web interface¹⁵. The complexity of provisioning resources and managing the resulting web application rests on end users who must install the tools and maintain the infrastructure. In contrast, DataGraft is bundled as-a-service, whereby the actual resources for transforming and hosting data are managed on behalf of the user. There is indeed an overlap in terms of operations on linked data (for example data hosting and querying) supported by both DataGraft and the Linked Data Stack, but there are also significant differences in the chosen approach. Whereas DataGraft focuses on higher level aspects such as providing an integrated framework for data cleaning, preparation, and transformation, such that users can interactively design and share transformations, the Linked Data Stack addresses lower-level

¹⁴ https://console.s4.ontotext.com/

¹⁵ http://demo.lod2.eu/lod2demo

aspects, such as classifications, that are not covered in DataGraft.

The LinDA project [18]¹⁶ developed a set of tools for linked data publishing, packaged into the LinDA Workbench¹⁷. It consists of a lightweight transformation to linked data tool, a vocabulary repository, a tool for converting RDF to conventional data structures, a visual query builder, and an analytics package. Similar to the Linked Data Stack, the tasks of provisioning resources and managing the LinDA tool ecosystem again rest on the end user. Furthermore, DataGraft's powerful data cleaning and transformation approach goes beyond the lightweight transformation tool provided by LinDA (which focuses primarily on the RDFisation). Nevertheless, LinDA provides more sophisticated support for visual querying through providing a query builder for SPARQL.

The COMSODE project [19]¹⁸ provided a set of software tools and methodology for open data processing and publishing. A relevant tool developed as part of this project was UnifiedViews¹⁹ - an ETL tool for RDF data. Its focus is on specifying, monitoring and debugging workflows composed of data processing units applied on data that is extracted from SPARQL endpoints. These features are orthogonal to DataGraft's transformation approach that focuses on lower level operations such as cleaning and transformation to RDF of the actual data (together with other aspects like sharing and reuse of transformations). Thus, UnifiedViews can be seen as a data workflow processing tool using data published via DataGraft. Similar to the aforementioned approaches, COS-MODE is not available as an online service, but rather as a set of tools that need to be individually managed, which implies additional burden on end users.

OpenRefine²⁰, with its RDF Refine plugin [20]²¹, implements an approach with similar capabilities to DataGraft with regards to data cleaning and transformation to RDF. The tool provides an interactive user interface that uses well-known spreadsheet-style interactions, which are convenient for manual data clean-up and conversion. However, OpenRefine is unsuitable for use in a service offering context, such as the one DataGraft was built for. Although Open-Refine was implemented as a web application, its design is monolithic and bears resemblance to an application meant for the desktop, rather than the web. Firstly, the code base is not well componentised e.g., the transformation engine is tightly-coupled to the OpenRefine core and does not expose an API. Additionally, the processing engine itself is not suitable for robust ETL processes, as it is inefficient with larger data volumes - it implements a multi-pass approach to individual operations, and is thus memoryintensive. Although there has been an attempt to provide support for batch processing in BatchRefine²², it inherits the issues with the tight coupling of the core components. OpenRefine also has security issues, which prevent it from being applicable in a fully hosted solution - OpenRefine was designed to be used as a desktop application, not a SaaS application, and it allows arbitrary code execution without applying a sandbox and policy. DataGraft was designed from the outset to be a hosted platform and executes transformation code inside a security sandbox. Nevertheless, OpenRefine provides more powerful RDF mapping features such as automatic reconciliation of data, more freedom in mapping, etc.

Datalift [21] is a software framework for linked data publishing. It consists of a set of modules such as vocabulary management, data conversion, and interlinking. Besides being a framework that needs to be installed, configured, provisioned, and maintained by the user, Datalift's approach to conversion of tabular data to linked data is rather lightweight in comparison to DataGraft. Furthermore, Datalift is considered as an "expert tool" [21]. For example, it comes with no GUI to support data publishers in the data publication process. A similar framework to Datalift is the Linked Data Integration Framework (LDIF) [22], focused on data integration using linked data. ClioPatria [23] is a more recent system, extending the SWI-Prolog RDF store with capabilities such as a SPAROL and LOD server, and mechanisms to browse and query data. DataGraft's triplestore goes beyond the capabilities of the SWI-Prolog RDF store in the sense that it's designed for cloud-based systems. DataGraft is a more comprehensive framework addressing wider aspects of data publishing such as being a public infrastructure for data and data transformations sharing and including capabilities for data cleaning and transformation, which appear to be outside of the scope of ClioPatria

PublishMyData²³ is a commercial Software-as-a-Service linked data publishing platform. DataGraft and PublishMyData share the data transformation approaches through the Grafter library. However,

¹⁶ <u>http://linda-project.eu/</u>

¹⁷ http://linda-project.eu/tools/

¹⁸ http://www.comsode.eu/

¹⁹ http://unifiedviews.eu/

²⁰ http://openrefine.org/

²¹ http://refine.deri.ie/

²² https://github.com/fusepoolP3/p3-batchrefine

²³ http://www.swirrl.com/publishmydata

DataGraft has taken Grafter further in the Grafterizer tool and the platform UI, by complementing it with interactive design of transformations, mechanisms for sharing transformations between users, and reliable data hosting and access. PublishMyData, in contrast to DataGraft, is not a public service for building and sharing data transformations.

The Linked Data AppStore [24] is a Software-as-a-Service platform prototype for data integration on the web. It integrates a set of linked data related tools for tasks such as data cleaning, transformation, entity extraction, data visualization, crawling in a in a loosely coupled service infrastructure and served as inspiration for the development of DataGraft.

Related systems that are not focused on the linked data paradigm include solutions for open data catalogues and more traditional ETL tools. Open data catalogues typically list open datasets, together with the metadata and references (e.g., URLs) to where the data are made available. In some cases the actual datasets are also hosted with the data catalogue. However, in most cases data catalogues provide only download links without any sophisticated infrastructure for querying data to support other aspects of the ETL process. Popular data catalogue solutions include CKAN²⁴ and Socrata²⁵. The core differences between DataGraft and these data catalogue solutions lay in the support for linked data and data transformations.

Commercial examples of relevant ETL tools include Pentaho Data Integration²⁶ and Trifacta Wrangler²⁷. Pentaho Data Integration is a powerful and efficient tool designed specifically for ETL processes with lots of plugins and components for many data formats. It does not come with linked data support and is rather hard to use for non-developers. Firstly, it does not provide an interactive preview such as a spreadsheet of the current state of the transformation workflow. Furthermore, its diagrammatic approach to transformations can be unclear and could potentially explode in complexity including constructs for loops and recursion. Finally, Pentaho Data Integration was not built for public cloud hosting environments, but is rather a desktop application. Trifacta Wrangler is yet another tool for data cleaning. Its focus is on supporting predictive interactions which enables users to clean data in a rather simple manner. Trifacta Wran-

²⁶ http://community.pentaho.com/projects/data-integration/

gler does not support linked data and capabilities or data hosting.

To summarize, none of the existing solutions in linked data tools, open data publishing platforms or ETL tools meet the requirements addressed by DataGraft. Firstly, all of the examined linked data tools outsource the technical complexity of provisioning and managing the infrastructure to their users. This means that they require expert knowledge to operate, which makes them costly to use and difficult to sustain. Furthermore, they are not well-suited for a cloud service environment (they are not designed to be scalable and reliable in a cloud-based environment) and most of them do not have an interactive user interface. In some cases linked data tools do have a user interface, but operate inefficiently and are not suitable for robust linked data publication. On the other hand, open data publication and hosting tools provide a serviced solution to their users. However, such tools lack support for data transformation and in some case leave the data provisioning and management tasks to their users. This causes data to be fragmented across many sources and thus difficult to use and integrate. Finally, ETL tools provide powerful capabilities for producing workflows diagrammatically. However, they are not well-suited for a cloudbased environment/hosting of data, do not provide support for linked data, and typically lack interactive previews of the state of the data at each step of the ETL process.

DataGraft addresses all these issues by providing a reliable cloud service for transforming and hosting data, whereby all upfront and operational costs for acquiring and maintaining technical infrastructure for provisioning the data are outsourced to the platform, additionally reducing the technical complexity for data publishers.

5. Summary and Outlook

DataGraft [25] is an emerging solution (as-a-Service) for making linked open data more accessible. It comes with a platform, portal, methodology, and APIs – all packaged in an online service, functional and documented²⁸. DataGraft has been validated in a number of use cases showing added-value based on its key capabilities: support for sharable, repeatable, and reusable data transformations, and reliable RDF Database-as-a-Service.

²⁴ http://ckan.org/

²⁵ http://www.socrata.com/

²⁷ https://www.trifacta.com/products/wrangler/

²⁸ <u>https://datagraft.net/documentation/</u> (API documentation available at <u>https://datagraft.net/api/</u>)

DataGraft's features include: interactive cleaning, preparation and transformation of data, repeatable and reusable data transformations, flexible deployment of transformations, RDF data publication and querying, support for integrating and visualising data from different sources. Additionally, DataGraft can be used with third party tools as it has been built with easy integration in mind using standard web technology. For example, users can browse data hosted on DataGraft with tools such as GraphRover²⁹ (through the SPARQL endpoint), connect to the hosted data store with a standard Sesame Client (using the OpenRDF APIs), or browse, perform queries or other actions using a REST client or command line tools such as httpi³⁰ (to access the RESTful APIs of DataGraft). This makes DataGraft attractive both for data workers and data developers interested in simplified and cost-effective solutions for managing their data. DataGraft was developed to provide better and easier to use tools for open data publishers, linked data developers, and data scientists who consider existing approaches to data transformation, hosting, and access too costly or technically complex.

Graftwerk and RDF DBaaS are closed source, while Grafter³¹, Grafterizer³², and the DaPaaS portal³³ are released under open-source (EPL v1.0).

DataGraft is currently under development and operated by the proDataMarket project³⁴. Changes and improvements to DataGraft are expected in the near future. Future releases of DataGraft will address some of the limitations identified in the cases in which DataGraft was used, and will contain new features and improvements. Examples of new features/improvements in future releases include: support for multiple files, joining of datasets and various data formats as input for data transformations (e.g., JSON, GML, Shapefile), better error reporting in data transformations, applying functions directly on the preview spreadsheet (rather than in pipeline operations), fully supporting streams of data as input in Grafterizer (rather than static files), better traceability for files, data pages, transformations; ability to store and share assets such as queries and visualization widgets; versioning of assets, social aspects (e.g., users following activity of other users); quantitative benchmarking; and better mechanisms to record the user interactions with the platform. On a longer term,

²⁹ http://www.metreeca.it/products/graph-rover/

- ³² https://github.com/dapaas/grafterizer
- ³³ https://github.com/dapaas/datagraft
- ³⁴ http://prodatamarket.eu/

there are plans to use DataGraft as an infrastructure for implementing the concept of "Trusted Data Mar-ketplaces" [26].

Acknowledgements. The development of DataGraft was co-funded through grants from the European Commission (EC). DataGraft was developed and operated by the DaPaaS project (GA no. 610988) until November 2015. Further development, maintenance, and operations continue under the proDataMarket project (GA no. 644497). The projects SmartOpenData (603824) and InfraRisk (603960) also contributed to DataGraft.

References

- Tim Davies, Raed. M Sharif, and Jose M. Alonso. Open Data Barometer. Global Report - Second Edition, 2015. Available via http://bit.ly/1OedPRd (Last accessed December 2015).
- 2] http://opendatamonitor.eu/frontend/web
- [3] Gang-Hoon Kim, Silvana Trimi, and Ji-Hyong Chung. Bigdata applications in the government sector. *Communications of the ACM*, 57(3):78-85, 2014. 10.1145/2500873.
- [4] Octavian Rusu, Ionela Halcu, Oana Grigoriu, Giorgian Neculoiu, Virginia Sandulescu, Mariana Marinescu, Viorel Marinescu. Converting unstructured and semi-structured data into knowledge. In *Networking in Education and Research, Roedunet International Conference (RoEduNet), 11th Edition, Proceedings, Siania, January 17-19, 2013.* IEEE, 2013. 10.1109/RoEduNet.2013.6511736.
- [5] Jürgen Umbrich, Sebastian Neumaier, and Axel Polleres. Quality Assessment and Evolution of Open Data Portals. In Irfan Awan, Muhammad Younas, and Massimo Mecella, editors, 3rd International Conference on Future Internet of Things and Cloud, FiCloud 2015, Rome, Italy, August 24-26, 2015, pages 404-411, IEEE Computer Society, 2015. 10.1109/FiCloud.2015.82.
- [6] Hadley Wickham. (2007). Reshaping data with the reshape package. Journal of Statistical Software, 21(12):1-20, 2007. 10.18637/jss.v021.i12.
- [7] Hadley Wickham. Tidy Data. Journal of Statistical Software, 59(10):1-23, 2014. 10.18637/jss.v059.i10.
- [8] Jeremy Tandy, Ivan Herman, I, and Gregg Kellogg: Generating RDF from Tabular Data on the Web, W3C Recommendation 17 December 2015. https://www.w3.org/TR/csv2rdf/.
- Bill Roberts and Rick Moynihan. Documented methodology and guidelines. DaPaaS Deliverable D4.1, October 2014. Available via http://bit.ly/1NMU8IJ (Last accessed December 2015).
- [10] Bill Roberts. Software tools integrated into platform. DaPaaS Deliverable D4.2, April 2015. Available via http://bit.ly/1PcM8v7 (Last accessed December 2015).
- [11] Dina Sukhobok, Nikolay Nikolov, Antoine Pultier, Xianglin Ye, Arne J. Berre, Rick Moynihan, Bill Roberts, Brian Elvesæter, Mahasivam Nivethika, and Dumitru Roman. Tabular Data Cleaning and Linked Data Generation with Grafterizer. In Harald Sack, Giuseppe Rizzo, Nadine Steinmetz, Dunja Mladenic, Sören Auer, and Christoph Lange, editors, The Semantic Web - ESWC 2016 Satellite Events, Heraklion, Crete, Greece, May 29 - June 2, 2016, Revised Selected Papers, vol-

³⁰ http://httpirb.com/

³¹ <u>https://github.com/Swirrl/grafter</u>

ume 9989 of Lecture Notes in Computer Science, pages 134-139, Springer, 2016. 10.1007/978-3-319-47602-5_27.

- [12] Alex Simov, Marin Dimitrov, Nikolay Nikolov, Antoine Pultier, Dina Suhobok, Xianglin Ye, and Dumitru Roman. *Open Data PaaS prototype*, v.2. DaPaaS Deliverable D2.3, July 2015. Available via http://bit.ly/1Jj86s4 (Last accessed December 2015).
- [13] Marin Dimitrov, Alex Simov, Nikolay Nikolov, and Dumitru Roman. Open DaaS prototype, v.2. DaPaaS Deliverable D1.3, July 2015. Available via http://bit.ly/1PgdhPU (Last accessed December 2015).
- [14] Momchill Zarev. Cross platform data delivery framework. DaPaaS Deliverable D3.2, July 2014. Available via http://bit.ly/10eSNIk (Last accessed December 2015).
- [15] Ivan Berlocher, Seonho Kim, and Tony Lee. Use case implementation, v1. DaPaaS Deliverable D5.2, October 2014. Available via http://bit.ly/11b5uzJ (Last accessed December 2015).
- [16] Seonho Kim, Ivan Berlocher, and Tony Lee. Use case final implementation and validation. DaPaaS Deliverable D5.3. October 2015. Available via http://bit.ly/1Nv3y5O (Last accessed December 2015).
- [17] Sören Auer, Lorenz Bühmann, Christian Dirschl, Orri Erling, Michael Hausenblas, Robert Isele, Jens Lehmann, Michael Martin, Pablo N. Mendes, Bert Van Nuffelen, Claus Stadler, Sebastian Tramp, and Hugh Williams. Managing the Life-Cycle of Linked Data with the LOD2 Stack. In Philippe Cudré-Mauroux, Jeff Heflin, Evren Sirin, Tania Tudorache, Jérôme Euzenat, Manfred Hauswirth, Josiane Xavier Parreira, Jim Hendler, Guus Schreiber, Abraham Bernstein, and Eva Blomqvist, editors, *The Semantic Web - ISWC 2012 - 11th International Semantic Web Conference, Boston, MA, USA, November 11-15, 2012, Proceedings, Part II, volume 7650 of Lecture Notes in Computer Science, pages 1-16, Springer, 2012. 10.1007/978-3-642-35173-0 1.*
- [18] Panagiotis Hasapis, Eleni Fotopoulou, Anastasios Zafeiropoulos, Spiros Mouzakitis, Sotiris Koussouris, Michael Petychakis, Barbara Kapourani, Norma Zanetti, Francesco Molinari, Salvatore Virtuoso, and Cinzia Rubattino. Business value creation from Linked Data analytics: The LinDA approach. In eChalienges e-2014 Conference, 29-30 October 2014, Belfast, Ireland, IEEE, 2014. http://ieeexplore.ieee.org/abstract/document/7058193/.
- [19] Peter Hanečák, Svetozár Krchnavý, and Ivan Hanzlík. COM-SODE publication platform – Open Data Node – final. COM-SODE Deliverable 4.3, July 2015. Available via http://bit.ly/1PcCGYS (Last accessed Dec 2015).
- [20] Fadi Maali. Getting to the Five-Star: From Raw Data to Linked Government Data. Master's thesis, National University of Ireland, Galway, Ireland (2011). Available via http://bit.ly/1TVLnaW (Last accessed Dec 2015).
- [21] François Scharffe, Ghislain Atemezing, Raphaël Troncy, Fabien Gandon, Serena Villata, Bénédicte Bucher, Fayçal Hamdi, Laurent Bihanic, Gabriel Képéklian, Franck Cotton, Jérôme Euzenat, Zhengjie Fan, Pierre-Yves Vandenbussche, and Bernard Vatant. Enabling Linked-Data Publication with the Datalift Platform. In Biplav Srivastava, editor, Proceedings of Semantic Cities Workshop at the Twenty-Sixth AAAI Conference on Artificial Intelligence, Toronto, Ontario, Canada, July 22, 2012 – July 23, 2012, pages 25-30, AAAI, 2012. http://www.aaai.org/ocs/index.php/WS/AAAIW12/paper/view File/5349/5678/.
- [22] Andreas Schultz, Andrea Matteini, Robert Isele, Christian Bizer, and Christian Becker. LDIF - Linked Data Integration Framework. In Olaf Hartig, Andreas Harth, and Juan Sequeda, editors, Proceedings of the Second International Conference

on Consuming Linked Data (COLD 2011), Bonn, Germany, October 23, 2011, volume 782 of CEUR Workshop Proceedings, pages 125-130, CEUR-WS.org, 2011. http://ceurws.org/Vol-782/SchultzEtA1 COLD2011.pdf.

- [23] Jan Wielemaker, Wouter Beek, Michiel Hildebrand, and Jacco van Ossenbruggen. ClioPatria: A SWI-Prolog Infrastructure for the Semantic Web. Semantic Web, 7(5):1-13, 2016. 10.3233/SW-150191.
- [24] Dumitru Roman, Claudia Daniela Pop, Roxana I. Roman, Bjørn Magnus Mathisen, Leendert Wienhofen, Brian Elvesæter, and Arne J. Berre. The Linked Data AppStore. In Rajendra Prasath, Philip O'Reilly, and T. Kathirvalavakumar, editors, *Mining Intelligence and Knowledge Exploration, Second International Conference, MIKE 2014, Cork, Ireland, December 10-12, 2014. Proceedings*, volume 8891 of Lecture Notes in Computer Science, pages 382-396, Springer, 2014. 10.1007/978-3-319-13817-6_37.
- [25] Dumitru Roman, Marin Dimitrov, Nikolay Nikolov, Antoine Putlier, Dina Sukhobok, Brian Elvesæter, Arne J. Berre, Xianglin Ye, Alex Simov, and Yavor Petkov. DataGraft: Simplifying Open Data Publishing. In Harald Sack, Giuseppe Rizzo, Nadine Steinmetz, Dunja Mladenic, Sören Auer, and Christoph Lange, editors, *The Semantic Web - ESWC 2016 Satellite Events, Heraklion, Crete, Greece, May 29 - June 2, 2016, Revised Selected Papers*, volume 9989 of *Lecture Notes in Computer Science*, pages 101-106, Springer, 2016. 10.1007/978-3-319-47602-5_21.
- [26] Dumitru Roman and Stefano Gatti. Towards a Reference Architecture for Trusted Data Marketplaces: Credit Scoring Perspective. In Irfan Awan and Muhammad Younas, editors, 2nd International Conference on Open and Big Data, OBD 2016, Vienna, Austria, August 22-24, 2016, pages 95-101, IEEE Computer Society, 2016. 10.1109/OBD.2016.21.