Big Data to Enable Global Disruption of the Grapevine-powered Industries

D3.4 - Linguistic Pipelines for Semantic Enrichment

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ACRONYMS LIST

BDG	BigDataGrapes
W3C	World Wide Web Consortium
KG	Knowledge Graph
KE	Knowledge Engine
LLD	Linked Life Data
ETL	Extract-Transform-Load
ChEBI	Chemical Entities of Biological Interest
TOS	Talend Open Studio
JET	Java Emitter Templates
JSP	Java Server Pages
GraphDB SE	GraphDB Standard Edition
GraphDB EE	GraphDB Enterprise Edition
IRIs	Internationalized Resource Identifiers
PR	processing resource

EXECUTIVE SUMMARY

This deliverable is the first report on the progress of T3.4 Semantic Enrichment. It will describe the progress on the design of advanced text analytics pipelines aiming to extract and semantically annotate information from unstructured textual data sources from the Big Data Grapes (BDG) data pool. It will describe in detail a proposed approach for named entity recognition and relation extraction from large natural language resources like scientific research, news articles and webpages- this approach has both proven very successful in practice with a variety of large corpora and is flexible enough to adjust to the specific content types relevant to the BDG use cases.

The proposed pipelines work by identifying entities that refer to instances from the conceptual **BDG** model so a crucial part of our discussion involves a theoretical definition of that model and detailing the approach to building, extending and enlarging the model with new facts and new provenance sources. We will also describe the process for building a reliable corpus of data that can be used to develop and evaluate the performance of the various pipelines as well as the proposed structure of the linguistic pipelines themselves.

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1 INTRODUCTION

In the huge flows of data available to work with, much of the most complex and critical information is contained within text. If we are to use texts with maximum productivity and minimum wasted effort, we need to identify this crucial information and enrich the text with machine-readable tags representing it. Only through the power of text analytics we can unlock the full power of computers in assisting us with interpreting the huge variety and complexity of these textual data streams.

At its core, text analytics is the process of turning words and phrases into data pieces and further interlinking them. It consists of a number of methods and processes, among which semantic annotation is key. Using series of various algorithms to analyze free flowing text, meaningful chunks of it are transformed into structured interconnected data elements. This enables organizations to easily and effectively use information, track and understand relationships in disparate textual sources, find topical information, discover facts.

In a word, text analytics extracts meaningful structured data from unstructured text. The aim of this deliverable is to describe the process by which we propose to do so for data relevant to partners in the Big Data Grapes project.

2 MOTIVATION: THE VALUE OF SEMANTIC TECHNOLOGY

Semantic technology is of immense help when it comes to creating, curating, exploring and using textual sources. A set of universal standards developed and agreed upon by the World Wide Web Consortium (W3C) international community, semantic technologies help enterprises discover data, infer links and extract knowledge from enormous sets of raw data in various formats from various sources.

The role of Semantic Technology is to define and link data on the web or within an enterprise by developing languages to express rich, self-describing interrelations of data in a form that machines can process. Thus, machines are not only able to process text as long strings of characters, but they are also able to store, manage and retrieve information based on the meaning and logical relations behind the text. Semantic technologies unlock this deeper layer of meaning and are able to show related facts and items instead of relying on crude text searches for exploring the data.

By leveraging the power of text analytics techniques to weave data into the textual content, we can make large textual corpora readable for machines, improve information retrieval capability (not just in speed but in quality of results produced), introduce connectivity between different data sources and make the move to working with highly-manageable chunks of knowledge.

Specifically, the use case of our partner APIGEA is concerned with finding certain kinds of relationships between a substance (chemical component, e.g. vitamin C, or a natural product, e.g. honey) and a specific biological function (a condition, e.g. diabetes, or a biological path e.g. ageing or a property e.g. antioxidant) within natural text. Semantic technology will allow their searches to move on from a simple keyword approach to working with semantic concepts and relationships between concepts.

2.1 OVERVIEW

There are several interconnected pieces required to build algorithms capable of semantic enrichment of datasets and in this deliverable, we will describe the steps to create each of them for the task at hand.

Firstly, there is the task of building a Knowledge Graph (KG) for the specific use case. Creating a seed of the knowledge graph is critical as it is necessary for the creation of working linguistic pipelines but the exact form the KG will take is dependent on both the nature of the documents in the corpus and the types of enrichments we choose to carry out. It is important to note that the KG is not a static entity but rather one that expands and grows both with the expansion of the corpus of documents, the increasing complexity of the enrichment tasks and the discovery of new candidate concepts and relations by the pipelines.

Secondly, we will explore the task of corpus building. More than a simple collection of text files, a semantic corpus leverages the power of the KG to represent the contents of each document with a conceptual document model that includes not just the raw text but a variety of higher-level enrichments. These enrichments can come either from human annotators or from the linguistic pipelines.

Finally, we delve into the implementation details of the annotation pipeline. Here we will present an in-depth description of a complete pipeline created for a similar task. The actual final implementation will be adjusted to correspond to the BK and corpus created by the project partners but will function in a very similar way conceptually.

2.2 USE CASE DISCUSSION

As a specific use case example, we will look at the requirements for the use case of partner APIGEA. For their needs, the knowledge base will need to contain information on the following classes of entities:

- Bio-active compounds: Such as specific antioxidants, proteins, phenols
- Genes: Genes responsible for a specific condition
- Natural products: Such as fruits, plants, honey
- Properties: antioxidant, anti-inflammatory
- Conditions: dehydration, balding, diabetes, fever
- Biological functions: Ageing, Digesting

Relevant ontologies and data sets will be identified and will be used to extend the current knowledge graph with the required entity classes. More specifically, we will recombine the relevant parts of these data sets with the use of a unifying ontology to produce the knowledge graph as discussed in Section 3, collect and process data from sources identified by the partner to build a corpus as discussed in Section 4 and finally use both for the creation and application of linguistic pipelines as discussed in Section 5.

3 KNOWLEDGE GRAPH

In the "Semantic Enrichment" task we are in the process of developing a generic infrastructure, capable of processing extremely large quantities of rapidly growing and potentially inconsistent or incomplete information. The current document presents general information integration concepts, the Knowledge Engine (KE) architecture and software infrastructure that will be used for the successful implementation of D3.4 "Linguistic Pipelines for Semantic Enrichment".

Data integration is the process of ensuring interoperability between different data sources by providing a unified view of the information contained in the data sources. A key objective for this process is to build a consistent and homogenous global data model that unifies all sources. Lenzerini (2002) gives a formal definition of data integration (I) as a triple consisting of I = (G, S, M), where G is the global schema (unified view towards the information), S is the source schema and M the mapping between G and S. The mapping between different data sources has to overcome four types of incompatibilities or heterogeneity levels of the information described by Sheth (1998):

- The system level reflects scenarios where data is accessed via an intermediate storage interface (i.e. a different file system or a physical separation between system and data);
- The syntactic or format level is concerned with the problems of cross-platform data encoding like ASCII, UTF-8, UTF-16 and etc. These compatibility issues are largely addressed by the XML 1.0 format specification and further refined by XML 1.1, so they are beyond the scope of our work;
- The structure (schema) level refers to heterogeneity in the entity modelling, their attributes, type hierarchy, cardinalities and the behaviour with respect to the schema constraints e.g. data integrity rules;
- The semantic (meaning) level refers to incompatibility in modelling generalisation/specialisations (e.g. drug versus organic chemical), composition/aggregation and value level interpretations like homonyms or synonyms.

Figure 1 shows the nested nature of the heterogeneity levels. Once a specific issue is unresolved, it will be propagated in a cascading way to all upper layers.

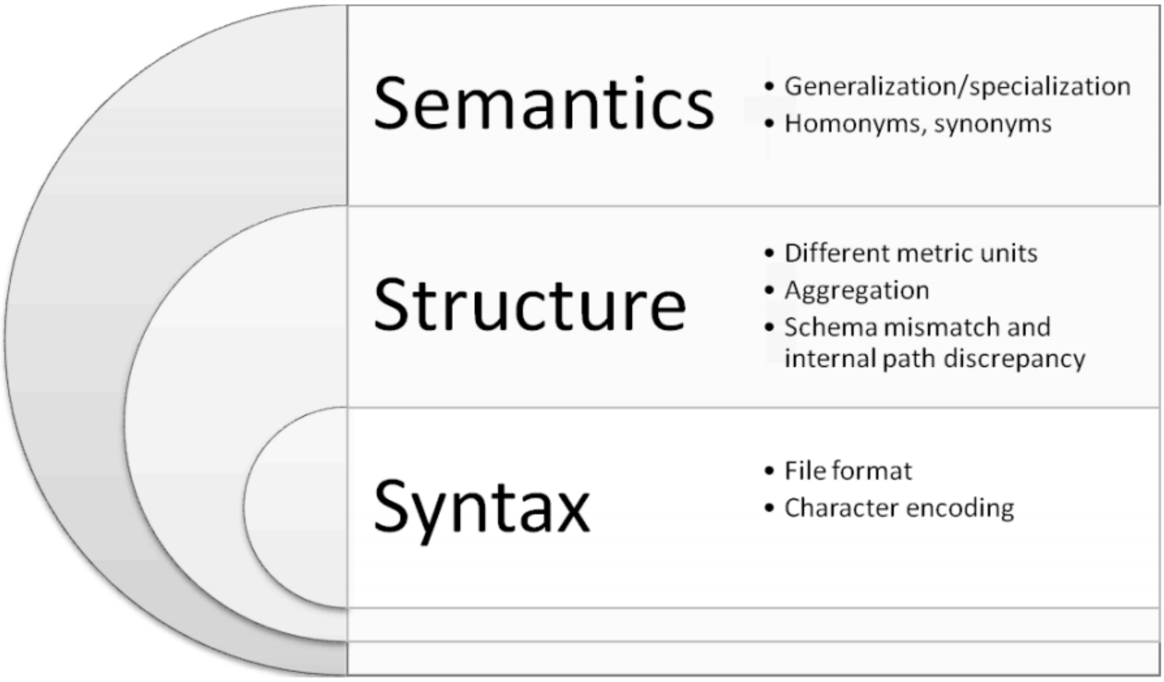


Figure 1: Syntax, Structure and Semantic Heterogeneity Levels

The work on Knowledge Graph creation in D3.4 "Semantic Enrichment" is focused on integrating information from heterogeneous sources and overcoming various types of structure and semantic level incompatibilities by developing extract and associate rules. After the semantic heterogeneities are addressed and the information is represented in a consistent knowledge graph, further analytics may be applied such as text mining, reasoning, semantic similarity prediction, etc. Thus, the aim of the Knowledge Graph creation is to address the challenges of data integration, semantic incompatibility and knowledge analysis. Later, this document provides an overview of the KE foundation and the choice of the underlying data model, suitable for semantic data integration and advanced knowledge analysis.

The proposed RDF data model is not constrained to a particular application domain and does not define a priori the semantics of any application domain (Lassila & Swick, 1999). Its abstract knowledge representation formalism fits into a wide range of use-cases and application scenarios from metadata publishing on the web, data integration, implementation of complex formal logical models (i.e. ontologies), etc. Such cross use case compatibility is achieved by a number of W3C standards, specifications and recommendations that cover different aspects of the ontology language layers. By the term ontology language layer, we mean the set of theoretical modelling primitives that every ontology language can be decomposed into:

- The data model determines the mathematical data-structure (e.g. directed acyclic graph) that describes the ontology, e.g. the RDF data model (Lassila & Swick, 1999);
- Epistemology defines the language at the conceptual level or specifies data model patterns, used to represent notions like concepts, classes, relations, properties, attributes, roles, etc.;
- The vocabulary determines what sort of symbols are valid for composing expressions in the ontology language by giving naming conventions for various primitives, defined in the data model and the epistemology levels (for instance the vocabularies of Dublin Core (DC), Simple Knowledge Organization System (SKOS), Web Ontology Language (OWL));
- The syntax determines the structure of the valid expressions within the language and its serialization formats (RDF/XML, Turtle, RDF/JSON, JSON Triples, etc.);
- Semantics is the top layer that determines the meaning of the expressions made in the ontology language; it is often defined in terms of pairs consisting of a mathematical model and a function, which define the correspondence between the expressions of the language and the elements of the model; any sort of inference or induction of implicit triples is performed on the basis of the semantics, e.g. OWL2-RL, SKOS, etc.

To summarize, the RDF data model is highly abstract and supports the layering of several ontology primitives, which makes it an excellent candidate for the KE internal representation format. Hence, a final contributing reason for its selection over the classical database technology is the fact that the latest SPARQL 1.1 specification (Prud'hommeaux and Seaborne, 2008) fully covers the relation algebra (Angles and Gutierrez, 2008).

3.1 SEMANTIC DATA INTEGRATION WITH RDF

This chapter presents an analysis of the different levels of performing data integration. Ziegler and Dittrich (Ziegler and Dittrich, 2004) define multiple integration levels depending on its specificity. They are the following:

1. Manual integration: no real integration is done since the interpretation is performed by the end-user;
2. Common user interface: data from relevant sources are displayed in a single view in the application;
3. Integration by applications or middleware: integration is done on the concrete application level where the developers are relieved only from implementing common integration functionality;
4. Uniform Data Access: information integration is realized by virtual data or data abstracted from its physical structure in runtime;

5. Common Data Storage: the existing data is physically replicated to new database storage and possibly reorganized to conform to a new global schema.

It is a general rule that the integration becomes more efficient when it is moved closer to the physical storage. Thus, when we need to operate with very large amounts of information as is likely to be the case in the context of the Big Data Grapes project, our choice for efficient data integration is undoubtedly to perform data consolidation (or warehousing).

Data warehousing is the process of centralizing the information into a common physical storage model. It requires the reorganization and consolidation of all data into a global schema, and may either fully replace the old databases or replicate the information on a regular basis. Either way, data consolidation requires the design and execution of extract transform and load scripts that need to resolve the structure and semantic heterogeneities between the source and the global schema during data loading.

3.1.1 RDF Warehousing

An RDF warehouse requires the translation of all data sources to RDF triples and loading the statements into different named graphs (contexts). Keeping different dataset in separate named graphs guarantees the minimal provenance information required in order to support incremental information updates.

Let us look at the Linked Life Data (LLD) service (Momtchev et al., 2009) as a concrete example of an RDF warehouse project that demonstrates excellent performance for a wide range of SPARQL queries against billions of RDF statements. The service relies on a highly efficient persistence of RDF, a query optimizer and an integrated forward chaining reasoner that enables the indexed search of implicit statements. Once all the information is consolidated into a single physical structure, resource alignment rules are defined to link related identifiers.

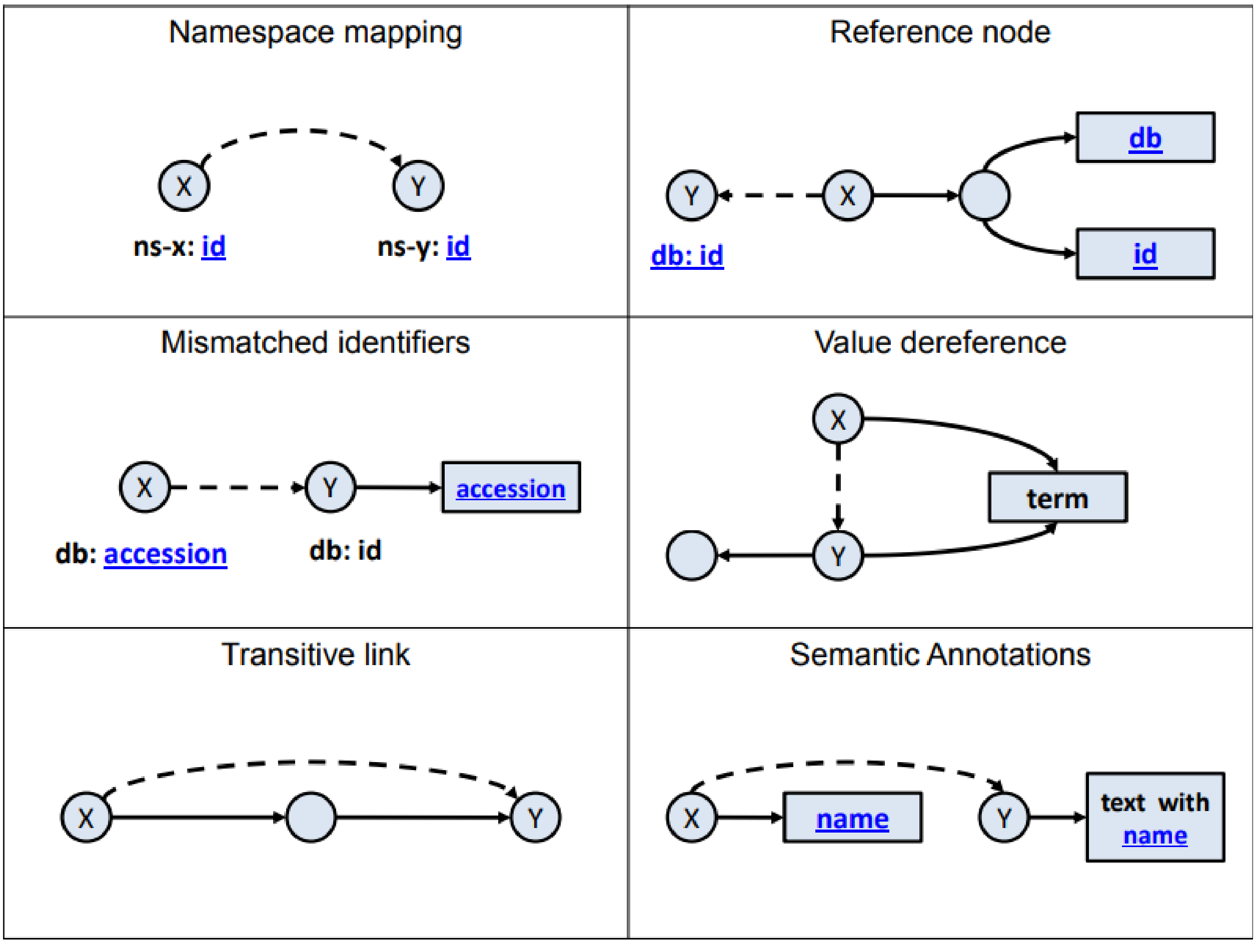


Figure 2: Resource alignment patterns in LLD

Figure 2 depicts six alignments rules, where the dashed lines and the blue text of the captions (used either as part of the URI or literals) designate the criteria for linking the information. Since the specified mapping rules are not universally applicable for arbitrary RDF datasets, they are manually controlled for each specific subset. Figure 3 illustrates the semantic aspect of the instance mappings.

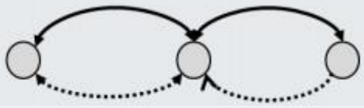
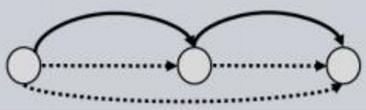
Relationship	Semantics	Example
Exact match	Transitive equivalence	
Close match	Equivalent only for search purposes	
Broader match	Generalization of a concept	
Narrower match	Specialization of a concept	Inverse of broader match

Figure 3: Instance mapping in LLD using the SKOS vocabulary

Local RDF storage engines can provide full control over the query optimisations and statistics on each value's associations, allowing the calculation of optimal execution plans for complex information joins. Queries with unbound predicates are especially difficult to optimize. The SPARQL query presented in Figure 4 lists all unique predicates for resources of type Protein. The first pattern executed against LLD 0.8 results in 16,505,340 possible bindings. The second pattern to be merged with the first one results in 5,120,886,447 possible bindings. This yields a total of 8.45E+16 tuples if naive optimisation is used. However, the total execution time for the presented query is less than 60 seconds despite its extreme complexity.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX uniprot: <http://purl.uniprot.org/core/>
SELECT DISTINCT ?predicate
WHERE {
    ?subject rdf:type uniprot:Protein .
    ?subject ?predicate ?object.
```

Figure 4: SPARQL query with unbound predicate

In conclusion, warehouse architectures, as the example presented here in the LLD project, guarantee fast queries because they offer a single data model, storage engine-provided query optimisation strategies and the possibility of data quality control and cleaning.

3.2 KNOWLEDGE ENGINE

The knowledge engine is then going to be a core component of the BDG use cases in this task. It contains the persistence layer responsible for the storage, retrieval and integration of information. Furthermore, it automates the execution of batch core services to process huge amounts of information.

3.2.1 Batch Processing and Extract Transform Load (ETL)

The BDG use cases are going to face the challenge of dealing with dynamic heterogeneous data, originating from many different sources. The relevant information will have to be extracted from the data sources, transformed into a format, supported by the system, and semantically disambiguated before loading it into the knowledge base. This process is commonly referred to as Extract-Transform-Load (ETL).

ETL is a data insensitive process, which requires high efficiency not only in terms of good performance and scalability, but also in easy maintenance and traceability of each individual step of the complete integration process.

There are fundamentally three kinds of data formats as far as the processing and ETL process is confirmed and we will briefly discuss the approach to each of them below. In each case we will explain the kinds of data suitable for that approach and the tools used to perform the process.

Importing RDF-formatted Data

The simplest and quickest method for incorporating new sources into the Knowledge Graph is applicable to sources that are already available in RDF format. While this will not be the case with all relevant data sources, at least a few major ones will be available in this format e.g. ChEBI (Chemical Entities of Biological Interest, a database and ontology of molecular entities focused on 'small' chemical compounds) and ChEMBL (a manually curated chemical database of bioactive molecules with drug-like properties).

This process is applicable to all valid RDF files including ttl, trig, trix, nt, nq, rdf, owl, jsonld and several other rarer formats.

Figure 5 shows an example of files being imported through the workbench directly. GraphDB allows the direct import of server files and use of the loadrdf tool in cases where the files being imported are particularly large which means that there is no limitation to the size of the files imported in this way. In fact, the purpose of the other procedures we are going to outline in this section is to transform data in other formats into RDF data while preserving all the useful information and potentially adding new one. That RDF data can then be imported into the KG either through the workbench as shown here or through one of the other methods like the loadrdf tool, rdf4j API or federated query.

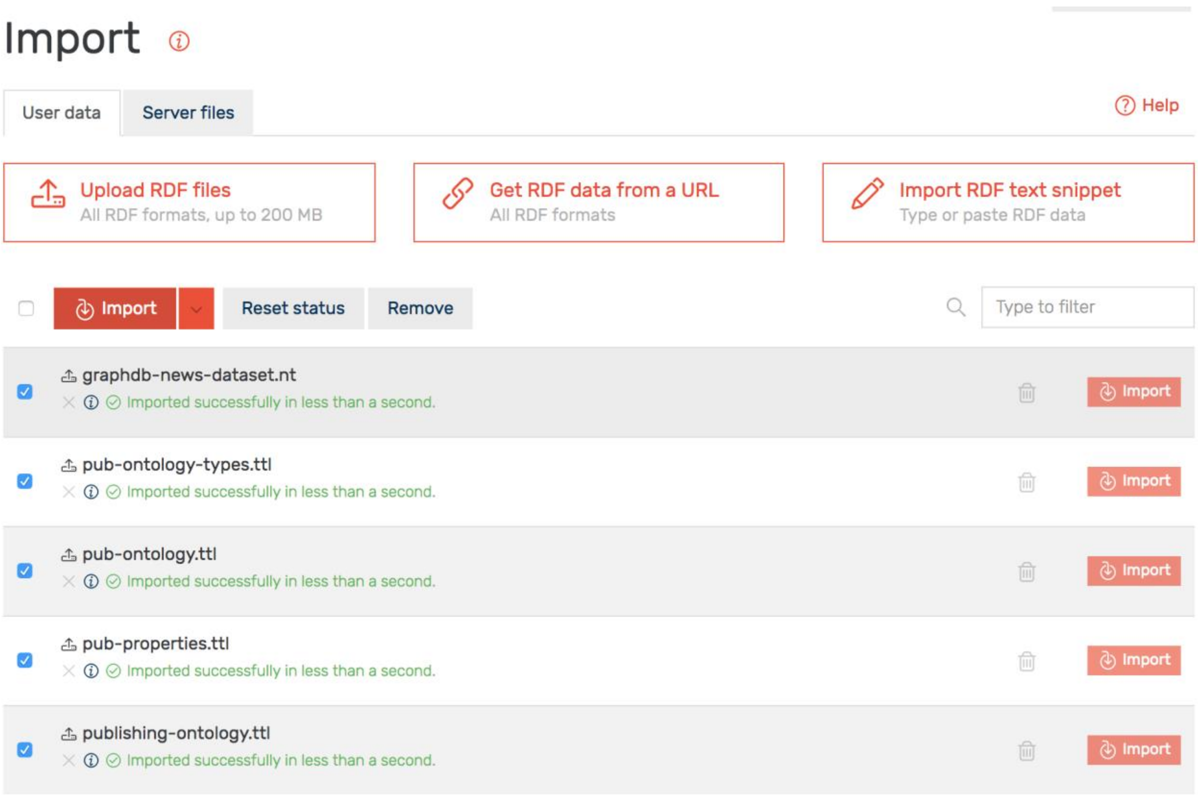


Figure 5: Importing RDF into GraphDB through the Workbench

Tabular Data and OntoRefine

The next level of complexity is working with tabular data which is, of course, a very popular format for data sets. This task is best accomplished through the use of GraphDB OntoRefine. It is a data transformation tool, based on OpenRefine and integrated in the GraphDB Workbench. It can be used for converting tabular data into RDF and importing it into a GraphDB repository, using simple SPARQL queries and a virtual endpoint. The supported formats are TSV, CSV, *SV, XLS, XLSX, JSON, XML, RDF as XML, and Google sheet.

```
PREFIX mydata: <http://example.com/resource/>
PREFIX spif: <http://spinrdf.org/spif#>

# Example query returning RDF data
CONSTRUCT  {
  ?presidentIRI a mydata:President ;
        mydata:tookOffice ?tookOfficeParsed ;
        mydata:leftOffice ?leftOfficeParsed ;
        mydata:nominatedBy ?party ;
        mydata:homeState ?stateIRI
} WHERE {
    # Triple patterns for accessing each row and the columns in contains
    # Note that no triples will be generated for NULL values in the table
    # You should inspect your data in Refine mode and add OPTIONAL accordingly
    ?row a mydata:Row ;
        mydata:Presidency ?Presidency ;
        mydata:President ?President ;
        mydata:Wikipedia_Entry ?Wikipedia_Entry ;
        mydata:Took_office ?Took_office ;
        mydata:Left_office ?Left_office ;
        mydata:Party ?Party ;
        mydata:Portrait ?Portrait ;
        mydata:Thumbnail ?Thumbnail ;
        mydata:Home_State ?Home_State .

   # Uses SPIN function to parse the dates
    bind(spif:parseDate(?Took_office, "dd/MM/yyyy") as ?tookOfficeParsed)
    bind(spif:parseDate(?Left_office, "dd/MM/yyyy") as ?leftOfficeParsed)
    # Uses several functions to construct IRIs for the presidents and their states
    bind(iri(concat("http://example.com/", spif:encodeURL(?President))) as ?presidentIRI)
    bind(iri(concat("http://example.com/", spif:encodeURL(?Home_State))) as ?stateIRI)
} LIMIT 100
```

Figure 6: Extracting RDF from transformed tabular data in OntoRefine

OntoRefine uses a straightforward process that consists of the following steps:

1. Create a new project and import the tabular data. Possible sources include:
    a. Local file
    b. URL
    c. Clipboard
2. Change the table configuration and parsing to properly represent the data. This involves steps like:
    a. Defining data types of columns
    b. Identifying column headers
    c. Specifying the separators between and within columns
3. Open the project and work on transforming the data. This is the most important and complex part of the procedure and will be described in more detail later.
4. RDFizing the data is the process of specifying how the transformed table is to be translated in RDF. This is done through a SPARQL construct query like the one shown in Figure 6.
5. Import the data in GraphDB from the remote virtual OntoRefine repository. This is based on executing the construct defined in the last step as an import with a federated body.

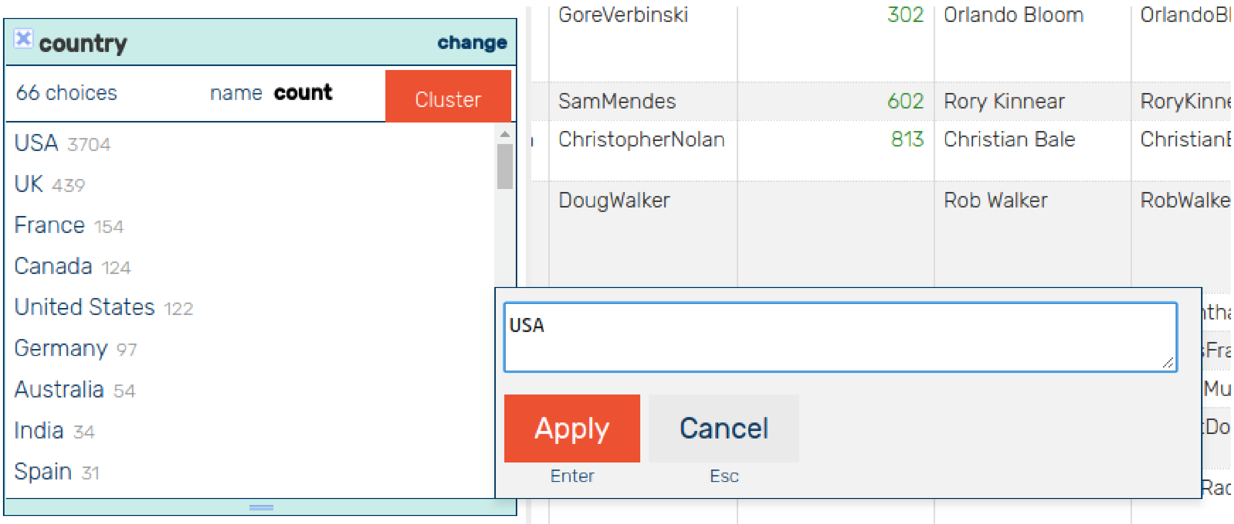


Figure 7: Normalizing text values

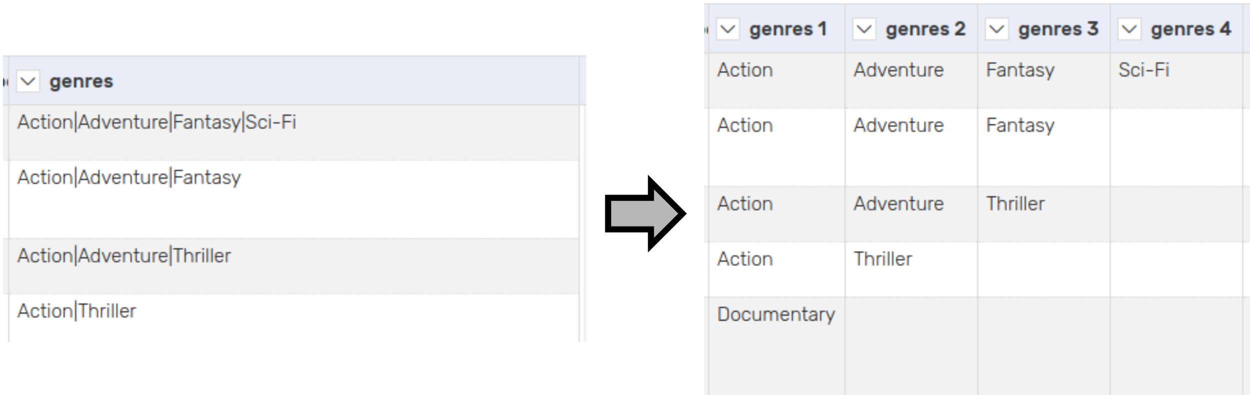


Figure 8: Splitting columns

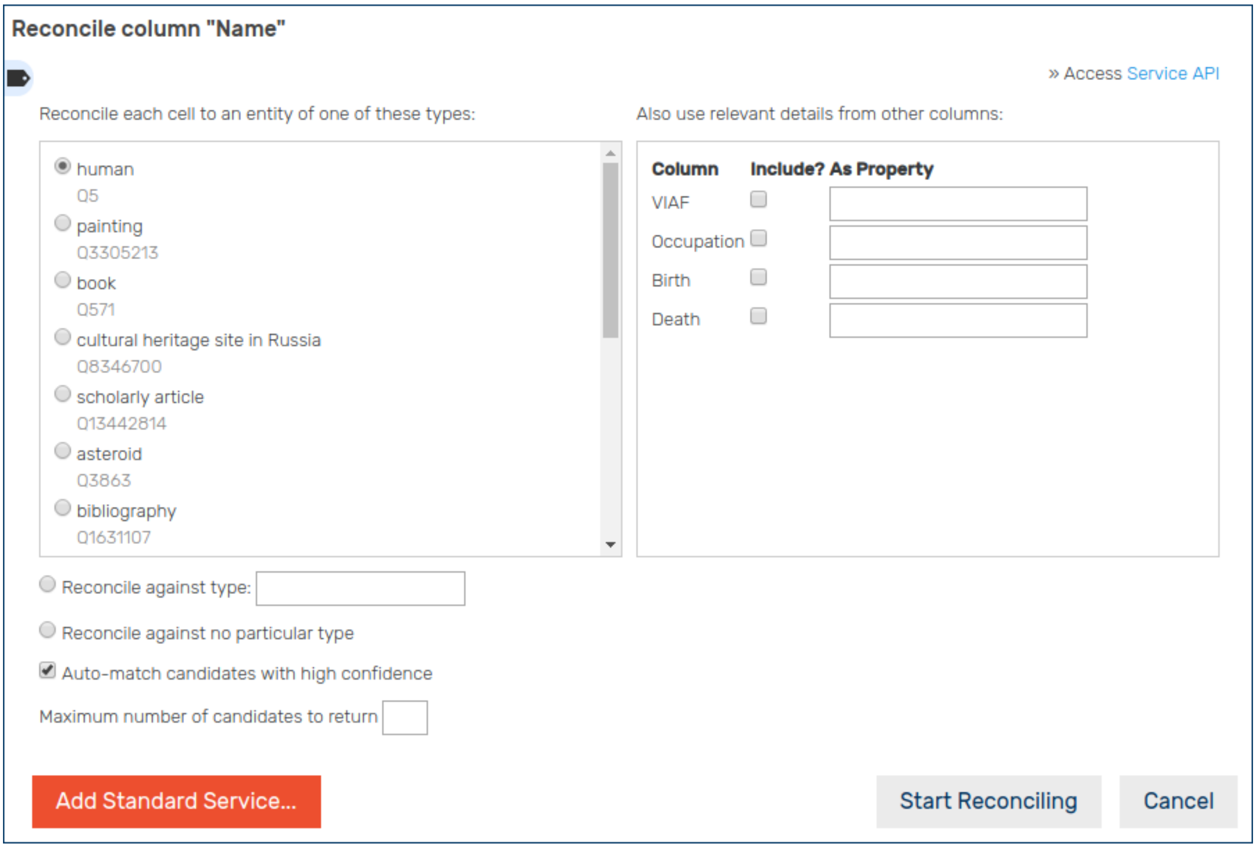


Figure 9: Reconciliation

The part that most depends on the specifics of the data source being processed is the transformation of the tabular data. There are a wide variety of possible operations that can be performed at that step but some example are cleaning up textual features like in Figure 7, splitting columns like in Figure 8 and performing reconciliation like in Figure 9.

Reconciliation is the process of linking free-text tabular cells to identifiers in knowledge bases i.e. making connections between the tabular data cells and our Knowledge Graph.

Data with Complex Structure and Talend Open Studio

Finally, there is data available in really complex formats. At the extreme end of this there is just free text data that needs to be processed using the linguistic pipelines we are developing in this task but there are structured data formats that, however, have very complex internal structures. For these kinds of tasks, we turn towards the tool described here.

Talend Open Studio (TOS) is an open-source solution for performing data integration, based on the Eclipse platform that offers off-the-shelf a powerful toolkit and infrastructure for designing data processing tasks known as jobs. TOS uses java code, generated by Java Emitter Templates (JET), a part of the Eclipse EMF Framework. The templates are based on the ETL process model and the data model, allowing for high-level abstraction programming or metaprogramming.

JET templates are similar to the Java Server Pages (JSP) syntax and primarily contain static code, which is output “as is”. The fixed content is enriched by a number of JSP-like tags that are evaluated and interpreted by the generation engine in various ways (Lassila and Swick, 1999). A summary of the available tags is given in Table 1 JET Template Tags:

Type	Syntax	Description
JET Directive	*<%@jet attributes %>*	**Declared the beginning of the template**
Include Directive	*<%@include file="URI" %>*	**Includes another template**
Expression	*<%= expression %>*	**Inserts the expression result**
Scriptlet	<% code %>	**Executes the code fragment**

Table 1: JET Template Tags

In order to get a better understanding of the code generation, used by TOS, consider the following excerpt from tGateDocumentToRDF – a component, responsible for the serialization of GATE semantic annotations to RDF. As a first step, the component has to create/open a file on the system for writing, based on user input:

```
<%@ jet
imports="
    org.talend.core.model.process.INode
    org.talend.core.model.process.IConnection
    org.talend.designer.codegen.config.CodeGeneratorArgument
    org.talend.core.model.process.ElementParameterParser
    "
    %>
<%
    CodeGeneratorArgument codeGenArgument =
(CodeGeneratorArgument)
    argument;
    INode node = (INode)codeGenArgument.getArgument();
    String cid = node.getUniqueName();
    boolean append = (Boolean)
    ElementParameterParser.getObjectValue(node, "__APPEND__");
    String location = (String)
    ElementParameterParser.getObjectValue(node, "__LOCATION__");
//      %>
java.io.Writer writer_<%=cid%> = null;
try {
  java.io.File f = new java.io.File(<%=location%>);
  writer_<%=cid%> = new java.io.OutputStreamWriter(
        new java.io.FileOutputStream(f, <%=append%>));
} catch (java.io.IOException e) {
  throw new RuntimeException(
        "Error while serializing data!", e);
```

Figure 10: Meta-programming with JET

JET templates enable the easy extension of the environment with custom components that introduce new features to be used within the graphical designer. A key advantage of the TOS environment, compared with the other data integration or mediation technologies, is that it uses the formal pipeline descriptions to generate executable java classes, which perform the actual work. A pair of formal description and generated java code is referred to as a job. Compared to the same tasks implemented in pure java code, these jobs have a performance decrease lower than 10-3. Jobs can be exported as standalone executable java archives (JARs) to be deployed to a production server. At the same time the intuitive TOS graphical user interface provides an easy way to debug the data flows and run them in a batch mode or scheduled sequences. Parallelization is another issue addressed by TOS on job-design level, allowing the simultaneous execution of sub-processes on multiple threads.

For the needs of the BDG use cases we will have to develop multiple text analytics components that will integrate existing tools and infrastructure. These custom extensions of TOS are going to provide a powerful infrastructure for populating and maintaining the BDG knowledge graph

3.3 SEMANTIC DATABASE

GraphDB is a product family of semantic databases, fully implemented in Java and compliant with the most popular RDF connectivity APIs – Sesame and Jena. It comes in three editions: GraphDB Free, GraphDB Standard Edition (SE), and GraphDB Enterprise Edition (EE) that all share the same inference mechanisms, rule language and rule compiler. Thus, the product family ensures smooth interoperability and capacity expansion from small research prototypes to big enterprise clusters, capable of processing millions of queries with industrial strength resilience and automatic failover.

GraphDB Free edition is a fully functional member of the GraphDB family. Its only limitation is that it can handle no more than two queries in parallel. It is appropriate for systems that require massive volumes of data, as it applies no constraints on the volumes of loaded data. It includes almost all the advanced features of GraphDB.

GraphDB SE allows organizations to manage tens of billions of semantic facts (data triples) on one commodity server. Fact statements can be loaded and queried at scale simultaneously.

GraphDB EE is an enterprise level triplestore proven to scale in production environments where simultaneous loading, querying, and inferencing of graph data statements occur in real time. It has been designed to run on an enterprise replication cluster scaling to any number of master and worker nodes. Replete with failover, backup and recovery, GraphDB EE has reliable data preservation, consistency and integrity.

GraphDB™ Feature Comparison	GraphDB Enterprise	GraphDB Standard	GraphDB Cloud	GraphDB Free
Manage unlimited number of RDF statements	✓	✓	✓	✓
Full SPARQL 1.1 support	✓	✓	✓	✓
Deploy anywhere using JAVA	✓	✓	✓	✓
100% compatible with RDF4J framework	✓	✓	✓	✓
Ultra fast forward-chaining reasoning	✓	✓	✓	✓
Efficient retraction of inferred statements upon update	✓	✓	✓	✓
Full standard-compliant reasoning for RDFS, OWL 2 RL and QL	✓	✓	✓	✓
Custom reasoning and consistency checking rulesets	✓	✓	✓	✓
Plugin API for engine extension	✓	✓	✓	✓
Support for Geo-spatial indexing & querying, plus GeoSPARQL	✓	✓	✓	✓
Query optimizer allowing effective query execution	✓	✓	✓	✓
Workbench interface to manage repositories, data, user accounts and access roles	✓	✓	✓	✓
Lucene connector for full-text search	✓	✓	✓	✓
Solr connector for full-text search	✓			
Elasticsearch connector for full-text search	✓			
High performance load, query and inference simultaneously	✓	✓	✓	✓
Automatic failover, synchronisation and load balancing to maximize cluster utilisation	✓			
Scale out concurrent query processing allowing query throughput to scale proportionally to the number of cluster nodes	✓			
Cluster elasticity remaining fully functional in the event of failing nodes	✓			
Instantly available as a fully managed service	✓		✓	
Community support	✓	✓	✓	✓
Commercial SLA	✓	✓	✓	

Figure 11: A side-by-side comparison of the functionalities available in each version of GraphDB.

All GraphDB editions come with several standard prebuilt rule-sets, namely RDFS, OWL-Horst (similar to pD*), OWL-Max (RDFS with most of OWL 2) and OWL 2 profiles RL and QL (Ziegler & Dittrich, 2014). Users also have the ability to build their own custom rule-sets using datalog like rules with inequality constraints.

3.4 SEMANTIC DATABASE EXTENSIONS

At the edges of semantic database abilities, there are often data intensive computations, which go well beyond the standard query expressivity either because 1) they tend to incorporate complex procedure logic or 2) the language algebra is not sufficient to cover it, like in the case of a vector space model. Regardless of the specific problem, the correct course of action is to push the computation as close to the data as possible, in order to guarantee query efficiency. Such an optimisation guarantees that no significant amounts of data will be moved outside the database process address space and the query execution planner can benefit from using a low-level interface.

In GraphDB, these types of data processing efficiency problem are resolved with the application of the plug-in API that allows the mapping between special predicates and a piece of software logic, added to the class path of the database. The special predicates are special purpose Internationalized Resource Identifiers (IRIs), used in SPARQL triple patterns on the predicate position to denote special query evaluation strategies. This approach has already been used to develop solutions for integration with state-of-the-art large-scale text search engines (lucene, elastic search, solr), complex geospatial operations (geosparql), semantic similarity computations (semantic vectors), large-scale document-oriented storage (MongoDB), graph prominence of nodes (RDFRank) and others.

3.4.1 GeoSPARQL Connector

GraphDB supports supports geospatial resource indexing through the GeoSPARQL plugin. In practice, it is not practical to store precomputed geospatial information with the forward-chaining reasoner so the GeoSPARQL plugin can be used to efficiently ask questions about distances, overlaps and other more complex spatial relationships between entities.

```
# F01: Airports near London
# GraphDB's geo-spatial plug-in allows efficient evaluation of near-by
# RDFRank brings the top 6 passenger airports at the top of a list of 80

PREFIX dbr: <http://dbpedia.org/resource/>
PREFIX geo-pos: <http://www.w3.org/2003/01/geo/wgs84_pos#>
PREFIX gdb-geo: <http://www.ontotext.com/owlim/geo#>
PREFIX dbo: <http://dbpedia.org/ontology/>
PREFIX rank: <http://www.ontotext.com/owlim/RDFRank#>

SELECT DISTINCT ?airport ?rrank
WHERE {
   { SELECT * { dbr:London geo-pos:lat ?lat ; geo-pos:long ?long . } LIMIT 1 }
   ?airport gdb-geo:nearby(?lat ?long "50mi");
       a dbo:Airport ;
       rank:hasRDFRank3 ?rrank .
} ORDER BY DESC(?rrank)
```

Figure 12: Special predicate query that uses geospatial indexes

The query shown in Figure 12 is an example of a geospatial query that uses a combination of semantic and geospatial data accessed through the GeoSPARQL plugin to return a list of airports within 50 miles of London ordered by their prominence within the graph.

4 CORPUS BUILDING

This section describes the approach to making a document selection for the building of a training and evaluation corpus. We describe in detail the proposed document inclusion criteria and document structure.

4.1 INCLUSION CRITERIA

In order to demonstrate our methodology, we are going to describe the details of a document collection procedure developed for and tested on existing linguistic pipelines in related fields. The first step in the procedure is to collect documents from a number of sources relevant to partner use cases. These can be crawled from the web or obtained as data dumps depending on availability and the nature of the specific source. The kinds of data we expect to collect includes research articles (e.g. PubMed), product brochures for pharmaceutical or cosmetics products (e.g. DailyMed), publications of clinical trials for pharmaceutical or cosmetics products and patent information. Here is a sample list of relevant sources as identified by our partners at APIGEA:

- https://www.sciencedirect.com/
- https://www.scopus.com/home.uri
- https://www.elsevier.com/
- https://scholar.google.com/
- https://patents.google.com/

As we can see, the sources are mostly concerned with biomedical research aggregators alongside patent and pharmaceutical trial information as we already discussed.

Some of these data sources might provide the documents with relevant metadata already attached, others might require defining procedures for extracting that metadata from the text (possibly with the assistance of ontologies). The process is complete when the disparate sources are combined into a single corpus with documents represented in a unified meta-model and with relevant metadata attached.

In this section we examine how this approach works and how well we can expect it to perform. It is important to stress that the presented approach is flexible enough to be applied to a modified list of domains relevant to the BDG partner use cases if new or additional source become available during the course of the project. The only requirement is that potential domains meet the following criteria for the documents they provide:

- The documents should have a clearly identifiable structure
- The sections naming should be consistent within each source, which will allow accurate mapping to their relevant semantic sections.
- Some of the sections should contain information, which can be looked up by our gazetteers, i.e. biomedical or agricultural data on known topics.

4.2 METHODOLOGY

This section describes in detail the methodology behind our approach. Our goal was to implement a generic process, which - based on the semantic sectioning of documents - could perform automatic document classification. The successfully classified documents were used as input to create semantic annotations that were subsequently linked to resources in the semantic repository (i.e. the KG). Both the sectioning and annotating steps were developed as GATE application processing pipelines (Cunningham et al., 2011) and each of them was built up using a specific collection of GATE processing resources (Cunningham et al., 2011). As the methodology depends on the user input for the document meta-model, in Section 4.7 we describe a methodology for general disambiguation of semantic terms, which can be used with any document relevant to the BDG use cases.

4.3 DOCUMENT META-MODEL

We define syntactic sectioning as the segmentation of a textual document into a tree of distinct parts, based on the structural and syntactic features of the latter – e.g. accented styles, font size, specific phrases in section title, etc. The resulting structure is a tree because the different structural parts exhibit a nesting pattern – section A can have a subsection B, which in turn can contain many subsubsections and so on.

Semantic sectioning is the process of mapping distinct parts of text, usually identified through syntactic sectioning, to a set of predefined categories that represent the document's logical structure. Unfortunately, there is no universal document structure, not even for documents from the same domain, with similar goals, or by the same organization. Therefore, the specific semantic sections for a document type have to be explicitly defined prior to performing information extraction. We call this formal description of a document's logical structure the document meta-model. The meta-model allows us not only to execute specific annotation pipelines over specific parts of the document, but also to do more precise semantics extraction, e.g. if a disease resource X is found in the indication section of document A and in the contra-indication section of document B, it is obvious that it has very different semantics in the context of these documents.

Because we aim at performing high precision semantic annotation, it is important to devise a methodology that allows us to specifically map syntactic sections to semantic sections, while at the same time allowing flexibility to define different rules for performing the segmentation over different classes of documents. In order to achieve this, a generic segmentation processing resource (PR) was developed that uses regular expressions to identify sections. Crucially, the actual regular expressions are not defined in the PR but are specified in the meta-model. The meta-model is then loaded as an initialisation parameter of the pipeline which means that the meta-model can be changed or multiple meta-models can be used without the need to modify the pipeline itself. In addition, you can have not only one document class but many, which re-use certain PRs. Therefore, the shareable PRs – a set of gazetteers, each populated with a different vocabulary (hence referred to as extraction types) – are also described in the metamodel. A formal description of the meta-model is given in Figure 13.

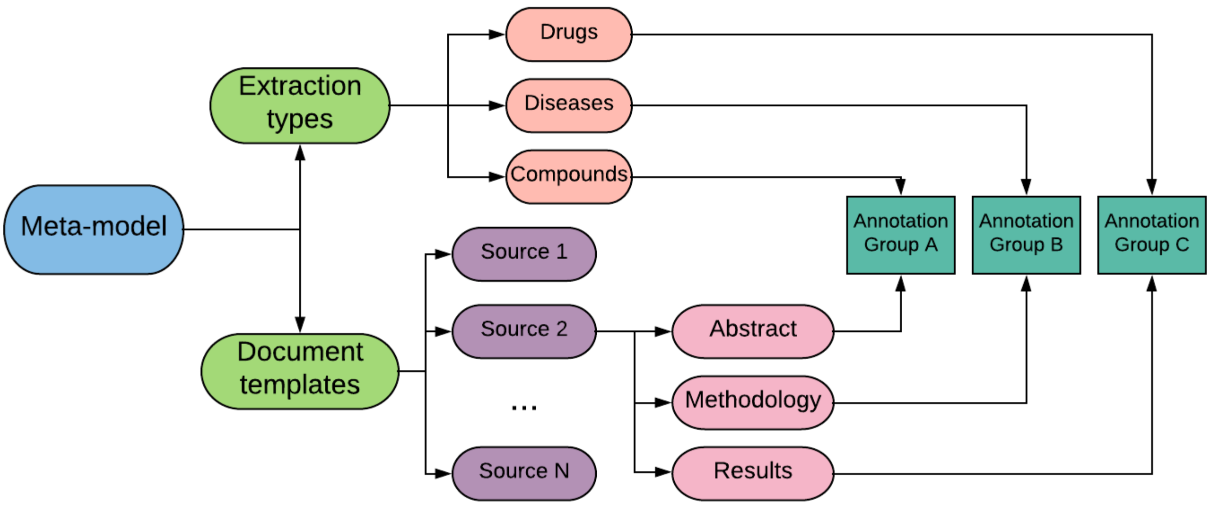


Figure 13: An example of a document meta-model. It is conceptually divided in predefined extraction types (gazetteers) and specified document templates (classes).

4.4 CLASSIFICATION

Classification is the process of assigning a document to a predefined document class from the metamodel. This is done based on the semantic sections from each template identified in the text. The classification process is implemented as part of the sectioning GAPP. It is initialised with the following parameters:

- encoding = "UTF-8"
- markupAware = true
- mimeType = "application/xhtml+xml"
- preserveOriginalContent = false

There are two types of annotations set by the GAPP: document features and section annotations. Some of these document features are dynamic, i.e. they are produced according to the metamodel. All these features are of *TYPE_XXX_SCORE type*, where *XXX* corresponds to Template Names defined in the system. Each *TYPE_XXX_SCORE* decimal value represents the number of matching regular expressions from a template against the input document. The formula used for calculating the score is $2*M/(A+C)$, where *M* is the number of the mapped sections in the input document to a given document template; *A* is the number of all syntactic sections, found in the document; C is the number of all semantic sections for a given document template. The highest *TYPE_XXX_SCORE* for each document is used to determine the document feature *TYPE.*

In practice the expected approach is to prepare one document template for each domain being processed or perhaps for collections of very similar domains.

4.5 NAMED ENTITY RECOGNITION

Once the document class and semantic sections are determined, we set up an annotation GAPP to extract appropriate information. In Figure 14 we provide a detailed description of the processing components in the GAPP.

Processing Resource	Description
Tokeniser	Standard GATE tokeniser
Sentence Splitter	GATE regular expression based sentence splitter
POS Tagger	GATE POS tagger trained on biomedical corpus (GENIA)
Morphological Analyser	FLEX based morphological analyser
Segmented Annotations	Governs which Gazetteer should be run on which semantic sections
Drugs Gazetteer	Gazetteer populated from DrugBank
Diseases Gazetteer	Populated with UMLS concepts from 14 semantic types related to diseases and body parts (T019, T020, T022, T023, T029, T030, T046, T047, T048, T049, T050, T184, T190, T191)

Figure 14: Processing resources used by annotation GAPPs. The distinct Gazetteers are always part of separate GAPPs

In order to extend the gazetteers' abilities to match not only the original but also derivative text chunks that did not exist in the KG, we apply a set of rewrite rules that are applied to each label entering the gazetteer during its population:

- The roots of words are determined (stemmer)
- A set of rewrite rules is applied:
    - the labels are filtered as follows:
        - filter out labels that contain an at (@) sign
        - filter labels that contain "not otherwise specified", "unspecified" "[NOS]" and similar
        - filter labels that contain "NEC", "not elsewhere classified", "unclassified" and similar
        - filter very short labels
    - derivative labels are created in the following ways:
        - remove angular brackets
        - remove multiple spaces
        - remove possessives
        - remove brackets at the end
        - remove parentheses at the end
        - invert labels that have a single comma: e.g. "pain, dorsal" → "dorsal pain"
    - labels with 6 or more tokens are removed.

The text chunks which are compared to the gazetteers' content are passed through a stemmer as well.

Due to the specificity of the biomedical knowledge domain and the knowledge source used (UMLS), many of the literals that had to be stored in the Diseases gazetteer were related to more than one concept. This problem may or may not be a concern for the Big Data Grapes KG as well but it can be mitigated to a large degree by a disambiguation priority mechanism elaboration which is already available. The implemented disambiguation mechanism is based on two assumptions:

- Each instance has one preferred label and all preferred labels are unique in the top-level Metathesaurus.
- Each instance has zero or more alternative labels and each of them has one or more sources.

Since the ambiguity is caused by a duplication of alternative labels for different instances combined with the simultaneous string and root usage as alternative token features, gazetteers population should be done by applying an eight-stage priority mechanism summarised below:

1. Strings matching preferred labels
2. Strings matching alternative labels with the highest number of distinct sources
3. Roots matching preferred labels
4. Roots matching alternative labels with the highest number of distinct sources
5. Strings matching rewritten preferred labels
6. Strings matching rewritten alternative labels with the highest number of distinct sources
7. Roots matching rewritten preferred labels
8. Roots matching rewritten alternative labels with the highest number of distinct sources

The longest non-nested annotations for a given text chunk with the lowest priority value (i.e. higher up in the list) are retained and all the other annotations are deleted.

Our approach to performing disambiguation has several advantages over other standard methods. First, removing the label ambiguity at the stage of populating gazetteer dictionaries has a huge performance impact, as it need only be done once during initialization. In contrast, having any rule- or ML-based analysis performed for each annotation will definitely slow down the process and might not be feasible for exceptionally large corpora. Second, the approach is deterministic which means that applying the same set of structured knowledge over the same text will always produce the same results. Therefore, it is easy to determine the cause of problematic annotations and correct them. The trade-off is that in this way we gain precision and sacrifice recall. However, we consider the trade-off beneficial as we aim for better precision because consistently returning correct results from a huge corpus is more useful than finding every single relevant instance at the cost of introducing a lot of noise in working with the corpus. Past evaluations on other projects have confirmed that this produces a more useful and satisfying product for the final user.

4.6 LINKING WITH STRUCTURED KNOWLEDGE

During the NER step, several attributes are specified for each annotation. First, the resource tag is set, the value of which is an instance URI from the semantic repository (KG), used for populating the gazetteers. Second, a rel attribute is set, which describes the relation of the instance to the section/document. The value assigned is a predicate URI, constructed from an application specific namespace prefix and a local name derived from the meta-model. The prefix is the domain name of the application serving the meta-model. The knowledge category associated with the section for the particular gazetteer, which made the annotation, defines the local name. Determining the relations is what we call interpretation. A summary of the annotation schema is given in Figure 15.

Annotation Type	Features
section	• cleanChapter – the section title • tocNumber – the section number (if exists) • level – the section level (e.g. level=1 for tocNumber=3, level=2 for tocNumber=3.1, etc. If there is no tocNumber, level=1.) • section_ids – an array of matching semantic section names for all defined document templates • ID – the semantic section name after the document classification • typeof – the URI of the semantic section for the document template • resource – the URI of the semantic section for the specific document
lookup	• gap – the GAPP name, which created the annotation • section – the semantic section name • level – the section level • rel – the URI of the annotation, defined for the combination of the semantic section and GAPP that was run over it • resource – the instance URI from the semantic repository • string – the annotation string • typeof – the class URI from the semantic repository

Figure 15: The proposed annotation scheme used for both classification and NER

The RDF statements are generated according to the scheme <section> <rel> <resource>. Finally, all statements are added back to the semantic repository (the KG). Inference rules and additional indexing is applied at this step. The knowledge categories hierarchy is also transformed to RDF in a similar manner, allowing for rich semantic queries over the document data using skos:broader and skos:narrower properties.

4.7 GENERIC DISAMBIGUATION OF TERMS

The disambiguation heuristics for ambiguous terms consists of three steps:

1. If a given span of text is covered by several terms, then only the longest will be retained. The intuition here is that the KG contains technical terms for both atomic concepts and more complex, compound ideas. We are interested in the compound terms as the atomic concepts may be derived from these at a later stage and a sequence of atomic terms that normally comprise a single compound term discovered in order almost certainly represent a mention of that compound term.
2. If a given span is covered by several terms of the same length (after the previous step), then any that are not considered “preferred” terms by the KG are rejected. Each concept in the KG may be described by multiple terms but one of these will always be considered the preferred term, i.e. the one that is most commonly encountered in practice. The intuition here is that if multiple concepts map to a span of text, the most likely concept being described is the one that is generally most often used in natural language.
3. If several terms remain spanning the text, then one is selected based on the heuristic used by Cengage Learning, as described in (King et al, 2011). This heuristic makes use of the concept identifier assigned to each concept in UMLS, the CUI. The CUI has a numeric portion. Although not designed to contain meaning, Cengage shows that the lower the numeric portion of a CUI, the more likely it is to refer to the common usage of a concept. This could be because the common usage is more general, and when CUIs are assigned to portions of the UMLS, they are assigned linearly.

5 ANNOTATION PIPELINE

This is the general architecture of the Annotation Pipeline. While some details in its structure remain to be determined by the specifics of the Knowledge Graph, document model and corpus, the high-level concepts and major building blocks should remain the same.

5.1 PIPELINE ARCHITECTURE

The pipeline consists of the following sub-pipelines:

1. Add and amend metadata (metadata): This sub-pipeline prepares all the metadata required for the Semantic search index. This includes accessing metadata that originates from the storage repository metadata fields and adding additional metadata which is not included or missing from the storage repository metadata fields. Depending on the later use of the metadata, it is added as either a document feature, annotations to existing document parts, or the document is edited, and additional document text added and annotated. The specific way this is done depends on the source and format of the document. Metadata is added in the form of document features, annotations of document text that already exists or gets added in this sub-pipeline, or zero-length annotations with features that contain the necessary metadata. This sub-pipeline consists of the following main processing resources:
   - **LongestEntryLookup**: this processing resource is used to store relevant data and to lookup the data for the longest known concept match. The preparation of the metadata stored with this processing resource is described in Section 5.2.
   - **basicMetadata:** this step tries to determine the kind of document being processed based on various clues from the existing metadata, document name, and document content. It also processes the following metadata which is identical for all kinds of documents retrieved from the storage repository: url, id, language, domain, dateCrawled
   - **createDefaultMeta:** this step processes the metadata for all crawled documents, but not documents obtained from other sources like Wikipedia articles or scientific article abstracts.
   - **createPubmedMeta**: this step processes the metadata for Pubmed abstracts
   - **createDailyMedMeta**: this step processes the metadata for DailyMed articles.
   - **createPatentsMeta**: this step processes the metadata for Patents abstracts
   - **createAllMeta2**: adds the *domainClass* metadata to all documents.
     Also determines the ISO 31661-1 two letter country code from the country name derived from the top-level domain name of the URL.
2. Detect publication dates for selected pages from selected hosts. In this sub-pipeline the URL of the processed page is checked against a known list of domains and regular expressions for URL path names. If there is a match, the following steps are carried out:
   - dates in a variety of formats, including dates which only consist of a month and year, or just a year alone, are detected on the page.
   - known publication date contexts are identified by nearby identifying text (e.g. “last updated:”) and by identifying parts of the HTML DOM tree.
   - dates within a publication date context are parsed and converted to a standardized date representation. This date is stored as metadata and also the information that a publication date has been found is stored as metadata for this page.
3. Basic linguistic annotations (basic-annots): This sub-pipeline performs basic tokenization and sentence splitting. In addition, it runs a POS tagger and morphological analyser which provides lemmata for English language documents.
4. Identify indexable content and boilerplate (findContent): this sub-pipeline annotates the parts of the documents which are likely to contain content (as opposed to boilerplate text like navigation menus,

company logos and the like). This is done in different ways depending on the kind of document: for Wikipedia documents, the whole document is marked as content. For Pubmed abstracts, the title and abstract are marked as content. For all other documents, the GATE BoilerPipe plugin is used to identify content and boilerplate parts of the document. The list of document types will be expanded to reflect the nature of specific sources collected for the Big Data Grapes use cases.

5. Identify stop words (annotate-stopwords): this sub-pipeline is executed for English language documents and uses gazetteer lists to mark tokens where the surface string or the lemma matches a stop word.
6. Semantic annotation of KG concepts (umls-extgaz): this sub-pipeline annotates occurrences of labels of KG concepts based on a set of gazetteer lists and then post-processes those annotations to create the annotation features needed later and remove obvious duplicates. The main steps of this sub-pipeline are:
   - **setWordFlags**: this step marks each token as a possible candidate for starting, ending or being part of a multi-word KG term, based on the POS tag of the label.
   - **ExtGaz:abbrvs**: annotate possible abbreviations that may denote KGconcepts
   - **ExtGaz:standard-root**: annotate potential KG concepts by matching a gazetteer lists of lemmata against the the lemmata of the tokens in the document
   - **ExtGaz:standard-string**: annotate potential KG concepts by matching a gazetteer lists of KG labels against the string of the tokens in the document.
   - **FeatureGaz:umls-types**: add information about the KG-types of potential matched concepts to the annotations.
   - **RemoveDupes:** this removes various kinds of duplicate annotations, for example duplicates for identical spans and CUIs which originate from identical matches from the lemmata and string gazetteers, or annotations of different length but for the same CUI where several labels exist in the KG and one label is a substring of the other.
   - there are additional steps where, among other things, known spurious matches are removed and the textual name of the KG class of a concept is added to the annotation.
7. Semantic annotation of chemical compounds and activities gazetteer: This annotates occurrences of terms that match labels for chemical compounds and activities from a gazetteer list.
8. Heuristic disambiguation between multiple possible concepts (umls-disambiguate): This sub-pipeline uses heuristic rules to choose between several possible semantic annotations which overlap at some position in the document. The heuristic rules use information about the source of the match (KG concepts, DrugBank labels, others), the kind of match (abbreviations, lemmatised matches, original string matches), the semantic type (as determined by the KG), the kind of overlap (shorter, equal span, arbitrary overlap) as well as the concrete CUI for KG concepts to disambiguate between several potential matches. The following main heuristic rules are applied:
   - DrugBank matches have priority over UMLS matches
   - longer matches have priority over shorter matches
   - overlapping matches that start earlier in the document have priority over those that start within another annotation
   - CUIs that denote a more specific concept have priority over more general ones
   - Note that the specific nature of these heuristic rules depends on the KG and corpus so they would be modified to conform to the Big Data Grapes use cases.
9. ML-based disambiguation between multiple possible concepts (**mlNN-features, mlNN-apply, mlNN-disambig**): This is done by three separate sub-pipelines which are responsible for creating the features used by the machine learning model, applying the machine learning model and creating the classification features, and using the classification features together with the results from the heuristic disambiguation to carry out the actual disambiguation. There will be various versions of each of these sub-pipelines, from the various iterations in the manual annotation process and from different experimental approaches of how to use machine learning for the disambiguation. Details of

this will be given in the final iteration of D3.4 as the ML training process is strictly dependent on all other parts of the system being fully implemented and completed.

5.2 METADATA PREPARATION

Metadata preparation for the pipelines is a process that transforms the relevant data available from the KG into gazetteers and other resources for the pipeline. The process of collecting, transforming and ingesting the data into the KG is discussed in detail in Section 3. The process of building gazetteers and other resources for the pipeline depends on the specific nature of the contents and pipeline and remain to be determined for the BDG use cases.

5.3 GAZETTEER FILES PREPARATION

The exact details of how the gazetteer files are prepared will depend very strongly on the nature of the KG created by the methodology described in Section 3. One or more gazetteers will be created based on the labels available for all concepts in the KG but before using the full list of labels as a gazetteer, we will carry out some simple filtering on it. As a first step, we will filter out concepts not directly relevant to BDG as the final KG might be larger than strictly necessary for the tasks at hand. Subsequently, morphological analysis can be applied on every single word label to remove labels that can easily be confused for function words, e.g. prepositions, conjunctions. In this way very few labels will be discarded from the list but many false positives will be fixed in the final results.

6 CONCLUSION

In this document we presented a tested approach for the design of advanced text analytics pipelines aiming to extract and semantically annotate information from unstructured data included in the BigDataGrapes data pool. This approach is based on defining a semantic KG, collecting and building a training and evaluation corpus for the relevant use cases, defining document meta-models describing the available documents and performing semantic NER with reference disambiguation based on those models. In future deliverables on this task we will report progress on the practical implementation of each of these steps to the specific use cases, starting with the definition of the KG and collection of documents from some trial domains and followed by the adaptation and optimization of the linguistic pipelines to the new domains.

7 REFERENCES

Angles, R., and Gutierrez, C. (2008). The Expressive Power of SPARQL. Proceeding ISWC '08 Proceedings of the 7th International Conference on The Semantic Web, Pages 114-129. Available at: http://www.dcc.uchile.cl/~cgutierr/papers/expPowSPARQL.pdf

Cunningham, H., Maynard, D., Bontcheva, K. (2011). Text Processing with GATE (Version 6). University of Sheffield, Department of Computer Science. ISBN 0956599311.

King, B., Wang, L., Provalov, I., and Jerry, Z. (2011). Cenagage Learning at TREC 2011 Medical Track. The Twentieth Text Retrieval Conference Proceedings, Gaithersburg, MD. National Institute for Standards and Technology.

Lassila, O., and Swick, R. R. (1999). Resource Description Framework (RDF) Model and Syntax Specification. Available at: http://www.w3.org/TR/PR-rdf-syntax/

Lenzerini, M. (2002). Data integration: a theoretical perspective. Proceedings of the twenty first ACM SIGMOD-SIGACT-SIGART symposium on Principles of Database Systems, June 3-5, Madison, Wisconsin, USA. ACM, New York, 233–246.

Momtchev, X., Peychev, D., Primov, T., and Georgiev, G. (2009). Expanding the Pathway and Interaction Knowledge in Linked Life Data. In Proc. of International Semantic Web Challenge.

Prud'hommeaux, E., & Seaborne, A. (2008). SPARQL Query Language for RDF. Available at: http://www.w3.org/TR/2008/REC-rdf-sparql-query-20080115/

Sheth, A. (1998). Changing Focus on Interoperability in Information Systems: From System, Syntax, Structure to Semantics, in Interoperating Geographic Information Systems. The Springer International Series in Engineering and Computer Science book series (SECS, volume 495), Interoperating Geographic Information Systems pp 5-29.

Ziegler, P. & Dittrich, K. R. (2004). Three decades of data integration - All problems solved? In 18th IFIP World Computer Congress (WCC 2004), Volume 12, Building the Information Society.