Universität Leipzig
Fakultät für Mathematik und Informatik
Institut für Informatik

LEARNING ARBITRARY RDF DATASET ENRICHMENT GRAPHS USING PRE- & POSTCONDITION BROADCASTING

Leipzig, Juli 2019

vorgelegt von
Kevin Dreßler
Studiengang Informatik

Betreuender Hochschullehrer:
Prof. Dr. Axel-Cyrille Ngonga Ngomo

ABSTRACT

The impact of Linked Data in applications on the World Wide Web as well as in businesses has been tremendous in the recent decade. Linked Data Integration is of paramount importance for this tendency to continue. Despite there being a great amount of literatue on lifting, interlinking and fusion of RDF Datasets, the field of RDF Dataset Enrichment has seen little attention. Specifically, there exist no accessible tools to power this step in the Linked Data Lifecycle.

This thesis attempts to address this gap by extending on a previous approach in RDF Dataset Enrichment to enable successful RDF Dataset Enrichment for a larger set of use cases. Since such tools require extensive configuration of their components in order to lead to satisfactory results, it is often not feasible for non experts to use them. Therefore, an efficient machine learning algorithm using novel improvements to enable the use of our tool by novice user is proposed. Evaluation suggests that our approach can successfully learn a larger class of RDF Dataset Enrichment specifications than the state of the art, using only a single training example.

ZUSAMMENFASSUNG

Linked Data konnten in der letzten Dekade in Anwendungen des World Wide Webs und der Wirtschaft große Erfolge erringen. Die Integration von Linked Data ist ein essentieller Bestandteil um diesen Erfolg fortzuführen. Obwohl das Liften, Verlinken und Fusionieren von RDF-Datensätzen in großem Umfang in der Literatur behandelt wird, hat das Gebiet der RDF-Datensatzanreicherung wenig Beachtung gefunden. Insbesondere existieren keine zugänglichen Werkzeuge, um diesen Schritt im Linked Data Lifecycle zu unterstützen.

Diese Arbeit versucht, eben jene Lücke zu schließen, indem sie einen bestehenden Ansatz der RDF-Datensatzanreicherung mit dem Ziel erweitert, die RDF-Datensatzanreicherung in einer größeren Klasse von Anwendungsfällen zu ermöglichen. Da solche Werkzeuge eine umfangreiche Konfiguration ihrer Komponenten erfordern, um zu zufriedenstellenden Resultaten zu führen, ist es für Laien häufig zu schwer, diese zu verwenden. Daher wird auch ein effizienter Algorithmus für maschinelles Lernen entwickelt, der neuartige Verbesserungen verwendet, um die Verwendung unseres Werkzeuges für unerfahrene Benutzer zu ermöglichen. Die Evaluation legt nahe, dass dieser Ansatz in der Lage ist, eine größere Klasse von RDF-Datensatzanreicherungsspezifikationen erfolgreich zu erlernen als bestehende vergleichbare Ansätze. Zudem benötigt er dafür nur ein einziges Trainingsbeispiel.

If you really want to escape
the things that harass you,
what you're needing is not
to be in a different place
but to be a different person.

— Lucious Annaeus Seneca

ACKNOWLEDGMENTS

I would like to thank everyone who supported me through the past three years.

First and foremost, thanks go to my supervisor Dr. Mohamed Ahmed Sherif for his professional as well as personal support, patience and believe in my abilities.

I also thank Prof. Dr. Axel-Cyrille Ngonga Ngomo for introducing me to research years ago, giving me the benefit of the doubt and enabling me to have my first journal paper before even handing in my bachelors thesis.

Further thanks goes to everyone in the DICE research group that answered my questions or helped me getting around organizational or software issues when running my experiments.

Last but not least, I most genuinely thank my parents for their unconditional love and support throughout all of my life.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LISTINGS

ACRONYMS

RDF	Resource Description Framework
SHACL	Shapes Constraint Language
W3C	World Wide Web Consortium
DEER	RDF Dataset Enrichment Framework
DEER2	RDF Dataset Enrichment Framework 2
DAG	Directed Acyclic Graph
GA	Genetic Algorithm
GP	Genetic Programming

PRNG	Pseudo Random Number Generator
MEP	Multi Expression Programming
LOD	Linked Open Data
HTTP	Hypertext Transport Protocol
SPARQL	SPARQL Protocol and RDF Query Language
URI	Uniform Resource Identifier
URL	Uniform Resource Locator
IRI	International Resource Identifier
DL	Description Logic
XSD	XML Schema Definition
RDFS	RDF Schema
OWL	Web Ontology Language
CBD	Concise Bounded Description
JDK	Java Development Kit
PF4J	Plugin Framework for Java
NER	Named Entity Recognition
FOX	Federated knOwledge eXtraction Framework
LIMES	Link Discovery Framework for Metric Spaces

1 INTRODUCTION

1.1 MOTIVATION

The Web of Data, also known as the Semantic Web, is growing from year to year[1], giving leeway to a vast amount of applications to harvest the knowledge cotained within the Linked Open Data (LOD) Cloud.

With growing numbers of datasets, we also see a growing number of domains being represented in the LOD Cloud, leading to the need for a growing number of novel ontologies and vocabularies. While some of these ontologies and vocabularies are well known and standardized by e.g. the World Wide Web Consortium (W3C), most are distributed over the web, hard to find and potentially model the same domain, therefore being redundant vocabularies.

This leads to a retrieval problem of ontologies and vocabularies for dataset curators which the term „Ontology Dowsing"[a] was coined[2] in order to capture the problematic unscientific guessing nature which is most common today when trying to locate a suitable ontology or vocabulary for modeling data in the Resource Description Framework (RDF). As a result, applications that comsume the Web of Data also often define their own specific vocabularies as it is not feasible to support, let alone be aware of, all potentially applicable ontologies and vocabularies for the specific application domain.

[a] *Dowsing is the practice of searching for ground water or metal ores using a Y-shaped rod.*

Moreover, limited resources on clients mean that the large datasets in the LOD Cloud, which are often schemaless due to the underlying Open World Assumption, have to be filtered and distilled before they can be used by applications.

We refer to the processes needed to solve the above mentioned problems as RDF Dataset Enrichment. RDF Dataset Enrichment is a quintessential part of Linked Data Integration, which also consists of the *linkage* and *fusion* of RDF Datasets.

While there has been a lot of work on the automatic linkage and fusion, RDF Dataset Enrichment has been paid little attention

1 https://lod-cloud.net
2 https://www.w3.org/wiki/Ontology_Dowsing

to, despite there being a critical need for better solutions in order to truly enable Semantic Web powered applications.

1.2 OBJECTIVES

In this thesis we address this shortcoming by extending RDF Dataset Enrichment Framework (DEER) [51], the only existing approach to automated RDF Dataset Enrichment we are aware of. While DEER implements a fixed set of so called enrichment functions and only allows chaining them lineraly in a pipeline, we argue that this approach is too limited to of use to the very specialized needs of real-world RDF Dataset Enrichment. Therefore, our first objective will be to build an extension of DEER, called DEER2, which should be (1) highly modular, meaning that the framework should be easily extendable by third party developers in order to create specialized enrichment functions and (2) allow to represent the enrichment process as a Directed Acyclic Graph (DAG) of modular operations. These extensions should provide enough flexibility for dataset curators as well as application developers to use DEER2 in real world RDF Dataset Enrichment workflows.

The original DEER publications main contribution was the introduction of a refinement operator-based learning algorithm which enabled novice users to define adequate RDF Dataset Enrichment workflows. As highly modular applications in general require a lot of manual configuration of their components and therefore presume expert knowledge to precisely define how the modules operate and interact with each other, a machine learning based approach to automatic configuration will be the second and main objective of this paper.

Since introducing DAG-shaped RDF Dataset Enrichment workflows in DEER2, the complexity of the learning problem is greatly increased in comparison to DEER. We will therefore base our approach on Genetic Programming (GP) instead of refinement operators, since GP is known for its ability to find good solutions for hard symbolic regression problems, albeit at the cost of being non-deterministic.

1.3 DESIGN GOALS AND RESEACH QUESTIONS

We set the following goals for the design of DEER2:

(G1) DEER2 should be highly modular

(G2) DEER2 should represent RDF Dataset Enrichment workflows efficiently as DAGs

(G3) DEER2 should include a GP based learning algorithm for automatic configuration of RDF Dataset Enrichment workflows

(G4) DEER2 should improve on all of the identified shortcomings of DEER.

In order to measure the success of our learning approach we will aim to answer the following research questions:

(Q1) What is the optimal set of hyperparameters?

(Q2) Does our approach generalize well?

(Q3) How does our approach perform on real world datasets?

1.4 STRUCTURE OF THIS THESIS

The remainder of this thesis is structured as follows: In Chapter 2 we explore the State of the Art for fields relevant to this work and introduce some of the basic concepts required to understand this thesis. After that, we present our approach DEER2 in Chapter 3. We evaluate our approach and answer the posed research questions in Chapter 4. Finally, we conclude in Chapter 5.

2 BACKGROUND

2.1 GENETIC ALGORITHMS

A Genetic Algorithm (GA) is a non-deterministic population-based global search metaheuristic that reformulates optimization problems in a vocabulary that makes heavy usage of metaphors on biological evolution, thus also being called a nature-inspired metaheuristic.

Genetic Algorithms typically represent solutions to a problem as bit vectors which correspond to the *genotype* in biological evolution. These genotypes encode a set of parameters which are passed to a so called *fitness function* which promotes a survival of the fittest and is thus the target of minimization or maximization in the underlying optimization problem.

A fixed size population of genotypes, in this context also called individuals is initially generated at random using a Pseudo Random Number Generator (PRNG). This population of genotypes, parameterized by the population size (μ), is then iteratively evolved where the iterations are typically referred to as *generations*. In each generation, a subset of the population is selected to join a so called recombination pool, which is parameterized per the *recombination pool size* (λ). The selection of individuals is carried out using a so called selection operator. An important property of a selection operator is the *selective pressure*, which is informally described as the emphasis of selection on the best individual, where a high (small) selective pressure means a strong (weak) emphasis. We will discuss two of the most prominent selection operators further down in this text.

The individuals selected for recombination are then passed in pairs to a crossover operator, which generates a pair of childs by swapping the bit vectors representing the individuals at a given crossover point[b]. The childs are then inserted into the next generations population together with the survivors, which are selected from the current population also using a selection operator.

A mutation operator is then applied to each individual in the next generation with a certain *mutation probability* (σ). The classic mutation operator mutates each selected individual by chang-

[b] *Note that the literature contains a vast number of variations on the crossover operator such as multi-point crossover*[54] *and uniform crossover* [58], *however they are of no particular interest to this work. There has also been a debate over the usefulness of crossover operators which resulted in several extensive theoretical analyses with minimalistic toy problems with the result that they „can provably be useful"*[13, 53].

ing the bit value of a given bit in its bit vector representation with a probability denoted by the *mutation rate* (ρ), i.e. a mutation rate of $\rho = \frac{1}{2}$ means that on average, half of the bits are changed to their opposing state.

These steps of selection, crossover and mutation are repeated until a certain termination criteria holds, which could include a maximum number of generations, a target fitness value or a test of population convergence.

Note that in the sense as defined above, Genetic Algorithms were reportedly[33] first conceived by John Holland in 1960 as an extension of general $(\mu + \lambda)$ Evolutionary Algorithms, the novelty being the introduction of crossover and selection operators whereas previous iterations of Evolutionary Algorithms only made use of mutation operators.

SELECTION OPERATORS While the literature contains a great number of selection operators, for sake of brevity we will only introduce the two selection operators used in the remainder of this text, namely the Elitist Selection[33] and the Tournament Selection[32].

The Elitist Selection is a simple selection procedure which includes the N best performing individuals in the next generation. It is typically used in conjunction with another selection operator, as it would just lead to a stochastic hill climbing algorithm when used as only selection operator and there are much more efficient hill climbing algorithms, such as [59] for discrete or [3] for continuous optimization problems.

The Tournament Selection is one of the most established selection operators, as it has been proven able to adjust the selective pressure independently from the population size and fitness function scaling[22]. It is parameterized by the tournament size k and the selection probability p. Initially, k individuals from the given population are randomly selected to enter a tournament. Then, the ith best individual in the tournament w.r.t. the fitness function is selected to win the tournament with the probability $p(1-p)^{i-1}$. This means that setting the probablity to $p = 1$ will result in a deterministic behaviour while setting $k = 1$ results in random selection.

2.1.1 *Genetic Programming*

Genetic Programming (GP) is a subfield of Genetic Algorithms which originated from the application of a GA in order to evolve computer programs in 1988 by John Koza[29]. While traditional GAs are commonly used for numerical optimization and search problems, GP can be used for symbolic regression and classification.

In Genetic Programming, programs are usually encoded as trees of operations and terminals, but other encodings have also been proposed. For example, Graff et al.[23] use DAGs to encode python programs, and Kvasnièka and Pospíchal[30] introduced a condensed encoding of DAGs, dubbed „Column Tables", which we will adapt and use in this work (see Section 3.1.2).

2.1.2 *Multi Expresssion Programming*

Multi Expression Programming (MEP), originally introduced by Ferreira[18] as „Gene Expression Programming" denotes a special kind of Genetic Programming where the genotype of an individual represents multiple solutions or subsolutions that has gained traction in recent years. Only the best amongst these multiple solutions is then used as the effective solution, also called the *phenotype* of the individual. This technique is used in problems where it does incur no additional cost to keep track of the fitness of subsolutions, such as is generally the case with the evaluation of a program represented as a tree: it can be easily seen that when evaluating such a tree-shaped program, one has to visit each node anyway in order to compute its result.

It can be used to evolve programs with the same complexity as traditional GP but much more efficient and excels in multiple-output problems. To this end it has been successfully applied to the TSP[43], data prediction[62], software effort estimation[2], on-the-fly hyperparameter optimization for Evolutionary Algorithms[44] and digital curcuit design[42].

2.1.3 *Semantic Genetic Operators*

Semantic Genetic Operators are a special kinds of crossover and mutation operators which take into account the semantics of a genotype rather than just discerning it as a bit vector without any further interpretation. They are therefore aware of the specific genotype encoding and manipulate the individuals w.r.t. the solution space rather than the encoding space.

Their recent successful application to a number of problems[11, 20, 45, 57] indicates that taking semantics into account is a promising novel direction for GP.

Table 2.1: The Five Stars of Linked Open Data

Stars	Requirements	Example
☆☆☆☆★	Published with an Open License	PDF, PNG, TXT
☆☆☆★★	Machine-Readable Structured Data	XLS, ODF
☆☆★★★	Non-proprietary File Format	XML, CSV, JSON
☆★★★★	Use URIs to identify things	RDF
★★★★★	Linked to other data	RDF

2.2 LINKED DATA

Linked Data[5, 7, 8] is a term coined by Tim Berners-Lee[5] in 2006. It refers to data available on the Web that is (1) structured, (2) uses URIs as identifiers and (3) is interlinked with other data on the Web. Linked Data is enabled by the use of standard Web technologies such as the Hypertext Transport Protocol (HTTP), the RDF and the SPARQL Protocol and RDF Query Language (SPARQL). It is closely related to the term Semantic Web[6, 48], which describes a Web of Data which, in opposition to the human-readable Web of Documents is specifically engineered to be machine-readable. The Semantic Web promotes a high interconnectedness of datasets by interlinking them with eath other, thereby enabling the ability to consume data from multiple datasets at once using semantic queries, e.g. using the SPARQL protocol.

When considering Linked Data published under open licenses, we speak of Linked Open Data (LOD). A quality scheme for LOD, namely the five stars of LOD, was given by Tim Berners-Lee in 2010[5] and is summarized in Table 2.1.

2.2.1 *The Resource Description Framework*

The Resource Description Framework (RDF) is a „standard model for data interchange on the Web"[24]. RDF models data in an abstract syntax which is defined in terms of an abstract graph-based data model. The nodes in this graph-based model belong to one of three atomic base types: *IRI resources*, *literals* and *blank nodes*. IRI resources and blank nodes denote a particular subject in the world, while literals only contain values which are subject to further interpretation. As blank nodes lack the notion of a global identifier, they serve as existential variables in the data model.

An RDF graph is a collection of *statements*, also called *triples*, which basically correspond to simple sentences in natural language. Each statement therefore consists of a subject, a predicate and an object. Every subject is either a IRI resource or a blank node, all predicates are IRI resources and objects can be either of the three basic types.

In the following, we will give a formal specification of an RDF Dataset on which we will rely in the remainder of this work.

RDF DATASET: Let $\mathcal{R}$ be the set of all RDF IRI resources, $\mathcal{B}$ be the set of all blank nodes and $\mathcal{L}$ be the set of all literals.

We call a set $D := \{(s, p, o) \in (\mathcal{R} \cup \mathcal{B}) \times \mathcal{R} \times (\mathcal{R} \cup \mathcal{B} \cup \mathcal{L})\}$ of triples an **RDF Dataset**.

Note that for sake of simplicity, we will not distinguish between an RDF Dataset and its abstract graph and therefore we from now on resort to referring to both as RDF Datasets.

2.2.2 *Vocabularies, Ontologies and Shapes*

While RDF specifies a basic set of vocabulary, it is not very expressive on its own and offers no mechanism to define vocabularies or data schemes.

In order to make statements about the nature of the data that is expressed, or to speak in terms of Description Logics (DLs), to define a TBox in RDF documents, other standards which extend on the RDF semantics have to be used.

This is a concious decision as it allows to use multiple semantics, i. e. DLs of different expressiveness to be used in conjunction with the RDF data model.

The two main standards that are used to that end are RDF Schema (RDFS) and Web Ontology Language (OWL).

Contrary to the typical notion of „schema", as for example in XML Schema Definition (XSD), RDFS is not used to define a closed schema in order to force adherence to it. Rather, it provides a set of standard predicates and resources that enable composing a simple TBox with mostly statements about class and predicate hierarchies, instances of classes and relationships between classes and predicates. It thereby enables the use of efficient reasoners for basic inference as well as more standardized tools for applications to discover and reason about what the data is about and how it is potentially shaped. The „potentially" in the last sentence is owed to the fact that RDF as well as RDFS semantics follow the *open-world assumption*, i. e. the absence of a fact is not enough to prove its negation holds true.

The Web Ontology Language is a standard which allows for much more expressive TBoxes compared to RDFS. There are three subsets of OWL: OWL Lite $\subset$ OWL DL $\subset$ OWL Lite. Their expressiveness increases from OWL Lite to OWL Full, which naturally comes at the cost of availability of efficient or even effective reasoning algorithms.

Another standard that can be used to accompany the RDF data model is the Shapes Constraint Language (SHACL). Contrary to the previously introduced standards, SHACL semantics follow the *Closed World Assumption* which on one hand decreases its effective usability alongside RDFS and OWL but on the other enables an important application that can not be realized with the latter two, namely that of schema validation.

2.3 LINKED DATA INTEGRATION

Generally speaking, Linked Data Integration denotes a process of processing data whose goal it is to return one or many RDF Dataset(s) for a specific use case, e. g. publication to the LOD Cloud or preparation for further usage by specific applications.

The input to Linked Data Integration can, but not necessarily must be Linked Data itself. Typical processing steps in Linked Data Integration include, but are not limited to (1) lifting, (2) linking, (3) fusion, (4) enrichment. Any one step could be left out, depending on the use case.

In the following, we will define each of these processing steps and give a narrow overview of the State of the Art.

2.3.1 *Lifting*

In the Linked Data community, lifting denotes the act of materializing RDF Datasets from sources of non-linked data. These sources may be relational databases, proprietary file formats, measurements from sensor networks and any other structured or unstructured data that is not Linked Data.

The term is closely related to RDF mapping, whereas in mapping the focus is often on ad-hoc transformation of an evolving non-linked data source in contrast to the materializing approach in lifting

After lifting, the data is expected to be at least four-star data according to the scheme presented in Table 2.1.

In [56], the authors attempt to lift event data from the interaction with Web pages. Bizer et al.[9] introduced a framework for discovering mappings to relational data sources on the Web.

In [34], [4], [47] and [19], the authors proposed approaches for lifting metadata on data portals, entries in the Docker registry, entries in file systems and whole spreadsheets, respectively. The approach in [25] considers a framework for continuously lifting sensor data to Linked Data in order to exploit the semantic interconnectedness of the sensor measurings for situation awareness.

2.3.2 *Linking*

The linking of RDF Datasets, sometimes also called instance matching, amounts to finding a mapping M between two RDF Datasets, commonly called the source dataset S and the target dataset T, such that the pairs $(s, t) \in M$ identified by the mapping abide to a given relation r.

This field is closely related to the instance matching and deduplication in databases. The main challenge here is that due to the very large number of instances in the Web of Data, the quadratic run time complexity of a brute force search can not be accepted.

To this end, it is necessary to derive algorithms that discard large numbers of potential pairs, preferably without losing the completeness or correctness property, i. e. all pairs (s, t) that abide by $r(s, t)$ should be in M and no pair in M should not abide by r.

A plethora of such approaches has been developed for textual data[15, 17, 27, 28, 60, 61], geospatial data[16, 49, 52] as well as temporal data[21].

Another challenge lies in the automatic configuration of so called link discovery tools.

A number of different approaches have been proposed.

The approaches in [26, 36, 38] use Genetic Algorithm in an unsupervised, an active learning setting and both, respectively. In [37], the authors use an altered grid search for unsupervised learning and finally [50], the approach outperforming all of the previously mentioned, uses refinement operators for unsupervised as well as supervised learning.

2.3.3 *Fusion*

The fusion of RDF Datasets is a task in which two interlinked datasets that contain information about the same set of instances are merged to produce a joint dataset. To this end, an ontology mapping has to be generated in a first step. Subsequently, the fusion is carried out following a set of so called fusion rules that are either predefined by the system, the user or dynamically learned.

In [39–41], the authors use a fusion architecture called *Kno-Fuss* which handles the end-to-end fusion of RDF Datasets. The apporach in [31] combines quality assessment and fusion of RDF Datasets. A probabilistic framework is applied to the fusion problem in[14] and [10] is an approach to automatic learning of fusion rules in the setting of cross-language fusion from the Wikipedia corpus.

2.3.4 *Enrichment*

Enrichment is the least well-defined step in the Linked Data Integration lifecycle. Informally, enrichment corresponds to applying a set of modifications to a given RDF Dataset such that it abides by certain use case-specific predefined criterias. We will call this set of modifications, i. e. addition and deletion of triples from the source dataset, an enrichment workflow in the remainder of this text. Examples of such modifications include the dereferencing of information from other datasets, the application of quality assurance methods to the dataset, the conformation of the used vocabulary or the filtering of its contents.

In practice this means, that RDF Dataset Enrichment is a problem that greatly differs from use case to use case. Notable applications of enrichment in the literature include [1], which considers the automatic extraction of interests from Twitter posts in order to enrich user profiles on the Social Web and [12], which applies a ranking method to the Youtube tag space in order to enrich datasets on the LOD Cloud with links to Youtube videos.

However, to our best knowledge, the only effort directed towards a general framework of RDF Dataset Enrichment together with an automatic learning approach can be found in [51], where the authors propose a framework and learning algorithm called DEER. We will thus have a deeper analysis of DEER in the following section, where we will try to identify potential shortcomings of the framework in order to underline the necessity for our contribution in this work, DEER2.

2.3.5 *DEER*

As we chose to build our approach based on the existing Open Source software DEER, we are going to highlight specific areas in the original paper resp. software, where we see chances of substantial improvement.

On Restrictiveness of Sequential Chaining

The RDF Dataset Enrichment Framework models RDF Dataset Enrichment workflows as ordered sequences of enrichment functions. These enrichment functions take as input exactly one RDF Dataset and return an altered version of it by virtue of addition and deletion of triples. It is argued that formally, any modification on a given dataset can be represented as a set of additions and deletions.

While this is certainly true, the application of two independent enrichment functions, that formally have no knowledge of each other, could be problematic as one function might delete triples which the other relies on in order to successfully apply the desired enrichment.

We therefore suggest replacing the simple sequential pipelining approach with a more sophisticated one based on arranging the enrichment functions in a DAG. In order to better distinguish our approach from the former, we will call atomic enrichment functions which allow for multiple inputs and multiple outputs *enrichment operators*.

On Modularity and Attractiveness of the System

The framework consists of five atomic enrichment functions that can be combined to form so called enrichment pipelines of arbitrary size. The language used implies that these enrichment functions are only examples and potentially more could be implemented. However, no implicit facility for easy extension of the framework is given and exploration of the code base suggests that the ability to implement new operators is restricted in the sense that it would require recompilation of the whole application.

In order to improve the real-world suitability of our contribution DEER2, we therefore will aim to attract developer interest by providing plugin facilities with low barriers to entry.

On Appropriateness of Fitness Function

The refinement operator-based learning approach in DEER is defined as the task of finding an appropriate enrichment pipeline given an input RDF Dataset K and a target RDF Dataset K'.

As the enrichment functions typically require manual configuration, the problem is twofold: it is not only the correct sequence of enrichment functions that is subject to the learning process but also the correct configuration of the enrichment functions that are part of the pipeline.

This is done by a combination of iterative construction of the enrichment pipeline and self-configuration of enrichment functions at each iteration.

That is, in order to decide which enrichment function should be next added to the current pipeline, each available enrichment function is self configured using the supplied training data. It is then applied to the result of the previous enrichment function and its result evaluated using a fitness function over the provided training data.

Note that one of the results of the evaluation of DEER was that it is sufficient to provide only a single training example. While it seems unusual for a learning method to rely on a single training example, it is a valid assertment in this specific case, as enrichment can be assumed to deal with more or less regularly shaped RDF Datasets.

The dataset produced by the intermediate pipeline in each iteration is denoted as K_i with i being the position of the enrichment function producing K_i in the pipline.

The fitness function used is the F_1-score[46] over the set of triples in K_i and K'.

We argue that this choice of fitness function is not optimal in a modular setting where solutions can be expected to be constructed in an iterative manner. We consider the following short example to illustrate the problem.

Let us assume without loss of generality that there exists one triple $t = (s, p, o) \in K$ for which we can intuitively identify at least one corresponding triple $t = (s', p', o') \in K'$. Then a first enrichment function might only alter our input triples predicates, yielding the intermediate result $t_1 = (s, p', o) \in K_1$. Now another enrichment function might alter the subject, yielding $t_1 = (s', p', o) \in K_2$ before we apply the final enrichment function and get to the desired result $t_3 = t' = (s', p', o') \in K_3$. While intuitively there are clearly improvements in each intermediate result w.r.t. our target triple t', a fitness function only measuring the correspondence between whole triples will not be able to detect these improvements.

We will therefore use an evenly weighted linear combination of the F_1-scores between all the subjects, all the predicates, all the objects and additionally all the whole triples in our input and target datasets.

On Information Masking

A more subtle problem with the refinement operator-based approach in DEER lies in the combination of deterministic learning and self configuration. By assuming that the training example contains the necessary information for learning the pipeline, which is a sane assumption to make for regularly shaped input datasets, it is also implicitly assumed that it contains enough information for the *self-configuration* of *all* the enrichment functions.

As a trivial counterexample, consider an enrichment pipeline where we filter out all triples that contain a certain predicate p_f using the enrichment function e_3. This means that no triple (s, p_f, o) will be present in the target training data.

Let us assume that some triple (s', p', o') present in the target training data were constructed by another enrichment function e_2 from a triple $t_{masked} = (s, p_f, o)$ that was previously constructed by yet another enrichment function e_1.

Without the triple t_{masked} in the training data, e_1 might not be able to determine its own configuration and therefore will never get picked. In the end, our pipeline will never get learned using the deterministic bottom-up approach in DEER. We call the underlying problem information masking.

As a result of this analysis, we will use a non-deterministic approach based on GP in DEER2. We will complement this with an idea dubbed pre- and postcondition broadcasting which is developed in order to increase the chance of successful self configuration in the light of information masking.

2.4 ADDITIONAL PRELIMINARY DEFINITIONS

In this section we will introduce some additional definitions required to understand the remainder of this work which did not fit into one of the previous sections.

2.4.1 *Concise Bounded Descriptions*

Let D be an RDF Dataset and $r \in D$ be an IRI resource in that dataset.

We define the **neighbourhood** $neighbours(r)$ of r in D as the set of triples that contain r as their subject. Formally, $neighbours(r) := \{(s,p,o) \in D \mid s \equiv r\}$.

Let $k \in \mathbb{N} > 0$. The Concise Bounded Description (CBD) $CBD(r,k)$ of a resource r in D is then recursively defined per Equation 2.1 where $CBD(r,0) := r$ and $CBD(r,1) := neighbours(r)$.

$$CBD(r,k) := CBD(r,k-1) \cup \left(\bigcup_{(s,p,o) \in CBD(r,k-1)} neighbours(o) \right) \tag{2.1}$$

2.4.2 *The F_β-Score*

The F_β-score is a measure of a tests accuracy, or more abstract, a measure of correspondence between two sets. Let A, B be two sets, where we call A the evaluated set and B the reference set. We define the precision and the recall of A w.r.t. B per Equation 2.2 and Equation 2.3, respectively. The F_β-score is then defined as the weighted harmonic mean of recall and precision as per Equation 2.4.

$$precision(A,B) = |A \cap B| / |A| \tag{2.2}$$

$$recall(A,B) = |A \cap B| / |B| \tag{2.3}$$

$$F_\beta(A,B) = (1+\beta^2) \cdot \frac{precision(A,B) \cdot recall(A,B)}{(\beta^2 \cdot precision(A,B)) + recall(A,B)} \tag{2.4}$$

2.4.3 *Directed Acyclic Graphs*

A directed graph is a pair $\mathbf{G} = (\mathbf{V}, \mathbf{E})$, where $\mathbf{V}$ denotes a finite set, called vertices, and $\mathbf{E} \subseteq \mathbf{V} \times \mathbf{V}$ denotes a set of 2-tuples, called edges. An entry $(u, v) \in \mathbf{E}$ represents a directed edge from u to v.

A sequence of edges $((u_1, v_1), \dots, (u_n, v_n)) \in \mathbf{E}^n$ for which $v_k = u_{k+1}\ \forall 1 \leq k \leq n-1$ holds, is called a walk of length n from u_1 to v_n in $\mathbf{G}$.

We call a directed graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ Directed Acyclic Graph (DAG) iff:

1. $\forall (u, v) \in \mathbf{E} : u \neq v$ and
2. there exists no walk from v to itself

Note that the second criteria is equivalent to the the demand that all walks in $\mathbf{G}$ are of finite length.

3 APPROACH

After the analysis of the DEER framework, which inspired this work, we now have a clear understanding of the design goals according to which we shall now develop our approach. The presentation of our approach in this chapter is structured into three parts. In the first part we will develop a formal specification of our approach. The second part contains implementation details about the system we implemented following our formal specification. Finally, in the third part, we describe the design of a GP-based learning algorithm based on our previous formal specification.

3.1 FORMAL SPECIFICATION

3.1.1 *Dataset Operator*

Let $\mathcal{D}$ be the set of all RDF Datasets. A function

$$\begin{aligned} \mathbb{o}_{(n,m)} &: \mathcal{D}^n \times \mathcal{D} \to \mathcal{D}^m \\ \left(\left(D_1^{(\text{in})}, \dots, D_n^{(\text{in})}\right), P\right) &\mapsto \left(D_1^{(\text{out})}, \dots, D_m^{(\text{out})}\right) \end{aligned} \tag{3.1}$$

is called a **dataset operator**. We call n the in-degree and m the out-degree of $\mathbb{o}_{(n,m)}$ and will resort to writing just $\mathbb{o}$ when n, m are clear or if the lack of their specification will incur no loss of generality. The set of all dataset operators is denoted as $\mathbb{O}$

Informally, a dataset operator takes a parameter datset and n input datasets as arguments and returns m output datasets. We specify the following naming scheme for dataset operators:

- $\mathbb{o}_{(0,1)}$ is called a **dataset emitter**,
- $\mathbb{o}_{(1,0)}$ is called a **dataset acceptor**,
- $\mathbb{o}_{(n,m)}$ is called an **enrichment operator** for $n, m > 0$ and
- $\mathbb{o}_{(n,1)}$ is called a **confluent enrichment operator**.

Moreover, a function

$$\begin{aligned} \mathbb{P}_{(n,m)} &: \mathcal{D}^n \to \mathcal{D}^m \\ \left(D_1^{(\text{in})}, \dots, D_n^{(\text{in})}\right) &\mapsto \left(D_1^{(\text{out})}, \dots, D_m^{(\text{out})}\right) \end{aligned} \tag{3.2}$$

is called a **parameterized dataset operator**. We denote the set of all parameterized dataset operators as $\mathbb{P}$.

We define a *configuration function*

$$\begin{aligned} \mathbb{c}\colon \mathbb{O} \times \mathcal{D} &\to \mathbb{P} \\ \left(\mathbb{o}_{(n,m)}, P\right) &\mapsto \mathbb{p}_{(n,m)} \end{aligned} \tag{3.3}$$

which takes a given dataset operator $\mathbb{o}$ together with a parameter dataset P and returns a parameterized dataset operator $\mathbb{p}$, which operates under the same semantics as $\mathbb{o}$ if it receives P as its last argument.

$$\begin{aligned} \mathbb{o}_{(n,m)}\colon \mathcal{D}^n \times \mathcal{D} &\to \mathcal{D}^m \\ \left(\left(D_1^{(\text{in})}, \dots, D_n^{(\text{in})}\right), P\right) &\mapsto \left(D_1^{(\text{out})}, \dots, D_m^{(\text{out})}\right) \end{aligned}$$

3.1.2 *Enrichment Graph*

$$\mathbf{V}_r := \{v \in \mathbf{V} \mid \forall u \in \mathbf{V} (u, v) \notin \mathbf{E}\} \tag{3.4}$$
$$\mathbf{V}_l := \{v \in \mathbf{V} \mid \forall u \in \mathbf{V} (v, u) \notin \mathbf{E}\} \tag{3.5}$$
$$\mathbf{V}_i := \mathbf{V} \setminus (\mathbf{V}_r \cup \mathbf{V}_l) \tag{3.6}$$

An Enrichment Graph $G = (\mathbf{V}, \mathbf{E}, \mathbf{L})$ is a Directed Acyclic Labeled Multigraph. A mapping $\Phi\colon \mathbf{V} \to \mathbb{P}$ maps vertices to parameterized dataset operators. We call the subsets of vertices per Equations 3.4 - 3.6 root vertices, leaf vertices and intermediate vertices, respectively.

$$v \in \mathbf{V}_r \wedge \mathbb{p}_{(n,m)} = \Phi(v) \to n = 0 \wedge m = 1 \tag{3.7}$$
$$v \in \mathbf{V}_l \wedge \mathbb{p}_{(n,m)} = \Phi(v) \to n = 1 \wedge m = 0 \tag{3.8}$$
$$v \in \mathbf{V}_i \wedge \mathbb{p}_{(n,m)} = \Phi(v) \to n > 0 \wedge m > 0 \tag{3.9}$$

The set of axioms defined per Equations 3.7 - 3.9 hold for Enrichment Graphs. Informally, they mean that all root vertices represent parameterized dataset emitters, all leaf vertices represent parameterized dataset acceptors and all intermediate vertices represent parameterized enrichment operators w.r.t. Φ.

$$\begin{aligned} \mathbf{L}\colon E &\to 2^{(\mathbb{N} \times \mathbb{N})} \\ e = (u, v) &\mapsto \{(i_1, j_1), \dots, (i_n, j_n)\} \end{aligned} \tag{3.10}$$

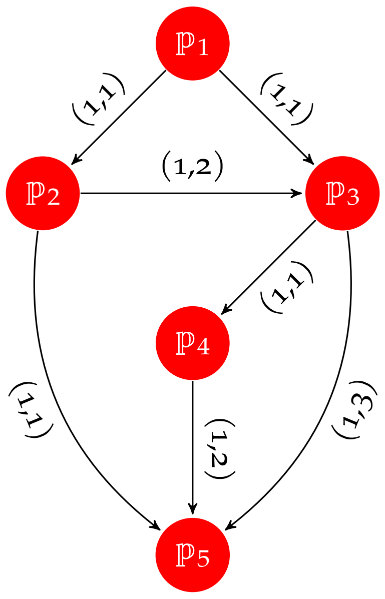


Figure 3.1: Example of an inherently confluent enrichment graph

An edge $(u, v) \in \mathbf{E} \subseteq \mathbf{V} \times \mathbf{V}$ represents flow of data. Consider the definitions given in Equation 3.10. The label function $\mathbf{L}$ induces a mapping from the components of images of $\Phi(u)$ to the arguments of $\Phi(v)$. That is, for $e = (u, v)$, an entry of the label multiset $l \in \mathbf{L}(e) = (i, j)$ establishes a flow of data from the ith component in the image of $\Phi(u)$ to the jth argument of $\Phi(v)$.

$$\begin{aligned} &\forall e_1, e_2 \in \mathbf{E} \colon e_1 = (u_1, v_1) \wedge e_2 = (u_2, v_2) \wedge v_1 = v_2 \\ \rightarrow\ &\forall l_1 \in \mathbf{L}(e_1) \forall l_2 \in \mathbf{L}(e_2) \colon l_1 = (i_1, j_1) \wedge l_2 = (i_2, j_2) \wedge j_1 \neq j_2 \end{aligned} \tag{3.11}$$

In order to be deemed valid, the label function has to abide by the criteria defined in Equation 3.11. Informally, this criteria forbids multiple mappings to the same argument of the same dataset operator.

We present a categorization of Enrichment Graphs as follows. Let $G = (\mathbf{V}, \mathbf{E}, \mathbf{L})$ be an Enrichment Graph.

- If $|\mathbf{V}_r| = |\mathbf{V}_l| = 1$ and for all vertices $u, v \in \mathbf{V}$ with $u \neq v$ there exists only a single walk from u to v, then G is called a linear Enrichment Graph.
- If $|\mathbf{V}_r| = |\mathbf{V}_l| = 1$ and there is a pair of vertices $u, v \in \mathbf{V}$, $u \neq v$ for which there there exist multiple walks from u to v, then G is called a semi-linear Enrichment Graph.

- If $|\mathbf{V}_r| > 1 \wedge |\mathbf{V}_l| = 1$, then G is called a confluent Enrichment Graph.
- Otherwise, G is called a general Enrichment Graph.

In order to evaluate an Enrichment Graph $G = (\mathbf{V}, \mathbf{E}, \mathbf{L})$, we start with obtaining the RDF Datasets as output by the dataset emitters in $\Phi(\mathbf{V}_r)$. These datasets then flow throught the graph as specified by the semantics we associated with the edge set $\mathbf{E}$ and the label multiset $\mathbf{L}$ above. Whenever a parameterized dataset operator $\mathbb{p}_{(n,m)} \in \Phi(\mathbf{V}_i)$ has received all its n input datasets, it is evaluated and the flow through the graph continues until eventually all vertices have been evaluated.

3.1.3 *Enrichment Table*

We call a confluent Enrichment Graphs in which only confluent parameterized enrichment operators are allowed, i.e. $\forall v \in \mathbf{V}_i \colon \mathbb{p}_{(n,m)} = \Phi(v) \rightarrow m = 1$, an inherently confluent Enrichment Graph. An example of such an Enrichment Graph is given in Figure 3.1.

An enrichment table is a condensed representation for inherently confluent Enrichment Graphs.

$$N(O) := \max\left\{k \mid \mathbb{o}_{(n,m)} \in O, k = n\right\} \tag{3.12}$$

Let P be a set of parameterized dataset operators. Moreover, let $N(P)$ denote the maximum in-degree in P as given in 3.12. Now, an enrichment table is a table with $2+N(P)$ columns and $|P|$ rows, where each row corresponds to one parameterized dataset operator.

The idea behind this representation is that we can go through this table from top to bottom and evaluate the corresponding parameterized dataset operators using only the results of the above rows. Note that this idea was taken from[30], where the authors call these tables „Column Tables".

The structure of the enrichment table is defined as follows. The first column contains parameterized dataset operators, the second column contains the in-degree of the parameterized dataset operator in the first column and the rest of the columns contain the indices of the rows used as input to the corresponding parameterized dataset operator.

Table 3.1: An example enrichment table which is equivalent to the inherently confluent enrichment graph in Figure 3.1

$\mathbb{P}_1$	0	0	0	0
$\mathbb{P}_2$	1	1	0	0
$\mathbb{P}_3$	2	1	2	0
$\mathbb{P}_4$	1	3	0	0
$\mathbb{P}_5$	3	2	4	3

The example in Table 3.1 depicts the enrichment table representation of the enrichment graph given in Figure 3.1.

A method to obtain an enrichment table from a given inherently confluent enrichment graph can be taken from [30] and we will not reformulate the whole method here.

In essence, the authors state that a Column Table can be easily obtained from the adjacency matrix of a given DAG $G = (\mathbf{V}, \mathbf{E})$ [c] when an indexing $\phi\colon \{1, \dots, |\mathbf{V}|\}$ of its vertices is provided such that $\forall (v, v') \in \mathbf{E}\colon \phi(v) > \phi(v')$.

[c] *Please note that our defintion of inherently confluent enrichment graphs corresponds to general DAGs without loss of generality.*

In order to obtain the results of a given enrichment table **T**, it just has to be evaluated from top to bottom. The last result is considered to be the result of the whole table.

The evaluation result in row i of table **T** is denoted as $\mathbf{T}_i$. We will now show this process exemplarily for the enrichment table given in Table 3.1.

$$\begin{aligned}
\mathbf{T}_1 &= D \in \mathcal{D} \\
\mathbf{T}_2 &= \mathbb{P}_2\left(D\right) \\
\mathbf{T}_3 &= \mathbb{P}_3\left(D, \mathbb{P}_2\left(D\right)\right) \\
\mathbf{T}_4 &= \mathbb{P}_4\left(\mathbb{P}_3\left(D, \mathbb{P}_2\left(D\right)\right)\right) \\
\mathbf{T}_5 &= \mathbb{P}_5\left(\mathbb{P}_2\left(D\right), \mathbb{P}_4\left(\mathbb{P}_3\left(D, \mathbb{P}_2\left(D\right)\right)\right), \mathbb{P}_3\left(D, \mathbb{P}_2\left(D\right)\right)\right)
\end{aligned}$$

3.1.4 *Enrichment Specification*

An enrichment specification is a pair $\mathcal{E} = (G, M)$, where G is an enrichment graph and $M \in \mathbb{O} \times \mathcal{D} \times \mathbf{V}$ is called a *configuration mapping*. For each entry $(\mathbb{o}, P, v) \in M$ the following relationship holds: $\mathbb{c}(\mathbb{o}, P) \equiv \Phi(v)$.

Informally, enrichment specifications correspond to the configuration files that are used to define an enrichment graph in the implementation of DEER2. We will go into more detail on this subject in the subsequent section on implementation details.

3.2 IMPLEMENTATION DETAILS

We implement DEER2[3] as a Java application using the Java Development Kit (JDK) version 9. DEER2 is based on a general engine for parallel data transformation workflows with the name `FARADAY-CAGE`, which we did also develop[4]. This engine enables DEER2 to automatically distribute the execution of a given enrichment graph to the available CPU cores.

The RDF features in `FARADAY-CAGE` and DEER2 are implemented using the Apache Jena Library[5].

For the configuration of enrichment workflows in DEER2, we use RDF files in the Turtle serialization format[6]. To this end, we developed two RDF vocabularies, namely the `fcage`[7] and the `deer`[8] vocabulary which can be used to specify enrichment graphs in RDF.

In order to be applicable to a wide domain of enrichment workflows, DEER2 implements eleven standard enrichment operators. We implement a command line interface as well as a RESTful Web service as end-user friendly frontends to our application.

Since this thesis does not serve the purpose of a technical documentation, we will ommit a detailed discussion of most of these parts here. Rather, we will focus on the mechanisms used to ensure the modularity of DEER2, since this was one of our leading design goals. Moreover, we will give a short overview of seven enrichment operators, since a basic understanding of their functionality is necessary to follow the development of our enrichment specification learning approach in Section 3.3.

3.2.1 *Modularity*

In order to allow other developers to supply custom enrichment operators to DEER2, we chose to use the Plugin Framework for Java (PF4J) as a foundation of our plugin system. PF4J allows to

3 https://github.com/dice-group/deer
4 https://github.com/dice-group/faraday-cage
5 https://jena.apache.org
6 https://www.w3.org/TR/turtle/
7 https://w3id.org/fcage
8 https://w3id.org/deer

annotate certain interfaces as so called extension points and supplies an automatic discovery system for classes implementing these interfaces using the Java reflection language feature.

Therefore, we do not make any assumptions about the enrichment operators that are available at runtime. We supply mechanisms for developers to retrieve a list of the currently loaded enrichment operators at runtime using a command line interface and a RESTful Web service.

Since each of the plugins can have their own configuration vocabulary, we implemented an approach to configuration validation using SHACL. The same SHACL shape graphs which we use for configuration validation could also be used in order to let frontends dynamically generate forms for convenient user interaction in the future.

Finally, we supply a dummy Apache Maven[9] project[10] that includes the necessary architecture and configurations for compiling custom code to enrichment operator plugins.

3.2.2 *Overview of Implemented Enrichment Operators*

In this section we will give a short descriptions of the functionality of each of the standard enrichment operators implemented in DEER2 that will be used in our learning approach.

Please note that all of these operators are based on the ones as defined in the original DEER publication[51] and share the same general functionality, despite being completely reimplemented.

Unless otherwise mentioned, their in-degree and out-degree amount to 1 and we denote their input and output RDF Datasets $D^{(\mathrm{in})}$ and $D^{(\mathrm{out})}$, respectively.

Filter Operator

The idea of the filter operator is to select a specific set of the input dataset triples. Then, the selected set of triples are generated by the filter operator as its output.

The `deer:selector` parameter accepts a resource with at least one of the three basic selectors types: `deer:subject`, `deer:predicate`

9 https://maven.apache.org
10 https://github.com/dice-group/deer/tree/master/examples/simple-plugin-example

and `deer:object`, which can be combined as required. For simple filtering tasks, e.g. if the task is to filter out everything but triples containing a few given properties, this is easier to set up than to write a SPARQL query.

Authority Conformation Operator

The idea of the authority conformation operator is to change a specified source IRI authority to a specified target IRI authority. By the authority of an IRI we mean the part of the IRI before the last slash or hash sign, which is also sometimes called the namespace.

One authority conformation operation is represented by the `deer:operation` property. The objects of `deer:operation` need to be blank nodes with the properties `deer:sourceAuthority` and `deer:targetAuthority` for specifying the source and target authorities, respectively.

Any number of authority conformation operations can be specified by declaring multiple `deer:operation` parameters.

Formally, given two IRIs called source authority (a_s) and a target authority (a_t), this operator will first set $D^{(\text{out})} := D^{(\text{in})}$. It will then find all triples $(s, p, o) \in D^{(\text{in})}, s \in \mathcal{R}$ for which a_s is a prefix of the IRI representing s. For each triple $t = (s, p, o)$ found that way, the operator will create a new triple $t' = (s', p, o)$ where s' is obtained by replacing a_s with a_t in s. It will then perform the set operation $D^{(\text{out})} := (D^{(\text{out})} \setminus \{t\}) \cup \{t'\}$ on the output dataset.

Predicate Conformation Operator

The idea of the predicate conformation operator is to replace all instances of specified source predicate to a specified target predicate with the same subject and object values.

One predicate conformation operation is represented by the `deer:operation` property. The objects of `deer:operation` must be blank nodes with the properties `deer:sourcePredicate` and `deer:targetPredicate` for specifying the source and target predicates, respectively.

Any number of predicate conformation operations can be specified by declaring multiple `deer:operation parameters`.

Formally, given two IRI resources called source predicate (p_s) and a target predicate (p_t), this operator will first set $D^{(\text{out})} := D^{(\text{in})}$. It will then find all triples $(s, p, o) \in D^{(\text{in})}, s \in \mathcal{R}$ for which $p_s = p$. For each triple $t = (s, p_s, o)$ found that way, the operator will create a new triple $t' = (s, p_t, o)$ and perform the set operation $D^{(\text{out})} := (D^{(\text{out})} \setminus \{t\}) \cup \{t'\}$ on the output dataset.

Dereferencing Operator

For datasets which contain IRI resources from remote RDF Datasets, the idea of the dereferencing enrichment operator is to deference a set of triples that contain a desired predicate from the remote dataset and add them to the output dataset using content negotiation on HTTP.

One dereferencing operation is represented by the `deer:operation` parameter, which takes as object a blank node with the following properties:

- `deer:lookUpPrefix` specifies the IRI prefix to identify the resources from the desired remote RDF Dataset.
- `deer:dereferencingProperty` specifies the predicate used to identify the desired triples from the remote RDF Dataset.
- `deer:importProperty` specifies the predicate used when importing the identified triples to the output dataset.

One can specify any number of `deer:operation` parameters and they will all be carried out and in case of overlapping lookup prefix, they will be carried out in a single HTTP request to save bandwidth.

Named Entity Recognition Operator

The idea of the Named Entity Recognition (NER) operator is to extract IRI resources from string literals using Federated knOwledge eXtraction Framework (FOX)[55], which is a NER framework for the Semantic Web. To that end, it uses a lookup predicate p_l to identify triples $(s, p_l, o), o \in \mathcal{L}$ containing interesting string literals in the input dataset. For each such triple, it extracts the textual data from the string literal o and sends it to an instance of the FOX Web service. The IRI resources referencing named entities in the string literal are returned by FOX and added to the output dataset using a configurable import predicate p_i

This operator specifies the following configuration properties:

- `deer:literalProperty` specifies the lookup predicate.
- `deer:importProperty` specifies the import predicate.
- `deer:foxUrl` specifies the Uniform Resource Locator (URL) of the FOX Web service.

Merge Operator

The merge operator has an in-degree of 2 and an out-degree of 1. The very simple idea of it is to merge two RDF Datasets. Formally, for given input datasets $D_1^{(\text{in})}, D_2^{(\text{in})}$, this operator returns $D^{(\text{out})} := D_1^{(\text{in})} \cup D_2^{(\text{in})}$.

Linking Operator

The linking operator has an in-degree of 2 and an out-degree of 1. Its idea is to perform Link Discovery on two input RDF Datasets using the Link Discovery Framework for Metric Spaces (LIMES) [35]. Note that the LIMES Java library is integrated into DEER2.

One can specify the following configuration properties for this operator:

- `deer:linkSpecification` specifies the link specification to be passed to LIMES.
- `deer:threshold` specifies the linking threshold to be passed to LIMES.
- `deer:linkingPredicate` specifies the predicate to be used for the generated links.

Given two input datasets $D_1^{(\text{in})}, D_2^{(\text{in})}$ and the RDF Dataset of links generated by the invocation of LIMES D_L, this operator returns $D^{(\text{out})} := D_1^{(\text{in})} \cup D_2^{(\text{in})} \cup D_L$

3.3 LEARNING APPROACH

In this section, we will develop a GP-based approach to the learning of enrichment specifications.

3.3.1 *The Learning Problem*

3.3.2 *Heuristic Self-Configuration of Enrichment Operators*

3.3.3 *Baseline Algorithm*

3.3.4 *Enrichment Graph Compaction*

3.3.5 *Semantic Genetic Operators*

4 EVALUATION

In this chapter we are going to define our experimental protocol as well as present and discuss our results.

4.1 EXPERIMENTAL SETUP

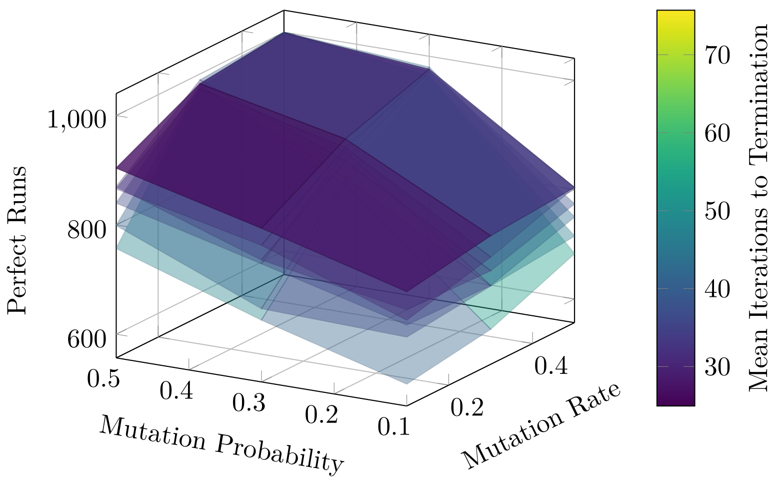
All experiments were carried out on a 64-core 2.3 GHz server running *OpenJDK* 64-Bit Server 1.8.0_151 on *Ubuntu* 16.04.3 LTS. Each experiment was assigned 128 GB RAM.

4.1.1 *Datasets*

4.1.2 *Experiments*

4.2 RESULTS

4.2.1 *Hyperparameter Optimization*



4.2.2 *Performance Evaluation*

4.3 DISCUSSION

5 CONCLUSION & FUTURE WORK

5.1 SUMMARY

5.2 FUTURE WORK

Part I

APPENDIX

A

APPENDIX

BIBLIOGRAPHY

[1] Fabian Abel, Qi Gao, Geert-Jan Houben, and Ke Tao. “Semantic Enrichment of Twitter Posts for User Profile Construction on the Social Web.” In: *The Semantic Web: Research and Applications*. Ed. by Grigoris Antoniou, Marko Grobelnik, Elena Simperl, Bijan Parsia, Dimitris Plexousakis, Pieter De Leenheer, and Jeff Pan. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 375–389. ISBN: 978-3-642-21064-8.

[2] Najla Akram, Al-Saati, and Taghreed Riyadh Alreffaee. “Using Multi Expression Programming in Software Effort Estimation.” In: *CoRR* abs/1805.00090 (2018). URL: https://dblp.org/rec/journals/corr/abs-1805-00090.

[3] M Altman. “A generalized gradient method of minimizing a functional.” In: *Commentationes Mathematicae* 14.1 (1970).

[4] Ahmed Ben Ayed, Julien Subercaze, Frédérique Laforest, Tarak Chaari, Wajdi Louati, and Ahmed Hadj Kacem. “Docker2RDF: Lifting the Docker Registry Hub into RDF.” In: *SERVICES*. IEEE Computer Society, 2017, pp. 36–39. DOI: 10.1109/SERVICES.2017.15. URL: https://dblp.org/rec/conf/services/AyedSLCLK17.

[5] Tim Berners-Lee. *Linked Data*. July 2006. URL: http://www.w3.org/DesignIssues/LinkedData.html (visited on 07/12/2019).

[6] Tim Berners-Lee, James Hendler, Ora Lassila, et al. “The Semantic Web.” In: *Scientific american* 284.5 (2001), pp. 28–37.

[7] Christian Bizer, Tom Heath, and Tim Berners-Lee. “Linked Data - The Story So Far.” In: *Int. J. Semantic Web Inf. Syst.* 5.3 (2009), pp. 1–22. DOI: 10.4018/JSWIS.2009081901. URL: https://dblp.org/rec/journals/ijswis/BizerHB09.

[8] Christian Bizer, Tom Heath, Kingsley Idehen, and Tim Berners-Lee. “Linked data on the web (LDOW2008).” In: *WWW*. ACM, 2008, pp. 1265–1266. DOI: 10.1145/1367497.1367760. URL: https://dblp.org/rec/conf/www/BizerHIB08.

[9] Christian Bizer and Andreas Schultz. "The R2R Framework: Publishing and Discovering Mappings on the Web." In: *Proceedings of the First International Workshop on Consuming Linked Data, Shanghai, China, November 8, 2010*. Ed. by Olaf Hartig, Andreas Harth, and Juan F. Sequeda. Vol. 665. CEUR Workshop Proceedings. CEUR-WS.org, 2010.

[10] Volha Bryl and Christian Bizer. "Learning conflict resolution strategies for cross-language Wikipedia data fusion." In: *WWW (Companion Volume)*. ACM, 2014, pp. 1129–1134. DOI: 10.1145/2567948.2578999. URL: https://dblp.org/rec/conf/www/BrylB14.

[11] Qi Chen, Bing Xue, Yi Mei, and Mengjie Zhang. "Geometric Semantic Crossover with an Angle-Aware Mating Scheme in Genetic Programming for Symbolic Regression." In: *EuroGP*. Vol. 10196. Lecture Notes in Computer Science. 2017, pp. 229–245. DOI: 10.1007/978-3-319-55696-3_15. URL: https://dblp.org/rec/conf/eurogp/ChenXMZ17.

[12] Smitashree Choudhury, John G. Breslin, and Alexandre Passant. "Enrichment and Ranking of the YouTube Tag Space and Integration with the Linked Data Cloud." In: *The Semantic Web - ISWC 2009*. Ed. by Abraham Bernstein, David R. Karger, Tom Heath, Lee Feigenbaum, Diana Maynard, Enrico Motta, and Krishnaprasad Thirunarayan. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 747–762. ISBN: 978-3-642-04930-9.

[13] Benjamin Doerr, Edda Happ, and Christian Klein. "Crossover can provably be useful in evolutionary computation." In: *Theor. Comput. Sci.* 425 (2012), pp. 17–33. DOI: 10.1016/J.TCS.2010.10.035. URL: https://dblp.org/rec/journals/tcs/DoerrHK12.

[14] Xin Dong, Evgeniy Gabrilovich, Geremy Heitz, Wilko Horn, Ni Lao, Kevin Murphy, Thomas Strohmann, Shaohua Sun, and Wei Zhang. "Knowledge vault: a web-scale approach to probabilistic knowledge fusion." In: *KDD*. ACM, 2014, pp. 601–610. DOI: 10.1145/2623330.2623623. URL: https://dblp.org/rec/conf/kdd/0001GHHLMSSZ14.

[15] Kevin Dreßler and Axel-Cyrille Ngonga Ngomo. "On the Efficient Execution of Bounded Jaro-Winkler Distances." In: *Proceedings of Ontology Matching Workshop*. 2014.

[16] Heshan Du, Natasha Alechina, Michael Jackson, and Glen Hart. "Matching geospatial instances." In: *OM*. Vol. 1111. CEUR Workshop Proceedings. CEUR-WS.org, 2013, pp. 239–240. URL: https://dblp.org/rec/conf/semweb/DuAJH13.

[17] Jianhua Feng, Jiannan Wang, and Guoliang Li. "Trie-join: a trie-based method for efficient string similarity joins." In: *VLDB J.* 21.4 (2012), pp. 437–461. DOI: 10.1007/S00778-011-0252-8. URL: https://dblp.org/rec/journals/vldb/FengWL12.

[18] Cândida Ferreira. "Gene Expression Programming: A New Adaptive Algorithm for Solving Problems." In: *Complex Systems* 13.2 (2001). URL: https://dblp.org/rec/journals/compsys/Ferreira01.

[19] Manuel Fiorelli, Tiziano Lorenzetti, Maria Teresa Pazienza, Armando Stellato, and Andrea Turbati. "Sheet2RDF: a Flexible and Dynamic Spreadsheet Import&Lifting Framework for RDF." In: *IEA/AIE*. Vol. 9101. Lecture Notes in Computer Science. Springer, 2015, pp. 131–140. DOI: 10.1007/978-3-319-19066-2_13. URL: https://dblp.org/rec/conf/ieaaie/FiorelliLPST15.

[20] Stefan Forstenlechner, David Fagan, Miguel Nicolau, and Michael O'Neill. "Semantics-Based Crossover for Program Synthesis in Genetic Programming." In: *Artificial Evolution*. Vol. 10764. Lecture Notes in Computer Science. Springer, 2017, pp. 58–71. DOI: 10.1007/978-3-319-78133-4_5. URL: https://dblp.org/rec/conf/ae/ForstenlechnerF17.

[21] Kleanthi Georgala, Mohamed Ahmed Sherif, and Axel-Cyrille Ngonga Ngomo. "An Efficient Approach for the Generation of Allen Relations." In: *Proceedings of the 22nd European Conference on Artificial Intelligence (ECAI) 2016, The Hague, 29. August - 02. September 2016*. 2016. URL: http://svn.aksw.org/papers/2016/ECAI_AEGLE/public.pdf.

[22] David E. Goldberg and Kalyanmoy Deb. "A Comparative Analysis of Selection Schemes Used in Genetic Algorithms." In: *FOGA*. Morgan Kaufmann, 1990, pp. 69–93. URL: https://dblp.org/rec/conf/foga/GoldbergD90.

[23] M. Graff, E. S. Tellez, S. Miranda-Jiménez, and H. J. Escalante. "EvoDAG: A semantic Genetic Programming Python library." In: *2016 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC)*. Nov. 2016, pp. 1–6. DOI: 10.1109/ROPEC.2016.7830633.

[24] RDF Working Group. *Resource Description Framework (RDF)*. Feb. 2014. URL: https://www.w3.org/RDF/ (visited on 07/12/2019).

[25] Souleiman Hasan, Edward Curry, Mauricio Banduk, and Sean O'Riain. "Toward situation awareness for the semantic sensor web: Complex event processing with dynamic linked data enrichment." In: *Proceedings of the 4th International Conference on Semantic Sensor Networks-Volume 839*. CEUR-WS. org. 2011, pp. 69–82.

[26] Robert Isele. "Learning expressive linkage rules for entity matching using genetic programming." PhD thesis. Universität Mannheim, 2013. URL: https://dblp.org/rec/books/daglib/0033457.

[27] Robert Isele, Anja Jentzsch, and Christian Bizer. "Efficient Multidimensional Blocking for Link Discovery without losing Recall." In: *WebDB*. 2011. URL: https://dblp.org/rec/conf/webdb/IseleJB11.

[28] Alexandros Karakasidis and Vassilios S. Verykios. "A Highly Efficient and Secure Multidimensional Blocking Approach for Private Record Linkage." In: *ICTAI*. IEEE Computer Society, 2012, pp. 428–435. DOI: 10.1109/ICTAI.2012.65. URL: https://dblp.org/rec/conf/ictai/KarakasidisV12.

[29] John R Koza. *Genetic programming: A paradigm for genetically breeding populations of computer programs to solve problems*. Vol. 34. Stanford University, Department of Computer Science Stanford, CA, 1990.

[30] Vladimír Kvasnièka and Jiøí Pospíchal. "Simple Implementation of Genetic Programming by Column Tables." In: *Soft Computing in Engineering Design and Manufacturing*. Ed. by P. K. Chawdhry, R. Roy, and R. K. Pant. London: Springer London, 1998, pp. 48–56. ISBN: 978-1-4471-0427-8.

[31] Pablo N. Mendes, Hannes Mühleisen, and Christian Bizer. "Sieve: linked data quality assessment and fusion." In: *EDBT/ICDT Workshops*. ACM, 2012, pp. 116–123. DOI: 10.1145/2320765.2320803. URL: https://dblp.org/rec/conf/edbt/MendesMB12.

[32] Brad L. Miller and David E. Goldberg. "Genetic Algorithms, Tournament Selection, and the Effects of Noise." In: *Complex Systems* 9.3 (1995). URL: https://dblp.org/rec/journals/compsys/MillerG95.

[33] Melanie Mitchell. *An introduction to genetic algorithms*. MIT Press, 1998. URL: https://dblp.org/rec/books/daglib/0019083.

[34] Sebastian Neumaier, Jürgen Umbrich, and Axel Polleres. "Lifting Data Portals to the Web of Data." In: *LDOW@WWW*. CEUR Workshop Proceedings. CEUR-WS.org, 2017. URL: https://dblp.org/rec/conf/www/NeumaierUP17.

[35] Axel-Cyrille Ngonga Ngomo and Sören Auer. "LIMES - A Time-Efficient Approach for Large-Scale Link Discovery on the Web of Data." In: *IJCAI*. IJCAI/AAAI, 2011, pp. 2312–2317. DOI: 10.5591/978-1-57735-516-8/IJCAI11-385. URL: https://dblp.org/rec/conf/ijcai/NgomoA11.

[36] Axel-Cyrille Ngonga Ngomo and Klaus Lyko. "EAGLE: Efficient Active Learning of Link Specifications using Genetic Programming." In: *Proceedings of ESWC*. 2012.

[37] Axel-Cyrille Ngonga Ngomo and Klaus Lyko. "Unsupervised learning of link specifications: deterministic vs. non-deterministic." In: *Proceedings of the Ontology Matching Workshop*. 2013.

[38] Axel-Cyrille Ngonga Ngomo, Klaus Lyko, and Victor Christen. "COALA—Correlation-Aware Active Learning of Link Specifications." In: *Proceedings of ESWC*. 2013.

[39] Andriy Nikolov, Victoria S. Uren, and Enrico Motta. "KnoFuss: a comprehensive architecture for knowledge fusion." In: *K-CAP*. ACM, 2007, pp. 185–186. DOI: 10.1145/1298406.1298446. URL: https://dblp.org/rec/conf/kcap/NikolovUM07.

[40] Andriy Nikolov, Victoria S. Uren, Enrico Motta, and Anne N. De Roeck. "Handling Instance Coreferencing in the KnoFuss Architecture." In: *IRSW*. Vol. 422. CEUR Workshop Proceedings. CEUR-WS.org, 2008. URL: https://dblp.org/rec/conf/esws/NikolovUMR08.

[41] Andriy Nikolov, Victoria S. Uren, Enrico Motta, and Anne N. De Roeck. "Integration of Semantically Annotated Data by the KnoFuss Architecture." In: *EKAW*. Vol. 5268. Lecture Notes in Computer Science. Springer, 2008, pp. 265–274. DOI: 10.1007/978-3-540-87696-0_24. URL: https://dblp.org/rec/conf/ekaw/NikolovUMR08.

[42] Mihai Oltean and D. Dumitrescu. "Evolving TSP Heuristics Using Multi Expression Programming." In: *International Conference on Computational Science*. Vol. 3037. Lecture Notes in Computer Science. Springer, 2004, pp. 670–673. DOI: 10.1007/978-3-540-24687-9_99. URL: https://dblp.org/rec/conf/iccS/OlteanD04.

[43] Mihai Oltean and Dumitru Dumitrescu. "Evolving TSP heuristics using Multi Expression Programming." In: *CoRR* abs/1509.02459 (2015). URL: https://dblp.org/rec/journals/corr/OlteanD15.

[44] Mihai Oltean and Crina Grosan. "Evolving Evolutionary Algorithms Using Multi Expression Programming." In: *ECAL*. Vol. 2801. Lecture Notes in Computer Science. Springer, 2003, pp. 651–658. DOI: 10.1007/978-3-540-39432-7_70. URL: https://dblp.org/rec/conf/ecal/OlteanG03.

[45] Dunlu Peng, Shaohong Wu, and Cong Liu. "MPSC: A Multiple-Perspective Semantics-Crossover Model for Matching Sentences." In: *IEEE Access* 7 (2019), pp. 61320–61330. DOI: 10.1109/ACCESS.2019.2915937. URL: https://dblp.org/rec/journals/access/PengWL19.

[46] Yutaka Sasaki et al. "The truth of the F-measure." In: *Teach Tutor mater* 1.5 (2007), pp. 1–5.

[47] Bernhard Schandl and Niko Popitsch. "Lifting File Systems into the Linked Data Cloud with TripFS." In: *LDOW*. Vol. 628. CEUR Workshop Proceedings. CEUR-WS.org, 2010. URL: https://dblp.org/rec/conf/www/SchandlP10.

[48] Nigel Shadbolt, Tim Berners-Lee, and Wendy Hall. "The Semantic Web Revisited." In: *IEEE Intelligent Systems* 21.3 (2006), pp. 96–101. DOI: 10.1109/MIS.2006.62. URL: https://dblp.org/rec/journals/expert/ShadboltBH06.

[49] Mohamed Ahmed Sherif, Kevin Dreßler, Panayiotis Smeros, and Axel-Cyrille Ngonga Ngomo. "RADON - Rapid Discovery of Topological Relations." In: *Proceedings of The Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17)*. 2017. URL: https://svn.aksw.org/papers/2017/AAAI_RADON/public.pdf.

[50] Mohamed Ahmed Sherif, Axel-Cyrille Ngonga Ngomo, and Jens Lehmann. "Wombat - A Generalization Approach for Automatic Link Discovery." In: *ESWC (1)*. Vol. 10249. Lecture Notes in Computer Science. 2017, pp. 103–119. DOI:

10.1007/978-3-319-58068-5_7. URL: https://dblp.org/rec/conf/esws/SherifNL17.

[51] Mohamed Ahmed Sherif, Axel-Cyrille Ngonga Ngomo, and Jens Lehmann. "Automating RDF Dataset Transformation and Enrichment." In: *12th Extended Semantic Web Conference, Portorož, Slovenia, 31st May - 4th June 2015*. Springer, 2015.

[52] Vivek R. Shivaprabhu, Booma Sowkarthiga Balasubramani, and Isabel F. Cruz. "Ontology-based Instance Matching for Geospatial Urban Data Integration." In: *UrbanGIS@SIGSPATIAL*. ACM, 2017, 8:1–8:8. DOI: 10.1145/3152178.3152186. URL: https://dblp.org/rec/conf/gis/ShivaprabhuBC17.

[53] William M. Spears and Vic Anand. "A Study of Crossover Operators in Genetic Programming." In: *ISMIS*. Vol. 542. Lecture Notes in Computer Science. Springer, 1991, pp. 409–418. DOI: 10.1007/3-540-54563-8_104. URL: https://dblp.org/rec/conf/ismis/SpearsA91.

[54] William M. Spears and Kenneth A. De Jong. "An Analysis of Multi-Point Crossover." In: *FOGA*. Morgan Kaufmann, 1990, pp. 301–315. URL: https://dblp.org/rec/conf/foga/SpearsJ90.

[55] René Speck and Axel-Cyrille Ngonga Ngomo. "Named Entity Recognition using FOX." In: *International Semantic Web Conference (Posters & Demos)*. Vol. 1272. CEUR Workshop Proceedings. CEUR-WS.org, 2014, pp. 85–88. URL: https://dblp.org/rec/conf/semweb/SpeckN14a.

[56] Roland Stühmer, Darko Anicic, Sinan Sen, Jun Ma, Kay-Uwe Schmidt, and Nenad Stojanovic. "Lifting Events in RDF from Interactions with Annotated Web Pages." In: *International Semantic Web Conference*. Vol. 5823. Lecture Notes in Computer Science. Springer, 2009, pp. 893–908. DOI: 10.1007/978-3-642-04930-9_56. URL: https://dblp.org/rec/conf/semweb/StuhmerASMSS09.

[57] Ranyart Rodrigo Suárez, Mario Graff, and Juan J. Flores. "Semantic Crossover Operator for GP based on the Second Partial Derivative of the Error Function." In: *Research in Computing Science* 94 (2015), pp. 87–96. URL: https://dblp.org/rec/journals/rcs/SuarezGF15.

[58] Gilbert Syswerda. "Uniform Crossover in Genetic Algorithms." In: *ICGA*. Morgan Kaufmann, 1989, pp. 2–9. URL: https://dblp.org/rec/conf/icga/Syswerda89.

[59] Diane E. Vaughan, Sheldon H. Jacobson, Shane N. Hall, and Laura A. McLay. "Simultaneous Generalized Hill-Climbing Algorithms for Addressing Sets of Discrete Optimization Problems." In: *INFORMS Journal on Computing* 17.4 (2005), pp. 438–450. DOI: 10.1287/IJOC.1040.0064. URL: https://dblp.org/rec/journals/informs/VaughanJHM05.

[60] Chuan Xiao, Wei Wang, and Xuemin Lin. "Ed-Join: an efficient algorithm for similarity joins with edit distance constraints." In: *PVLDB* 1.1 (2008), pp. 933–944. DOI: 10.14778/1453856.1453957. URL: https://dblp.org/rec/journals/pvldb/XiaoWL08.

[61] Chuan Xiao, Wei Wang, Xuemin Lin, Jeffrey Xu Yu, and Guoren Wang. "Efficient similarity joins for near-duplicate detection." In: *ACM Trans. Database Syst.* 36.3 (2011), 15:1–15:41. DOI: 10.1145/2000824.2000825. URL: https://dblp.org/rec/journals/tods/XiaoWLYW11.

[62] Qingke Zhang, Bo Yang, Lin Wang, and Jianzhang Jiang. "An improved multi-expression programming algorithm applied in function discovery and data prediction." In: *IJICT* 5.3/4 (2013), pp. 218–233. DOI: 10.1504/IJICT.2013.054952. URL: https://dblp.org/rec/journals/ijict/ZhangYWJ13.

ERKLÄRUNG

Ich versichere, dass ich die vorliegende Arbeit selbstständig und nur unter Verwendung der angegebenen Quellen und Hilfsmittel angefertigt habe, insbesondere sind wörtliche oder sinngemäße Zitate als solche gekennzeichnet. Mir ist bekannt, dass Zuwiderhandlung auch nachträglich zur Aberkennung des Abschlusses führen kann.

Leipzig, 15. Juli 2019

Kevin Dreßler