Technical Report

Faceted Semantic Search

by

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Abstract

The increasing amount of data on the Web bears potential for addressing complex information needs more effectively. Instead of keyword search and browsing along links between results, users can specify their needs in terms of complex queries and obtain precise answers right away. However, browsing is also essential on the Web of data as users might not always know a specific query language and more importantly, might not know the data. Particularly in cases where the information need is fuzzy, browsing is useful for exploring the data. Faceted search allows users to browse along facets. However, work on faceted search so far has been focused on search rather than browsing. In this paper, we propose a facet ranking scheme that targets the browsing experience. When there are too many facets given, user obtain a ranked list of facets, where the rank represents the facets' browse-ability. Furthermore, facets might be associated with a large amount of values. Also targeting browse-ability, we propose clustering mechanisms to decompose such facets into more fine-grained sub-facets. By means of a task-based evaluation, we demonstrate that the proposed solution enables more effective browsing, when compared to the state of the art that is rather focused on search-ability.

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List of Abbreviations

CBD	Concise Bounded Description.
FOL	First Order Logic.
HCI	Human-Computer Interaction.
IR	Information Retrieval.
OLAP	Online Analytical Processing.
OWL	Web Ontology Language.
RDF	Resource Description Framework.
RDFS	Resource Description Framework Schema.
URI	Uniform Resource Identifier.
WWW	World Wide Web.
XML	Extensible Markup Language.

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Section 1

Introduction

1.1 The User Information Need

1.1.1 Problem Definition

We live in a world, where information handling, i.e. acquiring, storing and accessing information, has become a key factor in everyday as well as professional life. To put in other words: *we live in an information age*. One indicator for this development is the amount of data available and how quickly it has increased over the last decades. As simple example, consider usage statistics of the *World Wide Web* (WWW); from 2000 to 2009 alone, usage grew around 380 percent. Nowadays, more than 1.7 billion people are connected via WWW.[1] Other examples include information, which has recently been made accessible via the Linked Open Data[2] (LOD) initiative. However, as the data available increased dramatically, ways of making this information searchable and manageable, became more and more challenging.

With respect to the underlying structure of the data, one has to distinguish between *unstructured* and *structured* information. For the latter case, depending on the data syntax used, formal query languages provide an efficient and effective way to access information. However, these languages not only demand users to know a given syntax, in which they may articulate their needs, they also require them to have a very specific information need in the first place. In particular, the latter constraint, however, is not always holding. For the sake of clarity, consider the following example:

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[1] See also http://www.internetworldstats.com, revised Nov. 2009.

[2] See also http://esw.w3.org/topic/SweoIG/TaskForces/CommunityProjects/LinkingOpenData, revised Dec. 2009.

✎ **Example 1.1.** Mary is new to computer science - she just started her studies at a local college. However, she is eager to learn more about this vast research field and decided to start by searching for prestigious computer science researchers and work they have done. Unfortunately, she does not know, how to search within the data-space and what *prestigious* in this context means. Due to the lack of specific domain knowledge as well as information about her item of interest, she makes use of heuristics. First of all, Mary decides that she is only interested in researchers that have already become a professor. However, Mary quickly notices that this helps only very little. Therefore, she continues to look for rather big and old schools. Chances might be high, Mary thinks, that people there are doing good research work. Also, as Mary continues her exploration, she observes that some people published very little papers, while others seem to have an endless publication list. Thus, she constraints her search to those scientists, who wrote at least a dozen papers. Still having a lot of different people satisfying her specifications, Mary continuous her quest.

As illustrated in the example above, searching is not always easy and it may differ, with respect to the actual information need as well as user knowledge concerning an item of interest. According to [Mar06], we may distinguish three elementary information needs, they range "[...] from basic facts that guide short-term actions [...] to networks of related concepts that help us understand phenomena or execute complex activities [...] to complex networks of tacit and explicit knowledge that accretes as expertise over a lifetime [...]". The corresponding search types are: *lookup*, *learning* and *investigation*.

- *Lookup* Search

  Lookup search is the most common activity. Here, users have a very specific information need and are able to fully express it by means of *query searching*. Discrete and well-structured objects are returned as a result (cf. [Mar06]). Consider e.g. an Information Retrieval (IR) context, where search is often solely lookup-based. Roughly speaking, this retrieval model consists of four parts: (1) the document collection being the data-source to be searched, (2) the documents in an abstract representation, (3) the user information need formulated as query and (4) the actual user information need (cf. [WR09]). See also figure 1 (p. 3). Notice, variants of this model are the most commonly used search implementations, with regard to the WWW.

- *Learning* Search

  In contrast to *lookup* tasks, learning searches require multiple human-computer interactions (HCI), each returning a set of objects that requires cognitive processing and interpretation. Search tasks falling under this category are e.g. acquisition of new knowledge or searching in social network systems (cf. [Mar06]).

- *Investigation* Search

  Investigation searches, like learning tasks, also involve multiple HCI and may require a long period of time. Here, typical tasks are the support of planing and forecasting or the discovery of faulty data. Note, however, investigation searches are generally more concerned with recall than precision. It is therefore not supported by most of todays web search engines (cf. [Mar06]).

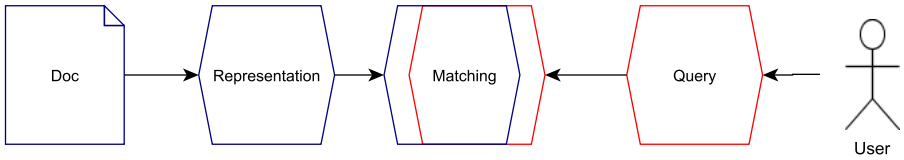

Figure 1: Lookup-based Information Retrieval (based on [WR09]).

Note, the above defined search activities are not strictly separated. On the contrary, they may be quite overlapping. E.g. learning activities often also require one or more lookup searches and so on. Furthermore, note that information needs differ from task to task. On the one hand, having very precise information about an item of interest, users may apply a simple lookup search. On the other hand, given rather fuzzy knowledge, with regard to an information need, they might be required to explore the underlying data-source and thus use a system supporting learning or investigation search (cf. [WR09]). Please see also figure 2 (p. 4).

1.1.2 Traditional IR Concepts: Browsing & Query Searching

There are two fundamental information retrieval paradigms, namely *browsing* and *query searching*. According to [Zha08], *browsing* and *query searching* respectively, are defined as follows:

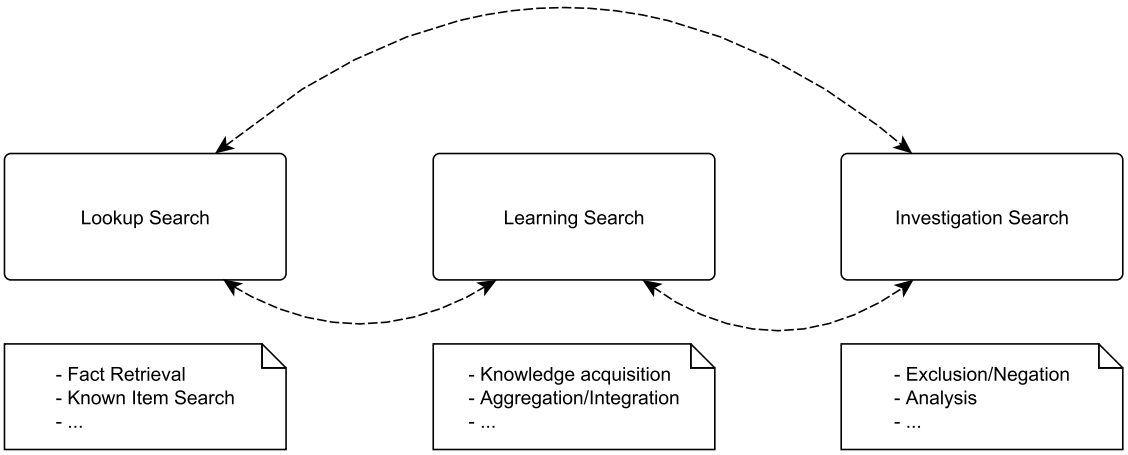

Figure 2: Search Types (based on [Mar06]).

☞ **Definition 1.1. Browsing**

"Browsing refers to viewing, looking around, glancing over, and scanning information in an information environment.", cf. [Zha08].

☞ **Definition 1.2. Query Searching**

"Query searching is a complex task which involves the articulation of a dynamic information need into a logical group of relevant keywords.", cf. [Zha08].

Obviously, with respect to their intended goals, these paradigms are quite different from each other. *Browsing* "[...] is an extremely important means to explore and discover information. [...]", cf. [Zha08]. *Query searching*, on the other hand, provides users with a list of best-matching documents, given an information need. Problems in this context arise from the translation of a need to its query as well as the mapping from a document to its representation (cf. [Zha08]). Please see also figure 1 (p. 3).
Hereafter, in compliance with [Zha08], I will further outline the differences between *browsing* and *query searching*.

(i) Relevance judgment

Query searching is based on an automated keyword matching strategy, mapping terms, describing a query, to terms describing documents contained in a collection. Also, in this context, relevance judgment is achieved solely by the systems themselves and is entirely based on a keyword level. However, when applying *browsing* strategies, relevance judgment is done manually by users, on a conceptual level (see [TC89, Zha08]).

(ii) Continuity

Browsing is a continuous process. The entire search, from selecting a browsing path, to context examination as well as decision making, is stepless and controlled by users. *Query searching*, on the other hand, is a rather interrupted process. After issuing a query, matching and relevance judgment is done automatically and works as a *black box*. Users regain control of the process, when results are being returned and have to be examined (cf. [Zha08]).

(iii) Time and effort costs

Browsing, in comparison to *query searching*, is a rather lengthy task. It might be quite time consuming, since the actual browsing path is selected by users. Each selection consists of multiple decisions, for which users have to process context information, maybe correct browsing mistakes and recall previous choices. When using a *query searching* mechanism, however, users solely articulate their information needs via a query, no further interaction is necessary (cf. [Zha08]).

(iv) Information seeking behavior

Browsing and *query searching* also differ, with regard to the underlying information seeking behavior. According to [Zha08], when *browsing*, users issue queries like: *Show me what you can offer*. Whereas, when using *query search* mechanisms, they ask something like: *What do I want?* Notice, these behaviors are quite contrary to each other. While the first one is a rather exploratory way of fulfilling an information need, the latter is a much more focused and straightforward approach (cf. [Zha08]).

(v) Iteration

With respect to the necessary search iterations, in order to reach an item of interest, *browsing* requires in general multiple iterations. *Browsing* "[...] involves successive acts of glimpsing, fixing on a target to examine visually or manually more closely, examining, then moving on to start the cycle over again", cf. [Bat02]. *Query searching*, however, comprises three single steps, i.e. (1) definition of search terms (2) formulation of a query and (3) analysis of returned, matching documents (cf. [Zha08]).

(vi) Granularity

In compliance with [TC89], *granularity* refers to the "[...] number of relevant items that are evaluated at one time at in the process of feedback". *Query searching* returns a set of relevant items for a given query, issued by users. *Browsing* differs here, as users may manually process only one item at a time, in order to determine its relevance (cf. [Zha08]).

(vii) Clarity of information needs

As illustrated in example 1.1 (p. 2), user information needs may vary drastically, with respect to their fuzziness: (1) Some users may have a very detailed and accurate need that they wish to be fulfilled with the least effort possible. (2) There might be other users, who have only a fuzzy need, resulting from a lack of domain or context knowledge (cf. [Zha08]). In accordance with [MS88], *browsing* is "[...] especially appropriate for ill-defined problems and for exploring new task domains.". *Query searching*, being the complete opposite, requires in general a precise and accurate information need, in order to provide meaningful results (cf. [Zha08]).

(viii) Interactivity

As outlined above, *query searching* comprises very few steps, i.e. (1) definition of search terms, (2) articulation of a query and (3) analysis of returned, matching documents. As a result, there is not much interaction required before an information need is fulfilled. *Browsing*, however, consisting of multiple iterations and user decisions, generally leads to much more user interaction necessary (cf. [Zha08]). Thus, according to [Zha08], *browsing* is "[...] more complicated and challenging because of the dynamic human factor".

(ix) Retrieval Results

Also, with regard to returned results, *query searching* strategies differ from *browsing* ones. While the former has a focus on single items or documents contained in a database, the latter one may produce much more diverse outcomes. More specifically, *browsing* may lead to contextual information, structural information, relational information, individual items or documents (cf. [Zha08]).

As outlined above, *query searching* and *browsing* are two fundamentally different

information retrieval approaches. However, both having their strengths and weaknesses, a combination and fluent interaction might prove to be beneficial. In the following, I will present a concept coined *exploratory search*, enabling exactly this integration of both paradigms.

1.1.3 Exploratory Search

1.1.3.1 Defining the Exploratory Search Concept

[Mar06] describe *exploratory search* (see section 1.1.1, p. 1) as an interaction of *learning* and *investigation* search activities (see also figure 3, p. 7). As a practical example, [Mar06] consider *social searching*, a task during which users intend to locate communities or people of interest. Another simple example of an exploratory search is *Mary's search for prestigious computer scientists*, as outlined earlier. Please remember, example 1.1 (p. 2) not only incorporates exploration, but also knowledge acquisition and development of intellectual skills. Note, however, the definition given in [Mar06], to be tightly coupled with *Bloom's* taxonomy of educational objectives. For further details, see [KBM56].

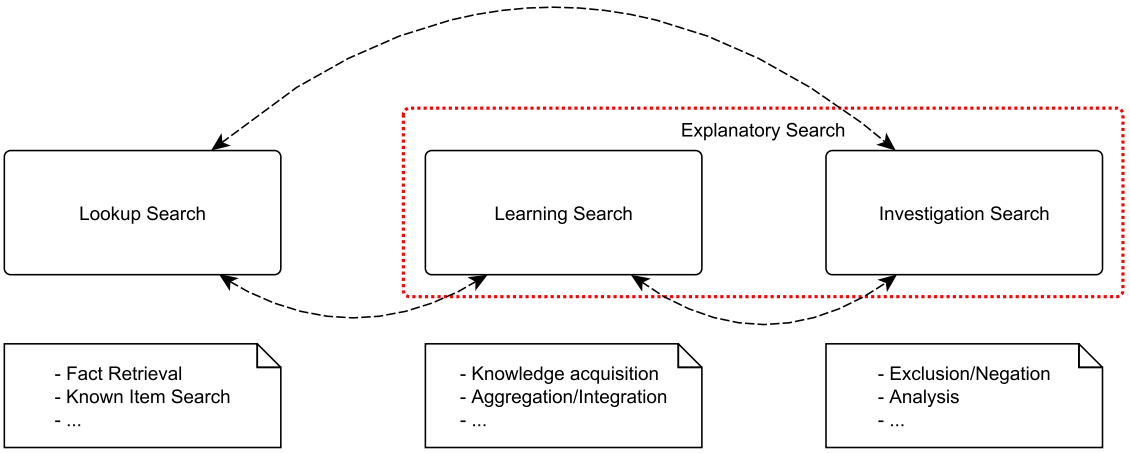

Figure 3: Exploratory Search (based on [Mar06]).

According to [WR09], *exploratory search* may be distinguished from other strategies as follows:

(i) Time and Effort

Exploratory search may involve multiple iterations, possibly even multiple sessions, in order to be completed. A system supporting such strategies, therefore

has to provide ways for users to store queries as well as history over time (cf. [WR09]).

(ii) Information Need

According to [WR09], user information need is "[...] generally open-ended, persistent and multifaceted. Open-endedness relates to the uncertainty over the information available or incomplete information on the nature of the search task". In a similar manner, [Ber60] refers to information needs in this context as "[...] a mixture of specific and curiosities", while also emphasizing the involved learning and investigation tasks.

(iii) Goal

The goal behind an exploratory search goes beyond simple information lookup. More precisely, search tasks tend to be either learning or investigation problems, in their nature. In most cases, the overall goal is, to help people in making a decision or deepen their understanding, with regard to a topic of interest (cf. [WR09]).

(iv) Interaction Behavior

Human-computer interactions used during an exploratory search are in most cases a combination of *query searching* and *browsing*. Please note, *browsing* here is mainly used to focus the search and resolve uncertainty (cf. [WR09]).

(v) Collaboration

Since *information usage* and *information understanding* are in general tightly coupled with exploratory search, it is quite likely that a search may involve more than one party. These parties may work together in setting the goals for a given need or may simply be involved in solving the task (cf. [WR09]).

(vi) Evaluation Requirements

An evaluation in this context has to determine whether a system is capable of addressing the fundamental elements of an exploratory search. Therefore, in order to evaluate a system supporting exploratory search, a methodology targeting learning and investigation, system outcome and system utility is needed (cf. [WR09]).

Please note, two of the above outlined characteristics are of particular importance.

First, *exploratory search* activities are always coupled with a vague and *fuzzy* information need. Reconsider example 1.1 (p. 2): Notice, Mary is not familiar with the underlying domain, i.e. the field of computer science, or the characteristics of her item of interest. Second, *exploratory tasks* require both of the above introduced paradigms, namely *query searching* and *browsing*. The latter, however, plays an important role, since it is used to resolve uncertainty, which in turn allows a more focused search.

1.1.3.2 Usage Scenarios for an Exploratory Search

In accordance with [WR09], one may use *exploratory search* techniques, given a context as outlined hereafter:

- Users may be unfamiliar with the domain of their information need. Therefore, they first have to deepen their understanding of the underlying space, by means of an exploration.

- Second, one may be uncertain, how to actually achieve a goals, i.e how to meet an information need.

- Lastly, users may have no specific knowledge about their item of interest, i.e. about its precise characteristics and relations to other items.

From another perspective, using the model introduced in [Mar06], users engage in different kind of searches, depending on the actual information need (see section 1.1.1, p. 1). In the past, especially in the *WWW*, systems mainly addressed the support of efficient and effective *lookup* search tasks. However, as outlined by [Mar06], there are other kinds of information needs, which are not met by simple *lookup* search. Systems supporting *exploratory* search, on the other hand, provide means of issuing *queries* that go far beyond simple fact retrieval. [Mar06] refer to needs, requiring such queries, as *higher-level* needs.

1.2 A brief Introduction to Faceted Search

Over the last years, *faceted search* became a very popular paradigm. On the one hand, with respect to the academic world, it has been proposed for searching documents [HSLY03, DRM+08, BYGH+08], for databases [DIW05, BRWD+08, ABC+02],

as well as for RDF data [ODD06, SSO+05, HMS+05]. On the other hand, this technique also rapidly gained importance in commercial applications, consider e.g. *Ebay*[3] or *Amazon*[4]. In the following, I would like to give a brief outline of its history, followed by a definition of facets and facet values respectively. Lastly, the reader will be presented one major benefit of faceted search, namely its role as an *enabler* for exploration. Note, in section 2 (p. 17), I will show how faceted search may be employed in a *Semantic Web* context.

1.2.1 What is the Faceted Search Paradigm?

1.2.1.1 A Short History of Faceted Search

Early days of Classification *Taxonomy* is originating from a combination of the Greek τάξις, meaning *order* or *arrangement*, and the Greek word νόμος, referring to *science* or *law*. From a historic perspective, Aristotle was the first researcher making use of such a taxonomy in his work *Classification of all living things*. Here, he created a system categorizing all living things, starting from a top-level perspective, dividing organisms into animals and plants and so on (see figure 4, p. 11).
"In modern use, taxonomy is any organization of things or abstractions into a hierarchy, or a tree structure. In keeping with the tree as a metaphor [...], there is a root node at the top, leaves at the bottom, and branches connecting each nonleaf parent node to its children. A parent may have many children, but each nonroot node has exactly one parent.", cf. [Tun09]. Such *taxonomies* are also referred to as being *strict*. This definition may be extended to a so called *polyhierarchy*, which allows an inner node to have multiple parents. Hereafter, however, the reader should assume a taxonomy to be strict.
Notice, the above given definition to be a rather structural one. On a semantic level, on the other hand, a taxonomy represents a tree with each edge being an *is-a* connection. To be more precise, the root node of a taxonomy stands for a top-level category, covering all elements, contained in a set to be described. This collection is then split into disjoint subsets, each symbolized by a child of the root node. Those subsets may again be split on a second hierarchical level, leading to further differentiation and so on.

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[3] See http://www.ebay.com, revised Dec. 2009.

[4] See http://www.amazon.com, revised Dec. 2009.

According to [Tun09]: "a key property of a taxonomy is that, for every object or set of objects that corresponds to a node, there is precisely one unique path to it from the root node". This property, however, imposes a harsh limitation, leading to a very restricted design and practical usage of taxonomies. Addressing this shortcoming, in the following, I will introduce the so called *colon classification*, a first version of a *faceted search* mechanism.

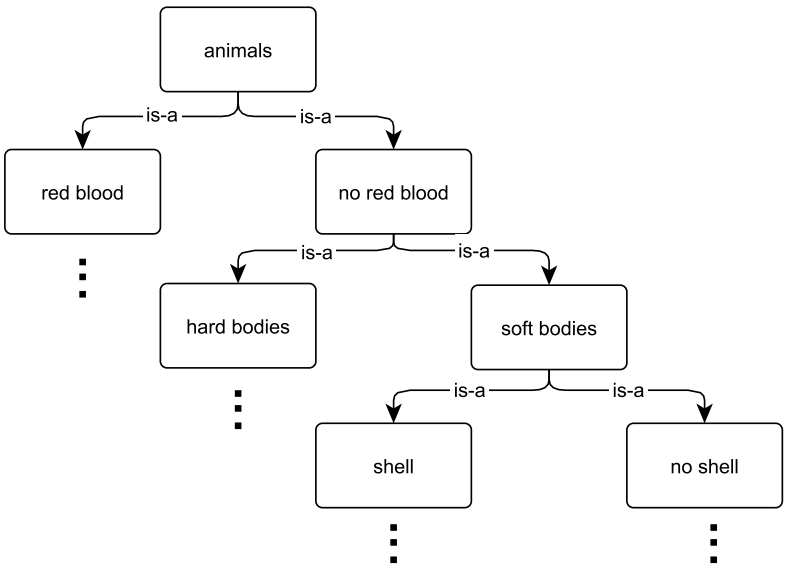

Figure 4: Aristotle's Classification of all living Things (based on [Tun09]).

The Colon Classification The first to observe the above outlined deficits, was the Indian library scientist S. R. Ranganathan, who developed 1933 the so called *colon classification* (cf. [Ran33]). Using his novel classification mechanism, Ranganathan modeled the world using five fundamental, mutually exclusive, taxonomies: *personality*, *matter*, *energy*, *space* and *time*. He described a specific item as a sequence of letters and numbers separated by colons, each block addressing a different taxonomy. Thus, every item is not classified according to one, but with regard to multiple taxonomies (cf. [Ran33]). The reader should notice that, to represent an item by means of several categorizations, is the key element of the *colon classification*. On the other hand, in contrast to a *polyhierarchy*, this separation enables one, to extend each category independently. As example, consider the below given classification of '*the statistical study of the treatment of cancer of the soft palate by radium*' as '*L2153:4725:63129:B278*' (cf. [Ran50]):

✎ **Example 1.2.** The Subject '*The statistical study of the treatment of cancer of the soft palate by radium*' results in a term '*L2153:4725:63129:B278*'. This classification is based on the following four facets:

- Medicine (L) ↦ Digestive Systems (L2) ↦ Mouth (L21) ↦ Palate (L215) ↦ Soft Palate (L2153)
- Disease (4) ↦ Structural Disease (47) ↦ Tumor (472) ↦ Cancer (4725)
- Treatment (6) ↦ Treatment by chemical substances (63) ↦ Treatment by a chemical element (631) ↦ Treatment by a group 2 chemical element (6312) ↦ Treatment by radium (63129)
- Mathematical study (B) ↦ Algebraical study (B2) ↦ Statistical study (B28)

1.2.1.2 Defining a Facet and a Facet Value respectively

In compliance with [TM06], facets are "clearly defined, mutually exclusive, and collectively exhaustive aspects, properties or characteristics of a class or a subject". [Hea08], on the other hand, define a facet in a slightly different manner as: "[...] categories used to characterize information items in a collection". [ODD06] have yet another notion of a facet: "In faceted browsing the information space is partitioned using orthogonal conceptual dimensions of the data. These dimensions are called facets and represent important characteristics of the information elements". However, for the rest of this paper, I will use the following definition:

☞ **Definition 1.3. Facet**
Facets represent mutually exclusive, conceptual dimensions of the underlying data collection (based on [ODD06]).

Each facet may have one or more values. [Hea08] refer to these values as *labels*, while [ODD06] call them *restriction values*. A value may be defined as:

☞ **Definition 1.4. Facet Value**
A facet value is a concrete realization of the data dimension it refers to.

Hereafter, I will refer to these values simply as *facet values*. Note, facets may be further classified according to their structure. [Hea08] distinguish *flat* from *hierarchical* facets. The former corresponds to a data dimension, which is mutually exclusive with regard to all other dimensions. In the latter case, two or more dimensions are

correlated via an *is-a* relation.

On the other hand, not only for two given facets might an *is-a* relation hold, also two values may be correlated in such a manner. Thus, one might wish to categorize facet values as *flat* or as *hierarchical*, depending on their correlation to other values. Please note, in the following, I will refer to *hierarchical* facets and facet values as *non-flat* facets and facet values respectively.[5] In order to clarify the above stated definitions, let me give you a brief example:

✎ **Example 1.3.** Recall Mary from our previous example 1.1 (p. 2). In this particular information space, there might be several dimensions of interest. First of all, Mary restricts her search results via a facet value pair *type:professor*. As value *professor* may have an *is-a* relation to a *full professor* or an *assistant professor*, this value is coined *non-flat*. Furthermore, Mary sets as additional constraint that institutions employing scientists of interest, should be rather old and big. In order to specify this restriction, she chooses a facet *works at*. However, *works at* is a *non-flat* facet, as there might be other facets, say *works at full time* and *works at part time*, which are associated with *works at* via an *is-a* relation. On the other hand, given a facet *age*, there is no such correlation, thus being referring to as *flat*.

A user selecting a facet value pair, say f:v, imposes a refinement of the currently given result set. Previously imposed constraints, either by facet operations or by *query searching*, are connected via conjunction with this new constraint, say $\hat{c}$. Therefore, all items contained in the current result must fulfill $\hat{c}$, in addition to all other given restrictions. Note, however, selecting f:v within a hierarchy is equivalent with forming a disjunction over all facet value pairs subsumed by f:v (cf. [Hea08]).

1.2.2 Faceted Search as Enabler for Exploration

1.2.2.1 Features of an Exploratory Search System

As outlined earlier (see section 1.1.3, p. 7), exploratory search systems go far beyond simple means, supporting solely *lookup* tasks. As prominent examples consider e.g. systems like *mSpace* (cf. [SSO+05]), *Relation Browser* (cf. [MB03]) or *flamenco* (cf. [HEE+02]).

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[5] More precisely, hierarchical facet values are a special case of *non-flat* values, given a Semantic Web environment (see section 2, p. 17).

According to [WR09], advanced systems, such as the above, have to provide a certain set of features, in order to fulfill high-level information needs. Below, please find these features outlined in more detail:

(i) Query Formulation & Refinement

A System must enable its users to articulate and instantly refine queries.

(ii) Facets & metadata-based Filtering

Facets need to be present, in order for users to quickly refine and explore a given result set. Also filtering via document metadata has to be possible.

(iii) Utilize Search Context

Search context, user information and search task information, need to be used for personalization of the search process.

(iv) Support Visualization

Systems must provide advanced result visualization means, for enabling decision making and gaining novel insights.

(v) Learning & Understanding

Information has to be visualized and processed in ways making it possible for users to gain new knowledge and skills.

(vi) User Collaboration

In order to complete high-level information needs, collaboration in a synchronous or asynchronous manner might be necessary.

(vii) History, Workspaces & Updates

Systems have to enable reversion and backtracking of user actions, visualization of progress updates and storage as well as manipulation of information needed during the completion of a particular task.

(viii) Task Management

Also, systems must enable multiuser and multisession usage and therefore provide means of a task management.

1.2.2.2 Faceted Search as Part of an Exploratory Search System

As briefly described earlier (see section 1.2.2.1, p. 13), exploratory systems need a set of features to be present, in order to support more advanced search tasks (cf. [WR09]). One of these features is a *faceted interface*, as a basis for instant result set refinement and user exploration of the underlying information space. In the following, let me explain in more detail, on how a *faceted search* may contribute to an exploratory search system.

In compliance with [WR09], "[...] search systems must offer the ability for searchers to filter result sets by specifying one or more desired attributes of the search results". Also, users are often overwhelmed by a given result set and wish to have a meaningful grouping of the result items, in order to deepen their understanding and continue the search process (cf. [Hea06]). This grouping may be accomplished by using either *clustering* techniques or a *faceted categorization* (cf. [WR09]). According to [Hea06], *faceted categories* summarize a given domain of interest, by providing a set of facets and facet values to users. Thus, allowing them to quickly identify important concepts and deepening their understanding of a given data-space. Furthermore, *faceted search* interfaces assist users, when being lost and help getting back on the right track, via expansion of the result set (cf. [WR09]).

On the other hand, there are also downsides associated with a *faceted categorization*. First of all, many faceted interfaces still depend on manual creation of facet hierarchies and their associated facet values. Please note, however, there are strong research efforts on automatic facet hierarchy discovery (see [SH04, DIW05]). Also, facets may restrict users in their exploration, due to the structural constraints, they might be imposing (cf. [WR09]).

1.3 Outline of this Paper

Hereafter, I will present a framework for a more *browse-able* faceted search in a Semantic Web environment. In contrast to current approaches, which are focused on efficient *query searching* strategies, i.e. support for users, in order to issue precise and specific information needs, rather than enabling them to browse and articulate *fuzzy* knowledge. In section 2 (p. 17), I am going to outline a search process, which allows a fluent interaction between *keyword search* and *browsing*. Also, I introduce definitions for a data, a query as well as a facet model. Continuing in section 3 (p.

36), again targeting at browse-ability, I will address the problem of vast and unclear facet ranges. In order to enable users to better understand and access these sets, I use clustering techniques for decomposing facets in more fine-grained sub-facets. In section 4 (p. 70), I present a ranking scheme making use of this sub-facet clustering as well as the individual facet characteristics. Keeping the above goals in mind, these metrics aim to rank facets high, which support *browsing* and specification of *fuzzy* knowledge, thus are suitable for exploration tasks. In section 5 (p. 91), I discuss results I obtained from a task-based user study, for comparison of the outlined novel ranking and clustering approach, with the current state of the art. Finally, in section 6 (p. 99), I present concluding remarks and give the reader a brief overview of future work, I am planning on pursuing.

Section 2

Faceted Search in a Semantic Web Context

2.1 The Need for a more *semantic* Web

As briefly outlined in section 1.1.1 (p. 1), nowadays, *we are living in an information age*. Efficient data storage as well as access, have become more and more challenging, with the rapidly increasing amount of content available. However, the current state of the art for data, or to be more precise, *knowledge* storage, bears significant flaws. First, and perhaps most importantly, today data is stored without making its implied semantics explicit. In other words, while data syntax is *machine accessible*, data semantics are only *readable* for humans. To be more precise, currently, it is up to the human reader to process a given information and *understand* its meaning. Search engines, consider e.g. *Yahoo*[6] or *Google*[7], compensate this lack of intelligence with IR strategies, trying to reconstruct the before lost semantics. In the long run, however, it is quite obvious that semantics have to be stored along with their data and should not be regenerated afterwards (cf. [AvH08, HKRS07]).

A second shortcoming of todays information storage results from its *heterogeneity*. It is currently not possible to integrate or reuse given data in any way. For enabling a more efficient data handling, on the other hand, it is essential to have a common representation for knowledge (cf. [AvH08, HKRS07]).

Lastly, not all information is stored using an explicit manner. On the contrary, most information needs are currently fulfilled, not by machines answering a query, but by users reasoning on an information space. Clearly, this is not a desirable state, since human reasoning capabilities are generally very limited (cf. [AvH08, HKRS07]).

Please note, a full discussion of the pros and cons of a Semantic Web is beyond the

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[6] See also http://www.yahoo.com, revised Nov. 2009.

[7] See also http://www.google.com, revised Nov. 2009.

limits of this paper. For more details, please see [BLHL01, SBLH06]. Hereafter, the reader is assumed to have basic knowledge of RDF(S) as well as Semantic Web technologies in general.

2.2 Semantic Search Process

2.2.1 Search Process - A technical Point of View

In recent years, the amount of data stored, using *semantic technologies* has increased drastically. As prominent indicators for more data being represented by means of *ontologies*, consider e.g. the increasing usage of languages like RDFa[8] or the Linked Open Data[9] initiative. This development enabled a new kind of information access, providing ways reaching, beyond simple *keyword search*. Notice, there are various definitions of *semantic search*, see e.g. [GMM03, ZYZ+05, CCPC+06]. In the following, however, *semantic search* is defined in compliance with [THS09]:

☞ **Definition 2.1. Semantic Search**
Semantic search is defined as an "[...] information access, in which information needs are addressed by considering the meaning of the user queries and available resources", cf. [THS09].

☞ **Definition 2.2. Semantic Faceted Search**
Semantic faceted search, on the other hand, may be defined as semantic search, employing the faceted search paradigm, in order to enable users to express their information needs.

In this context, please recall the different information needs as discussed in section 1.1.1 (p. 1). Given data represented via semantic technologies, the question arises, how to integrate the before introduced *faceted search* notion, within this new environment. However, before discussing an application of faceted search, with respect to a Semantic Web infrastructure, any further, allow me to first present semantic search in more detail. According to [THS09], *semantic search* may be regarded as a process having the following parts.

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[8] See also http://w3.org/TR/xhtml-rdfa-primer/, revised Dec. 2009.

[9] See also http://esw.w3.org/topic/SweoIG/TaskForces/CommunityProjects/LinkingOpenData, revised Dec. 2009.

(i) Query construction

The query construction phase comprises three individual steps. First, users specify their needs by means of *query searching*, i.e. a query consisting of one or more keywords, summarizing their information need. Next, using a graph exploration algorithm, one or more structured queries are computed for the given keywords. Each structured query, represented as a graph[10], stands for a possible *meaning*. Note, since natural language is ambiguous, there might be more than one structured query, resulting from this exploration phase. [THS09] refer to such a query as *interpretation*, while the procedure, i.e. translation from keyword query to structured query, is coined *query translation*. Lastly, the computed *interpretations* are presented to users, enabling them to choose a fitting one, thereby specifying their information needs precisely (cf. [THS09]).

(ii) Query processing

Query processing, i.e. the computation of a set, containing resources or literals, satisfying given query constraints, is accomplished via two separate operations. In order to reduce the number of joins and unions necessary as well as I/O, a preprocessing step is employed. This procedure results in a set of so called candidates. Each candidate is then further evaluated and matched against the data-source, in order to verify whether or not he fulfills a query (cf. [THS09]).

(iii) Result presentation

Query results are visualized during the so called result presentation step. Depending on the structure of a query, notice, it may be a *factual*, *entity* or *general conjunctive* query, different templates are used to present the current result set (cf. [THS09]).

(iv) Query refinement

In a final phase, facets may be used, i.e. *added*, *removed* or *edited*, in order to refine or expand the current result set. According to [THS09], these result set operations might be necessary in several cases: Maybe a chosen *interpretation* did not fit an information need precisely. Or, on the other hand, a need itself might have been vague in the first place (cf. [THS09]).

[10] For a formal *graph* definition, please see section 2.3 (p. 24).

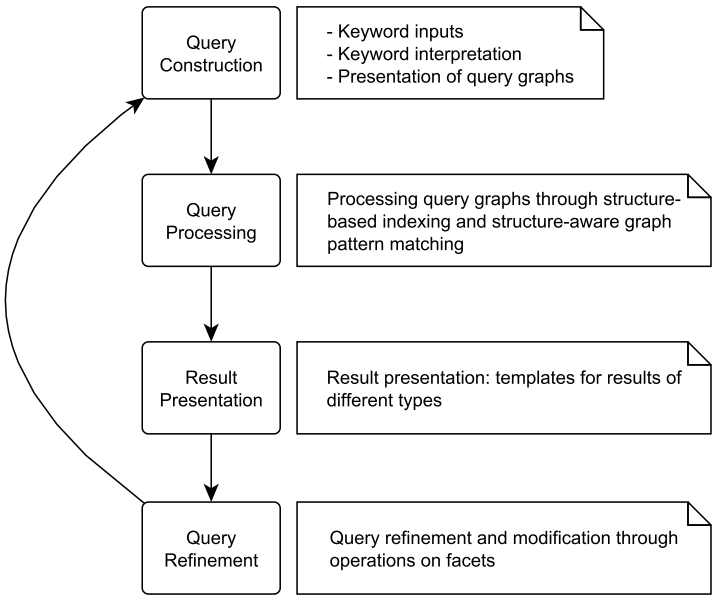


Figure 5: Overall Semantic Search Process (based on [THS09]).

Notice this search process to be summarized in figure 5 (p. 20). Further note, this description is a rather technical one. More specifically, the main focus lies on providing a complete overview of necessary steps, internal as well as external, starting with an unfulfilled and ending with a fulfilled information need. In the following, I will present another view on the very same search process, addressing the user-system interactions during a search. Please keep in mind, however, while having different angles, both views are fully complementary.

Lastly, the reader should be aware that *semantic search* is a broad research field and the above stated search process as well as the definitions are intended to give only a brief overview. For a more detailed introduction to *semantic search*, please see [GMM03, Man07, ULL+07].

2.2.2 Search Process - An Information Retrieval Point of View

As mentioned earlier, being complementary to the above description, I would like to introduce a process view, targeting more at user-system interactions. Please recall, there are two fundamental IR approaches, namely *query searching* and *browsing* (see section 1.1.2, p. 3). Also remember, in order to enable *exploratory search* strategies and thereby the fulfillment of higher-level information needs, a combination is necessary. The hereafter given definition aims at this fluent interaction of *query searching* and *browsing* (based on [HSLY03]).

According to [HSLY03], one may distinguish three different stages during a search

session. First of all, during the so called *opening* stage, users may familiarize themselves with a given *information space*. Next, there is the *middle game*, where users have already narrowed their search space down and intend to further refine the current result set via *browsing*. This phase is followed by what [HSLY03] coined the *end game*. Here, a single item of interest, fulfilling an initial information need, is presented to users. Please also find this process illustrated in figure 7 (p. 23).
In order to combine both IR paradigms in a meaningful manner, one has to make assumptions, by what means users specify their needs. Please recall, for *query searching* a well-defined and very specific information need is necessary. When using *browsing*, on the other hand, only vague needs are required. Also reconsider that *query searching* is generally less expensive, with respect to time and effort (see section 1.1.2, p. 3). Given these facts, first of all, I assume users to be aware of these differences and more importantly, to act in a *rational manner*. By *rational manner*, I mean that users prefer a cheaper path, leading to their item of interest, over a more expensive one. Thus, without loss of generality, I may have assumptions as follows:

➻ **Assumption 2.1.**

Specific information needs are always articulated via *query searching*.

➻ **Assumption 2.2.**

Fuzzy information needs are always entered via *browsing*.

Given these assumptions, one may combine them as:

➻ **Assumption 2.3.**

First of all, I assume users to be provided with means of *query searching* as well as *browsing*. Also, the reader may think of an information need as an *abstract* query, say Q_{Need}. With *abstract* in this context, I refer to queries being located at some level between a user need and its machine readable representation. Furthermore, I see Q_{Need} as a tuple having two elements, say Q^S_{Need} and Q^F_{Need} with Q^S_{Need} resulting from *specific* information needs and Q^F_{Need} from *non-specific* or *fuzzy* needs. Both, i.e. Q^S_{Need} and Q^F_{Need}, may be empty. In conclusion, I assume users to articulate Q^S_{Need} via *query searching*, while needs in Q^F_{Need} will be issued applying *browsing* strategies.

Please remember in this context also example 1.1 (p. 2). Reconsidering this scenario, the reader should notice that there are two dimensions of *fuzziness*[11]: (i) Users may only have vague knowledge, with regard to a given underlying domain. E.g. Mary cannot precisely define the term *prestigious*, whereas a domain expert would know that famous computer scientists often won a *Turing Award*. (ii) Secondly, users might have vague information, concerning the characteristics of their item of interest. Mary e.g. is not aware of name or age of any prestigious scientist. Below, also consider example 2.1 (p. 22), to further clarify assumption 2.3 (p. 21), as well as the outlined notion of *fuzziness*.

✎ **Example 2.1.** In figure 6 (p. 22), please find the novice computer science student Mary. Her initial information need was to *find famous computer science researchers* and learn more about their work. As shown below, this need may be represented by queries of different granularity.

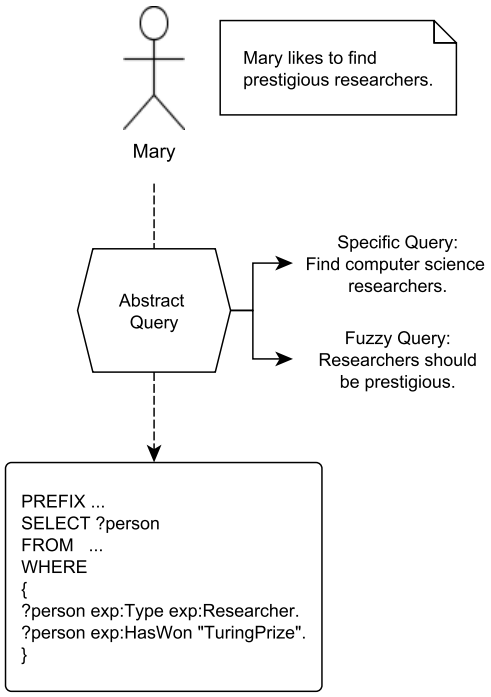


Figure 6: Information Need as an abstract Query Q_{Need}

Hereafter, I will further discuss the above mentioned search process model (based on [HSLY03]). I am going to present each stage as well as the transitions between the stages in more detail.

[11] In the following, *fuzzy*, *vague* or *unspecific* will be used synonymously.

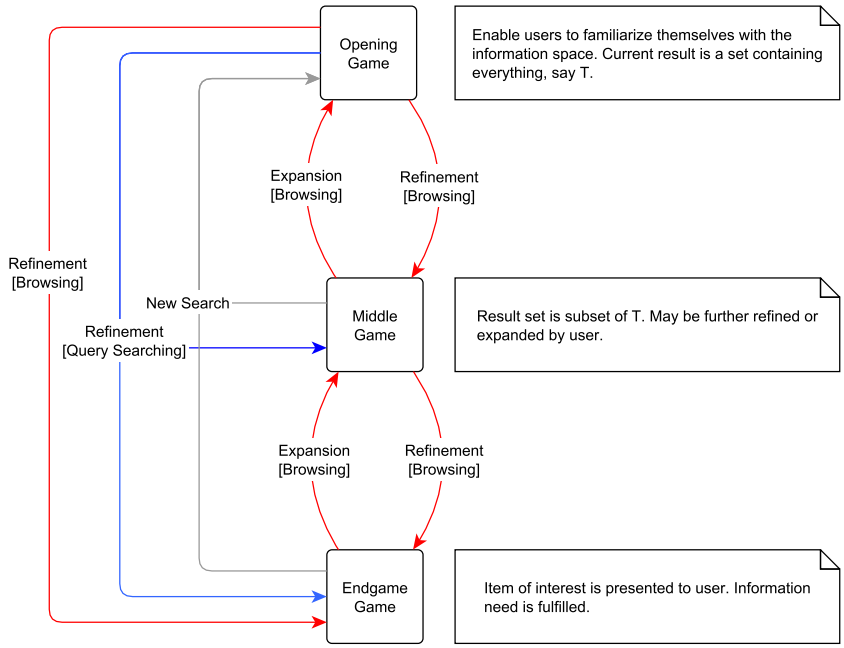


Figure 7: Integration of Query Search and Browsing (based on [HSLY03]).

☞ Definition 2.3. Opening Game

"The primary aims of the opening are to present a broad overview of the entire collection and to allow many starting paths for exploration", cf. [HSLY03].

In order to provide users with the means to familiarize themselves with a information space, top-level facets are presented, summarizing its dimensions. Also, systems should enable users to start a search process via *query searching*, if the user has specific knowledge, or otherwise, via *browsing*. Thus, in the beginning phase, refinement operations either using *browsing* strategies, i.e. facet addition, or *query searching* techniques, i.e. issuing an initial keyword query, should be possible. These refinement constraints may lead either to the *middle game* or the *end game*, depending on whether or not an information need is fulfilled (cf. [HSLY03]).

☞ Definition 2.4. Middle Game

"In the middle game the result set is evaluated and manipulated, usually to narrow it down", cf. [HSLY03].

In the *middle game* phase, an initial result set has been refined via *browsing* or *query searching*. However, further refinement using facets is necessary, in order to fulfill a user information need. On the other hand, if previously selected restrictions led to a result set not containing the item of interest anymore, a new search may be

started or the current result set may be expanded, using facet removal means (cf. [HSLY03]).

☞ **Definition 2.5. End Game**

"The endgame shows a single selected item in the context of the current query", cf. [HSLY03].

Lastly, during the *end game*, an item of interest has been discovered and is to be further explored. Also, a new search process may be started or, if related items are of interest, the result space may be expanded, using facet operations (cf. [HSLY03]).

2.3 Terminology & Definitions

Hereafter, I will first present basic definitions for the underlying data and schema model, as well as the query model. In a second step, I will introduce definitions for facets as well as facet values, given a Semantic Web context. Please note, there are several different definitions for the data, the semantic or the query model, commonly used in the literature. I, however, will use these concepts in compliance with [THS09], as defined below.

2.3.1 Data Model

According to [THS09], the *data model* or *resource space*, may be defined as:

☞ **Definition 2.6. Resource Space**

Let S_R be the resource space, i.e. is a set of RDF graphs $g_R = (V^R, L^R, E^R)$, where

- V^R is a finite set of vertices. V^R is a disjoint union $V_E^R \uplus V_V^R$ with E-vertices V_E^R (entities) and V-vertices V_V^R (data values),
- L^R is a finite set of edge labels, subdivided by $L^R = L_R^R \uplus L_A^R$, where L_R^R are relation labels and L_A^R are attribute labels.
- E^R is a finite set of edges of the form $e(v_1, v_2)$ with $v_1, v_2 \in V^R$ and $e \in L^R$. Moreover, the following types are distinguished:
  - $e \in L_A^R$ (A-edge) iff $v_1 \in V_E^R$ and $v_2 \in V_V^R$,
  - $e \in L_R^R$ (R-edge) iff $v_1, v_2 \in V_E^R$,
  - and type, a predefined edge label that denotes the class membership of an entity (based on [THS09]).

In other words, the *resource space* contains all resources of interest, i.e. all items made available for searching. These resources are represented as vertices in S_R, while relations and attributes are mapped to edges. Please note, in S_R, classes, i.e. groupings of similar instances, are not distinguished from resources. To be more precise, [THS09] do not differentiate schema knowledge from instance knowledge. In the hereafter defined *schema space*, on the other hand, both are made distinguishable (cf. [THS09]).

Also note, in the previous sections, I imprecisely referred to the *resource space* also as *information space* or *data-space*. Furthermore, for clarification purposes, please consider the exemplary resource space below.

✎ **Example 2.2.** Please reconsider Mary, the novice computer science student (example 1.1, p. 2). Her local college may be modeled as a resource space S_R, in compliance with the above given definition (see figure 8, p. 25).

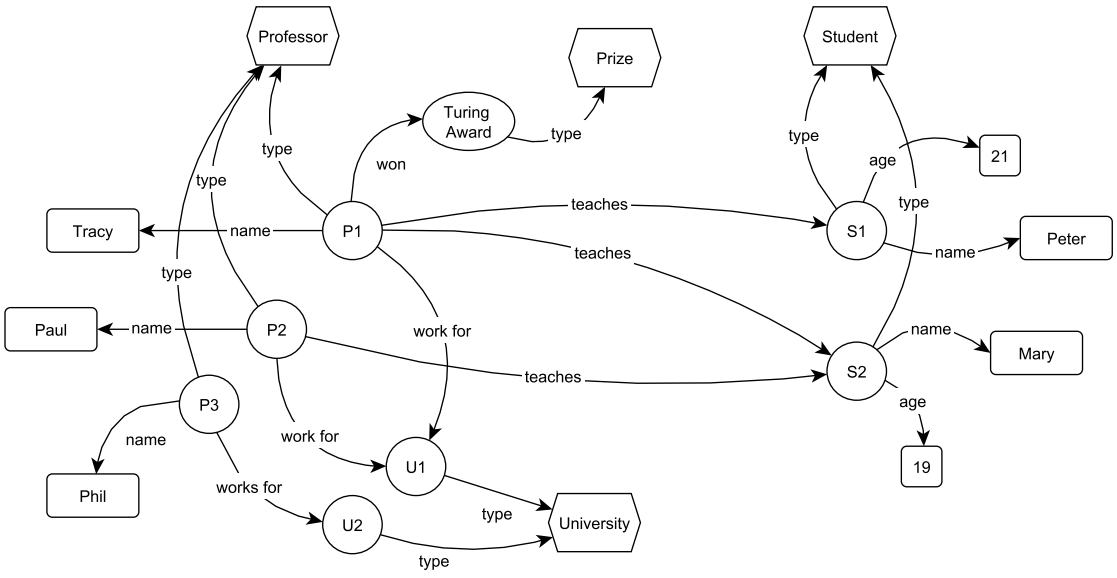


Figure 8: Resource Space Example (based on [THS09]).

2.3.2 Semantic Model

☞ **Definition 2.7. Schema Space**

Each resource graph has an associated schema, which here is a subset of RDFS. Let S_S be the schema space, i.e. a set of schema graphs $g_S = (V^S, L^S, E^S)$, where

- V^S is a finite set of vertices. V^S is a the disjoint union $V_C^S \uplus V_R^S \uplus V_A^S \uplus V_D^S$ with C-vertices V_C^S (classes), R-vertices V_R^S (relations), A-vertices V_A^S (attributes),

and D-vertices V_D^S (datatypes).

- L^S consists of the labels: *subClassOf*, *domain*, *range*, *subPropertyOf*.
- E^S is a finite set of edges of the form $e(v_1, v_2)$ with $v_1, v_2 \in V^S$ and $e \in L^S$, where
  - $e = domain$ iff $v_1 \in V_A^S \cup V_R^S$ and $v_2 \in V^S$
  - $e = range$ iff $v_1 \in V_A^S$, $v_2 \in V_D^S$ or $v_1 \in V_R^S$, $v_2 \in V_C^S$, and
  - $e = subclassof$ iff $v_1, v_2 \in V_C^S$ (based on [THS09]).

✎ **Example 2.3.** Continuing the example 2.2 (p. 25), below, please see figure 9 (p. 26) for a schema space associated with Mary's resource space S_R.

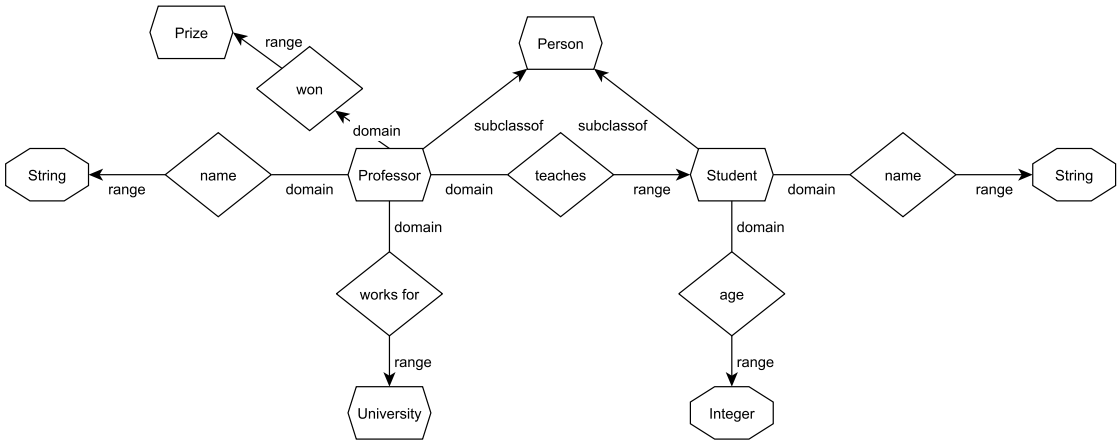


Figure 9: Schema Space Example (based on [THS09]).

2.3.3 Query and Result Model

After introducing the *resource space* S_R and *schema space* S_S, in the following I will focus on the *query model*. Please recall in this context the above (see section 2.2, p. 18) outlined search process. Specifically reconsider that an information need, formulated as *keyword query*, is mapped to an *interpretation*. This *interpretation* is represented as a so called *query graph*. In compliance with [THS09], for computing an *interpretation*, given a *keyword query*, three steps are necessary: "(i) Construction of the query space, (ii) top-k query graph exploration and (iii) query graph ranking".

With respect to the scope of this paper (see section 1.3, p. 15), the *query graph* as well as its underlying semantic model, i.e. the *query space*, are of great interest. Furthermore, hereafter, I will define *facet operations* as a special case of a *query graph*.

These *facet constraints* allow users to iteratively construct a query, matching their information needs (cf. [THS09]). Outlining the computation of an *interpretation*, however, exceeds the limits of this paper. The interested reader may see [TWRC09].

2.3.3.1 Query Model

In accordance with [THS09], the *query space*, i.e. the underlying semantic model of the *query graph*, may be given by:

☞ Definition 2.8. Query Space
Let $S_Q(\tilde{S}_S, N_K)$ be the query space, comprising keyword matching elements N_K (computed for a keyword query q) and elements of a special schema space, say $\tilde{S}_S$. S_Q consists of the graphs $g_S(V^Q, L^Q, E^Q)$, where

- V^Q is conceived as the disjoint union $V_C^S \uplus V_R^S$,
- L^Q comprises the predefined edge labels *subClassOf*, *domain*, *range* and *subPropertyOf*
- E^Q is a finite set of edges $e(v_1, v_2)$ with $v_1, v_2 \in V^Q$ and $e \in L^Q$ (based on [THS09]).

N_K, i.e. elements fulfilling keyword constraints, may be computed via matching keywords against labels of elements contained in S_R. Also note $\tilde{S}_S$ being a slightly modified version of our *schema space* S_S. $\tilde{S}_S$ is similar to the above *schema space*, however, it does not contain vertices $\hat{v} \in V_A \uplus V_D$, i.e. attributes or datatypes. Construction of $\tilde{S}_S$ seems necessary, as paths in S_S end at a datatype vertex and any edge $e(v_1, v_2)$, where $v_1 \in V_A$ and $v_2 \in V_D$, is thus not useful within this context (cf. [THS09]).

✎ **Example 2.4.** Given S_R as defined in example 2.2 (p. 25), and S_S as defined in example 2.3 (p. 26). Now, consider as a toy example a keyword query *professor teaches Mary 19*, say $\hat{q}$. Please see the resulting *search space* in figure 10 (p. 28), with elements matching keywords being colored in red.

Finally, a *query graph* g_q for a given query q, is defined as:

☞ Definition 2.9. Query Graph
Given $S_Q = (\tilde{S}_S, N_K)$ as query space and $K = \{k_1, \ldots, k_n\}$ as a set of keywords. Let $f : K \mapsto 2^{V_K \uplus E_K}$ be a function that maps keywords to sets of corresponding

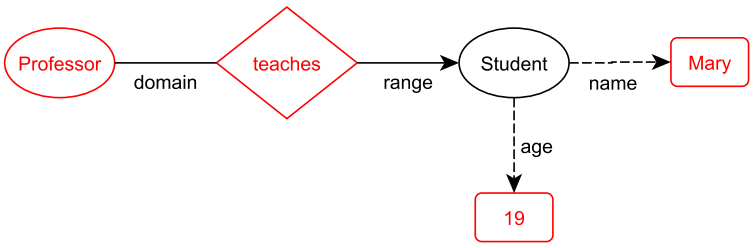


Figure 10: Search Space Example (based on [THS09]).

graph elements (where V_K^Q, $E_K^Q \subseteq N_K$). Then, a *query graph* is a matching subgraph $g_q = (V_q, L_q, E_q)$ with

- $V_q \subseteq V_C^S \uplus V_R^S \uplus N_K \uplus V_V^Q$ with V_V^Q being a set of variables and
- L_q, E_q comprising elements of $\tilde{S}_S$.

Furthermore, the following constraints have to hold:

- $\forall\, k \in K$: $f(k) \cap (V_q \cup E_q) \neq \varnothing$, i.e. g_q contains at least one representative keyword matching element, for each keyword contained in K, and
- g_q is connected, i.e. there exists a path from every graph element to every other element (based on [THS09]).

Note that there might more than one matching *query graph* for a given *query space*. For finding the best, i.e. top-ranked, k graphs g_{q_i}, [THS09] employ a top-k exploration procedure. Again, for details on the exploration algorithm, please see [TWRC09]. Hereafter, I assume to have g_q given and thus will treat the underlying algorithm as a black box.

✎ **Example 2.5.** Given example 2.2 (p. 25) as *resource space*, example 2.3 (p. 26) as *schema space* and example 2.4 (p. 27) as *query space*. After the exploration, a possible *query graph* is shown in figure 11 (p. 28). Please note, variables are marked blue and keyword matchings in red.

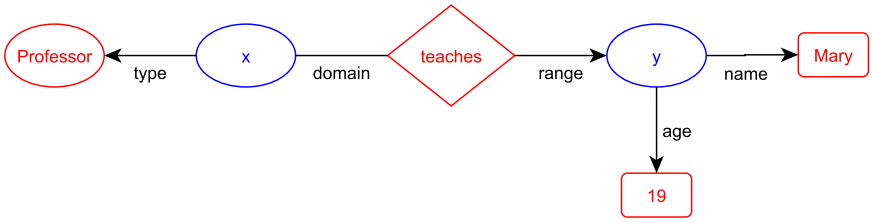


Figure 11: Query Graph Example (based on [THS09]).

2.3.3.2 Result Model

☞ **Definition 2.10. Result Space**

A result space for a query interpretation $g_p = (V_q, L_q, E_q)$ is a set, say S_{Res}, containing j result graphs $g_i^{Res} = (V^{Res}, L^{Res}, E^{Res})$ with $i \leq j$. Each $g_i^{Res} = (V^{Res}, L^{Res}, E^{Res})$ is a subgraph of one of the *resource graphs* g_R (see definition 2.6, p. 24). Furthermore, each g_i^{Res} satisfies g_p. More precisely, g_i^{Res} is said to satisfy g_p iff

- $E^{Res} = E_q$, i.e. every edge contained in g_q must be contained in g^{Res},
- $L^{Res} = L_q$, i.e. labels for these edges have to match,
- $\forall\, \hat{v} \in V_q \setminus V_V^Q : \hat{v} \in V^{Res}$ and
- there exists a surjective function $h : V_E^R \mapsto V_V^Q$, so that there is exactly one mapping $V_E^R \mapsto V_V^Q$, for each $\hat{v} \in V_E^R$.

Note, however, the definition of a *result space* to be depending on a given *query graph*. With respect to the chosen *interpretation*, the *result space* may vary significantly.

✎ **Example 2.6.** Reconsider the earlier examples. For a possible *result space*, given the above introduced *resource space* and *query graph*, please see figure 12 (p. 30). Notice the coloring to be consistent with the one before.

2.3.3.3 Facet & Facet Value Model

Facet and Facet Value Definitions In the following, I will introduce a facet model specifically suited for our Semantic Web context. Remember, I see *facet constraints* as a special case of a *query graph* and therefore will use them as means for specifying an information need.

☞ **Definition 2.11. Facet & Facet Domain**

Given a *resource space* S_R with g_R, a *result space* S_{Res} with g_i^{Res} and a *query graph* g_q, the set containing all facets, say F, may be defined as a *k-tuple* of sets with $F = \{F_i\}_{1 \leq i \leq k}$ and $k = |V_V^Q|$. Note that for each $v_i \in V_V^Q$, there exists a set, say $V_{E_i}^R \subseteq V_E^R$, containing its associated entities. To be more precise, there is an inverse relation $h^{-1} : V_V^Q \mapsto V_E^R$ and $V_{E_i}^R = \{\hat{v} \in V_E^R \,|\, \hat{v} \in h^{-1}(v_i)\}$ (see definition 2.10, p. 29). Now, let F_i be a set defined as $F_i = \{e \in L^R \,|\, e(v_1, *) \in E^R \wedge v_1 \in V_{E_i}^R\}$, i.e. F_i contains all *outgoing* edge labels of an entity $\hat{e} \in V_{E_i}$. Finally, a facet $\hat{f}_i$ is given by one element of F_i, i.e. $\hat{f}_i$ corresponds to one $\hat{e} \in F_i$. Hereafter, $\stackrel{b}{=}$ is used to associate

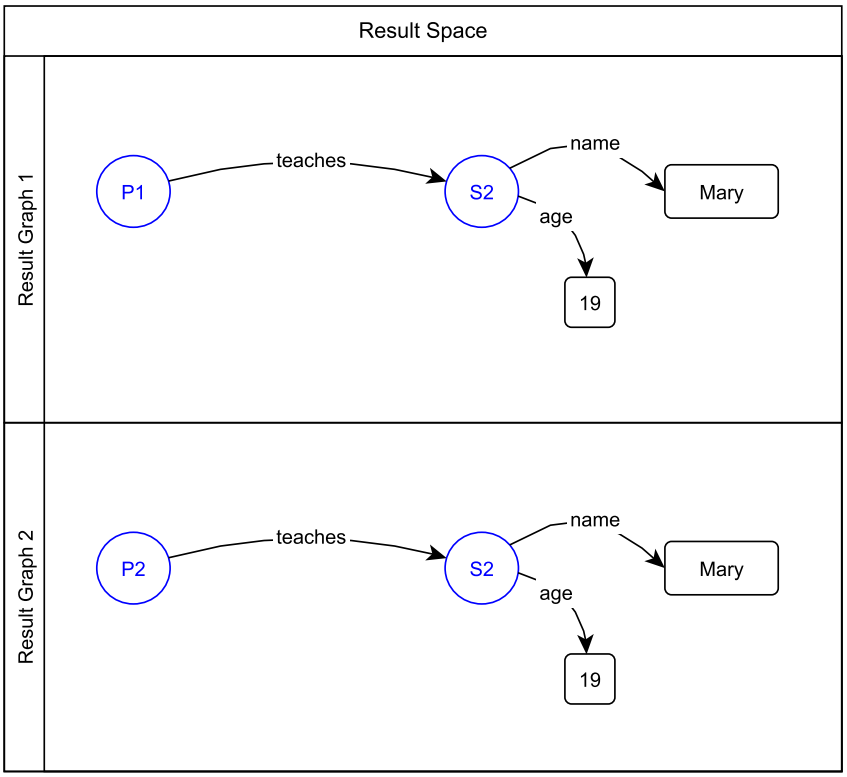


Figure 12: Result Space Example

a facet with its edge label. Informally speaking, one may say that $\hat{f}_i$ is *based on* $\hat{e} \in F_i$. Note, F_i describes all facets for a given set of entities $V_{E_i}^R$, which are mapped to a variable in the query graph v_i. v_i is in the following referred to as *domain* of facets in F_i. Furthermore notice, the set of all facets, given a *resource space* S_R, is denoted by F^R. Lastly, the reader should be aware that $F_j \in \{F_i\}_{1 \leq i \leq k}$ do not necessarily have to be pairwise disjoint, in fact, they might be overlapping.

Note that there are several varying definitions of a facet, given a Semantic Web context (see [ODD06, SVH07, HMS+05]). The above terminology is most similar to [ODD06], where facets are informally defined according to RDF triples. In [ODD06] predicates correspond to facets and their objects are mapped to facet values. However, there are also significant differences between our definition and the one given in [ODD06].

First of all, [ODD06] do not distinguish between *incoming* and *outgoing* predicates[12]. Therefore, both directions may be used as basis for a facet. I, on the other hand, argue, in accordance with RDF terminology (see e.g. [CK00]) as well as our defini-

[12] Note, *predicate* is used here in compliance with RDF terminology.

tions of a *resource space* and a *schema space*, that, given a triple (subject, predicate, object), the object, in combination with the predicate, specifies the subject and not the other way around. Thus, I think that only outgoing properties may provide a meaningful basis for a facet definition. Also, note that our terminology incorporates the different points of origin facets may have. Given a *query graph*, every variable $v \in V_V^Q$ may have its own facets associated. This leads to a far more advanced way of query modifications and thereby enables users to specify their needs more precisely.

☞ **Definition 2.12. Facet Value**

Given a *resource space* S_R with a graph g_R, a *result space* S_{Res} with g_i^{Res}, a *query graph* g_q and facets $F = \{F_i\}_{1 \leq i \leq k}$ with $k = |V_V^Q|$. For a facet $\hat{f} \in F_i \in F$, there is a set of associated resources[13] $O_i(\hat{f}) = \{v_j \in V^R \,|\, \hat{e}(v_i, v_j) \in E^R \wedge v_i \in V_{E_i}^R \wedge \hat{f} \stackrel{b}{=} \hat{e}\}$. Now, facet values may be defined as a set $FV_i(\hat{f})$ with $FV_i(\hat{f})$ being a subset of the power set of $O_i(\hat{f})$, i.e. $FV_i(\hat{f}) \subseteq P(O_i(\hat{f}))$. Finally, given a facet $\hat{f}$, a single facet value is hereafter denoted by $fv_i(\hat{f}) \in FV_i(\hat{f})$. In the following, the set of all facet values is referred to as FV^R. Furthermore, the reader should be aware that $FV_i(\hat{f})$ may be pairwise overlapping, with regard to different facet domains v_i.

Notice, since facet definitions tend to differ within the literature, other facet value definitions are also common (see [ODD06, SVH07, HMS+05]). Again, [ODD06] use the most similar terminology, to the one introduced. Recall, [ODD06] define facets and facet values respectively, according to RDF triples. Therefore, given a facet $\hat{f}$, the set of all facet values, i.e. $FV_*(\hat{f})$, equals the set $O_*(\hat{f})$ as defined above.
I, on the other hand, argue that, in order to truly support *exploration* (see section 1.1.3, p. 7), not only single facet values are necessary, but also partitions of the value space. Thus, our definition comprises not solely $O_*(\cdot)$, but rather $P(O_*(\cdot))$. Clearly, this goes hand in hand with facet value clustering techniques, taking $O_*(\cdot)$ as an input and resulting in a value partitioning. For more details on the actual algorithms, please see section 3 (p. 36). Furthermore, since I defined facets in a domain specific manner (see definition 2.11, p. 29), facet values are automatically also domain specific, allowing users to specify informations needs more accurately. With respect to the query model, facets, more precisely, facet value pairs $\hat{f}{:}fv$, correspond query predicates. Like predicates, $\hat{f}{:}fv$ may be combined via conjunction.

[13] Note that using RDF terminology, these resources would be referred to as objects.

More specifically, given a query graph $g_q = (V_q, L_q, E_q)$, for each variable $v_i \in V_V^Q$ and each $fv \in FV_i(\hat{f})$, a predicate, having a structure $\hat{e}{:}\hat{v}$ with $\hat{f} \overset{b}{=} \hat{e}$ and $\hat{v} \in fv$, may be added to v_i in g_q. This results in new graphs $\{g_q^i\}_i$ with $1 \leq i \leq |fv|$. Note, these $\{g_q^i\}_i$ are independent query graphs, each having an result space associated.[14] Furthermore, in a similar manner, a facet value pair may be removed from a current query graph.

☞ **Definition 2.13. Facet Value Count**

Given a *resource space* S_R with g_R, a *result space* S_{Res} with g_i^{Res}, a *query graph* g_q and facets $F = \{F_i\}_{1 \leq i \leq k}$, where $k = |V_V^Q|$. I distinguish two different *facet value counts*:

(i) Source Count

Given a facet $\tilde{f}$, the so called *source count*, say $count_S$, of a facet value $fv \in FV_*(\cdot)$ is defined as: $count_S(fv) = |C_S(fv) := \{v \in V^{Res} \,|\, \forall\, \hat{v} \in fv : \tilde{e}(v, \hat{v}) \wedge \tilde{f} \overset{b}{=} \tilde{e}\}|$. Note, what I coined *source count* is known in the literature simply as *count* (cf. [Tun09]).

(ii) Value Count

Please reconsider, according to definition 2.12 (p. 31), I essentially define facet values for a facet $\tilde{f}$, as an arbitrary set of objects connected via an edge $\tilde{e} \in E^{Res}$ and $\tilde{f} \overset{b}{=} \tilde{e}$. Therefore, I argue that a second count, reflecting the size of the set, represented by a facet value, is necessary. In conclusion, given a facet value fv, I define $count_V$ as: $count_V(fv) = |C_V(fv) := fv|$.

Note that both sets, i.e. C_S as well as C_V, are defined as mathematical sets, i.e. each element is only allowed one membership. I will refer to counts associated with these sets as *non-overlapping*. However, for ranking purposes (see section 4, p. 70), I extend above defined sets to multisets, say C_S^O and C_V^O respectively, thereby allowing elements to have more than membership. Counts resulting from C_S^O or C_V^O, I refer to as being *overlapping*. This differentiation is of particular importance in our context, since subjects may be mapped to objects[15] in a *one-to-one*, *one-to-many*, *many-to-one* or *many-to-many* manner. Please see figure 13 (p. 33) for a generic example.

[14] Clearly, depending on g_q^i, its result space may be empty.

[15] Note, the terms *subject* and *object* are used according to RDF terminology.

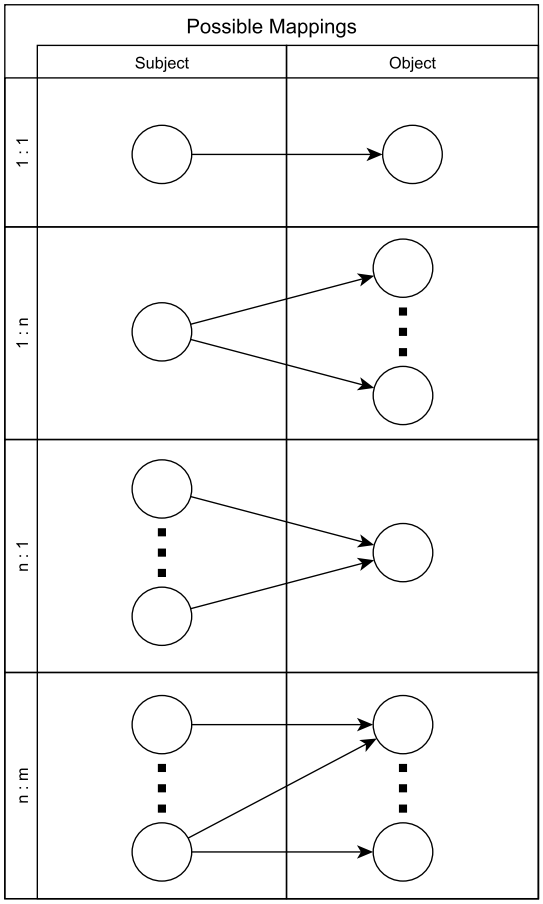


Figure 13: Subject to Object Mapping Example

☞ **Definition 2.14.** Given a set of facets F, where $F = \{F_i\}_{1 \leq i \leq k}$. Facet $f'' \sqsubseteq f'$ (f' is said to *subsume* f'') holds iff $subPropertyOf(e'', e')$ with $e'' \overset{b}{=} f''$ and $e' \overset{b}{=} f'$.

✎ **Example 2.7.** Continuing our example, please see figure 14 (p. 34) for a facet model, given our *result space*. Facets are colored in green, while facet values are gray or black, depending on whether or not they are contained in the *query graph*. Furthermore, there are two facet domains given, say '1' for the professors and '2' for the students; both are marked blue. More precisely, facets are given by $F = \{F_1, F_2\}$ with $F_1 = \{\text{name, teaches, works for}\}$ and $F_2 = \{\text{name, age}\}$. Facet counts are as follows: $count_S(S_2) = 2$, $count_S(Tracy) = 1$, $count_S(Paul) = 1$, $count_S(U_1) = 2$, $count_S(Mary) = 1$, $count_S(19) = 1$ and for all value counts, $count_V(\cdot) = 1$ holds.

Facet Characteristics Facets as described in definition 2.11 (p. 29), may be characterized with respect to different angles. Hereafter, I introduce *flat* and *non-flat*, *predefined* and *non-predefined* as well as *attribute-* and *relation-based* facets. Note, however, these characteristics are overlapping in their nature.

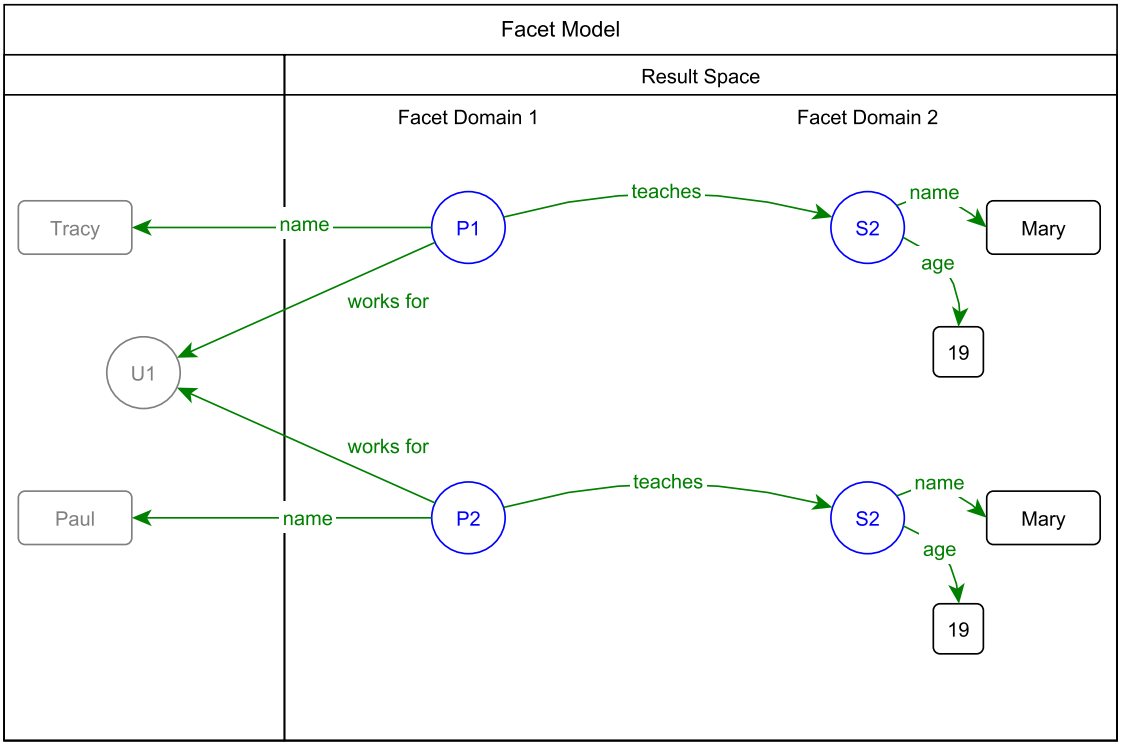


Figure 14: Facet Model Example

(i) Flat & Non-Flat Facets

One may distinguish *flat* or non-hierarchical facets, from facets that are *non-flat* or hierarchical. A facet $\hat{f}$, is said to be *non-flat* iff $\exists\, \tilde{f} : \tilde{f} \sqsubseteq \hat{f}$ or $\hat{f} \sqsubseteq \tilde{f}$ holds. If, on the other hand, no such $\tilde{f}$ exists, then $\hat{f}$ is said to be *flat* or non-hierarchical.

(ii) Predefined & Non-predefined Facets

With respect to the underlying language used to describe the *resource space* S_R, as well as the *schema space* S_S, one may differentiate between *predefined* and *non-predefined* relations and facets respectively. Please recall, I assume RDF(S) as a description language for the data model. Now, given RDF(S), there are several predefined relations, offering an interesting basis for a facet definition. Most notably, there is *rdf:type*, *rdf:label* and *rdfs:seeAlso*. *rdf:type* associates an instance with its class, enabling a categorization of resources contained in S_R. *rdf:label*, on the other hand, provides a human-readable name. Lastly, *rdfs:seeAlso* links a given resource to other resources, allowing further exploration. For a complete list of relevant predefined RDF properties, please see table 1 (p. 102) in the appendix. Note, all other properties, defined during ontology schema definition, are referred to as *non-predefined*.

(iii) Attribute-based & Relation-based Facets

Recall, our label set L^R comprises L^R_A, i.e. edges pointing to a data value, as well as L^R_R, i.e. edges mapping to other resources. Therefore, I distinguish facets according to whether they are based on $e_a \in L^R_A$ or $e_r \in L^R_R$. In the first case, I refer to facets as *attribute-based*, in the latter, as *relation-based*.

Facet Value Characteristics As outlined above, facets may be characterized with regard to different aspects. In the very same way, one may distinguish facet values. Hereafter, I define *flat* and *non-flat* values respectively.

(i) Flat Value

Recall, according to definition 2.12 (p.31), facet values are given by the power set of $O_*(\cdot)$, formally $FV_*(\cdot) \subseteq P(O_*(\cdot))$. Furthermore, depending on whether this facet is *attribute-based* or *relation-based*, $O_*(\cdot)$ is either a subset of V^R_E or V^R_V. Thus, a facet value fv is referred to as *flat* value iff $fv \subseteq V^R_V$.

(ii) Non-Flat Value

On the other hand, a facet value fv is a so called *non-flat* value iff $fv \subseteq V^R_E$, i.e. fv comprises entities[16].

[16] Further note that entities correspond to resources in RDF terminology.

Section 3

Facet Value Construction

3.1 Introduction

Motivation A major goal of faceted search is enabling an exploration of an underlying resource space S_R. In order to do so, users are provided with facets, each having one or more values. However, depending on the facet, it does not make sense to group every value by its own. Please recall our previously introduced assumption 2.3 (p. 21). Following this thought, users can not be excepted to be able to choose very specific values, as they do not possess the necessary knowledge. I therefore argue that $\hat{O}_*$ does not provide a useful basis for a facet value definition. In order to be helpful, a system has to provide *meaningful*[17] subsets of $\hat{O}_*$, i.e. $FV_*(\cdot) \subseteq P(O_*(\cdot))$. I think these subsets enable users to express their fuzzy knowledge and are thus essential, with regard to our scenario. In contrast, given a vast facet value space, state of the art systems simple present only top-ranked values and omit all others.[18] Clustering, on the other hand, enables a system to visualize the entire value space and thereby allows users to gain an overview, leading to a far better exploration and understanding of a resource space. Also, I argue that by applying hierarchical techniques, specification of fuzzy needs is further supported. More precisely, a hierarchical structure enables users to iteratively articulate vague knowledge via drill down operations. Thus, besides traditional clustering goals, namely intra- and inter-cluster similarity, in the following, I will also target browsing support, i.e. what I coined *browse-ability*.

Please recall, facet values may be *flat*, i.e. have no outgoing edges associated, or be *non-flat*, i.e. have own relations or attributes (see section 2.3.3.3, p. 35). Hereafter,

---

[17] Note, with *meaningful*, I refer to sets, sharing a certain pattern proximity.

[18] In most cases, systems apply a count-based ranking heuristic.

I distinguish between approaches for constructing *non-flat* values, on the one hand, and for *flat* facet values, on the other. More specifically, I present approaches to partition $\hat{O}_*$, comprising either literals or resources, resulting in $FV_*(\cdot) \subseteq P(O_*(\cdot))$.

Problem Definition Before discussing related work, present in the literature, let me first introduce the clustering terminology applied hereafter as well as a formal problem definition. Based on [JMF99], I make use of the following concepts:

☞ **Definition 3.1. Pattern**

"A pattern (or feature vector, observation, or datum) x is a single data item used by the clustering algorithm. It typically consists of a vector of d measurements: $x = \{x_1, \ldots, x_d\}$", cf. [JMF99].

☞ **Definition 3.2. Features**

"The individual scalar components x_i of a pattern x are called features (or attributes)", cf. [JMF99].

☞ **Definition 3.3. Class**

"A class, in the abstract, refers to a state of nature that governs the pattern generation process in some cases. More specifically, a class can be viewed as a source of patterns whose distribution in feature space is governed by a probability density specific to the class. Clustering techniques attempt to group patterns so that the classes thereby obtained reflect the different pattern generation processes represented in the pattern set.", cf. [JMF99].

☞ **Definition 3.4. (Hard) Clustering**

"Hard clustering techniques assign a class label l_i to each patterns x_i, identifying its class [...]", cf. [JMF99].

☞ **Definition 3.5. Distance Measure**

"A distance measure (a specialization of a proximity measure) is a metric (or quasi-metric) on the feature space used to quantify the similarity of patterns", cf. [JMF99].

Note, since *class* is already used in our Semantic Web terminology, I will hereafter refer to this concept simply as *cluster*. Lastly, below please consider a formal definition of the problem, I will address throughout this section.

☞ **Problem 3.1.** ***Facet Value Clustering Problem***

Given a facet f for a variable v, its values $FV_v(f)$ and a dissimilarity function

d, this problem consists of finding a partitioning of $FV_v(f)$, so that d, the browsing paradigm as well as the current result set are taken into consideration and associated goals are met.

Components of a Clustering Task In accordance with [JD88], a typical clustering process consists of parts, as briefly outline below:

(i) Pattern Representation

During this first step, the number of clusters and patterns, as well as the type, number and scale of features, which may be used by an algorithm later on, is specified. Optionally, a subset containing only the most effective features may be selected, during the so called *feature selection*. Furthermore, features might be transformed, via the *feature selection*, in order to produce novel and more efficient features (cf. [JD88, JMF99]).

(ii) Pattern Proximity

The proximity of a given pair of patterns is often defined by means of a distance function. E.g. given a vector space, such a distance may be estimated in compliance with the well-known *Euclidean* distance. However, notice, there are several ways introduced in the literature, addressing this problem (cf. [JD88, JMF99]).

(iii) Clustering

Depending on the actual algorithm, a grouping, i.e. a mapping of a pattern to a cluster, may vary significantly. A set patterns might be divided into partitions, i.e. each pattern is associated with exactly one cluster, resulting in a so called *hard* clustering. On the other hand, in case of a *fuzzy* clustering, an algorithm may assign one pattern to several different clusters (cf. [JD88, JMF99]). For further clustering variances, please see [JMF99].

(iv) Data Abstraction†

During the *data abstraction* phase, a dataset is represented in an *easy* and *compact* manner. Note, *easy* in this context is used either with respect to machine or human readability (cf. [JD88, JMF99]).

(v) Assessment of Output†

Assessment of output refers to a cluster validity analysis. It is intended to

determine whether or not a given clustering algorithm produces a meaningful output. However, in many cases a very specific and subjective notion of optimality is used (cf. [JD88, JMF99]).

Note † to mark optional steps. Please see also figure 15 (p. 39), summarizing the above outlined steps.

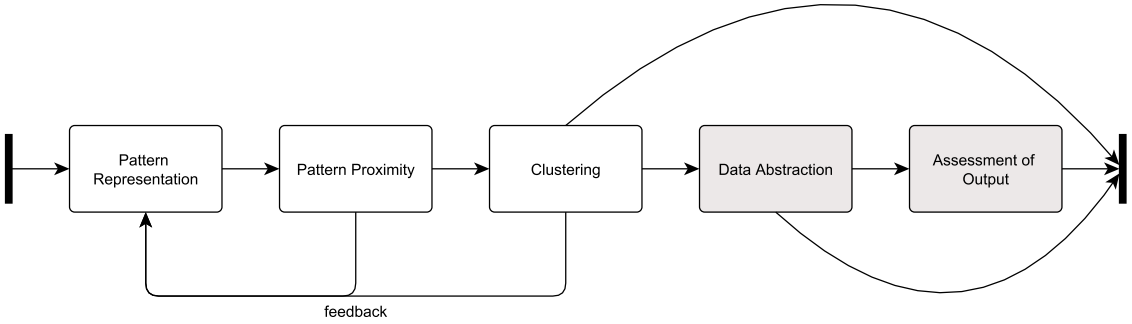


Figure 15: Components of a Clustering Task (based on [JMF99])

Clustering Intentions w.r.t. our Faceted Search Context Data clustering is a quite popular research area, where a lot of work has been done. However, our context is in some sense different, from those of other applications. Thus, before looking at related work, I would like to first describe our goals, I wish to accomplish, explicit.

- Strong intra-cluster similarity†

  Clearly, I wish entities contained in one cluster to have a strong sense of similarity, with respect to some predefined measure (see also [JD88]).

- Strong inter-cluster dissimilarity†

  Also, I want the resulting clusters to have, in compliance with the same measure, a weak similarity in-between each other (see also [JD88]).

- Support of fuzzy knowledge‡

  With regard to user knowledge and an information needs, I intend an algorithm to construct few clusters, in the best case, being approximately of equal size. By doing so, I minimize the amount of information necessary, in order to make a decision, given a set of facet values.

- Support of partial knowledge‡

  Lastly, I also wish an algorithm to address users on an individual basis, thereby supporting their, likely to be partial, knowledge. More precisely, users should be involved in early stages of the process and resulting clusters should reflect user knowledge the best way possible.

Please notice the former two aspects, marked by †, to represent common clustering goals. Both intend for a clustering algorithm to produce, with respect to a given similarity measure, meaningful groupings. However, the latter two, labeled with ‡, directly follow the previous assumption 2.3 (p. 21). Recall, I assume users to only issue information needs contained in Q^F_{Need}, i.e. fuzzy and unspecific needs, via *browsing*.

Furthermore note, the concept of similarity here is used in a very abstract manner. In particular, I do not assume a specific similarity function at this point in time. The notion of similarity may be substantiated, using intuitions by [Lin98], as outlined below:

- "The similarity between A and B is related to their commonality. The more commonality they share, the more similar they are.", cf. [Lin98].

- "The similarity between A and B is related to the differences between them. The more differences they have, the less similar they are.", cf. [Lin98].

- "The maximum similarity between A and B is reached when A and B are identical, no matter how much commonality they share.", cf. [Lin98].

Notice A and B to represent abstract entities to be compared.

3.2 Related Work

3.2.1 Overview

Please recall, I initially defined facet values, i.e. $FV_*(\cdot)$, as a subset of $P(O_*(\cdot))$. Therefore, with respect to clustering strategies, I wish to distinguish between facet values being a set comprising resources or comprising literals. I argue that this differentiation is necessary, since I intend to group similar items together. However, resources and literals differ heavily, with regard to their structure. Recall, while

literals are essentially flat values, typed according to XML schema, resources represent entities, having properties to other entities, or attributes, providing a further characterization.

In the following, let me first present related work for the clustering of resources. Afterwards, I will introduce other works, which may be used for grouping literals. However, as I will show, those techniques suffer from significant shortcomings, given our specific faceted search scenario. Please note, sometimes in the literature pattern proximity is described by means of a similarity function, while other approaches represent proximity via a distance measure. In the former case, similar patterns are assigned higher values, while dissimilar ones are associated with lower numbers. In the latter case, on the other hand, it is simply the other way around.

3.2.2 Clustering Approaches for Resources

Before looking at approaches, providing a distance measurement for RDF instances, I wish to point out an issue addressed by [GEP08]. In their work, they argue that defining a RDF instance in this context is a non-trivial problem. In other words, given a resource space, the question arises, what constitutes a RDF instance, i.e.: *Where does one instance end and another begins?* [GEP08] refer to this problem as *instance extraction*. According to their work, there are several ways on how to define an instance in a clustering context:

(i) Immediate Properties

[GEP08] argue that one solution would be, to only consider immediate properties to be relevant for a given resource, say r. However, they further outline that, while being a straight-forward solution, it is also the most discriminative one. Applying this approach, much important information concerning r could be lost (cf. [GEP08]).

(ii) Concise Bounded Description

A more sophisticated approach, on the other hand, may wish to also consider the graph structure as well as the node types (cf. [GEP08]). Concise Bounded Description (CBD) e.g., uses a recursive algorithm for *instance extraction*. Given an instance, say r, CBD takes r itself, its immediate properties and recursively all properties, if the associated object is a blank node (cf. [Sti05]). Another variant of this approach, would be, to also consider incoming edges

to be relevant for r (cf. [GEP08]). However, again, [GEP08] also outline shortcomings associated with this approach. More precisely, they argue that CBD, since it is strongly depending on blank nodes, is not truly independent from an underlying domain (cf. [GEP08]).

(iii) Depth-Limited Crawling

In compliance with [GEP08], another approach would be, to limit the subgraph associated with a resource in question, by restricting the edge distance to a given threshold value. In contrast to CBD, so [GEP08] argue, this approach has the advantage, to be completely domain independent, since it does not rely on specific node types (cf. [GEP08]).

To my knowledge, approaches for clustering RDF instance data may be categorized with respect to three different angles. On a side note, the reader should notice that there is currently much attention in the Semantic Web community, especially in the area of *ontology alignment*, on measuring entity similarity at schema level. However, hereafter, let me briefly introduce grouped approaches, targeting instance data.

(i) Vector Space Based Similarity

On the one hand, instances, represented as a RDF graph, could be projected into a vector space model. Therefore, all distance measures applicable in this traditional representation, may also be employed here. Obviously, the questions arises, how to transform resources into a high-dimensional projection. One solution for this problem is proposed in [GEP08]. Here, the authors argue that a simply mapping of RDF properties, to dimensions in a vector space is not sufficient. Thus, they present a rather different method. First, given a root node X and a graph G, [GEP08] introduce a notion of reachability as: $reachable(X, G) = \{n \,|\, (x, p, n) \in G\} \cup \{n' \,|\, n' \in R_G(n)\}$. Furthermore, with $shortestPath(R, X, G)$ denoting the shortest path from a given node R to a node X in G, they define a feature vector for an instance, say n, as:

$$FV(n) = \{shortestPath(R_n, x, G_n) \,|\, x \in reachable(R_n, G)\} \tag{3.1}$$

Now, they introduce the feature vector for a set of instances as union over all individual vector sets.

(ii) General Graph Based Similarity

Another perspective would be, to see RDF instance data simply as a graph, without having additional semantic information. Given this assumption, many existing distances measures, intended for node comparison in graphs, would be applicable. Consider e.g. work done in [MGL00], where the authors compare so called conceptual graphs. Note conceptual graphs to be quite similar to RDF data, thus providing a good example for potentially suitable metrics. Conceptual graphs comprise nodes standing for attributes, events or entities as well as nodes being relations, associating two given nodes (cf. [Sow84, Sow00]). In accordance with [Sow84, Sow00], a distance measure between two graphs, say G_1 and G_2, may be defined, with respect to a so called overlap graph $G_C = G_1 \cap G_2$. To be more precise, G_C contains overlapping concept nodes as well as overlapping relation nodes. In a second step, so [Sow84, Sow00] continue, a similarity value may be derived from G_C, by computing a combination of two different measures, namely the *conceptual similarity* and the *relational similarity*. While the former estimates the degree of similarity between concepts and actions in both graphs, the latter value measures the similarity of concept interrelations, i.e. information about concepts (cf. [Sow84, Sow00]). Please note these metrics to have been adopted to RDF data, see [GEP04, GEP08]. Further note, there is much interesting work present in the literature, for a survey on graph clustering see [Sch07].

(iii) Ontology Based Similarity

There has been a lot of work done on similarity measures in the context of *ontology alignment*. Generally, these metrics rely strongly on rich semantic schema data and, while obviously also working on graph structures, may therefore be distinguished from the above mentioned graph clustering algorithms. Summarizing these works goes clearly beyond the limits of this paper. For surveys providing such an overview, please see e.g. [SE05, CSH06, KS03]. In order to make it clearer to the reader, what kind of algorithms I subsume under this category, allow me to briefly outline one approach by [MZ02], focusing solely on instance data.

According to [MZ02], a similarity measure for resources may be defined with regard to three aspects, namely:

(a) Taxonomy Similarity (TS)

The taxonomy similarity value refers to the closeness of two instances, with respect to their associated concepts and their positioning in the taxonomy. More specifically, two concepts are compared by the number of common *super-classes*. The bigger this overlap is, the more similar two concepts, thus also their instances, are assumed to be (cf. [MZ02]).

(b) Relational Similarity (RS)

On the other hand, resources may be associated with further entities and literals via incoming and outgoing edges respectively. Using a second measure, [MZ02] compare two given resources, say r_1 and r_2, with regard to their associated entities. The authors assume r_1 and r_2 to be similar, if they share relations to the same or similar resources. Note, this similarity notion is recursively defined, thus, for avoiding cycles, a maximum depth threshold is applied (cf. [MZ02]).

(c) Attribute Similarity (AS)

Lastly, following the above outlined thought, [MZ02] define an attribute similarity, as the similarity of literals connected to the resources in question. Obviously, since essentially being data values, such an estimation may easily be computed, using traditional similarity measures, depending on the literal type (cf. [MZ02]).

Finally, using the introduced similarity notions as well as given weights, say t, r and s respectively, [MZ02] define the similarity of r_1 and r_2 as:

$$sim(r_1, r_2) = \frac{t \cdot TS(r_1, r_2) + r \cdot RS(r_1, r_2) + a \cdot AS(r_1, r_2)}{t + r + a} \tag{3.2}$$

Applying our instance definition as well as the described similarity measures, a specific clustering algorithm may be employed. Note, in recent years, there has been great interest in clustering, thus, a rich selection of techniques is available. One commonly used approach, however, I will introduce as an example, is *hierarchical clustering*. Given a set of n patterns, an agglomerative variant of a hierarchical strategy, may be briefly described as (cf. [JMF99]):

- Compute Proximity Matrix

In a first step, each pattern is regarded as its own cluster. For these clusters, a

so called proximity (n×n) - matrix, containing similarity values between every cluster combination possible, is initially computed.

- Merge Clusters
  During a second step, the two most similar clusters, with respect to a given similarity function, are chosen and merged.

- Update Proximity Matrix
  Now, for the reduced set of clusters, the proximity matrix is updated. Step two and three are repeated, until only one single cluster remains.

Note, hierarchical clustering techniques are often based on single-link (see [SS73]) or complete-link (see [Kin67]) intuitions. However, a comparison of techniques currently present, is not within scope of this paper. For further details, please see [JMF99, XW05].

3.2.3 Clustering Approaches for Literals

After the above provided overview of existing approaches for comparing resources, in the following, I give the reader a survey of clustering techniques and similarity measures concerning literals. Due to the fact that clustering is a topic of interest for a vast community, there have been many approaches presented in the literature for handling literals, i.e. data values (cf. [JMF99, XW05]).
Please recall, given a RDF data-source, one may have to deal with different types of literals, subsumed under different feature categories. In compliance with [GD92], features may be distinguished as follows:

(i) Quantitative features

- *Continuous* values, e.g. weight.
- *Discrete* values, e.g. number of inhabitants.
- *Interval* values, e.g. duration time.

(ii) Qualitative features

- *Nominal* (unordered), e.g. name.
- *Ordinal* (ordered), e.g. grade.
- *Combinational*, e.g. student to grade relation (name, grade).

Now, depending on the associated feature category of data values in question, there might be different similarity measures suitable (cf. [JMF99, XW05]). In the following, I will present exemplary measures for quantitative as well as qualitative features:

(i) Quantitative features

Since continuous features are quite common in real-world data, allow me to use these values as representatives for quantitative features in general. However, even with this restriction, there are still a number of popular measures applicable. Below please find two well-known distance metrics, namely the *Minkowski* as well as the *Mahalanobis* metric.

- Minkowski Metric

The Minkowski metric may be defined for two given pattern, say x_i and x_j, as:

$$d_p(x_i, x_j) = \left(\sum_{k=1}^{d} |x_{i,k} - x_{j,k}|^p\right)^{1/p} = \|x_i - x_j\|_p \tag{3.3}$$

Note the well-known *Euclidean* distance metric for $p = 2$, to be variant of equation 3.3 (p. 46) (cf. [JMF99]). For an application of this norm, see e.g. [HBH00].

- Mahalanobis Metric

Furthermore, two continuous features may be correlated, thereby influencing the similarity measure between a given set of patterns. This problem is addressed by the Mahalanobis metric. With x_i and x_j being patterns, a similarity estimation is calculated as:

$$d_M(x_i, x_j) = (x_i - x_j) \cdot \sum^{-1} x_i - x_j{}^T \tag{3.4}$$

where $\sum$ refers to the sample covariance matrix. Note $d_M(\cdot, \cdot)$ to use weights, based on variances and pairwise linear correlations of the associated features (cf. [JMF99]). For an exemplary implementation, consider e.g. [MJ96].

(ii) Qualitative features

With respect to qualitative features, there is again a rich selection of mea-

sures available in the literature. Thus, I will use strings as a common value representing this category. Note strings to be considered as a nominal feature.

- Edit-distance-based measures

  A well-known approach for computing the distance between two given strings, is the so called *edit* distance. Approaches using this technique, a dissimilarity score is based on edit operations necessary, in oder to transform one of the given strings, say t_1, into the other, say t_2. A simple algorithm employing this strategy is the *Levenshtein* distance. It is defined as the minimal amount of *insertion*, *deletion* or *substitution* operations, needed to rewrite t_1 as t_2 (cf. [Lev65]). Other common approaches include the *Hamming* distance (see [SK83]) or the *Episode* distance (see [DFG+97]).

- Token-based measures

  Besides using edit operations as a basis for a similarity measure, one could also argue that strings may be regarded as two multisets of letters, so called tokens. Probably the most simple representative in this context is the *Jaccard* similarity, first defined in [Jac12], as:

$$d_J(x_i, x_j) = 1 - \frac{|x_i \cap x_j|}{|x_i \cup x_j|} \tag{3.5}$$

  Note, another well-known approach falling under this category is e.g. the *cosine* similarity (cf. [CRF03]).

Furthermore note the presented similarity intuitions to be only a very short summary, which is clearly not intended to be complete. For a more detailed overview, please consider surveys present in the literature, see e.g. [JMF99, XW05]. For further string metrics, on the other hand, consider [CRF03, Nav01].
With respect to the actual clustering algorithm, the above mentioned techniques may also be applied, given data values. Again, a detailed discussion is not within the scope of this paper, please see [JMF99, XW05] for further information.

3.2.4 Contribution

As mentioned earlier, facet values may either be based on literals or based on resources. Thus, with regard to a faceted search application, one is in need of two al-

gorithms, the former for clustering literals, while the latter is applicable for resource-based values.

Concerning the first problem, i.e. literal clustering, I will present traditional similarity measures, depending on the type of a particular range. More precisely, as a clustering technique, I apply a well-known hierarchical, divisive clustering approach. Thereby, I enable users to drill down into a set of values, depending on their individual knowledge. In other words, I allow users to issue fuzzy knowledge and thus fulfill the earlier stated intuitions.

However, I see the main contribution in my solution for the latter task, namely the clustering of resources. While the above introduced works mainly target intra- and inter-cluster similarity, I think that, with regard to our use case, further goals need to be taken into consideration. Please recall the above presented additional intuitions to be (i) *support of partial knowledge* as well as (ii) *support of fuzzy knowledge*. Remember those to follow directly from our previous assumptions, concerning the search process and the user knowledge (see assumption 2.3, p. 21). Given these extra goals and their background, it becomes obvious that the feature selection step is a key aspect within this context. With respect to the algorithm itself, I argue that resources may be regarded as abstract entities, being described by their outgoing properties, i.e. by their relations and attributes. In other words, resources to be clustered, may simply be seen as a set of entities, which is characterized by its facets. I therefore conclude that facets should be treated as features. Each property and facet respectively, describes its associated instance, thus providing a suitable basis for clustering. Second, I argue that due to the partial knowledge, the feature selection phase is crucial and has to be controlled solely by an individual user. More specifically, users should be enabled to choose a facet, which they have knowledge about, resulting in a system grouping associated resources entirely with respect to this feature. Notice, however, if the selected facet is a based on a relation, its range will contain resources, which in turn will be described and clustered in accordance with their facets. By applying such a strategy, as the evaluation will show, highly complex queries may be constructed via simple faceted search interactions. In other words, I argue that clustering, given a faceted search system, should essentially boil down to a feature selection, i.e. a facet ranking problem. Let me emphasize that this way, complex user information needs may be addressed, while no additional paradigms are necessary.

3.3 Literal Clustering

3.3.1 Overview

In a first step, I will define dissimilarity metrics and a clustering technique with regard to literals. Recall, by doing so, I establish the necessary partitioning of $\hat{O}_*$, in order to construct $FV_*(\cdot) \subseteq P(O_*(\cdot))$.

As mentioned earlier, a clustering approach and, in particular, a similarity measure to be applied, for a given set of literals, depends on their assigned type. Also, please recall that I assume a data-source to be represented by RDF(S). However, given this framework, there are no built-in datatypes (cf. [MM04]). More specifically, datatypes are identified by a Uniform Resource Identifier (URI), linking to an externally described concept.[19] These type concepts are then defined using the Extensible Markup Language (XML) Schema framework (cf. [MM04]).

In compliance with [MM04], a datatype may be defined as:

☞ Definition 3.6. XML-S Datatype

"In this specification, a datatype is a 3-tuple, consisting of a) a set of distinct values, called its *value space*, b) a set of lexical representations, called its *lexical space*, and c) a set of facets that characterize properties of the value space, individual values or lexical items", cf. [BM04].

With respect to our context, the former two are of particular interest. [BM04] define these concepts as outlined below:

(i) Value Space

"A value space is the set of values for a given datatype. Each value in the value space of a datatype is denoted by one or more literals in its lexical space", cf. [BM04].

(ii) Lexical Space

The so called lexical space comprises a set of strings, being used to represent values contained in a value space. More precisely, only elements of a given lexical space, may be used as representatives for their corresponding elements in the value space (cf. [BM04]).

[19] Note, *rdf:XMLLiteral* to be an exception of this rule. RDF(S) makes use of this built-in datatype in order to express XML content as a literal value (cf. [MM04]).

(iii) Lexical-to-value Mapping

Clearly, after defining a lexical as well as a value space, a relation between these two sets is necessary. To be more precise, such a mapping specifies, which element in the values space, a given string contained in the lexical space, is associated with (cf. [BM04]).

For further information concerning the RDF datatype concept or related issues, please see [MM04]. However, with this background knowledge, let us take a closer look at the actual datatypes being defined using XML Schema. According to [BM04], one may distinguish *predefined*, so called primitive, from *non-predefined*, i.e. derived, datatypes.

☞ **Definition 3.7. Primitive Datatypes**

Datatypes, which are not defined on basis of other existing types, may be referred to as being *primitive* (cf. [BM04]).

☞ **Definition 3.8. Derived Datatypes**

On the other hand, if a datatype is defined by means of other types, it is coined *derived* (cf. [BM04]).

Clearly, covering all possible datatypes by a similarity measures is not possible. Thus, I will focus solely on common primitive types. However, please note this definitions to be based on well-known metrics and easily expandable to cover additional types, if necessary. More precisely, hereafter, I introduce measures for *decimal*, *float* and *double*, *string*, *time* as well as *date*. For a complete hierarchy of primitive datatypes present in XML Schema, please see figure 23 (p.103). By means of these metrics, I then apply a traditional, however slightly adapted, divisive hierarchical clustering technique.

3.3.2 Definition of a suitable Similarity Measure

In a similar manner, as in the previous section, I first will define type-specific similarity measures. Then, during a second step, I will introduce a clustering technique, making use of these metrics.

3.3.2.1 Similarity Notion for a single Value

Please remember that facet values are defined as $FV_*(\cdot) \subseteq P(O_*(\cdot))$ (see definition 2.12, p. 31). In other words, values I intend to compare are generally sets, each containing one or more literals. Thus, first of all, let me define a similarity notion with respect to literals, i.e. single values. Afterwards, I will extend this notion to also cover sets of literals, i.e. values contained in $FV_*(\cdot)$.

XML-Schema Type String In accordance with [BM04], a string in this context may be seen as:

☞ Definition 3.9. String

"The string datatype represents character strings in XML. The value space of string is the set of finite-length sequences of characters [...]. A character is an atomic unit of communication; it is not further specified except to note that every character has a corresponding Universal Character Set code point, which is an integer.", cf. [BM04].

Please note that literals being typed as strings are flat, i.e. they only have one feature associated. Recall, one objective for clustering to be the *support of fuzzy knowledge*. In order for users, however, to issue their unspecific knowledge and information needs respectively, clusters need to be as intuitive and as self-explanatory as possible. On the other hand, a very well-known way of sorting strings, is given by their lexical order. With respect to our string distance, I therefore argue that an edit-based approach may suffice, however, editing costs should be based on the lexicographic distance between the associated letters. Using such an approach, given two literals, say s_1 and s_2, a similarity value would be correlated with their lexical positioning in a given alphabet, say Σ. Following this thought, a distance between s_1 and s_2 may be written as:

$$
\begin{aligned}
dis^a(s_1, s_2) = \sum_{i=1}^{h} & \begin{cases} 0 & \text{if } s_1(i) = s_2(i) \\ \sigma^{-i}(\rho(s_2(i)) + \rho(s_1(i))) & \text{otherwise} \end{cases} \\
+ & \begin{cases} \sum_{j=|s_1|}^{|s_2|} \sigma^{-j} \rho(s_2(j)) & \text{if } |s_1| \leq |s_2| \\ \sum_{k=|s_2|}^{|s_1|} \sigma^{-k} \rho(s_1(k)) & \text{otherwise} \end{cases}
\end{aligned}
\tag{3.6}
$$

with $h = \min\{|s_1|, |s_2|\}$, $\sigma = |\Sigma|$ standing for the size of the alphabet used, $s_*(j)$ referring to the j$^{\text{th}}$ character in string s_* and ρ being a relation, mapping characters to their lexical position in Σ.

Note that by employing this metric in combination with an hierarchical strategy, the cluster representation problem may easily be addressed. More precisely, one might simply use an interval-like naming scheme, i.e. visualize a given cluster by its left and right border value.

XML-Schema Basic numerical Types As mentioned earlier, most common numerical types to accrue in real-world data, I think to be *decimal*, *float* or *double*. Notice that these types are also the most basic ones, according to the hierarchy defined in [BM04] (see figure 23, p. 103). Further note the below defined measure to be intended to be generic. Thus, if provided with more specific types, e.g. a *positiveInteger*, measures may easily be adapted. However, before discussing our similarity notion any further, allow me to first outline how *decimal*, *float* and *double*, may be defined in compliance with [BM04]:

☞ **Definition 3.10. Decimal**

"Decimal represents a subset of the real numbers, which can be represented by decimal numerals. The value space of decimal is the set of numbers that can be obtained by multiplying an integer by a non-positive power of ten, i.e., expressible as $i \times 10^{-n}$ where i and n are integers and $n \geq 0$. [...] The order-relation on decimal is the order relation on real numbers, restricted to this subset.", cf. [BM04].

☞ **Definition 3.11. Float**

"Float is patterned after the IEEE single-precision 32-bit floating point type [...]. The basic value space of float consists of the values $m \times 2^e$, where m is an integer whose absolute value is less than 2^{24}, and e is an integer between −149 and 104, inclusive. [...] The order-relation on float is: $x \leq y$ iff $y - x$ is positive for x and y in the value space. [...]", cf. [BM04].

☞ **Definition 3.12. Double**

"The double datatype is patterned after the IEEE double-precision 64-bit floating point type [...]. The basic value space of double consists of the values $m \times 2^e$, where m is an integer whose absolute value is less than 2^{53}, and e is an integer between

−1075 and 970, inclusive. [...] The order-relation on double is: $x \leq y$ iff $y - x$ is positive for x and y in the value space.[...]", cf. [BM04].

Note, with respect to those definitions, numerical-based literals only comprise one continuous feature. Now, having a closer look at this problem, one might notice that a solution is actually quite simple. Since being well-known and accepted, I decided to use a traditional approach for these patterns, namely the *Euclidean* distance. Thus, given two literals, say n_1 and n_2, a distance measure is given by:

$$dis^a(n_1, n_2) = \left(\sum_{k=1}^{1} (n_1(k) - n_2(k))^2\right)^{1/2} \tag{3.7a}$$

$$= |n_1(1) - n_2(1)| \tag{3.7b}$$

where $n_*(j)$ refers to the j$^{\text{th}}$ feature of pattern n_*.

XML-Schema Type Time In compliance with [BM04], datatype time is given by:

☞ **Definition 3.13. Time**

"Time represents an instant of time that recurs every day. The value space of time is the space of time of day values as defined in 5.3 of [ISO 8601]. Specifically, it is a set of zero-duration daily time instances.", cf. [BM04].

However, targeting at real-world data, which is generally noisy and incomplete, I assume time-type literals to be three-dimensional. In other words, I make use of common dimensions only, i.e. *hour*, *minute*, and *second*. Again, I apply a standard distance measure, more precisely, the *Euclidean* distance. Thus, given two literals, say t_1 and t_2, I may define our notion of dissimilarity as:

$$dis^a(t_1, t_2) = \left(\sum_{k=1}^{3} (t_1(k) - t_2(k))^2\right)^{1/2} \tag{3.8}$$

with $t_*(j)$ being the j$^{\text{th}}$ feature of t_*.

XML-Schema Type Date [BM04] define the date XML Schema type as follows:

☞ **Definition 3.14. Date**

"Date represents a calendar date. The value space if date is the set of Gregorian calendar dates as defined in 5.2.1 of [ISO 8601]. Specifically, it is a set of one-day

long, non-periodic instances [...], independent of how many hours this day has.", cf. [BM04].

Note, just like the above introduced time type, date comprises several dimensions or features. However, I again argue that in most applications noisy and incomplete data is being used. Therefore, I only expect the most common features, i.e. *year*, *month* and *day*, to be present. Given two dates, say d_1 and d_2, this leads to a similar problem as before, so I may apply the *Euclidean* distance notion, resulting in:

$$dis^a(d_1, d_2) = (\sum_{k=1}^{3} (d_1(k) - d_2(k))^2)^{1/2} \tag{3.9}$$

where $d_*(j)$ stands for the j$^{\text{th}}$ feature of d_*.

3.3.2.2 Similarity Notion for Value Sets

In the above section, I outlined how similarity may be defined for single literals. However, when considering sets, containing more than one literal, one may need to extend this notion. For clarification purposes, please consider example 3.1 (p. 54).

✎ **Example 3.1.** Please find figure 16 (p. 54) presenting nine clusters. Consider e.g. S, being one big cluster, containing three singleton sets, namely $\{S_i\}_{i \in \{1,2,3\}}$. Furthermore, a second large cluster, say T, is given, comprising again singleton sets, i.e. $\{T_j\}_{j \in \{1,\dots,4\}}$. Note that a similarity, or to be more accurate, a dissimilarity value, between any of the singleton sets in S or in T may be computed as discussed earlier. However, the question arises, how a similarity between the big clusters, i.e. S and T, might be defined.

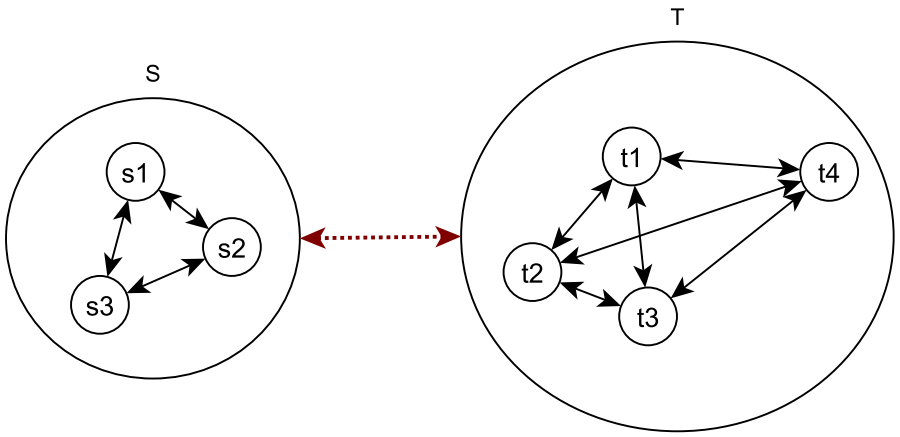


Figure 16: Generic Example for a Similarity Notion w.r.t. Sets

Clearly, this problem is well-known in the literature and various solutions would be applicable. However, hereafter, allow me to briefly describe two traditional approaches, which could be easily integrated.

(i) Single-Link

According to [SS73], a distance between two given clusters, say c_1 and c_2, may be described as *minimum* distance value of all distances, between a pattern contained c_1, while the other element being in c_2.

(ii) Complete-Link

On the contrary, [Kin67] argue that the dissimilarity of c_1 and c_2, may be represented as *maximum* value of all dissimilarities, between a pattern contained c_1 and one in c_2.

Clearly, other known solutions may also be employed here (see e.g. [JMF99, XW05]). However, as I will show in the next section, with respect to the clustering technique applied, a *single-link* strategy makes the most sense.

3.3.3 Hierarchical Clustering

Quasi-Order First of all, allow me to shortly introduce a *quasi-order*, defined on a set of literals, say L with $L \subseteq O_*(\cdot)$. By a quasi-order, I mean a relation, say $\preceq$, on a set, say M, satisfying constraints as shown in equation 3.10a and 3.10b below:

$$a \preceq a \quad \textit{reflexivity} \tag{3.10a}$$

$$a \preceq b \wedge b \preceq c \implies a \preceq c \quad \textit{transitivity} \tag{3.10b}$$

This relation, in our context denoted by $\overset{L}{\preceq}$, may be defined on L, depending on the specific literal datatype. Note, I again consider only types, I assume to be common, namely the basic *numerical types*, *string*, *time* as well as *date*. Further note, however, definitions given below, may easily be adapted to cover additional types.

(i) XML-Schema Type String

Let L be a set of k strings, say $L = \{s_i\}_{1 \leq i \leq k}$ as well as a given underlying alphabet, say Σ, with Σ having a quasi order defined, with regard to a relation $\preceq$. Then a string, say s_i with $|s_i| = m$, may be seen as one element of Σ^m =

$\underbrace{\Sigma \times \ldots \times \Sigma}_{\text{m}}$. In conclusion, for two given strings, say s_1 and s_2 with length m, our relation $\overset{L}{\leq}$ may be defined as:

$$\begin{gathered}(s_{11}, \ldots, s_{1m}) \overset{L}{\prec} (s_{21}, \ldots, s_{2m}) \\ \Updownarrow \\ \exists\, j : s_{1j} \prec s_{2j} \wedge \forall\, h \leq j : s_{1h} \sim s_{2h}\end{gathered} \tag{3.11}$$

Note this definition to be easily expandable, in order to compare strings of arbitrary lengths. To be more precise, one may add a new symbol to Σ, referring to the empty string, say ε. Further, ε might be defined as first symbol in Σ, with respect to $\preceq$. Now, given strings, say s_1 and s_2 with $|s_1| = n$ and $|s_1| = m$ and $n \leq m$, for applying equation 3.11 (p. 56), s_1 is rewritten as $\tilde{s}_1$, with $\tilde{s}_1 = s_1 \oplus \underbrace{\varepsilon \oplus \ldots \oplus \varepsilon}_{\text{m - n}}$, $|\tilde{s}_1| = m$ and $\oplus$ being a concatenation operation defined on Σ.

Notice that I defined $\overset{L}{\leq}$ based on a lexicographic order for an alphabet Σ. Obviously, given Σ being quasi ordered, $L = \{s_i\}_{1 \leq i \leq k}$, with respect to relation $\overset{L}{\leq}$, satisfies above stated constrains.

(ii) XML-Schema Basic numerical Types

In this context, please reconsider the defined order relations for basic numerical datatypes (cf. [BM04]) as stated above, i.e.:

- Decimal

  "[...] The order-relation on decimal is the order relation on real numbers, restricted to this subset.", cf. [BM04].

- Float

  "[...] The order-relation on float is: $x \leq y$ iff $y - x$ is positive for x and y in the value space.[...]", cf. [BM04].

- Double

  "[...] The order-relation on double is: $x \leq y$ iff $y - x$ is positive for x and y in the value space.[...]", cf. [BM04].

Note, since real numbers are totally ordered, i.e. satisfy our quasi-order criteria, defining a relation $\overset{L}{\leq}$ for decimal-typed literals is trivial. On the other

hand, given the order defined for float or double types, it is obvious, they also fulfill equations 3.10a and 3.10b (p. 55). In conclusion, one may introduce a relation $\overset{L}{\leq}$ for $L = \{n_i\}_{1 \leq i \leq k}$, with n_i being a numerical-based literal, via the underlying relations for decimal, float and double respectively.

(iii) XML-Schema Type Time

Concerning the latter two types, i.e. *time* and *date*, notice the problem of defining a relation $\overset{L}{\leq}$, to be slightly different. In both cases, data provided has multiple features. Considering time as a given type, I again assume to have three features given, namely *hour*, *minute* and *second*. Each feature has its value space as a subset of $\mathbb{N}$. Obviously, there is an order relation present, due to the implied semantics in *time*. One may formalize this relation, say $\preceq$, for two given time values, say t_1 and t_2, as:

$$t_1 \prec t_2 \iff \begin{cases} (t_1(1) < t_2(1)) \vee \\ (t_1(1) = t_2(1) \wedge t_1(2) < t_2(2)) \vee \\ (t_1(1) = t_2(1) \wedge t_1(2) = t_2(2) \wedge t_1(3) < t_2(3)) \end{cases} \tag{3.12}$$

where $t_*(j)$ denotes the j^{th} feature value of pattern t_*, while the first feature refers to the *hour* dimension, the second one to *minute* and the last to *second*. Thus, an order-relation $\overset{L}{\leq}$ for a set of time literals, say $L = \{t_i\}_{1 \leq i \leq k}$, can be defined, based on the relation $\preceq$ given above. Clearly, $\overset{L}{\leq}$ fulfills our quasi-order conditions.

(iv) XML-Schema Type Date

In a very similar manner, one may introduce a relation $\overset{L}{\leq}$, given set of date-based literals, say $L = \{d_i\}_{1 \leq i \leq k}$. Again, I define $\overset{L}{\leq}$ via its underlying semantics.

Some of the definitions and relations discussed above may seem trivial or even unnecessary to the reader. I, on the other hand, argue that there might be types, especially when considering complex XML Schema types, where such a relation $\overset{L}{\leq}$ is non-trivial. Thus, one should be careful, when assuming literals to have an order implied.

Interdependencies of Quasi-Order & Dissimilarity Measures The reader should be aware that, in order for the presented approach to make sense, there have to be interdependencies between an *order* relation and the *similarity measures* introduced earlier. More precisely, due to the sorting process being applied before the distance measurement, similarities between certain pairs of values are not taken into consideration. Given n values, say $\{v_1, \ldots, v_n\}$, instead of calculating n^2 distances, one only computes $n-1$ values, namely those in-between neighboring literals. Obviously, given a single-link strategy, this only results in meaningful clusterings, if the equation below holds:

$$v_i \overset{L}{\preceq} v_j \overset{L}{\preceq} v_k \iff dis(v_i, v_j) \leq dis(v_i, v_k) \tag{3.13}$$

However, with regard to our type-specific order relations as well as the type-specific dissimilarity measure, equation 3.13 (p. 58) clearly is satisfied. Unfortunately, a detailed discussion is not within the scope of this paper.

Divisive Clustering Technique As very briefly mentioned before, the applied clustering technique is based on a traditional divisive hierarchical approach. Reconsidering the additional clustering intuitions, i.e. the *support of partial knowledge* as well as *fuzzy knowledge*, I adjusted it slightly, in order to better suit the resulting needs.

Now, let us discuss the algorithm applied in more detail. Hereafter, I will first address important phases separately, followed by a pseudocode describing their interaction as well as examples, further clarifying the procedure.

- Literal Sorting

  Given a set of literals, say L with $L = \{l_i\}_{1 \leq i \leq k}$, I start by sorting L with regard to $\overset{L}{\preceq}$. Remember, depending on the literal type, our relation $\overset{L}{\preceq}$ may be reduced to an underlying order, say $\preceq$. This results in a tuple, say $\tilde{L}$ with $\forall\, i : l_i \overset{L}{\preceq} l_{i+1}$. Given such a sorting, literals may be regarded as projected into an one-dimensional space. Constructing intuitive clusters being the goal, I argue that in this space, users tend to associate the distance between two sets, as the distance between their borders. Therefore, while other approaches are still applicable, I thought a single-link strategy to be most suitable.

- Dissimilarity Computation

  In a next step, I compute dissimilarities, say d_*, in-between all neighboring literals in $\tilde{L}$. The resulting $\{d_i\}_{1 \leq i \leq k-1}$ are stored in a queue, say Q, and sorted with respect to their value.

- Split Clusters

  The algorithm starts with all literals being contained in one big cluster. The current maximum dissimilarity, say $d_{max}(l_i, l_j)$, is removed from Q and a cluster, say $\hat{c}$, containing l_i and l_j, is split. Note, by splitting $\hat{c}$, I mean that $\hat{c}$ is dissolved and instead two new clusters, say $\hat{c}_1$ and $\hat{c}_2$, are being added. $\hat{c}_1$ is formed in such a manner that it contains every literal l_h with: $l_h \in \hat{c} \wedge l_h \overset{L}{\leq} l_i$. Analogously, $\hat{c}_2$ may be constructed.

  This step is to be repeated, until a halt criterion is met. To be more specific, the stop criterion is satisfied, if every cluster contains only one single element or if users have no further knowledge, i.e. perform no further drill down operations. Note that I employ a fixed branching threshold, say $\hat{k}$, thus, if a hierarchical level is being constructed, always $\hat{k}$ clusters are split.[20]

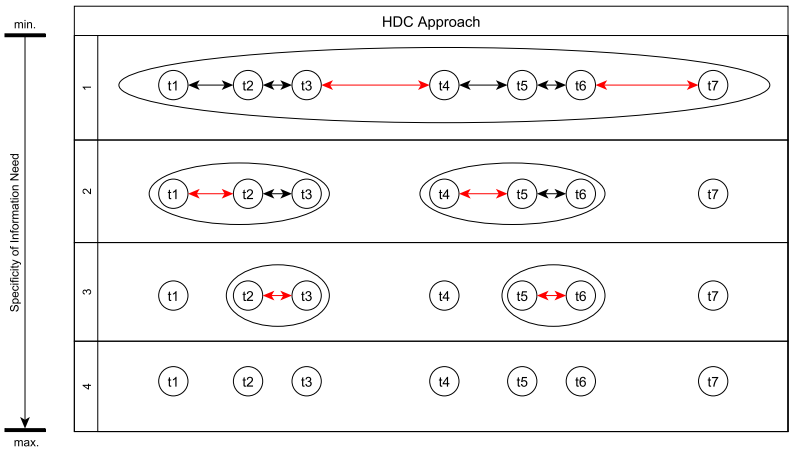
Please also see example 3.2 (p.59), in order to clarify the outlined steps.

✎ **Example 3.2.** Given a set $T = \{t_i\}_{1 \leq i \leq 7}$, comprising literals, see figure 17(a) and 17(b) (p. 60), for details on how our approach groups T. More precisely, applying the above technique, first T is sorted in compliance with a defined order relation, say $\leq$. Afterwards, the pairwise distances between each two neighboring literals are being calculated as well as sorted in a descending manner. Now, at each iteration during the clustering, the maximum distance, marked in red, is fetched and the containing cluster is being split.

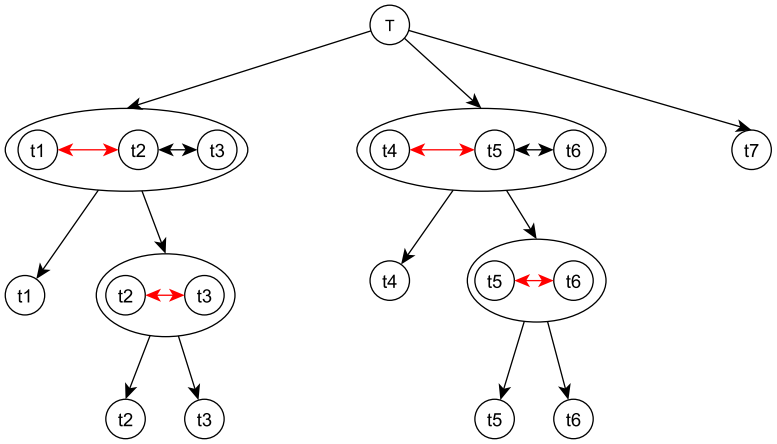
After this generic example, find below a more practical one (see example 3.3, p. 59).

✎ **Example 3.3.** Mary, the computer science student, is still searching in her free time for famous researchers. While talking to her friend Peter the other day, he mentioned some prestigious scientists. Unfortunately, Mary can't recall their names precisely. She is, however, sure that one name started with letters 'al'. Thus, when given a result containing a set of researchers, Mary chooses the facet *name*. With

[20] Clearly, at leave level, there might be less than $\hat{k}$ clusters left to split.



(a) Divisive Clustering Algorithm



(b) Resulting Cluster Tree

Figure 17: Generic Example for Literal Clustering

regard to our clustering technique, Mary is first presented a cluster containing all names. She drills down, specifying the first letter and therefore finding a subset of all names starting with 'a'. She continuous her search, slowly articulating her needs, until reaching a partitioning {*Allan*, *Allen*, *Alonzo*}. Given this set, Mary is sure, Peter mentioned *Allen* the other day, so she continuous exploring the work of *Frances E. Allen*.

Please also find a pseudocode implementation of the outlined algorithm, provided in the appendix (see algorithm 6, p. 104). In particular, the reader should notice, how tightly users are incorporated in the whole clustering process. By means of rich user-system interactions, individual, maybe *fuzzy*, knowledge is articulated.

Concluding Remarks Hereafter, allow me to make a few final remarks, targeting mainly at a cluster representation as well as the above mentioned intuitions, with

regard to well suited clustering algorithms.

(i) Cluster Representation

One benefit of the presented approach is that cluster representation is reduced to a trivial problem. More precisely, I argue that, given a set of clusters, an intuitive representation would simply be provided, by a concatenation of the left and the right border value. Recall that during the first step, literals were sorted in accordance with an order relation $\overset{L}{\leq}$. Therefore, when being provided with such a labeling scheme, users may intuitively conclude, clusters to contain all values in-between these given bounds.

(ii) Genericness of our Approach

Also, let me point out the genericness of the outlined solution. Note that, while restricting the literals to a small set of handpicked datatypes, which are assumed to be common, others may be easily integrated. Furthermore, no assumption with regard to a particular similarity measure, to be applied during the clustering process, has been made. Thus, the reader should regard the above represented metrics to be solely used for exemplary purposes. Lastly, note our above defined notion of an order $\overset{L}{\leq}$, to be completely application-specific. Any intuitive order, fulfilling the basic constraints of a quasi-order, may be employed.

(iii) Satisfying above given Clustering Intuitions

Recall before stated intuitions for a *good* clustering approach, given our faceted search context. Hereafter, let me outline how the provided approach may meet these expectations.

- Traditional Clustering Goals

  First, let us take a look at the traditional goals, i.e. strong intra-cluster similarity as well as strong inter-cluster dissimilarity. I respected these intuitions by imposing similarity measures and constructing a cluster hierarchy by splitting the most dissimilar clusters in half. Thus, the approach aims at minimizing the dissimilarity within one grouping of literals, while resulting in low similarity values in-between clusters.

- Support of fuzzy knowledge

  Remember, I adapted a divisive clustering strategy, i.e. first one big

cluster is being presented, which is then step-by-step broken into sub-clusters, as users drill down. By using such an approach, I intended to support fuzzy and unspecific knowledge. More precisely, users are able to fully control the granularity, i.e. specificity, of the range clustering, by deciding to drill down into a given cluster or not.

- Support of partial knowledge

  Since literals are flat values, i.e. have no further objects associated, this intuition is not applicable here.

3.4 Resource Clustering

3.4.1 Overview

After the presented discussion concerning dissimilarity metrics and clustering techniques applicable to literals, hereafter, resources will be addressed in a similar manner. Again, the reader should recall that by doing so, I establish a partitioning of $\hat{O}_*$, leading to $FV_*(\cdot) \subseteq P(O_*(\cdot))$, as defined in the previous section.
Please also reconsider the presented related work, with respect to resource clustering. Specifically remember, there are two main problems to be faced, namely the *instance extraction* as well as the *similarity definition*. In the following, I will present an approach, by first describing a notion of resource extraction, secondly outlining how similarity with respect to these patterns may be defined and lastly introducing a concrete clustering technique. Note, however, I still keep the overall intuitions in mind and intend to pursuit these goals.

3.4.2 Reduction to a Facet Ranking Problem

Instance Extraction Similar to the work presented in [GEP08], I also regard instance extraction as the first problem to be addressed, in order to cluster a set of resources. Note that this step may be subsumed under what [JMF99] refer to as *pattern representation*.
Please recall that [GEP08] outlined three basic solutions with regard to this task, i.e. (i) *selection of immediate properties*, (ii) *usage of the Concise Bounded Description approach* or (iii) *a depth-limited crawling strategy* (see also section 3.2.2, p. 41). However, given our previously stated assumptions concerning user knowledge, I

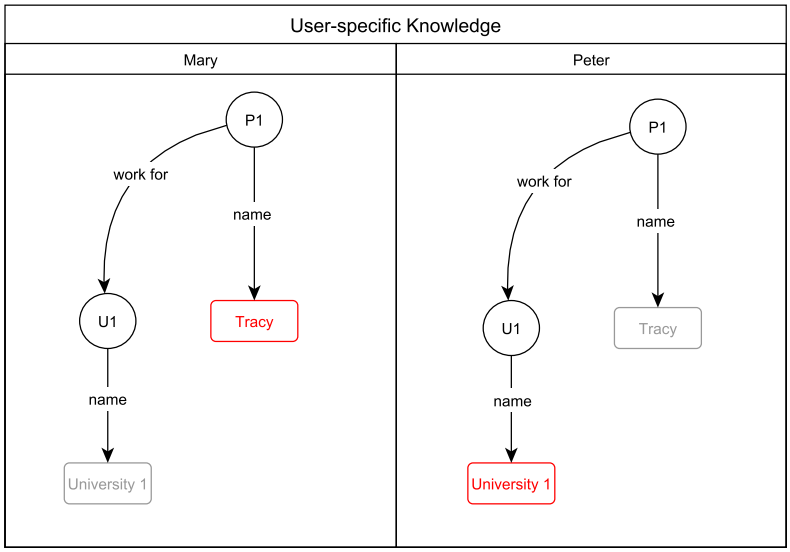
think these approaches to be quite limiting. More precisely, I argue that a suitable approach should be strongly depending on the actual user knowledge, rather than on some generic constraints. Reconsider, I intend to use clustering in an application-specific context, namely as a *browsing* strategy within a faceted search system. Thus, one may wish an algorithm to be flexible in a sense that instances match individual knowledge boundaries. I refer to this notion of resource extraction as being *user-specific*. For clarification, please consider example 3.4 (p. 63) below.

✎ **Example 3.4.** Continuing our earlier examples, in figure 18 (p. 64), please find a user-specific extraction illustrated. Note that the same instance, i.e. professor P_1, is provided to both users. However, depending on their knowledge, the resulting patterns differ. With regard to Mary, who is able to identify P_1 by her name, only the *name* feature is relevant. Peter, on the other hand, has no knowledge concerning the professor's name, however, he does know that she is working at a specific university, say *university1*. Thus, for Peter only her *university*, to be more precise, its *name*, is important.

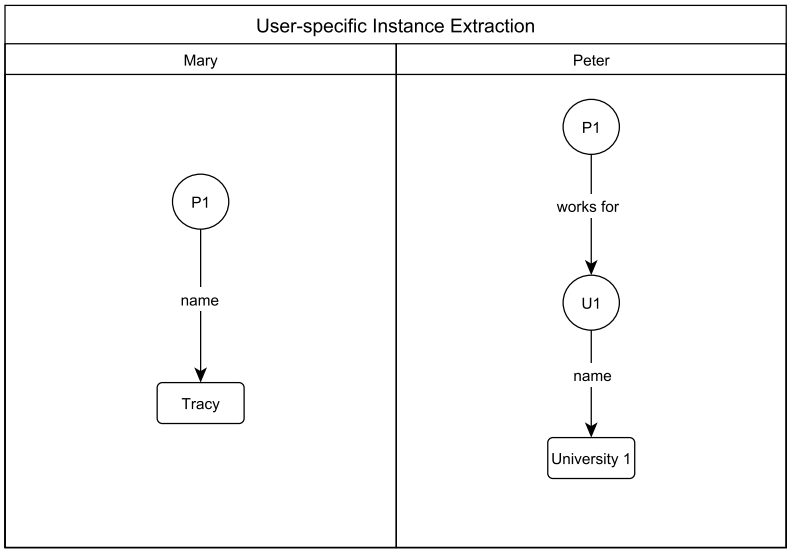
For enabling such a user-specific process, I think the faceted search paradigm might prove suitable. Much like a result space (see definition 2.10, p. 29), a given set of resources to be clustered, may be described by their outgoing edges. Note, this set is hereafter referred to as R_C. Following these thoughts, outgoing attributes or relations, may provide a basis for a facet definition as introduced earlier (see section 2, p. 17). Therefore, I argue that the instance extraction process should be user-controlled and supported via facet operations. To be more precise, instances in R_C might be described by their facets, enabling users to iteratively specify patterns, they are interested in. Note relation-based facets to be pointing at resources. Thus, to be consistent, these resources should again be described by their associated properties, i.e. via their facets. In other words, by selecting a facet path, i.e. iteratively choosing properties, users may extract patterns on an individual basis.

✎ **Example 3.5.** Please reconsider above example 3.4 (p. 63): Using the proposed extraction strategy, Mary may simply select a facet *name*. In contrast, Peter, having a different background, prefers to choose *works-for*, followed by *name*, resulting in another facet path, i.e. (*works-for*, *name*).

However, before defining a similarity measure, allow me to point out key aspects of



(a) User knowledge



(b) Resulting instance extraction

Figure 18: User-specific Instance Extraction

this strategy:

(i) *Path*-shaped Structure of Resource Patterns

It is important for the reader to observe that the resulting pattern structure will always be *path*-shaped. To be more specific, an instance may be described by multiple connected properties, chosen via facet operations. However, there will be no node contained in this graph, having more than one outgoing edge. On the other hand, notice, due to the iterative nature of our overall search process, users may define arbitrary *tree* patterns over time.

(ii) Attribute-based Description of Resources

Also note that R_C, as well as associated sets comprising resources, are characterized via their outgoing properties. Therefore, resources in R_C are described either by their own attributes or by related resources, which in turn may be characterized by associated attributes or further instances. Seen in an abstract way, a path specifying a given instance, may only terminate, when reaching an attribute.[21] At first glance, such an *attribute-based* description might seem odd to the reader. I, on the other hand, argue that this is a quite intuitive way of representing resources. I see an attribute generally as a mean of providing further information directly associated with an entity. A relation, on the other hand, I think of as a link to other entities, which in turn may be characterized via attributes or associated with other entities using relations. Thus, eventually, attributes characterize entities, while relations solely link them to each other.

Notice, given a set of resources R_C, a n-step facet path, denoted by F^n and leading to a literal set, say $\hat{A}$, may be written hereafter as $R_C \xrightarrow{F^n} \hat{A}$. Furthermore, the reader should be aware that this extraction process is a key element in the overall clustering approach. More precisely, the similarity measure as well as the clustering technique presented earlier, may easily be adapted to this use case. Thus, I argue that our clustering task, may actually be reduced to a ranking problem. In the following, allow me to discuss these steps in more detail.

Similarity Measure Recall, by applying the faceted search paradigm, I essentially enable users to describe a set of resources by means of an attribute, associated via a n-step facet path. Recalling the initial problem, namely to measure similarity between resources and to cluster accordingly, one may now redefine the similarity measure. First, however, let me introduce the notion of $R_C \xrightarrow{F^n} \hat{A}$ more accurately:

$$\begin{aligned} \vartheta(v, F^n) = \{\hat{v} \in V_V^R \,|\, \exists\,(v_1, \ldots, v_n) : e_1(v, v_1), \ldots, e_n(v_n, \hat{v}) \wedge \\ \forall\, j : e_j \overset{b}{=} f_j, 1 \leq j \leq n \wedge \\ \forall\, k : v_k \in V_E^R\, 1 \leq k \leq n\} \end{aligned} \tag{3.14}$$

[21] Please note, for resources having no outgoing attributes, simply a new attribute pointing at their URIs might be added.

with $v \in R_C$ and $f_i \in F^n$ being the i$^{\text{th}}$ facet, contained in a given facet path. Note that data values mapped to by function ϑ, are connected to resource $v \in R_C$ via n hops and are thus suitable to characterize v. Further note that, since F^n being selected by users, this description is user-, more precisely, knowledge-specific. In conclusion, a similarity measure for two given resources may be rewritten as the similarity between user-specific, associated attributes. Formally, it may be written as:

$$dis^r(v_i, v_j) = dis^a(\vartheta(v_i, F^n), \vartheta(v_j, F^n)) \tag{3.15}$$

with $v_i, v_j \in V_E^R$ and F^n referring to a user-selected facet path. Since ϑ generally maps to a set of data values, note that $dis^a(\cdot,\cdot)$ compares two sets with each other. However, this is a problem we already addressed, please reconsider the above discussion in section 3.3.2.2 (p. 54).[22]

Hierarchical Clustering Concerning the clustering technique, I argue that a hierarchical, divisive approach might prove suitable. Remember, using such a technique, in the beginning one big cluster is constructed, which is then iteratively divided into sub-clusters, by means of drill down operations. With regard to the intuition of letting users slowly specify their knowledge, one may wish an algorithm to stop, if users have no further information. Thus, I argue such a top-down approach to provide meaningful clusterings, given this background. Furthermore, the reader should notice that the interaction between instance extraction, on the one hand, and similarity measuring and clustering, on the other hand, is rather fluent. More specifically, after a user-specific instance extraction, i.e. a facet path selection, leading to an attribute of interest, resources are instantly clustered in accordance with this attribute.
To illustrate this process, especially with regard to the actual clustering phase, please consider example 3.6 (p. 66).

✎ **Example 3.6.** Continuing example 3.4 (p. 63) as well as example 3.5 (p. 63): Given a set of resources, say $\{P_1, P_2, P_3\}$, Mary chooses a facet path (*name*), resulting first in a clustering $\{\{P_1\}, \{P_2, P_3\}\}$ and followed by $\{\{P_1\}, \{\{P_2\}, \{P_3\}\}\}$, on the next level. Note, the second tree level is only computed, if Mary drills down

[22] Notice, in my implementation, I applied a single-link approach.

into [Paul, Phil]. With respect to Peter, a completely different grouping would be given. Recall Peter to only remember the name of the university and therefore selecting a facet path (*works for*, *name*). Also notice, given a resources description via this path, $\{P_1, P_2\}$ are not distinguishable.

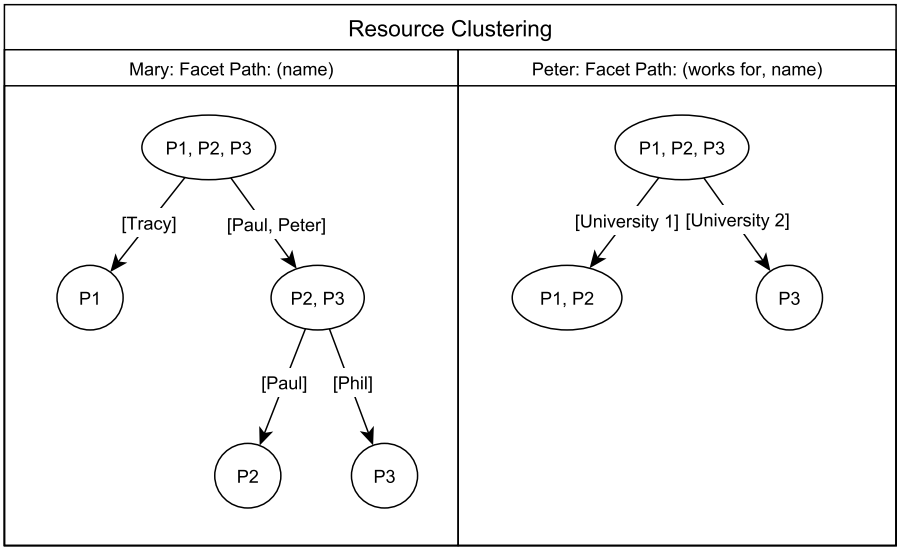


Figure 19: User-specific Resource Clustering

3.4.3 Concluding Remarks

In the following, allow me to briefly present final remarks, concerning resource clustering.

(i) Cluster Representation

With respect to their representation, clusters containing resources may be visualized in the same manner, as groups comprising literals. However, when dealing with resources, additionally the facet extraction process needs to be addressed. As outlined before, this problem may be solved by means of the faceted search paradigm, i.e. via a facet path selection.

(ii) Genericness of our Approach

Concerning the adaptability of our clustering strategy, the same benefits as for the literal clustering apply here. Note, however, the instance extraction step to be compatible with any facet ranking mechanism. Thus, providing additional means for a domain-specific configuration.

(iii) Satisfying above given Clustering Intuitions

Lastly, I would like to outline, how the presented strategy meets our overall clustering intuitions.

- Traditional clustering Goals

  Since I reduced the initial resource clustering problem to a facet ranking and attribute clustering task, the same arguments as discussed above do apply here.

- Support of fuzzy knowledge

  Again, as a top-down clustering approach is supported, users may articulate their information needs in a quite fuzzy or, via drilling down, in very specific manner.

- Support of partial knowledge

  With respect to clustering resources, notice this aspect to target at a key point. Consider that by giving users full control over the instance extraction process, they are able to specify their knowledge precisely. By means of a user-selected facet path, a basis for a similarity measure as well as a clustering process may be provided, while supporting partial user information completely.

3.5 Cluster Tree

It is very important for the reader to realize that the structure established by the described clustering strategies is tree-shaped, thus leading to a notion of a so called *cluster tree*. More precisely, flat, as well as non-flat values, are in their nature hierarchical. Therefore, given a facet f, the partitioning of its values results in a cluster tree, say $Tree(f)$. Each node n in $Tree(f)$ corresponds to a facet value, with $V(n)$ denoting literals or resources contained in this cluster. Furthermore, the current result set is split into subsets, so that each node n may be mapped to a result cluster. Let $R(n)$ denote the set of all result items being associated with a value contained in $V(n)$. Note that these sets could be overlapping, as a result item may have values contained in several different clusters $V(n)$. Thus, in other words, there are two relations, say V and R, mapping each node n in $Tree(f)$ to sets $V(n)$ and $R(n)$, respectively. Formally, given a facet f, V may be defined as

$V : N_f \mapsto P(O_*(f))$, whereas R is given by $R : N_f \mapsto P(V^{Res})$ with N_f being a set, comprising nodes contained in $Tree(f)$. In conclusion, $V(n)$ may be written as:

$$V_f(n) = \{\tilde{v} \in O_*(f) \,|\, l(\tilde{v}) = n\} \tag{3.16}$$

with $l(\cdot)$ standing for a function, assigning a class label to a given element. Furthermore, $R(n)$ is defined by:

$$\begin{aligned} R_f(n) = \{\tilde{v} \in V^{Res} \,|\, &\exists V \subseteq P(O_*(f)) : \{\tilde{v}\} \xrightarrow{F^n} V \wedge \\ &\exists \bar{v} \in V : l(\bar{v}) = n \wedge \\ &F^n = (*, \ldots, *, f)\} \end{aligned} \tag{3.17}$$

Notice, $V(n)$ and $R(n)$ are hereafter referred to as *value* and *result segmentation*, respectively. Also, please find a generic example for a $Tree(f)$, together with its relations V and R, provided in the appendix (see figure 24, p. 105).

Section 4

Facet Ranking

4.1 Introduction

Motivation Please remember the introduced facet (see definition 2.11, p. 29) as well as facet value (see definition 2.12, p. 31) definition. In particular, observe these notions to be very fine-grained. Thus, given a large and well-structured data-source, one might have to deal with an overwhelming facet and facet value set, respectively. That being said, it is obvious for several reasons that a crucial part of a faceted search system is facet and facet value ranking. Hereafter, allow me to further elaborate the need for a ranking heuristic, given our context.

First of all, users tend to have very rarely complete knowledge of their item of interest. Thus, naturally only a small number of facets may be relevant for them. On the other hand, from a technical point of view, visualizing all available facets and facet values respectively, would exceed the capabilities of any graphical interface and will be confusing for users. Lastly, even if users would have complete knowledge of their item of interest, facets might differ, with respect to their usefulness for the fulfillment of a particular task. In this context, please recall the above discussion of varying needs in section 1.1.1 (p. 1). Notice, in the following, I am going to focus on *higher-level* needs, which are often associated with little precise user knowledge. For the outlined ranking purposes, the current cluster tree is taken into consideration. More precisely, ranking is accomplished by defining metrics over the tree and aggregating them, using an integrated ranking function. Note, I first explain the intuitions behind the chosen metrics and afterwards describe a specific scoring function.

Problem Definition Before going into more details on possible applications for a ranking mechanism or on the actual ranking paradigm, I will first introduce defi-

nitions for facet and facet value ranking functions:

☞ **Definition 4.1. Facet and Facet Value Ranking Function**
Given a *resource space* S_R with g_R, a *result space* S_{Res} with g_i^{Res}, a *query graph* g_q and a set F containing all facets, a facet ranking function, say r_f, is defined as $r_f : F^R \mapsto \mathbb{R}$. In a similar manner, given a facet value fv with $fv \in FV_*(\cdot) \subseteq P(O_*(\cdot))$, a ranking function, say r_v, may be defined as $r_v : FV^R \mapsto \mathbb{R}$.

In simple terms, a ranking function r_* maps a facet or facet value to a score in $\mathbb{R}$, representing its importance, in compliance with application-specific settings and goals. Given this notion of a ranking function, please find hereafter a formal definition of the *ranking problem*, which I will address within this section.

⇝ **Problem 4.1.** ***Ranking Problem***
Given a facet $f \in F$, the problem consists of defining a function, which maps a facet to a ranking score, in compliance with the browsing paradigm as well as a current result space.

Note, for a facet value, say fv, a problem may be defined in a similar manner.

Use-Cases for Ranking According to my knowledge, there are two common applications of facet ranking. First, there is the simple *sorting* of facets or facet values, in compliance with their ranking weight. Meaning, the higher a weight, the higher sorted a facet or facet value is, with regard to a list presented to users. The second common ranking application is a facet *hiding* strategy. Here, in order to make the navigation easier and more intuitive for users, less important, i.e. facets or facet values with low scores associated, are omitted. Users may be provided an option like *show other* or *show all*, for having access to all available facets.

4.2 A short Survey of present Ranking Approaches

4.2.1 Overview

In the following, I would like to provide a short overview of present facet ranking approaches and their associated paradigms. As mentioned earlier, faceted search became popular during recent years, thus, also ranking heuristics were discussed extensively within the research community. However, before looking at more complex

techniques, let us start with a quite easy and straight-forward approach, namely the so called *count*-based or *frequency*-based ranking.

4.2.2 Ranking Approach: Frequency-based Ranking

Frequency-based[23] or often also called *count*-based ranking, is probably the most commonly used metric. The overall idea is as follows: the more items, contained in a result space, are associated with a particular facet value pair, the more important and representative this pair has to be. In compliance with [DIW05], this technique has the benefit of presenting those facets first that contain the most information. Thereby, such approaches guarantee lower ranked properties, to comprise only a small fraction of the result to represent (cf. [DIW05]). For details, please see [DIW05, KZL08, ODM+06].

4.2.3 Ranking Approach: Set-cover Ranking

Furthermore, according to [DIW05], there is also the so called *set-cover*-based ranking. "The objective of *set-cover* ranking is to maximize the number of distinct objects that are accessible from the top-k ranked categories.", cf. [DIW05].[24] Thus, their objective is to maximize a function, say $Cover$, defined as:

$$Cover(C) = o(C_1) \cup \ldots \cup o(C_k) \tag{4.1}$$

with C standing for the set of all categories, $\{C_1, \ldots, C_k\}$ being the top-k ranked categories and $o(C_j)$ referring a function, returning all objects subsumed under a given category C_j (cf. [DIW05]). [DIW05] apply a greedy strategy for finding a subset, say $\tilde{C}$, of C maximizing equation 4.1 (p. 72). The algorithm may be briefly outlined as follows:

4.2.4 Ranking Approach: Merit-based Ranking

[DIW05] also introduced a ranking technique, targeting at costs associated with discovering an item of interest. According to their work, user costs may be represented by the time necessary for the fulfillment of a given information need. More specifically, given a category C, costs, say $T(C)$, comprise components as follows:

---

[23] Terminology is used in compliance with [DIW05].

[24] Note, what [DIW05] refer to as category, I introduced as facet.

Algorithm 1 Greedy *set-cover* Algorithm

Require: set state of all objects as *uncovered*

1: **repeat**
2: $C_{max} \leftarrow$ C' having max. number of uncovered objects
3: **for all** $c \in C_{max}$ **do**
4: mark c as *covered*
5: **end for**
6: **until** all objects $o \in C$ are covered **or** ranked k categories

(i) Reading the category headings

In compliance with [DIW05], time spent for reading category headings is said to be linear in $b(C_i)$ with $b(\cdot)$ referring to a function, mapping a given category to its number of children.

(ii) Correcting mistakes

Given a category C_i and a likelihood, say P_e, for selecting a wrong subcategory, an additional effort, i.e. $P_e(C_i) \cdot T(C_i)$, is needed on average, to correct a browsing mistake (cf. [DIW05])

(iii) Browsing the correct subtree

Lastly, given a category C_i and assuming users to choose a correct subtree, $(1 - P_e(C_i)) \cdot T(C_{i+1})$ time is necessary, for reaching an item of interest (cf. [DIW05]).

Therefore, the total time, say $T(C_i)$, is given by:

$$T(C_i) = \frac{\kappa b(C_i)}{1 - P_e(C_i)} + T(C_{i+1}) \tag{4.2}$$

with κ as a constant. Based on these thoughts, a metric, say $merit(C)$, may be defined as:

$$merit(C) = \frac{2 \cdot \frac{1}{T(C)} \cdot o(C)}{\frac{1}{T(C)} + o(C)} = \frac{2 \cdot o(C)}{1 + T(C) \cdot o(C)} \tag{4.3}$$

with $o(C)$ as number of objects, having values associated with C (cf. [DIW05]).

4.2.5 Ranking Approach: Interestingness-based Ranking

[DRM+08] introduced a ranking notion centering around the concept of *interestingness*. More specifically, this well-known concept, originating from the *OLAP*

community, is redefined as "[...] how surprising an actual aggregated value is, given a certain expectation", cf. [DRM+08]. Before having a closer look at this approach, however, allow me to first give a brief outline over the terminology and definitions used hereafter:

- A repository, in our terminology the *resource space*, is denoted by D.
- D_q stands for the set of documents in D, matching a given query q.
- A facet is written as F, while a facet value is given by f.

Now, given $\{f_1, \ldots, f_n\}$ as facet values, associated with $\{F_1, \ldots, F_n\}$. Furthermore, assume $C_D(f_1, \ldots, f_m)$ to denote the count of documents with respect to D. Similarly, $C_q(f_1, \ldots, f_m)$ stands for the count of documents with regard to D_q. Given $E(\cdot)$ as the expected value, in compliance with [DRM+08], the above mentioned expectations may be computed as described hereafter:

(i) Natural Way

Assume documents, contained in D, are distributed over each facet according to a natural distribution, e.g. an equal distribution. Also, say all facets are pairwise independent. Then, according to [DRM+08], for a facet value pair (F:f), $E(C_q(f))$ may be given by:

$$E(C_q(f)) = \frac{|D_q|}{\text{number of unique values in F in } D_q} \tag{4.4}$$

Given (F_1,...,F_m:f_1,...,f_m), on the other hand, we have:

$$E(C_q(f_1, \ldots, f_m)) = |D_q| \prod_{i=1}^{m} \frac{C_q(f_i)}{|D_q|} \tag{4.5}$$

(ii) Navigational

With regard to the so called navigational method, an expectation value is estimated in accordance with the user navigation. Assume a user issues a query q_1, then counts are set proportionally based on the data distribution in the repository. In conclusion, $E(\cdot)$ is defined as:

$$E(C_{q_1}(f_1, \ldots, f_m)) = |D_{q1}| \frac{C_D(f_1, \ldots, f_m)}{|D|} \tag{4.6}$$

Given, the same user enters a second query, say q_2, the expectation is recomputed as:

$$E(C_{q2}(f_1, \ldots, f_m)) = |D_{q2}| \frac{C_{q1}(f_1, \ldots, f_m)}{|D_{q1}|} \tag{4.7}$$

See also [DRM+08].

(iii) Ad hoc

If both methods don't prove to be suitable, users may set counts for each facet value proportionally, based on the distribution of a result space, with respect to an arbitrary query, say q (cf. [DRM+08]).

Making use of the above defined expectation values, [DRM+08] compute their actual scores as follows. First, they define *interestingness* for a facet instance. During a second step, [DRM+08] apply this intermediate result, in order to measure the weight of an entire facet, say F.

(i) Single facet instance

With regard to a single facet instance, an interestingness score is based on the actual and expected count. More precisely, say f occurs in r out of R documents as well as in q out of Q documents, contained in the result set for a given query. Furthermore, let equation $\frac{r}{R} > \frac{q}{Q}$ hold. Given both assumptions, an interestingness value may be defined as the probability, say $\hat{p}$, that a random set with size Q, contains at least q documents having a facet value f associated. In accordance with [DRM+08], $\hat{p}$ is computed as:

$$\sum_{k=0}^{q} \frac{\binom{r}{k}\binom{R-r}{Q-k}}{\binom{R}{Q}} \tag{4.8}$$

Note, if given $\frac{r}{R} < \frac{q}{Q}$, an interestingness score may be calculated analogously (cf. [DRM+08]).

(ii) Entire Facet F

In compliance with [DRM+08], one may either use all facet values or just k top-ranked instances, in order to estimate the interestingness value with regard to F. Notice, hereafter, I will use the latter option. Thus, given a facet F, one may consider $\{f_1,...,f_k\}$ with $p_1 < ... < p_k$. Furthermore, a function S_i with

$S_i = -\log(p_i)$ is being computed for each $i = 1, \ldots, k$. Note that $S_1 \geq \cdots \geq S_k$ holds. Finally, the degree of interestingness for F is $\sum_{i=1}^{k} W_i \cdot S_i$ with W_i as a weight (cf. [DRM+08]).

4.2.6 Ranking Approach: Indistinguishability-based Ranking

[BRWD+08] rank facets with regard to their suspected associated navigational costs. More specifically, they aim at minimizing the necessary users costs, in order to fulfill an information need. [BRWD+08] argue that facet ranking is very similar to building a decision tree. "Essentially, the task is to build a decision tree which distinguishes each tuple by testing attribute values (asking questions). Each node of the tree represents an attribute, and each edge leading out of the node is labeled with a value from the attribute's domain.", cf. [BRWD+08]. Having such a perspective on ranking, costs may simply be defined as the expected number of necessary queries, before reaching an item of interest. Meaning, given a tree, say T, $cost(T)$ may be represented by the average tree height, i.e. $\sum_i \frac{h(t_i)}{n}$ with function h mapping leaf t_i to its height (cf. [BRWD+08]). [BRWD+08] use a greedy algorithm for solving this problem. Hereafter, let me briefly describe it as:

- Use as a root an attribute, say A_l, that distinguishes a maximum number of tuple pairs. Please note, by choosing A_l, one divides the data-source, say D, into subsets $D_{x1}, D_{x2}, \ldots, D_{x|Dom_l|}$ (cf. [BRWD+08]).
- [BRWD+08] employ the above step, until no further splitting of D_{xq} is possible.

Formally, [BRWD+08] thereby intend to minimize a so called $Indg$ function, defined as:

$$Indg(A_l, D) = \sum_{1 \leq q \leq |Dom_l|} |D_{xq}| \frac{|D_{xq}| - 1}{2} \tag{4.9}$$

4.2.7 Ranking Approach: Probability-based Ranking

In [KZL08], another ranking technique is presented. In their work, the authors argue that facet value pairs and thus facets, may be sorted with respect to their likelihood of being associated with a relevant document.[25] Furthermore, [KZL08]

[25] Note, in our Semantic Web environment, documents may be seen as resources.

outline two ways for estimating such relevance scores, leading to a *personalized* relevance probability as well as a *collaborative* relevance probability:

(i) *Personalized* Probability

In the former case, only relevance judgments issued by a particular user are considered. To be more precise, [KZL08] introduce a framework, which I would like to outline shortly in the following. Say $P(rel\,|\,u)$ denotes the likelihood of a document, contained in the repository, being relevant for a user, say u. Furthermore, let $P(x_k\,|\,rel,\,u)$ and $P(x_k\,|\,non{-}rel,\,u)$ respectively be the distribution of facet value pairs x_k, given a user u and a relevant and non-relevant document respectively. Following these thoughts, [KZL08] describe u in a triple-based manner:

$$\Theta_u = \{P(rel|u),\, P(x_k\,|\,rel,\,u),\, P(x_k\,|\,non,\,u)\} \tag{4.10}$$

(ii) *Collaborative* Probability

Given the latter case, [KZL08] not only compute relevance scores on the basis of a single, but of several users. However, gathering that much data from different sources may easily get expensive. On the other hand, one may assume that several users share common criteria, interaction patterns or preferences. Therefore, in accordance with [KZL08], information may be exchanged in-between users. More precisely, [KZL08] motivate in their work the use of a *Bayesian modeling* approach.

4.2.8 Ranking Approach: Mutual Information-based Ranking

In compliance with [KZL08], the well-known *mutual information* quantity may also be used for ranking purposes. However, before going into more detail, allow me first, to shortly remind the reader, how mutual information may be defined (cf. [Sha48]). Given two discrete random variables, say X and Y, the mutual information between X and Y, is given by a function I with:

$$I(X,\,Y) = \sum_{x,\,y} P_{XY}(x,\,y) \log \frac{P_{XY}(x,\,y)}{P_X(x) \cdot P_Y(y)} \tag{4.11}$$

Please see [Sha48, CT91] for further information. With regard to our ranking context, [KZL08] apply this measure for two random variables, say X_1 and X_2. Let the

first variable describe the likelihood of a facet value pair being associated with a document, while the latter one represents the probability of a document being relevant, given a user query. According to [KZL08], those facet value pairs, resulting in a maximal mutual information score, should be sorted the highest.

4.2.9 Ranking Approach: Descriptors and Navigators

Last, [ODD06] argue that there are two main aspects to be considered, when judging facets or, to be more precise, their underlying properties: First, facets ranked high, should *describe* a dataset and result set respectively. Secondly, facets should enable users to *navigate* a data-source (cf. [ODD06]). Hereafter, allow me to outline metrics the authors developed, aiming at maximizing both criteria.

Descriptors [ODD06] base their argumentation on [Ran62], when reciting that intuitive facets and properties respectively should be either *temporal*, *spatial*, *personal* or *energetic*. Continuing this thought, the authors point out that facets could be assigned weights, with respect to whether or not they are based on properties belonging to one of these categories. The necessary meta-data could be provided by additional ontologies. However, [ODD06] argue that in many use cases such extensive knowledge is not available, which in turn makes this criterion hard to employ.

Navigators As described above, [ODD06] regard efficient navigation as a second key quality criterion. Please note, like [BRWD+08], the authors reduce the ranking problem to a construction of a decision tree. Thus, hereafter, when referred to a tree, also a decision tree is meant, which in turn implies a facet sorting. For measuring how well a given facet supports navigation, [ODD06] propose a metric, comprising three parts, namely *predicate balance*, *object cardinality* and *predicate frequency*.

(i) Predicate Balance

[ODD06] think of a tree being well-balanced as an important factor for efficient navigation. The balance of a predicate p, in compliance with [ODD06], is calculated as:

$$balance(p) = 1 - \frac{\sum_{i=1}^{n} n_s(o_i) - \mu}{(n-1)\mu + (N_s - \mu)} \tag{4.12}$$

where $n_s(o_i)$ represents a distribution of subjects over objects, μ being the mean vector, N_s the total number of subjects and n standing for the number of possible objects associated with p.

(i) Object cardinality

A predicate, having a large amount of objects associated, might be confusing for users and may be difficult to visualize properly, [ODD06] continue. Thus, the authors argue that an ideal predicate should only have a limited number of objects. A metric, denoted by *card*, is estimated as:

$$card(p) = \begin{cases} 0 & \text{if } n_o(p) \leq 1 \\ \exp^{-\frac{(n_o(p)-\mu)^2}{2\cdot\sigma^2}} & \text{otherwise} \end{cases} \tag{4.13}$$

(i) Predicate frequency

Lastly, frequency of a given predicate is considered as being important for effective navigation (cf. [ODD06]). In their work, [ODD06] state that a useful predicate, say p, should occur frequently within a given data-source, thereby properly dividing the underlying space. In accordance with [ODD06], the frequency of p, may be defined by means of a function $freq$ as:

$$freq(q) = \frac{n_s(p)}{n_s} \tag{4.14}$$

where function $n_s(p)$ returns the number of subjects contained in a data-space S^R, having p as relation associated, and n_s referring to the number of distinct subjects in S^R.

4.2.10 Contribution

Please recall our basic assumptions introduced earlier. In particular, remember assumption 2.3 (p. 21). To be more specific, given users having an information need, I assume needs contained in Q^S_{Need} to be issued via *query searching*, while unspecific and fuzzy information, i.e. Q^F_{Need}, may be articulated using *browsing* strategies. Following these thoughts, one may conclude that facet operations, since representing basic *browsing* techniques, will mainly be used for articulation of unspecific and fuzzy knowledge.

However, reconsidering the above presented approaches, I argue that none addresses

these assumptions properly and enables users to act accordingly. Throughout the literature, users are expected to be following a specific need as well as having precise knowledge about their item of interest and the underlying domain. Note, hereafter, such heuristics are referred to as *search-ability*-based ranking. In contrast, I aim at a ranking maxim, preferring those facets and properties respectively that allow users to issue fuzzy informations needs via *browsing* techniques. By doing so, I wish to enable a *more* exploratory search and thereby the fulfillment of higher-level information needs (see also section 1, p. 1). Below, I address these shortcomings by introducing a novel ranking paradigm, namely what I coined *browse-ability*-based ranking.

4.3 Facet Ranking with respect to *Browse-Ability*

4.3.1 Introduction to *browse-ability*-based Ranking

Basic Assumptions Given above outlined thoughts, in order for a ranking maxim to result in a meaningful sorting of facets, an approach should rather target *browsing*, than *searching*. More precisely, given a setting, as outlined in assumption 2.3 (p. 21), I wish to prefer such facets, which enable users to issue *fuzzy* information needs and slowly *explore* an unknown domain of interest. In other words, facets should support *browsing* strategies, given needs solely contained in Q^F_{Need}.
Recall, in section 2 (p. 17) I introduced the faceted search paradigm, given a Semantic Web context. With a facet, say f, being based on a property contained in a *resource space* S_R, there are essentially two interesting sets associated with f, i.e. $R(n)$ and $V(n)$. In this context, it is important for the reader to remember the so called *cluster tree*, I defined in section 3.5 (p. 68). Given such a facet value hierarchy as well as relations R and V, projecting nodes to their associated result item and object sets respectively, one may define metrics, addressing our notion of *browse-ability*.

Intuition behind our *browse-ability* Maxim Hereafter, for clarification purposes, allow me to present intuitions, I believe to be important, with regard to a *browse-ability*--based ranking heuristic. More precisely, given a fuzzy information need, I argue that there are three relevant issues, namely *uniform steps to an item of interest*, *many steps leading to a single item* and a *comprehensible result parti-*

tioning. Please find these points further discussed below:

(i) Uniform Steps to an Item of Interest

Since I assume needs to be contained in Q^F_{Need}, I except users to articulate rather fuzzy knowledge via means of browsing. For enabling exploration of a given resource space, I believe that users should be guided in *uniform steps* to their item of interest. In particular, with regard to users facing unknown datasets and having only vaguely information concerning their needs, I argue that all result items are a priori of equal importance. Thus, it is not possible to prefer one set of results over another. With respect to a cluster tree, which users explore, notice that one may not favor a particular path over the others.

(ii) Many Steps leading to a single Item

Related to my first intuition, I further argue that users should be guided in *small steps*. More specifically, each exploration step should lead to uniform and small changes of a given result space. Note, with small steps, I refer to minor restrictions of a current result set, generated by *browsing* decisions. I thereby allow users to slowly *dive* into an unfamiliar space, rather than rapidly restrict it to only few specific items. In other words, I wish to avoid rapid drill downs, which, given our context, are likely to result in browsing mistakes.

The reader should observe this intuition to differ significantly from above implied ones. Reconsider approaches presented in section 4.2.4 (p. 72) or 4.2.6 (p. 76) as examples. Both works intend to minimize user effort needed, for fulfilling a given information task. However, by doing so, the authors rank the most discriminative facets the highest and thus prefer rapid result set restrictions, over slow and small ones.

(iii) Comprehensible Result Partitioning

Continuing the above argumentation, I wish to support users in making *intuitive* decisions at each step, while requiring the least amount of knowledge possible. Thus, given a cluster tree, users should be able to choose a value, i.e. a path, without much effort, especially without issuing additional queries. Note, I refer to a decision as being intuitive, if leading to clear and comprehensible modifications of a result set. More precisely, each decision should lead to a true restriction, with regard to the current space. Also, given a facet, differ-

ent paths in its associated cluster tree, should lead to different modifications, i.e. varying sets of result tuples.

4.3.2 *Browse-ability*-based Ranking: A novel Facet Ranking Approach

4.3.2.1 Indicators for a browse-able Facet

Hereafter, please find specific indicators for the presented intuitions. The reader should be aware that I first discuss effects on the value segmentation, i.e. $V(n)$, and afterwards examine the browse-ability notion, with regard to the result space, i.e. $R(n)$.

Indicators for a *browse-able* Value Segmentation

(i) Uniform Steps to Item of Interest

Recall, according to the first presented intuition, facets should *guide* users in very small, equal-sized steps to their item of interest. Therefore, I believe the following two indicators might prove useful:

- Height Balance

  Since I wish every path, originating from the root and leading to an arbitrary leaf, to be approximately equal-sized, the tree height might be of interest. To be more specific, the cluster tree should be height-balanced.

- Equal-sized Value Clusters

  Value clusters $V(n)$, with regard to a given hierarchical level in a cluster tree, should be approximately equal-sized. Meaning, at each hierarchical level, cluster sizes, i.e. $|V(n)|$, should only differ by a factor smaller than a given threshold, say $\hat{t}$.

(ii) Many Steps leading to a single Item

Secondly, I argue that users should be guided in *small steps* to their item of interest, thereby avoiding rapid space modifications. Below find two indicators for this intuition.

- Maximal Height

  Please remember, I assume users to have no specific knowledge. Therefore, a rather *long path*, requiring not much information and leading users to their item of interest, is desirable.

- Limited Branching Factor

  On the other hand, I argue that each hierarchical level should have a *limited number of outgoing branches*. Thereby, situations may be avoided, where users have to choose from a large number of value partitions, i.e. paths in a cluster tree, which in turn would require specific knowledge.

Indicators for a *browse-able* Result Segmentation Before looking at more indicators for measuring the degree of browse-ability, let me motivate how it is possible that a result clustering is not suitable for *browsing*, while a *browse-able* value space segmentation is given.

✎ **Example 4.1.** Hereafter, please see figure 20 (p. 84), as a generic example for a *browse-able* value segmentation, leading to a result clustering not being suitable for *browsing*. More specifically, while the value clustering clearly fulfills the above stated indicators, its associated result segmentation leads to rapid drill downs and thus seems not desirable for slow exploration of an underlying space. Note the current result set to be circled in green and types, by which resources are grouped, colored in gray.

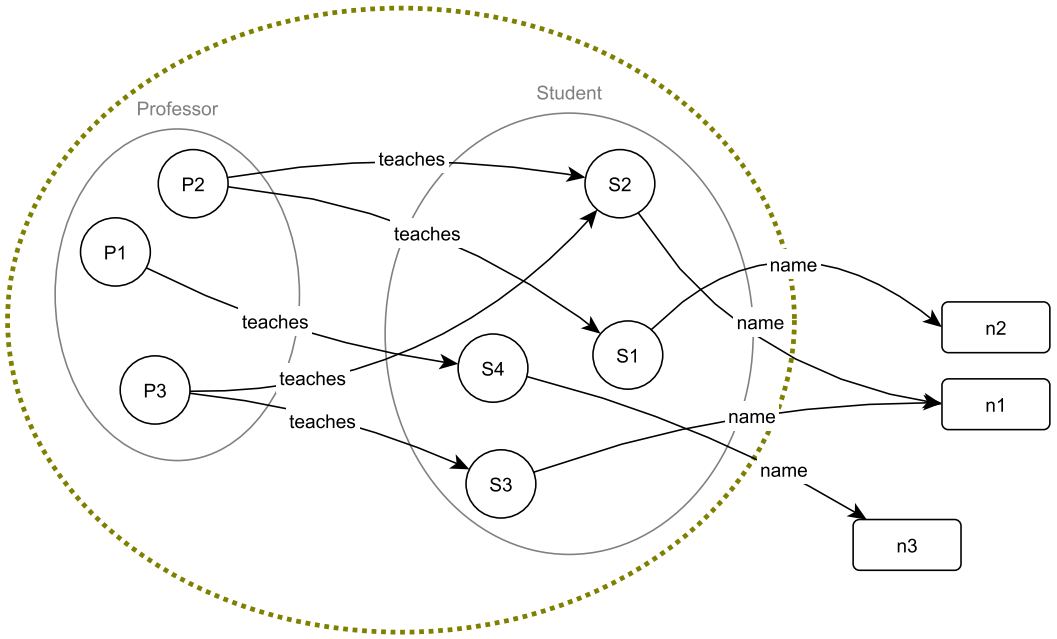
In the following, let me introduce influencing factors, I believe to be meaningful indicators for a result segmentation being regarded as *browse-able*.

(i) Uniform Steps to Item of Interest

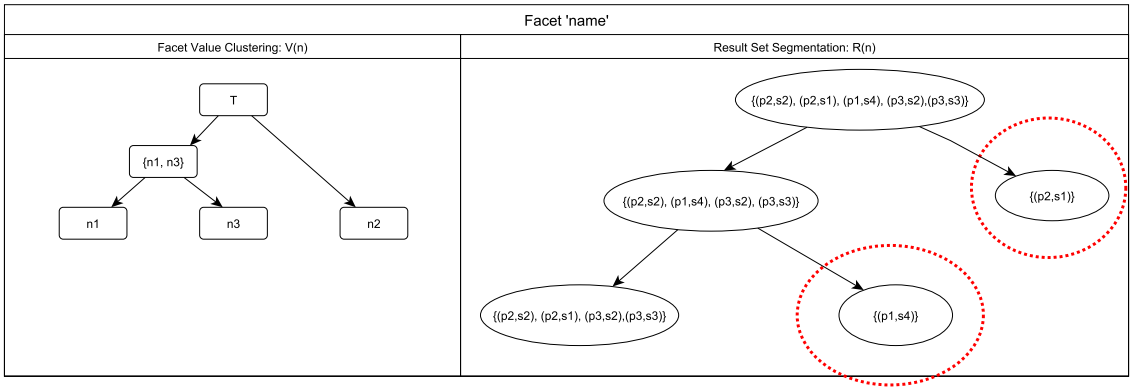
Reconsidering the above mentioned first intuition, i.e. facets should guide users in *uniform steps* to their item of interest, I believe the result segmentation size to be an interesting value. Thus, result clusters, i.e. $R(n)$, associated with nodes in a cluster tree should be of equal size, so that exploration steps are uniform, in terms of their effects on a result set. To be more precise, given a tree level, I compute the maximum cluster size as well as the minimum. The difference between both values, I then wish to be smaller than a given threshold.

(ii) Comprehensible Result Partitioning

Remember, I intend a heuristic to support users in making *intuitive* decisions. Thus, comprehensible result space interactions are necessary. Below, please see two indicators, I find meaningful:



(a) Resource Space



(b) $V(n)$ and $R(n)$ for a facet *name*.

Figure 20: *Browse-able* $V(n)$ and *non-browse-able* $R(n)$ Segmentation

- Minimum Result Partition Overlap

  Given paths in a cluster tree, I argue that a suitable facet should lead to a minimal overlap between its associated result segmentations $R(n)$, thereby resulting in different modifications, depending on a user-specific selection.

- Result Tuple distinguishability

  Also, targeting at this intuition, I believe leaves of $Tree(\cdot)$ to be an interesting pointer. More precisely, distinguishability is defined with regard to $R(n)$ segments at leaf level, i.e. one may simply compare the cardinality of these sets, with a desired threshold value.

4.3.2.2 A Metric for Browse-ability

In the following, I will propose a metric applying the presented indicators and thereby realizing our *browse-ability* intuitions. Note, I distinguish between facets that are based on attributes and those based on relations.

Attribute-based Facets Hereafter, I define metrics for attribute-based facets, measuring their individual indicators and aggregating them, resulting in a final score. Furthermore, I will distinguish between metrics measuring effects on the value space, i.e. $V(n)$, and other metrics applying to the result set segmentation, i.e. $R(n)$. Given an attribute-based facet f, its cluster tree $Tree(f)$, N as a set, containing its nodes as well as r referring to its root, measures are as follows:

(i) **Measures for a *browse-able* Value Segmentation**

(a) Maximal Height[26]

A height function h, i.e. $h : N \mapsto \mathbb{N}_0$, with regard to a given node, say n, may be defined as the maximal distance from n to a leaf. Furthermore, in a top-down manner, a height score is calculated as: Given an inner node n, with $n_k = \sum_i |subtree_i(n)|$ as its associated size, its deviation from the maximal possible height is: $\rho_h^V = \frac{h(n)}{n_k} \in [0,1]$. However, the higher a node is located, with respect to a given root, the more important fluctuations are. Thus, I suggest a weight function, depending on $h(n)$, to be applied. Notice, this weight is only required to be a strictly monotonically decreasing function, e.g. $\omega(n) = \frac{c}{\log(|n|+\epsilon)} \in [0,1]$ with $k \geq 1$ and c as constant. In conclusion, a height score may be given by:

$$score_{\rho_h}^V(n) = \omega(n)\rho_h^V(n) \in [0,1] \tag{4.15}$$

(b) Cluster Tree should be height-balanced

Furthermore, I compute in a top-down manner a height balance score as follows: Given an inner node n with k subtrees $\{s_j\}_j$, each having a height h_j, the maximum height difference is: $\delta_h^V(n) = 1 - \frac{\max_t\{h_t\} - \min_t\{h_t\}}{h(n)} \in [0,1]$. A height balance score for node n, thus, may be written as:

[26] Note the node height to be approximated in my implementation.

$$score^V_{\delta_h}(n) = \omega(n)\delta^V_h(n) \in [0,1] \tag{4.16}$$

(c) Value Clusters $V(n)$ should be equal-sized

Concerning the size balance, a score is computed in the following manner: Given an inner node n having k subtrees $\{s_j\}_j$ associated, size differences may be estimated by: $\delta^V_s(n) = 1 - \frac{\max_j\{V(s_j)\} - \min_j\{V(s_j)\}}{V(n)} \in [0,1]$. Again, I argue that the higher n is located in a tree, the more important fluctuations are. Therefore, a final score for n is given by:

$$score^V_{\delta_s}(n) = \omega(n)\delta^V_s(n) \in [0,1] \tag{4.17}$$

(d) Limited Branching Factor of $Tree(f)$

Lastly, given an inner node n as well as a function e, mapping n to its outgoing edges, a deviation from a branching threshold, say κ, is: $\rho^V_e(n) = \frac{|\kappa - e(n)|}{e(n)} \in [0,1]$. Following the above thoughts, an edge deviation score is computed as:

$$score^V_{\rho_e}(n) = \omega(n)\rho^V_e(n) \in [0,1] \tag{4.18}$$

(ii) **Measures for a *browse-able* Result Set Segmentation**

(a) Value Clusters $R(n)$ should be equal-sized

A score, with regard to result cluster size deviations, may be computed similarly to the above defined $score^V_{\delta_s}$, as:

$$score^R_{\delta_s}(n) = \omega(n)\delta^R_s(n) \in [0,1] \tag{4.19}$$

where δ^R_s denotes the size deviation.

(b) Result Tuple distinguishability[27]

Concerning the distinguishability of tuples contained in a result space, a score may be calculated as: Given a node n, consider only its leaves, say $\{l_1, \ldots, l_m\}$. Also, let L, i.e. $L : N \mapsto L$ and $L \subseteq P(N)$, be a function mapping each node in N, to a set containing its reachable leaves. Furthermore, $\lambda^R(n) = \frac{\sum_{l \in L(n)} |R(l)| - 1}{\sum_{l \in L(n)} |R(l)|} \in [0,1]$ may be used to estimate the

[27] Note, due to performance reasons this score is approximated in my implementation.

distinguishability with regard to n. Again, I will use ω as defined above. In conclusion, a distinguishability-based score for node n is given by:

$$score^R_\lambda(n) = \omega(n)\lambda^R(n) \in [0,1] \tag{4.20}$$

(c) Minimum Result Segment Overlap

Lastly, I compute a score, measuring the overlap between a given pair of result segmentations as: Given a node n, let C, i.e. $C : N \mapsto C$ and $C \subseteq P(N)$, denote a function mapping each node in N to its directly associated children. Therefore, the overlap may be represented as $\varphi^R(n) = 1 - \frac{|\bigcap_{c_i \in C(n)} R(c_i)|}{|R(n)|} \in [0,1]$. Furthermore, a score is given by:

$$score^R_\varphi(n) = \omega(n)\varphi^R(n) \in [0,1] \tag{4.21}$$

(iii) **Final Score**

Let $F' : \mathbb{R} \mapsto [0,1]$ denote a strictly monotonic increasing function. Then, aggregating the before measured indicators, a final score for an attribute-based facet is defined as:

$$score_a(f) = F'(score^V_{\delta_h}(r), \ldots, score^R_\varphi(r)) \in [0,1] \tag{4.22}$$

Relation-based Facets In the paragraph above, I introduced a ranking metric for attribute-based facets. Hereafter, I intend to expand this definition, to also include facets based on relations. The ranking score of a relation-based facet, say f, with facet values $FV(f)$ associated, consists of two parts:

(i) Score, with respect to *attributes* connected to $FV(f)$. Each attribute score incorporates elements as follows:

- Browse-ability of $V(n)$.
- Browse-ability of associated result set segmentation $R(n)$.

(ii) Score, with respect to *nearby* browse-able entities, comprised by a set, say $FV'(f)$. In this latter case, one has as influencing factors:

- Distance from $FV(f)$ to $FV'(f)$.
- Browse-ability of $V'(n)$.
- Browse-ability of associated result set segmentation $R'(n)$.

Obviously, in order to avoid cycles and guarantee an algorithm to terminate, a distance threshold is necessary. First of all, however, find below both presented factors, outlined in more detail.

(i) **Score with respect to Attributes**

Given a set of m attributes, say $A = \{f_1^a, \ldots, f_m^a\}$, associated with resources contained in $FV(f)$, one may compute a score as described earlier for each facet contained in A. This results in $S_A = \{score_a(f_1^a), \ldots, score_a(f_m^a)\}$, i.e. a set of scores, which may be aggregated via F'', resulting in:

$$score_r^a(f) = F''(score_a(f_1^a), \ldots, score_a(f_m^a)) \in [0,1] \tag{4.23}$$

with F'' being a strictly monotonic increasing function. Please note, hereafter, I will refer to this score as *attribute-based* score.

(ii) **Score with respect to nearby *browse-able* Entities**

Recall, resources in $FV(f)$ may be connected via relations to further individuals, which in turn may or may not be suitable for browsing. Thus, I argue that one also needs to rank $FV(f)$, with respect to the *browse-ability* of its nearby entities. In conclusion, given a set of n relation-based facets, say $R = \{f_1^r, \ldots, f_n^r\}$, associated with $FV(f)$, a score may be recursively defined in a similar manner as introduced earlier.

(iii) **Final Score**

Lastly, with respect to its relations as well as its attributes, f may be assigned a total score given by:

$$score_r(f,k) = \begin{cases} \delta(k)\, score_r^a(f) & \text{if } k = k_{max} \\ \sum_{f' \in R} F'''(score_r(f', k+1), \delta(k+1)\, score_r^a(f')) & \text{otherwise} \end{cases} \tag{4.24}$$

with k as current hop-distance, k_{max} as maximum hop threshold, δ being a monotonic decreasing weight function and F''' as a strictly monotonic increasing function.

For clarification purposes, please see a toy example provided below.

✎ **Example 4.2.** After exploring the profile of *Frances E. Allen*, Mary continues her search for famous scientists. Unfortunately, she can't recall any further names, Peter mentioned the other day. Therefore, in her case, a discriminatory facet such as *name*, having e.g. values $\{Jane, Rachel, Peter\}$, should not be ranked high. More specifically, given such a value set, *name* is a unique identifier, thus leading to rapid result set modifications. In particular, *name* forces Mary to instantly decide what entity to choose, which in turn requires very specific knowledge. Plus, it does not provide the necessary freedom to properly explore the given result set. On the other hand, a facet such as *type* or *works at*, might prove more suitable. E.g. via *works at*, a cluster tree of greater height may be constructed. Thereby allowing Mary to iteratively chose a path along this tree, while exploring the space. On the other hand, *type* would result in smaller modifications of the current result, as several scientists may share a common value, e.g. *PhD-Student*. Thus, by means of *type*, Mary is able to slowly and iteratively familiarize herself with this unknown domain.

Concluding Remarks Below, please find concluding remarks, targeting at further aspects of our browse-ability-based ranking approach.

(i) Choosing a proper Aggregation Function

Note, the above defined aggregation functions, i.e. F^*, are only required to be strictly monotonic increasing. Obviously, there are several meaningful ways to implement F^*, consider e.g. $F^*(\cdot) = \max\{\cdot\}$, $F^* = \min\{\cdot\}$ or $F^*(\cdot) = \text{avg}\{\cdot\}$. Furthermore, as different functions have varying impacts on a *browse-ability* score, it might be wise to use an application-specific realization. However, in order to keep the metric as generic as possible, I left F^* defined in a fuzzy manner. Note, I currently implemented these aggregation functions as weighted summations.

(ii) Choosing a proper Weight & Discount Function

For the same reason, namely to define our *browse-ability* metric in a generic manner, I also left ω as well as the discount function δ open, to be implemented later on. Note, due to performance reasons, I realized the weight function simply as $\omega(n) = \frac{|R(n)|}{|R_{total}|}$ with $R_{total} = |V^{Res}|$. Furthermore, since I used a strict distance threshold $k_{max} = 1$, there was no need for a discount mechanism δ.

(iii) Integration of Property Hierarchies

Recall, a *subproperty-of* link between two given properties, say p_1 and p_2, indicates a subset relation, with respect to their domain as well as their range. Thus, given p_1 and p_2, their associated ranking scores are obviously correlated. However, as a simple workaround for this dilemma, I group properties and facets respectively, so that there is no *subproperty-of* connection between any facet pair, presented to users at the same level. Note, by grouping I mean a clustering strategy, making use of property hierarchies.

(iv) Facet Value Ranking

Lastly, the facet ranking strategy, as discussed above, is based on ranking nodes in a cluster tree. Thus, transferring the introduced indicators and measurements, to also cover facet values contained in $FV_*(\cdot)$, is fairly easy. Given an attribute-based facet, say f, and a facet value, say v, e.g. $score_a$ might be rewritten as:

$$score_a(v) = F'(score^V_{\delta_h}(n_v), \ldots, score^R_{\varphi}(n_v)) \in [0,1] \tag{4.25}$$

with n_v being the node in N, associated with v.

Section 5

Evaluation

5.1 Evaluation Setting

Since the overall intuition behind our faceted search application is, to enable a more effective way of *browsing* in an unknown resource space, I felt that a user-oriented evaluation with focus on fuzzily defined tasks would be best. Thus, for assessment of the novel ranking scheme, as well as the discussed facet value clustering approach, I chose a *task-based user study*.

User Tasks I divided the evaluation process in two steps: The first part covers the ranking strategy, while the latter one addresses our value clustering. Each part contained 12 tasks. Correspondingly, I formed two groups of participants. Each is associated with a set of 12 tasks, resulting in a total of 24 tasks.
With regard to the ranking mechanism, I presented six tasks to each user. In four of these tasks, a very fuzzy and unspecific information need was given to the subject, e.g.: *Starting with a keyword search for Karlsruhe. Find an entity having something to do with traveling.* For the remaining two tasks, I gave users a very broad exploration task, i.e. to find outlier, interesting or strange values. Consider as an example: *Start with keyword search Karlsruhe. Explore the given result set.* Note, for a complete list of tasks, please see table 2 (p. 108), provided in the appendix. Hereafter, the first type is referred to as ranking type (a), while the latter group of tasks may be denoted by type (b). Evaluation subjects were only allowed to use the five top-ranked facets during their assignments. Also, for tasks of type (a), one group was only presented a search-ability-based sorting, while the other one was given a ranking, based on our *browse-ability* approach. For assignments (b), on the other hand, subject groups were given two different sortings, i.e. one for each ranking scheme.

As for the second group of tasks, being concerned with facet value clustering, again a situation was simulated, where users faced imprecise and fuzzy information needs. There were two sets comprising six tasks each, therefore assigning twelve tasks in total. More precisely, in each set, two tasks were targeting literal clustering, while four other tasks correspond to our resource clustering strategy. To give the reader an idea of these tasks, please consider the following to two examples: (i) For the first group, i.e. the literal clustering tasks, one assignment was: *Start with keyword search for London. Find all artists (an artist is a person) born some time in November 1972*. Notice, in the following, this set is denoted by type (a). (ii) Concerning the clustering of resources, please consider as exemplary task: *Start with keyword search for Paris. Find all Things, having as genre a music genre, which has as instrument an electric guitar*. Hereafter, this set of tasks is referred to as type (b). Again, a complete list of tasks is provided in table 2 (p. 108). Further notice, for solving their assignments, evaluation subjects first used our system, having a clustering approach implemented, and afterwards, a baseline system, providing no clustering.

Evaluation Subjects In total, there were 24 subjects taking part in the evaluation. However, the reader should notice, our participants to have very heterogeneous backgrounds. In particular, six users had no experience with computer science technologies at all. Furthermore, of the remaining 18 subjects, 10 had no or only very little experience with Semantic Web technologies. On the other hand, all participants were familiar with search technologies common in the WWW.

Time-based Interaction Costs With regard to user effort, I argue that *refinement*, *expansion* and *browsing* interactions are crucial for the time needed to fulfill an information task. In the following, these operations are defined as intervals. To be more specific, browsing comprises operations, which users perform, in order to select a facet, navigate along a facet path or drill down into a given cluster tree. Accordingly, a browsing interaction is defined as a time interval, staring with the completion of a last browsing operation and terminating, as users move to the next node in the hierarchy or decide to abort browsing this particular facet. On average, I measured users to need 4.4 sec for a single interaction. On the other hand, I collected the time users required, to modify a given space. Note, this means adding a terminal node in a cluster tree, i.e. a facet value node, which restricts results to only

those, fulfilling the additional constraint, or removing one respectively. Accordingly, the time interval spans from the completion of a browsing operation, until users add such a node (refinement) or remove one (expansion). Here, I measured 8 sec in the former and 18 sec in latter case, on average.

System With respect to the system employed, I made use of the *Information Workbench*, providing means for a collaborate management of data and publicly accessible at http://iwb.fluidops.com/. The faceted search layer has been realized using Java Berkeley DB and Lucene, based on design patterns and index structures introduced in [BYGH+08, DRM+08]. More precisely, while the back-end, including the keyword and faceted search modules, was implemented in Java 6, the front-end uses Ajax technologies, running on a Jetty server. Experiments were carried out in a supervised manner, on a PC with a T7300 Intel CPU, 4 GB memory and a Microsoft Vista OS. The search process for each user and task was recorded via a screencast.

Data Concerning the data-source, I used *DBpedia*, which is covering a large amount of broad-ranging knowledge [BLK+09]. This enabled me to design evaluation tasks, not targeted at a specific field, but being rather domain-independent.

5.2 Browse-ability-based Ranking

5.2.1 Baseline for Ranking Evaluation

Search-ability-based Ranking As introduced in section 4.2 (p. 71), much of the recent work is devoted to search-ability-based ranking. Thus, I decided to compare our approach against this type of schema. However, I did not implement a particular strategy, but rather intended to use the abstract search-ability paradigm as a baseline. I developed a heuristic, reflecting this intuition on a higher-level, written as a monotonic aggregation function M with $M(h, \lambda^R, \varphi^R)$.[28] Correspondingly, M targets at reducing users costs, in particular, the amount of interactions necessary to fulfill an information need. More precisely, the tree height, say h, is minimized and thereby user decisions required are being reduced. Furthermore, facets should be discriminative. Thus, I prefer those facets, leading to results with

[28] Note that currently M is simply realized as a weighted summation.

high distinguishability score as well as few result segment overlaps, given by λ^R and φ^R respectively.

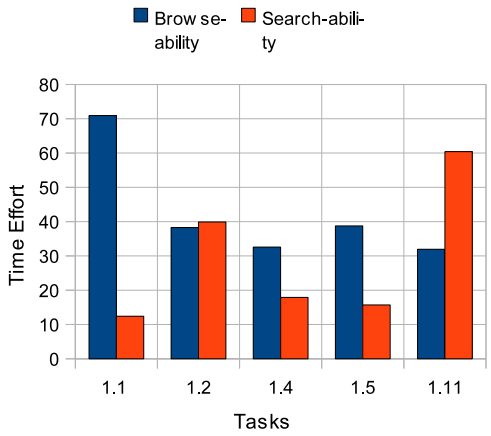
5.2.2 Ranking Effectiveness

Regarding effectiveness of search-ability versus browse-ability ranking, I compared the average success rate of tasks of type (a), as well as the average browsing experience, for tasks of type (b). Results are provided in figure 21(c) (p. 95) as well as 21(c) (p. 95) to the reader. Here, I observed, given search-ability-based ranking, participants succeeded in tasks, where small result sets, i.e. less than 50 items, had to be explored. To be more specific, on the one hand, users selected facets for browsing and refinement in a brute-force manner (cf. tasks 1.1, 1.4, 1.5, 1.11). On the other hand, some participants had specific background knowledge (cf. task 1.2), enabling them to solve their tasks. However, if a keyword search resulted in larger sets, i.e. more than 150 hits, I noticed participants not being able to accomplish their tasks (see tasks 1.7, 1.8, 1.10). Browse-ability ranking outperforms the baseline, with regard to all assignments, particularly, given large sets for exploration. Furthermore, I noticed participants to prefer non-discriminating or unspecific facets, e.g. *type* or *genre*, over specific ones, e.g. *population* or *name*. In many cases, I noted subjects using *type* for an initial restriction, followed by further exploration via other facets. Concerning the second type of assignments, i.e. a exploration a given space, browse-ability-based ranking also performs very well. Please consider figure 21(c) (p. 95). Overall, exploration using our novel scheme was rated by participants between 4 and 4.5, given a scale [1–5]. Facets sorted with regard to search-ability ranking, on the other hand, were regarded as not suitable for exploration purposes. This setting was rated between 2 and 2.7. I explain this result with users not being able to explore or understanding a result set, by means of specific and discriminative facets.

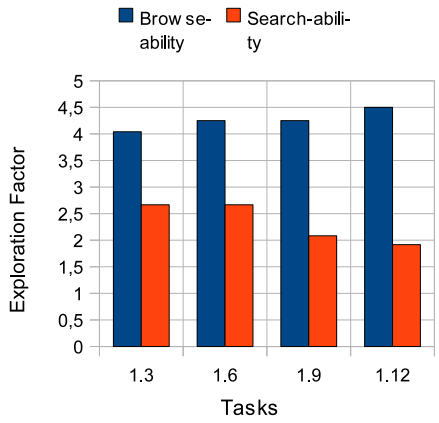
5.2.3 Ranking Efficiency

Please see figure 21(a) (p. 95) for the average users costs, measured with regard to a time effort, users needed to fulfill their tasks. Similar to the effectiveness study, I observed the number of results to be a crucial factor, with respect to the problem solving strategies applied: On the one hand, given a small result set (less than 50 hits) to browse as well as a search-ability-based heuristic, participants tend to fulfill

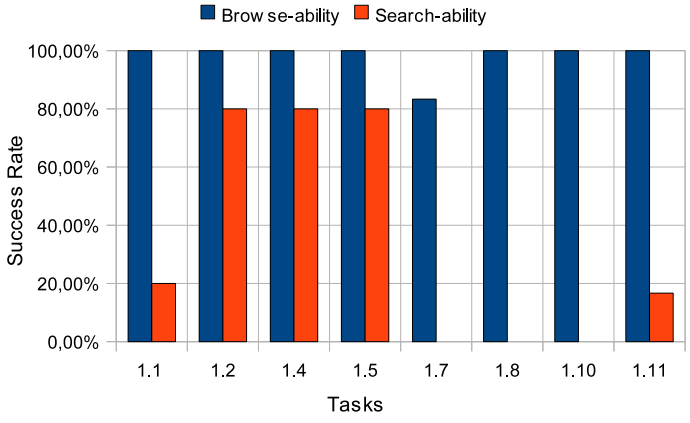
their assignments with equal or less effort on average, as compared to our approach (cf. tasks 1.1, 1.2, 1.4, 1.5). More specifically, users were able to efficiently choose paths in a provided cluster tree and refine a space, using a goal-oriented manner, leading to less associated costs. When having larger result sets (more than 150 hits) provided, on the other hand, more time and effort was necessary or participants were not able to solve their assignments at all (see tasks 1.11, 1.7, 1.8 or 1.10). Note that task 1.11 was not completed by all users, however, if fulfilled, subjects made use of a brute-force-like approach, in order to cover all paths. Therefore, I conclude that while not necessarily leading the cheapest way to an item of interest, our approach seems to perform well, given large spaces combined with fuzzy needs.



(a) Average effort (type a)



(b) Average exploration (type b)



(c) Average success rate (type a)

Figure 21: Efficiency & Effectiveness Results w.r.t. Ranking Schema

5.2.4 Ranking Usability

Lastly, I intended to estimate the general usability of our ranking technique. In this context, please recall the evaluation subjects to have a fairly heterogeneous background. After completing their assignments and having worked with both approaches, each subject was asked how *useful* the browse-ability-based strategy has proven itself as well as how *intuitive* a sorting has been. See also the complete questionnaire, provided to the reader in table 3 (p. 110). Given a scale [1–5], ratings were quite good, namely for the former question a 4.31 and for the latter one a 4.17, on average.

5.3 Facet Value Construction

5.3.1 Baseline for Clustering Evaluation

With respect to the evaluation of the clustering technique, producing a hierarchical facet value structure, finding a fitting baseline was non-trivial. Note, I'm not aware of any faceted search system, be it in the commercial or in the academic field, using clustering as means to partition a facet range. Thus, I decided to use a traditional approach, i.e. a system employing no clustering for either literals or resources. However, notice the chosen system to work on a similar data-source, i.e. *DBepdia*. Also, it is publicly available at http://dbpedia.neofonie.de.

5.3.2 Clustering Effectiveness

Concerning literal clustering, I observed that, given a specific information need, there is not much of a difference between our system and the baseline (cf. task 2.7, figure 22(b), p. 98). However, the more fuzzy information needs are, the more I noticed users to depend on clustering being provided, in order to solve their assignments (see tasks 2.1, 2.4, 2.10). Please consider task 2.10, where a fuzzy need is given. Without clustering enabled, I observed some users to be not willing to fulfill this assignment, because of the extra effort needed, while other subjects seemed not to be aware of ways to complete it. If clustering was given, on the other hand, participants achieved overall a high success rate (cf. figure 22(b), p. 98). I explain these results with our clustering techniques enabling participants to articulate fuzzy needs in a fairly easy manner. Subjects seemed to handle drill down operations as a mean for

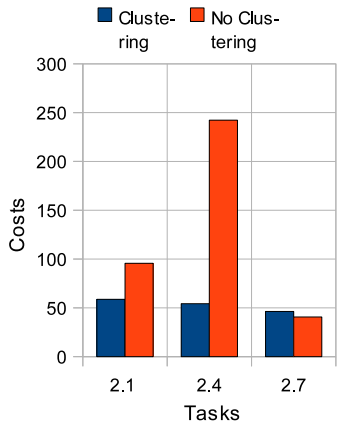
slowly specifying knowledge well.

With respect to resource partitioning, users did not manage to complete their tasks using the baseline system (cf. figure 22(c), p. 98). Again, a number of participants did notice and outline possibilities of solving their assignments, but also realized the substantial time required and balked the effort. On the other hand, having means of value partitioning provided, a success rate of over 67 percent was achieved (cf. figure 22(c), p. 98). These results are very promising, as all tasks involve high-level information needs that can only be satisfied by means of complex, more-hop *queries*. To be more specific, participants solved assignments via iterative construction of facet paths. I explain these accomplishments with faceted search being a well-known and well-accepted paradigm. Many users seemed to very intuitively choose the correct path.

5.3.3 Clustering Efficiency

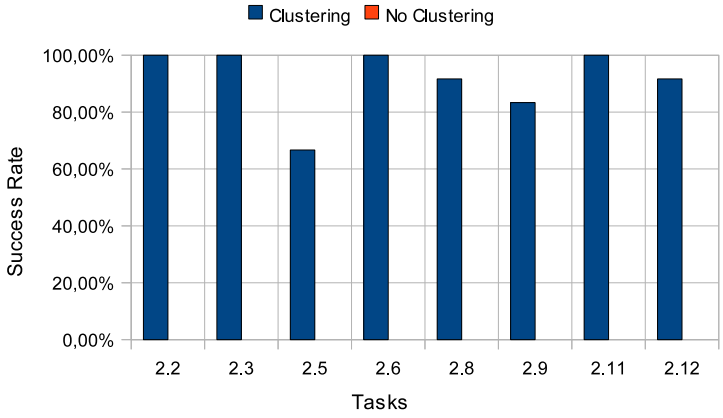
Given this context, I again distinguish between clustering of literals and clustering of resources. In the former case, I observed that, if participants managed to fulfill their assignments, they made use of a brute-force-like strategy, in order to explore the entire result space. Obviously, such a strategy is very expensive in terms of user effort, as it requires more system interaction (cf. tasks 2.1, 2.4, figure 22(b), p. 98). On the other hand, given tasks involving a specific information need, I noted many participants to use *query searching* as a strategy to fulfill their assignment. This resulted in both strategies having an equal performance, with regard to user effort. As a matter of fact, our approach tends to be slightly more expensive, as sometimes more browsing interactions were necessary (cf. task 2.7).

Concerning the latter case, i.e. the clustering of resources, I already outlined above that during the evaluation no participant succeeded using the baseline system (cf. figure 22(c), p. 98). However, it is important for the reader to notice that trivial tasks, requiring only a simple, one-hop restriction of values in FV (e.g. constraining entities via *name*), may have been easily completed in both systems. Actually, I expect that *browsing* strategies would have led to higher users costs, when compared with *query searching*.



(a) Average user costs (type a & b)

(b) Average success rate (type a)



(c) Average success rate (type b)

Figure 22: Efficiency & Effectiveness w.r.t. Clustering

5.3.4 Cluster Usability

Especially in combination with high-level information needs, usability is an important issue. Thus, after completing their assignments, users were given a set of questions, targeting at usability aspects of the clustering technique. For details, please see table 3 (p. 110). In particular, users were asked to rate how *useful* and how *intuitive* the clustering has been. Note, results achieved were quite good. More precisely, concerning the former question, users judged the clustering strategy to be a 4.5 and, with respect to the latter one, a 3.8 (given a scale [1–5]). Asking the same for resource clustering, users again seemed quite satisfied, rating the usefulness a 4.6 and the intuitiveness a 4.2.

Section 6

Conclusion

Concluding Remarks The web of data nowadays offers a vast amount of information, allowing complex and high-level user needs. However, in order to issue such needs, one is required to employ a specific query language as well as to possess precise knowledge about the underlying domain and an item of interest. Faceted search, on the other hand, as a newly emerging paradigm, offers ways for users to iteratively issue their queries, without having to use a given language. Thus, enabling users to *browse* an unfamiliar space, without having prior knowledge of its schema or syntax. State of the art faceted search approaches, however, focus rather on supporting *query searching* than *browsing* strategies. As a result, current systems do not enable exploration and thus seem not suitable for high-level information needs, given a certain *fuzziness*, with regard to user knowledge.

Addressing this weakness, I presented in section 3 (p.36) techniques for clustering of resources and literals, resulting in more *browse-able* facet values, which explicitly support fuzzy user information needs. Continuing in section 4 (p. 70), a novel ranking scheme, targeting at support of exploration of an unknown resource space, was introduced. This *browse-ability*-based ranking is designed to prefer such facets, which guide users in small and non-discriminatory steps to their item of interest, while resulting in observable and comprehensible result set modifications. Lastly, in section 5 (p. 91), by means of a task-based user study, involving 24 participant as well as 24 tasks, I evaluated these approaches. The results seem very promising, as they clearly indicate that these techniques outperform state of the art systems, given users with *vague* information needs. On the other hand, I noticed that participants having specific knowledge, were able to fulfill their assignments with less effort using traditional systems, i.e. approaches addressing *search-ability*. Therefore, I conclude that while not necessarily leading the cheapest way to an item of interest,

browse-ability-based strategies enable users to explore and search more *effectively*.

Future Work Concerning our future work, I wish to target a tightly integrated approach using both paradigms, i.e. *search-ability* as well as *browse-ability*. Clearly, depending on user background knowledge and specificity of an information need, the former or latter strategy, may be more or less suitable. Furthermore, the runtime performance was currently not addressed properly, leading to high I/O during a search phase. Thus, a more efficient index structure, supporting common operations, like facet *browsing*, *refinement* or *expansion* is needed. The reader should be aware that state of the art structures[29], are not applicable in our context, as they do not scale well, with regard to our fine-grained facet and facet value definition (see section 2, p. 17). A novel index design, adressing both, i.e. space complexity and time complexity, is necessary.

[29] Consider e.g. http://lucene.apache.org/solr/, a Lucene-based faceted search system, revised Dec. 2009.

Appendix

RDF Properties

Name	Domain	Range
rdf:type	rdfs:Resource	rdfs:Class
rdfs:isDefinedBy	rdfs:Resource	rdfs:Resource
rdf:value	rdfs:Resource	rdfs:Resource
rdfs:label	rdfs:Resource	rdfs:Literal
rdfs:comment	rdfs:Resource	rdfs:Literal
rdfs:member	rdfs:Resource	rdfs:Resource
rdfs:seeAlso	rdfs:Resource	rdfs:Resource

Table 1: Relevant predefined Properties in RDF(S) language

XML Schema built-in Datatypes

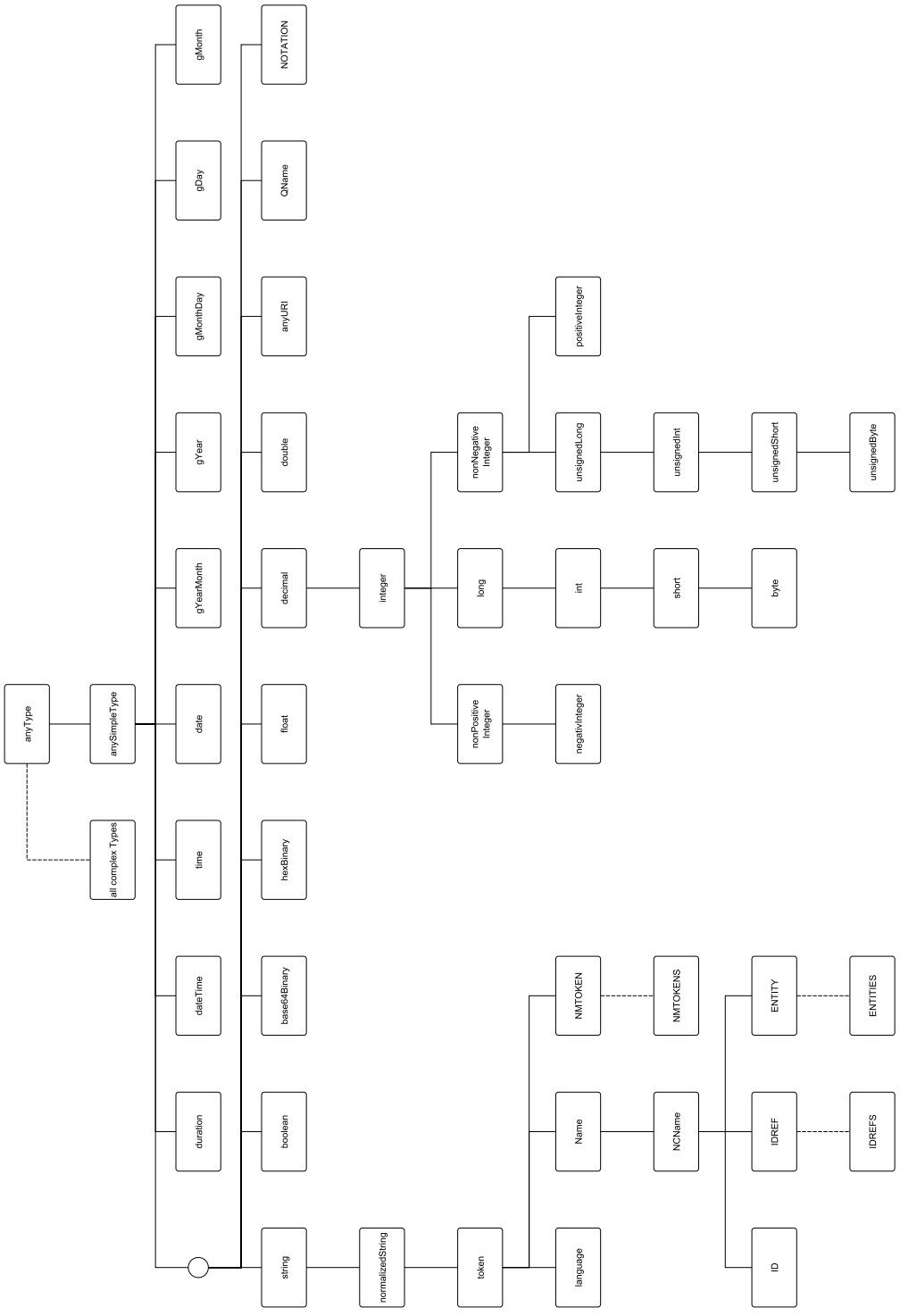


Figure 23: XML Schema built-in Datatypes (based on [BM04])

Pseudocode for Literal Clustering

Algorithm 2 Pseudocode for Literal Clustering

Require: $\hat{k} \leftarrow$ branching factor

Require: $L \leftarrow \{l_i\}_{1 \leq i \leq k}$ *//L is assigned all literals within this range*

$Q \leftarrow \varnothing$ *//Initialize sets.*

$C \leftarrow \varnothing$

$L \leftarrow \varnothing$

$L \leftarrow sort(L)$ *//L is sorted with respect to* $\overset{L}{\leq}$

for all $l_i, l_{i+1} \in \tilde{L}$ **do**

  $d_{current} \leftarrow dissimilarity(l_i, l_{i+1})$

  $Q \leftarrow Q \cup \{d_{current}\}$

end for

$Q \leftarrow sort(Q)$ *//Q is sorted*

$C \leftarrow C \cup \{L\}$ *//Begin clustering. Top-level cluster is added first.*

repeat

  $i \leftarrow 1$

  while $i \leq \hat{k}$ **do**

    $d_{max} \leftarrow pop(Q)$ *//Obtain and remove maximum distance from Q.*

    $c_{current} \leftarrow cluster(d_{max})$ *//Get cluster with maximum distance.*

    $C \leftarrow C \setminus c_{current}$

    $(c_1, c_2) \leftarrow split(c_{current}, d_{max})$ *//Split* $c_{current}$ *at position* d_{max}*.*

    $C \leftarrow C \cup c_1 \cup c_2$

    $i \leftarrow i + 1$

  end while

until $(Q = \varnothing) \vee$ (no drill-down is performed)

Generic Cluster Tree Example

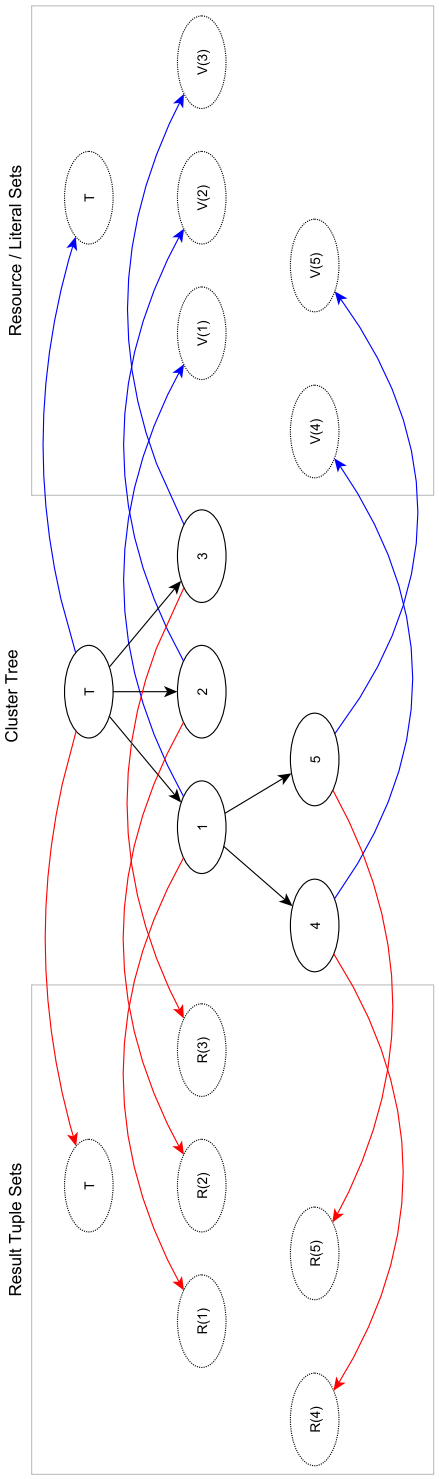


Figure 24: Generic Cluster Tree Example

Evaluation

Evaluation Tasks

Evaluation of ...	Task No.	Task Description
Ranking (A)	1.1	*Start with keyword search Karlsruhe. Find something (prefer top ranked facets), where people live and doesn't fit in.*
	1.2	*Start with keyword search Karlsruhe. Explore (prefer top ranked facets) the given result set: Find an item that got something to do with traveling.*
	1.3	*Start with keyword search Karlsruhe. Explore (using only the top five facets) the given result set.*
	1.4	*Start with keyword search Heidelberg. Find something (prefer top ranked facets), having to do with sports and that doesn't fit in.*
	1.5	*Start with keyword search Heidelberg. Explore (prefer top ranked facets) the given result set: Find an item that's got something to do with music.*
	1.6	*Start with keyword search Heidelberg. Explore (using only the top five facets) the given result set.*
Clustering (A)	2.1	*Start with keyword search for Paris. Find all places, having names starting with 'Paris, I ...', 'Paris, J ...' or 'Paris, K ...'. Of those places, which one is the smallest (population wise]?*

Table continued on next page ...

Table 2 - Continued

Evaluation of ...	Task No.	Task Description
	2.2	*Start with keyword search for Paris. Find all things, having as genre a music genre, which has as instrument an electric guitar.*
	2.3	*Start with keyword search for Paris. Find all works, having an actor as writer.*
	2.4	*Start with keyword search for London. Find all artists (an artist is a person), born some time in November 1972. Also, find out in which area(s) those people were born.*
	2.5	*Start with keyword search for London. Find all works, having as subsequent work a television show (episode).*
	2.6	*Start with keyword search for London. Find all works, having an artist born 1926.*
Ranking (B)	1.1	*Start with keyword search Barcelona. Find an educational institution (prefer top ranked facets) not quite fitting in.*
	1.2	*Start with keyword search Barcelona. Find an international jazz-band drummer (prefer top ranked facets), who played together with Louis Armstrong.*
	1.3	*Start with keyword search Barcelona. Explore (using only the top five facets) the given result set.*
	1.4	*Start with keyword search Seattle. Find a hospital for minors (prefer top ranked facets).*

Table continued on next page ...

Table 2 - Continued

Evaluation of ...	Task No.	Task Description
	1.5	*Start with keyword search Seattle. Find an international Airport (prefer top ranked facets).*
	1.6	*Start with keyword search Seattle. Explore (using only the top five facets) the given result set.*
Clustering (B)	2.1	*Start with keyword search for Berlin. Find the orchestra 'Berliner Philharmoniker'.*
	2.2	*Start with keyword search for Berlin. Find a work, having as producer someone who is also a musical artist.*
	2.3	*Start with keyword search for Berlin. Find a work, having as artist a band (a band is an organization), which has their hometown located in Japan.*
	2.4	*Start with keyword search for Hamburg. Find all places, having a name starting with 'K', 'L', 'M', 'N' or 'U'. Which of the above places is not located in Germany?*
	2.5	*Start with keyword search for Hamburg. Find all works, having as artist a solo-artist. Select the latest of the above works.*
	2.6	*Start with keyword search for Hamburg. Find some building, owned by an organization, founded in the early 20th century.*

Table 2: User Tasks for Evaluation

Evaluation Questionnaire

No.	Question
1	*Reconsider task 1.1/1.2/1.4/1.5. How helpful was the facet ranking for completing this task?* ❒ Very Helpful. ❒ Pretty Helpful. ❒ Sometimes Helpful. ❒ In most cases not helpful. ❒ Not helpful at all.
2	*Reconsider task 1.1/1.2/1.4/1.5. Did you have any previous knowledge about the item of interest?* I had no previous knowledge. Tasks: ____ I had some knowledge. Tasks: ____ I had full knowledge. Tasks: ____
3	*Reconsider task 1.3/1.6 . In your opinion, how well did you explore the given result set (scale [1–5])?* a.) Using the browse-ability ranking: ____ b.) Using the search-ability ranking: ____
4	*With respect to exploration as our goal, how intuitive was the browse-ability-based facet ranking?* ❒ Very intuitive. ❒ Understandable. ❒ Fairly intuitive. ❒ Sometimes unclear. ❒ Not intuitive at all.
5	*Reconsider task 2.1/2.4. How intuitive was the literal clustering?* ❒ Very intuitive. ❒ Understandable. ❒ Fairly intuitive. ❒ Sometimes unclear. ❒ Not intuitive at all.
6	*Reconsider task 2.1/2.4. How helpful was the literal clustering for completing the tasks?* ❒ Very intuitive. ❒ Understandable. ❒ Fairly intuitive. ❒ Sometimes unclear. ❒ Not intuitive at all.

Table continued on next page . . .

Table 3 - Continued

No.	Question
7	*Reconsider task 2.2/2.3/2.5/2.6. How intuitive was the resource clustering?* ❒ Very intuitive. ❒ Understandable. ❒ Fairly intuitive. ❒ Sometimes unclear. ❒ Not intuitive at all.
8	*Reconsider task 2.2/2.3/2.5/2.6. How helpful was the resource clustering for completing the tasks?* ❒ Very intuitive. ❒ Understandable. ❒ Fairly intuitive. ❒ Sometimes unclear. ❒ Not intuitive at all.
9	*How would you describe the search experience in comparison with classical information search systems (like Google or Wikipedia)?* ❒ I liked the new features a lot. ❒ The new features were interesting. ❒ The new features were interesting, but a little confusing. ❒ The new features made searching harder.
10	*Would you use the system again?* ❒ Yes, definitely. ❒ Maybe. ❒ Not very likely. ❒ No, definitely not.
11	*Did you have any other problems while using the system? What did you like? What did you not like?* Comments: _____

Table 3: Questionnaire for Evaluation

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