Facetedpedia: Automatic and Dynamic Discovery of Query-Dependent Faceted Interfaces for Wikipedia

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ABSTRACT

We propose Facetedpedia, a faceted retrieval system for information discovery and exploration in Wikipedia. Given the set of Wikipedia articles resulting from a keyword query, Facetedpedia discovers a faceted interface for navigating the articles. To the best of our knowledge, Facetedpedia is the first such system for Wikipedia. Compared with other faceted retrieval systems, Facetedpedia is fully automatic and dynamic in both facets discovery and hierarchy construction, and the facets are based on rich semantic information. The essence of our approach is to build upon the collaborative vocabulary in Wikipedia, more specifically the intensive internal hyperlinks and folksonomy (category system). Given the sheer size and complexity of Wikipedia, the space of possible choices of faceted interfaces is prohibitively large. We propose metrics for ranking individual facet hierarchies by users' navigational costs, and metrics for ranking interfaces (each with k facets) by both their average pairwise similarities and average navigational costs. We thus develop faceted interface discovery algorithms that optimize the ranking metrics. Our experimental evaluation and user study verify the effectiveness of the system.

1. INTRODUCTION

Wikipedia has become the largest encyclopedia ever created, with 2.6 million English articles by far. It is one of the 10 most popular Websites by user traffic. The prevalent manner in which the Web users access Wikipedia articles is keyword search, through either general search engines or its own search interface. Although keyword search has been quite effective in finding specific Web pages matching the keywords, we often encounter more sophisticated information discovery and exploratory tasks that call for complementary access apparatus. Such tasks become typical on Wikipedia, as we often want to explore "entities" that fascinate us. Given an information exploratory task, with only keyword search, one would have to digest the list of search result articles, follow hyperlinks to connected articles, adjust the query and perform multiple searches, and synthesize information manually. This procedure is often time-consuming and error-prone.

One access mechanism that is potentially useful is the *faceted interface*, or the so-called *hierarchical faceted categories* (HFC) [9]. A faceted interface for a set of objects is a set of category hierarchies, where each hierarchy corresponds to an individual *facet* (dimension, attribute, property) of the objects. The user can navigate an individual facet through its hierarchy of categories and ultimately a specific "property" value if necessary, thus reaching those objects associated with the categories and the value on that facet. The user navigates multiple facets and the intersection of the chosen objects on individual facets are brought to the user's attention. The procedure therefore analogously corresponds to repeated constructions of conjunctive queries with selection conditions on multiple dimensions.

1.1 Motivations

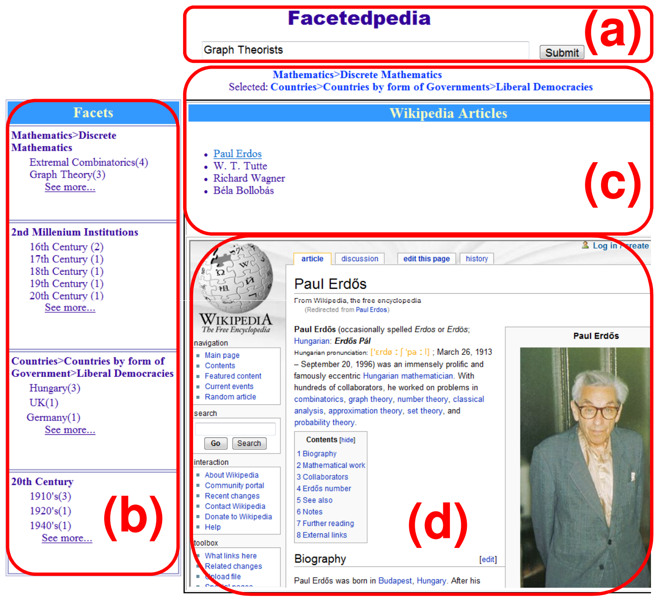
In this paper we propose Facetedpedia, a faceted retrieval system over Wikipedia. To illustrate its promise, we give below a motivating example.

Example 1 (Motivating Example): Imagine that a graduate student, Amy, doing her PhD in Theoretical Computer Science, is exploring information about renowned graph theoreticians. Impressed by the rich content and popularity of Wikipedia, she decides to explore its relevant articles. The current tools available for this kind of exploration are search engines where she can issue a keyword query like "Graph Theorists". With a flat list of search results, Amy may have to exhaustively look through many articles in order to find what she needs.

In contrast, a faceted interface where multiple facets are automatically and dynamically derived to cover the result articles will show a multi-dimensional view of the search results, which would be more helpful than a simple flat list. For example, related to "Graph Theorists", these dimensions can include *Field*, *Country*, *Institution*, *Year of Birth*, and so on. Each facet is associated with a hierarchy of categories. Given the facet hierarchies, each article can be assigned to the nodes in these hierarchies, with each assignment representing an attribute value of the article. Thus the Wikipedia article on graph theoretician Paul Erdös might be described by the following attribute values, which are all real Wikipedia categories. [1] For example, the third line above is a path of categories related to educational institution. The path indicates that Paul Erdös has a relationship with Princeton University, which is in New Jersey, and so on.

- Mathematics> Discrete Mathematics> Graph Theory> Graph Theorists
- Countries> Countries by Form of Government> Liberal Democracies> Hungary
- Universities and Colleges by State> New Jersey> Princeton University
- 20th Century> 1910's> 1913

[1] A Wikipedia article may belong to one or more categories. These categories are listed at the bottom of the article.



Facetedpedia

Graph Theorists

Submit

(a)

Mathematics>Discrete Mathematics
Selected: Countries>Countries by form of Governments>Liberal Democracies

Facets

Mathematics>Discrete Mathematics
- Extremal Combinatorics(4)
- Graph Theory(3)
- See more...

2nd Millenium Institutions
- 16th Century (2)
- 17th Century (1)
- 18th Century (1)
- 19th Century (1)
- 20th Century (1)
- See more...

Countries>Countries by form of Government>Liberal Democracies
- Hungary(3)
- UK(1)
- Germany(1)
- See more...

20th Century
- 1910's(3)
- 1920's(1)
- 1940's(1)
- See more...

(b)

Wikipedia Articles

- Paul Erdos
- W. T. Tutte
- Richard Wagner
- Béla Bollobás

(c)

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Paul Erdős

From Wikipedia, the free encyclopedia
(Redirected from Paul Erdos)

Paul Erdős (occasionally spelled *Erdos* or *Erdös*; Hungarian: ***Erdős Pál*** Hungarian pronunciation: [ˈɛrdø ː ʃ ˈpa ː l] ; March 26, 1913 – September 20, 1996) was an immensely prolific and famously eccentric Hungarian mathematician. With hundreds of collaborators, he worked on problems in combinatorics, graph theory, number theory, classical analysis, approximation theory, set theory, and probability theory.

Contents [hide]
1 Biography
2 Mathematical work
3 Collaborators
4 Erdős number
5 See also
6 Notes
7 Further reading
8 External links

Biography [edit]

Paul Erdős was born in Budapest, Hungary. After his

Paul Erdős

WIKIPEDIA
The Free Encyclopedia

navigation
- Main page
- Contents
- Featured content
- Current events
- Random article

search

Go | Search

interaction
- About Wikipedia
- Community portal
- Recent changes
- Contact Wikipedia
- Donate to Wikipedia
- Help

toolbox
- What links here
- Related changes
- Upload file

(d)

Figure 1: The faceted retrieval interface.

The interface of Facetedpedia is shown in Figure 1. The system takes a keyword query from Amy as the input (region (a)) and obtains a ranked list of search result articles. The system generates k facets (region (b)) for the top s articles in the ranked list. Amy can navigate through multiple facets to explore the result articles. On each facet, Amy can navigate through the category path which is formed by parent-children relationships of Wikipedia categories. The interface also shows the navigation path and article titles in (region (c)). When Amy clicks one article title, the corresponding Wikipedia article would be shown in (region (d)). ■

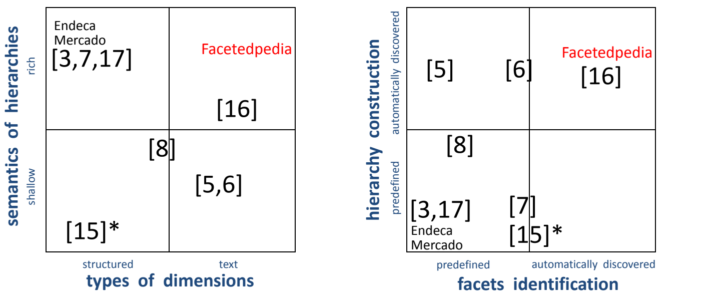
1.2 Overview of Challenges and Solutions

We focus on the problem of *automatic* and *dynamic* discovery of *query-dependent* faceted interfaces. Given the set of top-s ranked Wikipedia articles as the result of a keyword query, Facetedpedia produces an interface of multiple facets for user exploration.

The facets here cannot be pre-computed due to the query-dependent nature of the system. In applications where faceted interfaces are deployed for relational tuples or schema-available objects, the tuples/objects are captured by prescribed schemata with clearly defined dimensions (attributes), therefore a query-independent static faceted interface (either manually or automatically generated) may suffice. By contrast, the articles in Wikipedia are lacking such predetermined dimensions that could fit all possible dynamic query results. Therefore efforts on static facets would be futile. Even if the facets can be pre-computed for some popular queries, say, based on query logs, the computation must be automatic and dynamic. Given the sheer size and complexity of Wikipedia and its rapid growth, a manual approach would be prohibitively time-consuming and cannot scale to stay up-to-date. The main challenges in realizing Facetedpedia are summarized as below:

Challenge 1: The facets and their category hierarchies are not readily available.

The concept of faceted interface is built upon two pillars: facets (i.e., dimensions or attributes) and the category hierarchy associated with each facet. The definition of "facet" itself for Wikipedia does not arise automatically, leaving alone the discovery of a faceted interface. Therefore we must deal with two tasks: (1) *facets identification*– What are the facets of a Wikipedia article?; and (2) *hierarchy construction*– Where does the category hierarchy of a facet come from?



(a) Facet types and semantics. (b) Degree of automation and dynamism.

* The work does not support hierarchy on facets.

Figure 2: Taxonomies of faceted retrieval systems.

Challenge 2: We need metrics for measuring the "goodness" of facets both individually and collectively.

Not all facets retrieved above may be useful, thus we need to find the "good" facets which is most helpful for user navigation. A goodness metric for ranking facet is needed. The problem gets even more complicated because the utilities of multiple facets do not necessarily build up linearly on single ones: since the facets in an interface should ideally describe diverse aspects of the result articles, a set of individually "good" facets may not be "good" collectively.

Challenge 3: We must design efficient faceted interface discovery algorithms based on the ranking criteria.

It is infeasible to directly apply the above ranking metric exhaustively on all possible choices, due to the prohibitively large search space. The search space needs to be reduced. Furthermore, the interactions between the facets in a faceted interface make the computation of its exact cost intractable. Even computing the costs of individual facets without considering the interactions is non-trivial, given the size and the complexity of Wikipedia.

1.3 Summary of Contributions and Outline

- **Concept: Faceted Wikipedia.** We propose an automatic and dynamic faceted retrieval system for Wikipedia. To the best of our knowledge, this is the first system of its kind. The key philosophy of our approach is to exploit collaborative vocabulary as the backbone of faceted interfaces. (Section 3)
- **Metrics: Facets Ranking**. Based on a user navigation model, we propose metrics for measuring the "goodness" of facets, both individually and collectively. (Section 4)
- **Algorithms: Faceted Interface Discovery**. We develop effective and efficient algorithms for discovering faceted interfaces in the large search space. (Section 5)
- **System Evaluation: Facetedpedia**. We conducted user study to evaluate the effectiveness of the system and to compare with alternative approaches. We also measured its quality and efficiency quantitatively. (Section 6)

2. FACETED RETRIEVAL SYSTEMS: A COMPARATIVE STUDY

Faceted interface has become influential over the last few years and we have seen an explosive growth of interests in its application [11, 17, 9, 17, 9, 16, 6, 5, 14, 15, 8, 7, 3]. Commercial faceted search systems have been adopted by vendors (such as Endeca, IBM, and Mercado), as well as several E-commerce Websites (e.g., eBay.com, Amazon.com). The utility of faceted interfaces is investigated in various studies [11, 9, 12, 17, 10, 12, 13, 9], where it has been shown users engaged in exploratory tasks often prefer such result groupings over simple ranked result-lists (commonly provided by search engines), as well as over competing ideas that also organize retrieval results, such as clustering and classification [4, 18, 10].

In this section we present taxonomies to characterize the relevant faceted retrieval systems and compare them with Facetedpedia. Existing research prototypes or commercial faceted retrieval systems mostly cannot be applied to meet our goals, because they either are based on manual or static facets construction, or are for structured records or text collections with prescribed metadata. Many of them in fact focus on user-interface issues or applications. Very few have investigated the problem of automatic and dynamic faceted interface discovery and none has provided faceted interface over Wikipedia. (CompleteSearch [2] supports query completions and query refinement in Wikipedia by a special type of "facets" on three dimensions: query completions matching the query terms; category names matching the query terms; and categories of result articles. Clearly these facets are different from the notion of facets as dimensions or attributes, which is our focus.)

Figure 2(a): Taxonomy by Facet Types and Semantics

Previous systems roughly belong to two groups on this aspect. In some systems the facets are on relational data (e.g., Endeca, Mercado, [15]) or structured attributes in schemata (e.g., [17, 7, 3]) and the hierarchies on attribute values are predefined based on domain-specific taxonomies. The hierarchies could even be manually created, thus could contain rich semantic information. In some other systems a facet is a group of textual terms, over which the hierarchy is built upon thesaurus-based IS-A relationships (e.g., [16]) or frequency-based subsumption relationships between general and specific terms (e.g., [6, 5]). These systems cannot leverage as much semantic information. The work [8] is in the middle of Figure 2(a) since it has both structured dimensions and a subsumption-based topic taxonomy.

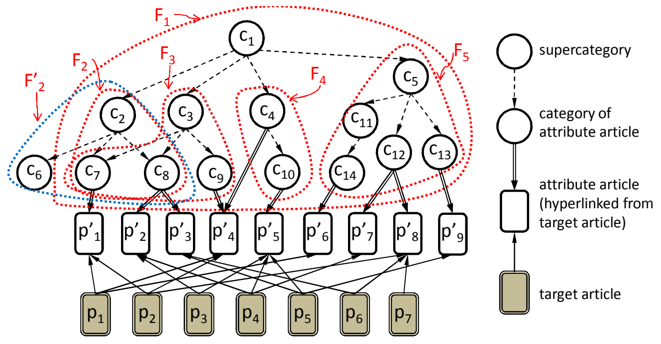
In contrast, Facetedpedia enables semantic-rich facet hierarchies (distilled from Wikipedia category system) over text attributes (hyperlinked Wikipedia article titles). In the absence of predefined schemata, it builds facet hierarchies with abundant semantic information from the collaborative vocabulary, instead of relying on IS-A or subsumption relationships.

Figure 2(b): Taxonomy by Degree of Automation and Dynamism

When building the two pillars in a faceted interface, namely the facet and the hierarchy, Facetedpedia is both automatic and dynamic, as motivated in Section 1.2. On this aspect, none of the existing systems could be effectively applied in place of Facetedpedia, because none is fully automatic in both facets identification and hierarchy construction.

In some systems (e.g., Endeca, Mercado, [15, 3, 17, 7]) the dimensions and hierarchies are predefined, therefore they do not discover the facets or construct the hierarchy. ([15] does not provide category hierarchies on attributes.) In [7, 15] a subset of interesting/important facets are automatically selected from the predefined ones. In [6, 5] the set of facets are predefined, but the hierarchies are automatically created based on subsumption. [6] also selects the most important portion of the hierarchy for displaying in an limited space. In Diederich et al. [8] only one special facet (a topic taxonomy) is automatically generated and the rest are predefined.

With respect to the automation of faceted interface discovery, the closest work to ours is the Castanet algorithm [16]. The algorithm is intended for short textual descriptions with limited vocabularies in a specific domain. It automatically creates facets from a collection of items (e.g., recipes). The hierarchies for the multiple facets are obtained by first generating a single taxonomy of terms by IS-A relationships and then removing the root from the taxonomy.



F_1
F_2
F'_2
F_3
F_4
F_5
c_1 c_2 c_3 c_4 c_5 c_6 c_7 c_8 c_9 c_{10} c_{11} c_{12} c_{13} c_{14}
p'_1 p'_2 p'_3 p'_4 p'_5 p'_6 p'_7 p'_8 p'_9
p_1 p_2 p_3 p_4 p_5 p_6 p_7
supercategory
category of attribute article
attribute article (hyperlinked from target article)
target article

Figure 3: The concept of facet.

3. FACETED INTERFACE FOR WIKIPEDIA BY COLLABORATIVE VOCABULARY

In discovering faceted interfaces for Wikipedia, the fundamental basis of our approach is to exploit its user-generated *collaborative vocabulary* such as the "grassroots" category system. Even internal Wikipedia hyperlinks are an instance of collaborative vocabulary in a broader sense, as they indicate the users' collaborative endorsement of relationships between entities. The collaborative vocabulary represents collective intelligence of many users and rich semantic information, and thus constitutes the promising basis for faceted interfaces. With regard to **the concept of facet dimension**, the Wikipedia articles hyperlinked from a search result article are exploited as its attributes. The fact that the authors of an article collaboratively made hyperlinks to other articles is an indication of the significance of the linked articles in describing the given article. This view largely enriches the semantic information associated with the result articles. With regard to **the concept of category hierarchy**, the category system in Wikipedia provides the category-subcategory relationships between categories, which will give user the ability of making more specific conditions.

We now formally define the concepts in our framework and then deliver the problem definition.

Definition 1 (Target Article, Attribute Article): Given a keyword query q, the set of top-s ranked Wikipedia articles, $\mathcal{T}=\{p_1, ..., p_s\}$, are the *target articles* of q. Given a target article p, each Wikipedia article p' that is hyperlinked from p is an *attribute article* of p. This relationship is represented as $p' \leftarrow p$. Given $\mathcal{T}$, the set of attribute articles is $\mathcal{A}=\{p'_1, ..., p'_m\}$, where each p'_i is an attribute article of at least one target article $p_j \in \mathcal{T}$. [2] ■

Definition 2 (Category Hierarchy): Wikipedia *category hierarchy* is a connected, rooted directed acyclic graph $\mathcal{H}(r_\mathcal{H}, \mathcal{C}_\mathcal{H}, \mathcal{E}_\mathcal{H})$, where the node set $\mathcal{C}_\mathcal{H}=\{c\}$ is the set of categories and edge set $\mathcal{E}_\mathcal{H}=\{c \dashrightarrow c'\}$ is the set of category-subcategory relationships between category c and subcategory c'. The root category of $\mathcal{H}$, $r_\mathcal{H}$, is Category:Fundamental [1].

Definition 3 (Facet): A *facet* $\mathcal{F}(r, \mathcal{C}_\mathcal{F}, \mathcal{E}_\mathcal{F})$ is a rooted and connected subgraph of the category hierarchy $\mathcal{H}(r_\mathcal{H}, \mathcal{C}_\mathcal{H}, \mathcal{E}_\mathcal{H})$, where $\mathcal{C}_\mathcal{F} \subseteq \mathcal{C}_\mathcal{H}$, $\mathcal{E}_\mathcal{F} \subseteq \mathcal{E}_\mathcal{H}$, and $r \in \mathcal{C}_\mathcal{F}$ is the root of $\mathcal{F}$. ■

[2]Note that target articles and attribute articles may overlap.

Example 2 (Running Example): Figure 3 illustrates the basic concepts. There are 7 target articles (p_1, ..., p_7) and 9 attribute articles (p'_1, ..., p'_9). The category hierarchy has 14 categories (c_1, ..., c_{14}). The figure highlights 6 facets ($\mathcal{F}_1$, ..., $\mathcal{F}_5$, and $\mathcal{F}'_2$). For instance, F_2 is rooted at c_2 and consists of 3 categories (c_2, c_7, c_8) and 2 edges ($c_2 \dashrightarrow c_7$, $c_2 \dashrightarrow c_8$). There are many more facets since every rooted and connected subgraph of the hierarchy is a facet. Note that the figure may give the impression that edges such as $c_5 \dashrightarrow c_{12}$ and $c_7 \Rightarrow p'_1$ are unnecessary since there is only one choice under c_5 and c_7, respectively. The example is small due to space limitations. Such single outgoing edge is very rare in the real Wikipedia category hierarchy. We will use Figure 3 as the running example throughout the paper. ∎

The categories in the facet can "*reach*" the target articles $\mathcal{T}$ through attribute articles $\mathcal{A}$. That is, by following the category-subcategory hierarchy of the facet, we could find a category, then find an attribute article belonging to the category, and finally find some desirable target articles that have the attribute value. These target articles are considered as *reachable target articles*. And A *facet* is considered as *safe reaching facet* if $\forall c \in \mathcal{C}_{\mathcal{F}}$, there exists a target article $p \in \mathcal{T}$ such that c reaches p, i.e., there exists $c \dashrightarrow ... \Rightarrow p' \leftarrow p$, a navigational path of $\mathcal{F}$, starting from c, that reaches p. In order to capture the notion of "reach", we formally define *navigational path* as follows.

Definition 4 (Navigational Path): With respect to the target articles $\mathcal{T}$, the corresponding attribute articles $\mathcal{A}$, and a facet $\mathcal{F}(r, \mathcal{C}_{\mathcal{F}}, \mathcal{E}_{\mathcal{F}})$, a *navigational path* in $\mathcal{F}$ is a sequence $c_1 \dashrightarrow ... \dashrightarrow c_t \Rightarrow p' \leftarrow p$, where,

- for $1 \leq i \leq t$, $c_i \in \mathcal{C}_{\mathcal{F}}$, i.e., c_i is a category in $\mathcal{F}$;
- for $1 \leq i \leq t-1$, $c_i \dashrightarrow c_{i+1} \in \mathcal{E}_{\mathcal{F}}$, i.e., c_{i+1} is a subcategory of c_i (in category hierarchy $\mathcal{H}$) and that category-subcategory relationship is kept in $\mathcal{F}$.
- $p' \in \mathcal{A}$, and c_t is a category of p' (represented as $c_t \Rightarrow p'$);
- $p \in \mathcal{T}$, and p' is an attribute article of p (i.e., there is a hyperlink $p \rightarrow p'$).

Given a navigational path $c_1 \dashrightarrow ... \dashrightarrow c_t \Rightarrow p' \leftarrow p$, we say that the corresponding category path $c_1 \dashrightarrow ... \dashrightarrow c_t$ *reaches* target article p through attribute article p', and we also say that category c_i (for any $1 \leq i \leq t$) *reaches* p through p'. Interchangeably we say p is *reachable* from c_i (for any $1 \leq i \leq t$). ∎

Example 3 (Navigational Path): Continue the running example. In Figure 3, two examples of navigational paths are $c_2 \dashrightarrow c_8 \Rightarrow p'_3 \leftarrow p_5$ and $c_5 \dashrightarrow c_{13} \Rightarrow p'_9 \leftarrow p_5$. ∎

Definition 5 (Faceted Interface): Given a keyword query q, a faceted interface $I = \{\mathcal{F}_i\}$ is a set of safe reaching facets of the target articles $\mathcal{T}$. That is, $\forall \mathcal{F}_i \in I$, $\mathcal{F}_i$ safely reaches $\mathcal{T}$. ∎

Example 4 (Faceted Interface): Continue the running example. In Figure 3, $I = \{\mathcal{F}_2, \mathcal{F}_5\}$ is a 2-facet interface. However, $\{\mathcal{F}'_2, \mathcal{F}_5\}$ is not a valid faceted interface because $\mathcal{F}'_2$ is not a safe reaching facet, as category c_6 cannot reach any target articles. ∎

Based on the formal definitions, the **Faceted Interface Discovery Problem** is: Given the category hierarchy $\mathcal{H}(r_{\mathcal{H}}, \mathcal{C}_{\mathcal{H}}, \mathcal{E}_{\mathcal{H}})$, for a keyword query q and its resulting target articles $\mathcal{T}$ and corresponding attribute articles $\mathcal{A}$, find the "best" faceted interface with k facets. We shall develop the notion of "best" in Section 4.

4. FACETS RANKING

The search space of the faceted interface discovery problem is prohibitively large. Given the set of s target Wikipedia articles to a keyword query, $\mathcal{T}$, there are a large number of attribute articles which in turn have many categories associated with complex hierarchical relationships. To just give a sense of the scale, in Wikipedia there are about 2.6 million English articles with hundreds of millions of internal links. The category system $\mathcal{H}$ contains close to half a million categories and several million category-subcategory relationships. By definition, any rooted and connected subgraph of $\mathcal{H}$ that safely reaches $\mathcal{T}$ is a candidate facet, and any combination of k facets would be a candidate faceted interface. Given the large space, we need ranking metrics for measuring the "goodness" of facets, both individually and collectively as interfaces.

Given that a faceted interface is for a user to navigate through the associated category hierarchies and ultimately reaching the target articles, it is natural to rank the interfaces by the user's navigational cost, i.e., the amount of effort undertaken by the user during navigation. [3] The "best" k-facet interface is the one with the smallest cost. Therefore as the basis of such ranking metrics, we model users' navigational behaviors as follows.

User Navigation Model: A user navigates multiple facets in a k-facet interface. At the beginning, the navigation starts from the roots of all the k facets. At each step, the user picks one facet and examines the set of subcategories available at the current category on that facet. She follows one subcategory to further go down the category hierarchy. Alternatively the user may select one of the attribute articles reachable from the current category. The selections made on the k facets together form a conjunctive query. After the selection at each step, the list of target articles that satisfy the conjunctive query are brought to the user. The navigation terminates when the user decides that she has seen desirable target articles.

Example 5 (Navigation in Faceted Interface): Continue the running example in Figure 3. Consider a faceted interface $I = \{\mathcal{F}_2, \mathcal{F}_5\}$. A sequence of navigational steps on this interface are in Figure 4. At the beginning, the user has not selected any facet to explore, therefore all 7 target articles are available (step 1). Once the user decides to explore $\mathcal{F}_2$ which starts from c_2, p_7 is filtered out since it is unreachable from $\mathcal{F}_2$ (step 2). The user then selects c_5, which further removes p_3 from consideration (step 3). After the user further explores $\mathcal{F}_2$ by choosing c_8 (step 4), c_{11} is not a choice under c_5 anymore because no target articles could be reached by both $c_2 \dashrightarrow c_8$ and $c_5 \dashrightarrow c_{11}$. The user continues to explore $\mathcal{F}_5$ by choosing c_{13} (step 5), which removes p'_2 and also trims down the satisfactory target articles to $\{p_5\}$. The user may decide she has seen desirable articles and the navigation stops. ∎

4.1 Single-Facet Ranking

In this section we focus on how to measure the costs of facets individually. Based on the navigational model, we compute the navigational cost of a facet as the average cost of its navigational paths. The core of this metric thus is the measure of the cost of a navigational path. Intuitively a low-cost path, i.e., a path that demands small user effort, should have a small number of steps and at each step only requires the user to browse a small number of choices. Therefore, we formally define the cost of a navigational path as the summation of the fan-outs (i.e., the number of choices) at every step, in logarithmic form. [4]

[3] [15] also selects facets based on navigational costs, although their system is of a different nature, as discussed in Section 2.

[4]The intuition behind the logarithmic form is: When presented

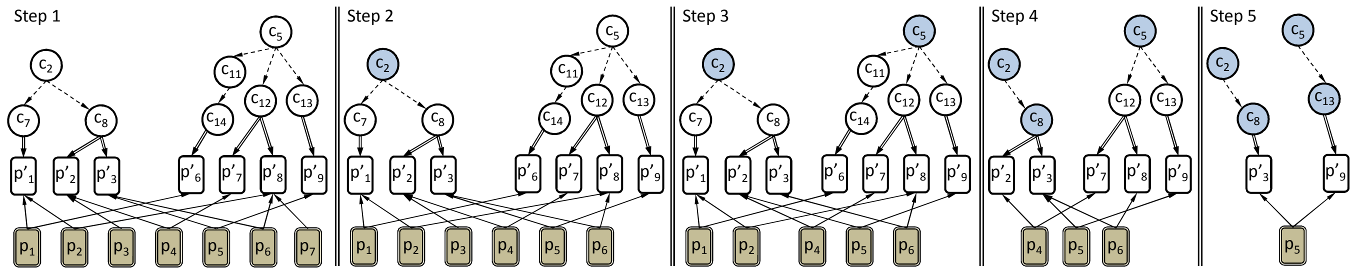


Figure 4: The navigation on a 2-facet interface $\mathcal{I} = \{\mathcal{F}_2, \mathcal{F}_5\}$.

Definition 6 (Cost of Navigational Path): With respect to the target articles $\mathcal{T}$, the corresponding attribute articles $\mathcal{A}$, and a facet $\mathcal{F}(r, \mathcal{C}_\mathcal{F}, \mathcal{E}_\mathcal{F})$, the cost of a navigational path in $\mathcal{F}$ is

$$cost(l) = log_2(fanout(p')) + \sum_{c \in \{c_1,\dots,c_t\}} log_2(fanout(c)) \qquad (1)$$

where $l{=}c_1 {\dashrightarrow} ... {\dashrightarrow} c_t {\Rightarrow} p' {\leftarrow} p$.

In Equation 1, $fanout(p')$ is the number of (directly) reachable target articles through the attribute article p',

$$fanout(p') = |\mathcal{T}_{p'}| \qquad (2)$$

$$\mathcal{T}_{p'} = \{p | p \in \mathcal{T} \wedge p \rightarrow p' \text{(i.e., } \exists \text{ a hyperlink from } p \text{ to } p')\} \qquad (3)$$

In Equation 1, $fanout(c)$ is the fanout of category c in $\mathcal{F}$,

$$fanout(c) = |\mathcal{A}_c| + |\mathcal{C}_c| \qquad (4)$$

where $\mathcal{A}_c$ is the set of attribute articles belonging to c,

$$\mathcal{A}_c = \{p' | p' \in \mathcal{A} \wedge c \Rightarrow p'\} \qquad (5)$$

and $\mathcal{C}_c$ is the set of subcategories of c in $\mathcal{F}$,

$$\mathcal{C}_c = \{c' | c' \in \mathcal{C}_\mathcal{F} \wedge c \dashrightarrow c' \in \mathcal{E}_\mathcal{F}\} \qquad (6) \quad ■$$

Note that we made several assumptions for simplicity of the model. The cost formula only captures the "browsing" cost. A full-fledged formula would need to incorporate other costs, such as the "clicking" cost in selecting a choice and the cost of "backward" navigation when the user decides to change a previous selection. Furthermore, we assume the user always completes the navigational path till reaching the target articles. In reality, however, the user may stop in the middle when she already finds desirable articles reachable from the current selection of category. We leave the investigation of more sophisticated models to future study.

Example 6 (Cost of Navigational Path): We continue the running example. Given $l{=}c_5 {\dashrightarrow} c_{12} {\Rightarrow} p'_8 {\leftarrow} p_6$, a navigational path of $\mathcal{F}_5$ in Figure 3, $cost(l){=}fanout(c_5){+}fanout(c_{12}){+}\ fanout(p'_8)$ $={log_2}(3){+}log_2(2){+}log_2(3){=}4.17$. ■

Albeit the basis of our facets ranking metrics, the definition of navigational cost is not sufficient in measuring the goodness of a facet. It does not consider such a scenario that a facet cannot fully reach all the target articles,which presents an unsatisfactory user experience. In fact, low-cost and high-coverage could be two qualities that compete with each other. On the one hand, a low-cost facet could be one that reaches only a small portion of the target articles. On the other hand, a comprehensive facet with high coverage may tend to be wider and deeper, thus more costly. Therefore we must incorporate into the cost formula the notion of "coverage", i.e., the ability of a facet to reach as many target articles as possible.

To combine navigational cost with coverage, we penalize a facet by associating a high-cost *pseudo path* with each unreachable article. We then define the cost of a facet as the average cost in reaching each target article based on the assumption that they are all equally important (since they are the top ranked results to a keyword search).

with a number of choices, the user does not necessarily scan through the choices linearly but by a binary search.

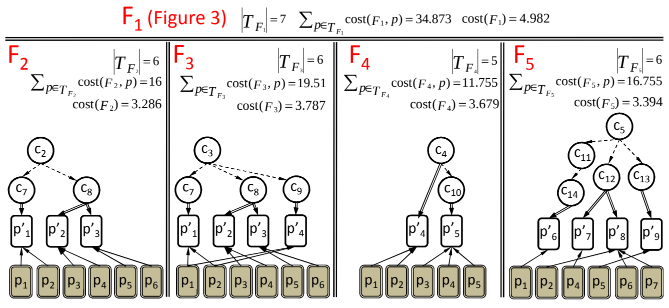


Figure 5: Navigational costs of facets.

Definition 7 (Cost of Facet): With respect to the target articles $\mathcal{T}$, the cost of a safe reaching facet $\mathcal{F}(r, \mathcal{C}_\mathcal{F}, \mathcal{E}_\mathcal{F})$, $cost(\mathcal{F}_r)$, is the average cost in reaching each target article. The cost for a reachable target article is the average cost of the navigational paths that start from r and reach the target, and the cost for an unreachable target is a pseudo cost *penalty*.

$$cost(\mathcal{F}_r) = \frac{1}{|\mathcal{T}|} \times (\sum_{p \in \mathcal{T}_r} cost(\mathcal{F}_r, p) + penalty \times |\mathcal{T} - \mathcal{T}_r|) \qquad (7)$$

where $cost(\mathcal{F}_r, p)$ is the average cost of reaching p from r,

$$cost(\mathcal{F}_r, p) = \frac{1}{|l_p|} \times \sum_{l \in l_p} cost(l) \qquad (8)$$

where l_p is the set of navigational paths in $\mathcal{F}$ that reach p from r,

$$l_p = \{l | l = r \dashrightarrow ... \Rightarrow p' \leftarrow p\} \qquad (9) \quad ■$$

In Formula 7, *penalty* is the cost of the aforementioned expensive pseudo path that "reaches" the unreachable target articles, i.e., $\mathcal{T} - \mathcal{T}_r$, for penalizing a facet for not reaching them. Its value is empirically selected (Section 6).

Example 7 (Cost of Facet): We continue the running example. Figure 5 shows the costs of the 5 highlighted facets in Figure 3, together with their category hierarchies and reachable attribute and target articles. It does not show $\mathcal{F}_1$ which is Figure 3 itself excluding c_6. The costs of facets are obtained by Formula 7, with $penalty{=}7$. $cost(\mathcal{F}_2){=}\ \frac{1}{7}{\times}(\sum_{p \in \{p_1,p_2,p_3,p_4,p_5,p_6\}} cost(\mathcal{F}_2, p)$ $+penalty{\times}|\mathcal{T}{-}\mathcal{T}_{\mathcal{F}_2}|){=}\ \frac{1}{7}{\times}(16{+}7{\times}1){=}3.286$. $\mathcal{F}_2$ and $\mathcal{F}_5$ achieve lower costs than other facets. Even though the paths in $\mathcal{F}_4$ are cheap, $\mathcal{F}_4$ has higher cost due to the penalty for unreachable target articles (p_6 and p_7). $\mathcal{F}_1$ is even more costly due to its wider and deeper hierarchy, although it reaches all target articles. ■

4.2 Multi-Facet Ranking

Even with the cost metrics for individual facets, measuring the "goodness" of a faceted interface, i.e., a set of facets, is not straightforward. This is because the best k-facet interface may not be simply the cheapest k facets. The reason is that when the user navigates

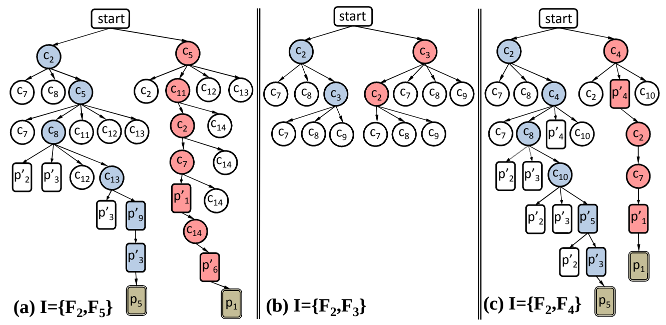


Figure 6: The sequences of navigational steps.

multiple facets, the selection made at one facet has impact on the available choices on other facets, as illustrated by Example 5.

To directly follow the approach of ranking faceted interfaces by navigational cost, in principle we could represent the navigational steps on multiple facets as if the navigation is on one *"integrated" facet*. To illustrate, consider the navigation on a 2-facet interface $\mathcal{I}$=$\{\mathcal{F}_2, \mathcal{F}_5\}$ from Figure 3. Two possible sequences of navigational steps are shown in Figure 6(a). One is c_2, c_5, c_8, c_{13}, p'_9, p'_3, p_5, which are the steps taken by the user in Figure 4, followed by choosing p'_9, p'_3, and finally p_5. (Remember, for simplification of the model, we assumed that the user will always complete navigational paths till reaching the target articles.) At each step, the available choices from both facets are put together as the choices in the "integrated" facet. Note that after c_8 is chosen, c_{12} and c_{13} are still valid choices but c_{11} is not available anymore because c_{11} cannot reach the target articles that c_8 reaches. For the same reason, after c_{13} is chosen, p'_3 is still a valid choice but p'_2 is not anymore. The other highlighted sequence is c_5, c_{11}, c_2, c_7, p'_1, c_{14}, p'_6, p_1. There are many more possible sequences not shown in the figure due to space limitations.

With the concept of "integrated" facet, one may immediately apply Definition 7 to define the cost of a faceted interface. That entails computing all possible sequences of interleaving navigational steps across all the facets in the interface. The interaction between facets is query- and data-dependent, rendering such exhaustive computation practically infeasible.

However, the "integrated" facet does shed light on what are the characteristics of good faceted interfaces. In general an interface should not include two facets that overlap much. Imagine a special case when two facets form a subsumption relationship, i.e., the root of one facet is a supercategory of the other root. Presenting both facets would not be desirable since they overlap significantly, thus cannot capture the expected properties of reaching target articles through different dimensions. As a concrete example, consider the navigational steps of $\mathcal{F}_2$ and $\mathcal{F}_3$ in Figure 6(b). After the user selects c_2 from $\mathcal{F}_2$ and then c_3 from $\mathcal{F}_3$, the available choices become $\{c_7, c_8, c_9\}$, which all come from the "dimension", $\mathcal{F}_3$. The same happens if the user selects c_3 and then c_2.

Based on the above observation, we propose to capture the overlap of the k facets in an interface by their *average pair-wise similarity*. The pair-wise similarity of two facets is the degree of overlap of their category hierarchies and associated attribute articles, defined below.

Definition 8 (Average Similarity of k-Facet Interface): The average pair-wise similarity of a k-facet interface is

$$sim(\mathcal{I} = \{\mathcal{F}_1, ..., \mathcal{F}_k\}) = \frac{\sum_{1 \le i < j \le k} sim(\mathcal{F}_i, \mathcal{F}_j)}{k(k-1)/2}, \qquad (10)$$

where $sim(\mathcal{F}_i, \mathcal{F}_j)$ is defined by the Jaccard coefficient,

$$sim(\mathcal{F}_i, \mathcal{F}_j) = \frac{|\mathcal{C}_{\mathcal{F}_i} \bigcap \mathcal{C}_{\mathcal{F}_j}| + |\mathcal{A}_{\mathcal{F}_i} \bigcap \mathcal{A}_{\mathcal{F}_j}|}{|\mathcal{C}_{\mathcal{F}_i} \bigcup \mathcal{C}_{\mathcal{F}_j}| + |\mathcal{A}_{\mathcal{F}_i} \bigcup \mathcal{A}_{\mathcal{F}_j}|} \qquad (11)$$

where $\mathcal{C}_{\mathcal{F}_i}$ is the set of categories in $\mathcal{F}_i$ (Definition 3) and $\mathcal{A}_{\mathcal{F}_i}$ is the set of attribute articles reachable from $\mathcal{F}_i$,

$$\mathcal{A}_{\mathcal{F}_i} = \{p' | p' \in \mathcal{A} \wedge \exists c \in \mathcal{C}_{\mathcal{F}_i} \; s.t. \; c \Rightarrow p'\} \qquad (12) \quad \blacksquare$$

We choose Jaccard coefficient since it is one of the simplest set-similarity measures. While more complex measures that give different weights to nodes higher in the hierarchy are possible, we do not follow that in the interest of simplicity.

Example 8 (Similarity of Facets): Consider facets $\mathcal{F}_1, \ldots, \mathcal{F}_5$ in Figure 3. $sim(\mathcal{F}_2, \mathcal{F}_3)$= $\frac{|\mathcal{C}_{\mathcal{F}_2} \bigcap \mathcal{C}_{\mathcal{F}_3}|+|\mathcal{A}_{\mathcal{F}_2} \bigcap \mathcal{A}_{\mathcal{F}_3}|}{|\mathcal{C}_{\mathcal{F}_2} \bigcup \mathcal{C}_{\mathcal{F}_3}|+|\mathcal{A}_{\mathcal{F}_2} \bigcup \mathcal{A}_{\mathcal{F}_3}|}$ $= \frac{|\{c_7,c_8\}|+|\{p'_1,p'_2,p'_3\}|}{|\{c_2,c_7,c_8,c_3,c_9\}|+|\{p'_1,p'_2,p'_3,p'_4\}|}$=5/9. Other pair-wise similarities can be computed in the same way. The average pari-wise similarity of $\mathcal{I}$=$\{\mathcal{F}_2, \mathcal{F}_3, \mathcal{F}_5\}$ is $sim(\mathcal{I}) = (sim(\mathcal{F}_2, \mathcal{F}_3) + sim(\mathcal{F}_2, \mathcal{F}_5) + sim(\mathcal{F}_3, \mathcal{F}_5))/3 = 5/27$. $\blacksquare$

We do not design a single function to combine the average pair-wise similarity of a faceted interface with its navigational cost, since they represent two measures with different natures. Instead, in Section 5.3 we discuss how to search the space of candidate interfaces by considering both measures.

5. ALGORITHMS

A straightforward approach for faceted interface discovery is to enumerate all possible k-facet interfaces with respect to the category hierarchy $\mathcal{H}$ and apply the ranking metrics directly to find the best interface. Such a naïve method results in the exhaustive examination of all possible combinations of k instances of all possible facets, i.e., rooted and connected subgraphs of $\mathcal{H}$. Clearly it is a prohibitively large search space, given the sheer size and complexity of Wikipedia. The naïve technique would be extremely costly. Therefore finding the best k-facet interface is a challenging optimization problem.

Our k-facet discovery algorithm hinges on (1) reducing the search space; and (2) searching the space effectively and efficiently.

Reducing the Search Space: There are two search spaces in finding a good k-facet interface: the space of facets and the space of k-facet interfaces, which are sets of k facets. To reduce the space of candidate facets, we focus on a subset of the safe reaching facets, $\mathcal{RCH}$-induced facets, which are the facets that contain all the descendant categories of their roots (Section 5.1). To further reduce the space of faceted interfaces, we rank the facets individually by their navigational costs (Section 5.2) and only consider the top ranked facets that do not subsume each other (Section 5.3).

Searching the Space: Instead of exhaustively examining all possible interfaces, we design a hill-climbing based heuristic algorithm to look for a local optimum (Section 5.3). To further tackle the challenge of modeling the interactions of multiple facets in measuring the cost of an interface, the hill climbing algorithm optimizes for both the average navigational cost and the pair-wise similarity of the facets.

Our k-facet discovery algorithm is outlined as three steps: construction of relevant category hierarchy, ranking single facet, and searching for k-facet interface.

5.1 Relevant Category Hierarchy (Algorithm 1)

By Definition 5, the facets in a faceted interface must be safe reaching facets, i.e., they do not contain "dead end" categories that cannot reach any target articles. Therefore the categories appearing in any safe reaching facet could only come from the *relevant category hierarchy* ($\mathcal{RCH}$), which is a subgraph of the Wikipedia category hierarchy $\mathcal{H}$, defined below.

Algorithm 1: Construct RCH and Get Attribute Articles

```
   Input: $\mathcal{T}$: target articles; $\mathcal{H}$: category hierarchy.
   Output: $\mathcal{A}$:attribute articles; $\mathcal{RCH}$:relevant category
           hierarchy.
   // get attribute articles.
1  $\mathcal{A}\leftarrow\phi$; $\mathcal{C}_{\mathcal{RCH}}\leftarrow\phi$; $\mathcal{E}_{\mathcal{RCH}}\leftarrow\phi$
2  foreach $p \in \mathcal{T}$ do
3      foreach $p \rightarrow p'$, i.e., a hyperlink from p to $p'$ do
4          $\mathcal{A}\leftarrow\mathcal{A}\cup\{p'\}$
   // start from the categories of attribute articles.
5  foreach $p' \in \mathcal{A}$ do
6      foreach $c \Rightarrow p'$, i.e., a category of $p'$ do
7          $\mathcal{C}_{\mathcal{RCH}} \leftarrow \mathcal{C}_{\mathcal{RCH}} \cup \{c\}$
   // recursively obtain the supercategories.
8  $\mathcal{C}\leftarrow\mathcal{C}_{\mathcal{RCH}}$; $\mathcal{C}' \leftarrow \phi$
9  while $\mathcal{C}$ is not empty do
10     foreach $c \in \mathcal{C}$ do
11         foreach $c' \dashrightarrow c \in \mathcal{E}_{\mathcal{H}}$ do
12             $\mathcal{E}_{\mathcal{RCH}} \leftarrow \mathcal{E}_{\mathcal{RCH}} \cup \{c' \dashrightarrow c\}$
13             if $c' \notin \mathcal{C}_{\mathcal{RCH}}$ then
14                 $\mathcal{C}_{\mathcal{RCH}} \leftarrow \mathcal{C}_{\mathcal{RCH}} \cup \{c'\}$; $\mathcal{C}' \leftarrow \mathcal{C}' \cup \{c'\}$
15     $\mathcal{C} \leftarrow \mathcal{C}'$; $\mathcal{C}' \leftarrow \phi$
16 return $\mathcal{A}$ and $\mathcal{RCH}(r_{\mathcal{H}}, \mathcal{C}_{\mathcal{RCH}}, \mathcal{E}_{\mathcal{RCH}})$
```

Definition 9 (Relevant Category Hierarchy): Given the category hierarchy $\mathcal{H}(r_{\mathcal{H}}, \mathcal{C}_{\mathcal{H}}, \mathcal{E}_{\mathcal{H}})$, the target articles $\mathcal{T}$, and the attribute articles $\mathcal{A}$, the *relevant category hierarchy* ($\mathcal{RCH}$) of $\mathcal{T}$ is a subgraph of $\mathcal{H}$. Given any category in $\mathcal{RCH}$, it is either directly a category of some attribute article $p' \in \mathcal{A}$ or a supercategory or ancestor of such categories. There exists an edge (category-subcategory relationship) between two categories in $\mathcal{RCH}$ if the same edge exists in $\mathcal{H}$. By this definition the root of $\mathcal{H}$ is also the root of $\mathcal{RCH}$. ■

The procedural algorithm for getting $\mathcal{RCH}$ is in Algorithm 1. Based on definition, straightforwardly we could prove every safe reaching facet of the target articles $\mathcal{T}$ is a (rooted and connected) subgraph of $\mathcal{RCH}$. However, not every rooted and connected subgraph of $\mathcal{RCH}$ is a safe reaching facet. Therefore, even though $\mathcal{RCH}$ is much smaller than $\mathcal{H}$, the search space is still very large which needs us to further shrink the space by considering only one type of safe reaching facets, the *$\mathcal{RCH}$-induced facets*.

Definition 10 ($\mathcal{RCH}$-Induced Facet): Given the relevant category hierarchy $\mathcal{RCH}$ of the target articles $\mathcal{T}$, a facet $\mathcal{F}(r, \mathcal{C}_{\mathcal{F}}, \mathcal{E}_{\mathcal{F}})$ is *$\mathcal{RCH}$-induced* if it is a rooted induced subgraph of $\mathcal{RCH}$, i.e., in $\mathcal{F}$ all the descendants of the root r and their category-subcategory relationships are retained from $\mathcal{RCH}$. ■

Example 9 ($\mathcal{RCH}$ and $\mathcal{RCH}$-Induced Facet): Continue the running example. In Figure 3, the $\mathcal{RCH}$ contains all the categories in the category hierarchy $\mathcal{H}$ except c_6 (and thus the edge $c_2 \dashrightarrow c_6$), since c_6 cannot reach any target article. $\mathcal{F}_2$ is an $\mathcal{RCH}$-induced facet, but would not be if it does not contain c_7 (or c_8). ■

Note that every $\mathcal{RCH}$-induced facet is safe reaching, and the ranking for single facet and searching for k-facet will be performed on it.

5.2 Ranking Single Facet (Algorithm 2 and 3)

Among all the $\mathcal{RCH}$-induced facets, only the top n facets with the smallest navigational costs are considered in searching for a faceted interface. In ranking the facets by their costs, one straightforward approach is to enumerate all the $\mathcal{RCH}$-induced facets and to separately compute the cost of each facet by enumerating all of its navigational paths. This approach is exponentially complex due to repeated traversal of the edges in $\mathcal{RCH}$, because the $\mathcal{RCH}$-induced facets would have many common categories and category-subcategory relationships.

Algorithm 2: Facets Ranking

```
   Input: $\mathcal{T}$:targets;$\mathcal{A}$:attributes; $\mathcal{RCH}$:relevant category
          hierarchy.
   Output: $\mathcal{I}_n$: top $n$ $\mathcal{RCH}$-induced facets with smallest costs.
   // get reachable target articles for each attribute article.
1  foreach $p' \in \mathcal{A}$ do
2      $\mathcal{T}_{p'} \leftarrow \{p | p \in \mathcal{T} \wedge \exists\, p \rightarrow p'$ (hyperlink from $p$ to $p'$) $\}$
3      $fanout(p') \leftarrow |\mathcal{T}_{p'}|$
4  initialize $visited(r)$ to be $False$ for every $r \in \mathcal{C}_{\mathcal{RCH}}$.
5  $ComputeCost(r_{\mathcal{H}})$ // recursively compute the costs of all
       the $\mathcal{RCH}$-induced facets, starting from the root of $\mathcal{RCH}$.
6  $\mathcal{I}_n\leftarrow$ the top $n$ $\mathcal{RCH}$-induced facets with the smallest costs.
7  return $\mathcal{I}_n$
```

Algorithm 3: ComputeCost(r)

```
   Input: $r$: the root of an $\mathcal{RCH}$-induced facet.
   Output: $cost(\mathcal{F}_r)$: cost of $\mathcal{F}_r$; $cost(\mathcal{F}_r, p)$: average cost of
           reaching target article $p$ from $\mathcal{F}_r$; $pathcnt(\mathcal{F}_r, p)$: #
           of navigational paths reaching $p$ from $\mathcal{F}_r$; $\mathcal{T}_r$:
           reachable target articles of $r$.
1  if $visited(r)$ then
2      return
3  $visited(r) \leftarrow True$;
4  $\mathcal{C}_r\leftarrow\{c | r \dashrightarrow c \in \mathcal{E}_{\mathcal{RCH}}\}$ // subcategories of $r$.
5  foreach $c \in \mathcal{C}_r$ do
6      $ComputeCost(c)$
7  $\mathcal{A}_r\leftarrow\{p' | p' \in \mathcal{A} \wedge r \Rightarrow p'\}$ // attribute articles belong to $r$.
8  $fanout(r)\leftarrow |\mathcal{A}_r| + |\mathcal{C}_r|$
9  $\mathcal{T}_r\leftarrow (\cup_{p' \in \mathcal{A}_r} \mathcal{T}_{p'}) \bigcup (\cup_{c \in \mathcal{C}_r} \mathcal{T}_c)$ // reachable target articles
       of $r$.
10 foreach $p \in \mathcal{T}_r$ do
11     $pathcnt(\mathcal{F}_r, p)\leftarrow|\{p' | p' \in \mathcal{A}_r, p \in \mathcal{T}_{p'}\}| + \sum_{c \in \mathcal{C}_r} pathcnt(\mathcal{F}_c, p)$
12     $cost_1\leftarrow\sum_{p' \in \mathcal{A}_r s.t. p \in \mathcal{T}_{p'}} (log_2(fanout(r)) + log_2(fanout(p')))$
13     $cost_2\leftarrow\sum_{c \in \mathcal{C}_r} (log_2(fanout(r)) + cost(\mathcal{F}_c, p)) \times pathcnt(\mathcal{F}_c, p)$
14     $cost(\mathcal{F}_r, p)\leftarrow\frac{cost_1 + cost_2}{pathcnt(\mathcal{F}_r, p)}$
15 $cost(\mathcal{F}_r)\leftarrow\sum_{p \in \mathcal{T}_r} cost(\mathcal{F}_r, p) + penalty \times |\mathcal{T} - \mathcal{T}_r|$
16 return
```

To avoid the costly exhaustive method, we design a recursive algorithm that calculates the navigational costs of all the $\mathcal{RCH}$-induced facets by only one pass depth-first search of $\mathcal{RCH}$. The details are in Algorithm 2. The essence of the algorithm is to, during the recursive traversal of $\mathcal{RCH}$, book-keep the number of navigational paths in a facet in addition to its navigational cost. The bookkeeping is performed for each reachable target article because the cost is averaged across all such articles by Definition 7. The cost of a facet rooted at r can be fully computed based on the book-keeped information of the facets rooted at r's direct subcategories, without accumulating the individual costs of the facets rooted at r's descendants. Therefore it avoids the aforementioned repeated traversal of $\mathcal{RCH}$. More specifically, the lines 11-14 in Algorithm 3 are for computing $cost(\mathcal{F}_r, p)$ in Formula 7. However, the algorithm does not compute it by a direct translation of Formula 8 and 1, i.e., enumerating all the navigational paths that reach p. Instead, line 12 gets $cost_1$, the total cost of all the navi-

```
Algorithm 4: Facets Selection
  Input: $\mathcal{I}_n$: the top $n$ $\mathcal{RCH}$-induced facets with the smallest
         costs.
  Output: $\mathcal{I}_k$: a discovered faceted interface with $k$ facets
          ($k<n$).
  // remove subsumed facets from $\mathcal{I}_n$
1 $\mathcal{I}_{n^-} \leftarrow \{\mathcal{F}_c | \nexists \mathcal{F}_{c'} \in \mathcal{I}_n$ s.t.$\mathcal{F}_c$ is subsumed by $\mathcal{F}_{c'}$, i.e., $c$ is a
  descendant category of $c'\}$
  // hill climbing
2 $\mathcal{I}_k \leftarrow$ a random $k$-facet subset of $\mathcal{I}_{n^-}$;  $\mathcal{I}' \leftarrow \mathcal{I}_{n^-} \backslash \mathcal{I}_k$
3 repeat
5     make $\mathcal{I}_k$=<$\mathcal{I}_k[1]$,...,$\mathcal{I}_k[k]$> sorted in increasing order of
      cost.
6     make $\mathcal{I}'$=<$\mathcal{I}'[1]$,...,$\mathcal{I}'[n-k]$> sorted in increasing order
      of cost
7     for $i = k$ to $1$ step $-1$ do
8         for $j = 1$ to $n-k$ do
9             $\mathcal{I}_{new} \leftarrow (\mathcal{I}_k \backslash \{\mathcal{I}_k[i]\}) \cup \{\mathcal{I}'[j]\}$
10            $S_1 \leftarrow \sum_{\mathcal{F}_c, \mathcal{F}_{c'} \in \mathcal{I}_{new}, \mathcal{F}_c \neq \mathcal{F}_{c'}} sim(\mathcal{F}_c, \mathcal{F}_{c'})$
11            $C_1 \leftarrow \sum_{\mathcal{F}_c \in \mathcal{I}_{new}} cost(\mathcal{F}_c)$
12            $S_2 \leftarrow \sum_{\mathcal{F}_c, \mathcal{F}_{c'} \in \mathcal{I}_k, \mathcal{F}_c \neq \mathcal{F}_{c'}} sim(\mathcal{F}_c, \mathcal{F}_{c'})$
13            $C_2 \leftarrow \sum_{\mathcal{F}_c \in \mathcal{I}_k} cost(\mathcal{F}_c)$
14            if ($S_1 \leq S_2$ and $C_1 < C_2$) or ($S_1 < S_2$ and $C_1 \leq C_2$)
              then
15                $\mathcal{I}_k \leftarrow \mathcal{I}_{new}$;  $\mathcal{I}' \leftarrow \mathcal{I}_{n^-} \backslash \mathcal{I}_k$
16                go to line 5
17 until $\mathcal{I}_k$ does not change ;
18 return $\mathcal{I}_k$
```

gational paths $r \Rightarrow p' \leftarrow p$, i.e., the ones that reach p without going through any other categories; line 13 computes $cost_2$, the total cost of all the navigational paths that go through other categories, by utilizing $cost(\mathcal{F}_c, p)$ and $pathcnt(\mathcal{F}_c, p)$ of the subcategories c, but not other descendants. We omit the formal correctness proof due to space limitations.

5.3 Searching for k-Facet Interface (Algorithm 4)

Algorithm 4 searches for k-facet interface. To reduce the search space, our algorithm only considers $\mathcal{I}_n$, the top n facets from Algorithm 2. We further reduce the space by excluding those top ranked facets that are subsumed by other top facets (line 1). In other words, we only keep $\mathcal{I}_{n^-}$, the maximal *antichain* of $\mathcal{I}_n$ based on the graph (category hierarchy) subsumption relationship. This is in line with the idea of avoiding large overlap between facets (Section 4.2).

Given $\mathcal{I}_{n^-}$, instead of exhaustively considering all possible k-element subsets of $\mathcal{I}_{n^-}$, we apply a *hill-climbing method* to search for a local optimum, starting from a random k-facet interface $\mathcal{I}_k$. At every step, we try to find a better neighboring solution, where a k-facet interface $\mathcal{I}_{new}$ is a neighbor of $\mathcal{I}_k$ if they only differ by one facet (line 9). Given the $k \times (n-k)$ possible neighbors at every step, we examine them in the order of average navigational costs (line 5, 6, and 9). The algorithm jumps to the first encountered better neighbor. The algorithm stops when no better neighbor can be found. As the goal function to be optimized in hill-climbing, $\mathcal{I}_{new}$ is considered better if the facets of $\mathcal{I}_{new}$ have both smaller pair-wise similarities and smaller navigational costs than that of $\mathcal{I}_k$ (line 14). The idea of considering both similarity and cost is motivated in Section 4.2.

6. EXPERIMENTAL EVALUATION

6.1 Experimental Settings

number of articles	$2,445,642$
number of hyperlinks between articles	$109,165,108$
average number of hyperlinks per article	45
number of distinct categories	$329,007$
average number of categories per article	3
number of category-subcategory relationships	$731,097$

Figure 7: Characteristics of the dataset.

Facetedpedia is implemented in C++ and the dataset is stored in a MySQL database. The experiments are executed on a Dell PowerEdge 2900 III server running Linux kernel 2.6.27, with dual quad-core Xeon 2.0 GHz processors, 2x6MB cache, 8GB RAM, and three 1TB SATA hard drivers in RAID5.

Dataset: We downloaded the Wikipedia dump of July 24, 2008 from http://download.wikimedia.org and loaded the data into a MySQL database. In particular, we used the tables *page.sql*, *pagelinks.sql*, *categorylinks.sql*, and *redirect.sql*, which provide all the relevant data including the hyperlinks between articles, categories of articles, and the category system. We performed several preprocessing tasks on the tables, including the detection and removal of cycles in the category hierarchy. Although cycles should usually be avoided as suggested by Wikipedia, the category system in Wikipedia contains a very small number (594 in the dataset) of elementary cycles [5] due to various reasons. We applied depth-first search algorithm to detect the elementary cycles. The category hierarchy is made acyclic by removing the last encountered edge in each elementary cycle during the depth-first search. Other performed preprocessing steps include: removing tuples irrelevant to articles and categories; replacing redirect articles by their original articles; removing special articles such as lists and stubs. We also applied basic performance tuning of the database, including creating additional indexes on *page_id* in various tables. The characteristics of the dataset are summarized in Table 7. The total size of the database tables is 1.2GB.

Queries: We experimented with 20 keyword queries that we designed (Figure 8), in addition to the open queries that the users came up with during user study (Section 6.3).

Parameters in algorithms: Each query was sent to Google with site constraint *site:en.wikipedia.org* to get the top 200 (s=200) English Wikipedia target articles. The relevant category hierarchy $\mathcal{RCH}$ was then generated by applying Algorithm 1 on the aforementioned MySQL database. By default, Algorithm 2 returns top 200 (n=200) facets and Algorithm 4 generates 10 facets (k=10). The value of *penalty* in Definition 7 was set as 7. It was empirically selected by investigating the relationship between the number of unreachable target articles ($|\mathcal{T} - \mathcal{T}_r|$) and the total navigational costs of reachable targets ($\sum_{p \in \mathcal{T}_r} cost(\mathcal{F}_r, p)$).

6.2 Faceted Interface Sample

Snippet of a faceted interface discovered by Facetedpedia for query “country singer" is shown in Figure 9. Due to space limitations, we only list 3 facets and a small number of attribute and target articles. The 3 facets are “songs by year”, “record labels”, and “producers”. For example, the target article “John Denver” can be found by navigating in the first facet following “songs by year”$\dashrightarrow$“20th century songs”$\dashrightarrow$“1970 songs” $\dashrightarrow$ “1970s pop songs”$\Rightarrow$“Take Me Home, Country Roads”$\leftarrow$“John Denver”.

[5]A cycle is elementary if no vertices in the cycle (except the start/end vertex) appear more than once.

$Q1$	action film	$Q2$	country singer
$Q3$	philosophers	$Q4$	Texas universities
$Q5$	Turing Award winner	$Q6$	missile
$Q7$	Ivy League schools	$Q8$	NBA players
$Q9$	historic landmarks	$Q10$	cartoon characters
$Q11$	Microsoft acquired game companies	$Q12$	stand up comedian
$Q13$	graph theorists	$Q14$	lakes in North America
$Q15$	American presidents	$Q16$	battle far east
$Q17$	waterfall national park	$Q18$	Chinese cuisine
$Q19$	premier league clubs	$Q20$	PS3 game

Figure 8: Experiment queries.

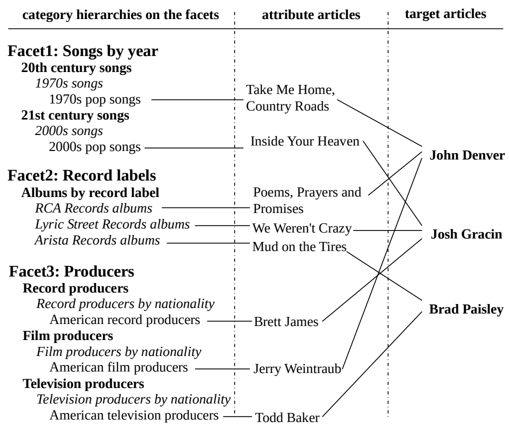


Figure 9: Snippet of a sample faceted interface generated by Facetedpedia

One limitation of the generated faceted interface is that it does not indicate the exact relationship between the attribute articles and target articles. For instance, a country singer may write or also produce a song, which would make the song an attribute article of the singer. The facet would not be able to differentiate between a song written or sung by a country singer. Even some noise page links will appear in the interface, since not all these page links are equally important and some may be even irrelevant.

6.3 User Studies

We conducted user studies to evaluate the effectiveness of Facetedpedia, and to compare the quality of the faceted interfaces generated by Facetedpedia and Castanet [16]. We obtained the implementation of Castanet from its authors. Note that Castanet is intended for static, short, and domain-specific documents with limited vocabularies. Nevertheless, we applied Castanet on the dynamic keyword search results. Although not originally designed for such purposes, Castanet still appears to be possibly the closest related work. In the study, we use the same graphical user interface for both systems, to make the comparison irrelevant to interface design.

The user studies were conducted online. The users all have college degrees or are in college, including university students, faculty, staff, and financial and IT company workers. We believe these users are experienced with Web search and comfortable with more sophisticated access mechanisms, matching the target users of our system. To reduce the overhead of the user, we partitioned the 20 queries in Figure 8 into 4 equal-size groups and asked each user to only participate in the 5 queries of one group. For each query group, we sent user-study invitations to roughly equal number of people. Ultimately we were able to collect opinions from totally 36 users, 8 each for 2 groups, and 10 each for the other 2 groups.

For each query, we showed the query keywords and objective

Choices– 1: useless; 2: not very useful; 3: useful to some extent; 4: useful; 5: very useful	
R1	My rating about usefulness of Facetedpedia.
R2	My rating about usefulness of Castanet.

Choices– Facetedpedia; Castanet	
R3	Which interface is better than the other?

Choices– 1: strongly disagree; 2: disagree; 3: neutral; 4: agree; 5: strongly agree	
R4	The facets in Facetedpedia conveys important concepts regarding the articles related to the query.
R5	Facetedpedia is useful for browsing and exploration purposes.
R6	I look forward to use this interface even in the future for exploratory browsing purposes.

Figure 10: User study questions and available answers.

	Average R1	Average R2	R3-Facetedpedia	R3-Castanet
$Q1$	3.5	2.5	7	1
$Q2$	3.5	2.625	5	3
$Q3$	3.5	2.875	5	3
$Q4$	3.625	2.5	7	1
$Q5$	3.375	2.5	7	1
$Q6$	3.625	3.375	6	2
$Q7$	4.0	3.625	5	3
$Q8$	3.75	3.625	4	4
$Q9$	4.125	3.25	7	1
$Q10$	3.5	3.875	4	4
$Q11$	4.2	3.1	9	1
$Q12$	3.8	3.2	8	2
$Q13$	3.8	3.5	6	4
$Q14$	3.7	3.5	6	4
$Q15$	3.7	3.7	6	4
$Q16$	3.9	2.9	9	1
$Q17$	4.1	3.1	9	1
$Q18$	4.2	2.9	9	1
$Q19$	3.7	2.7	7	3
$Q20$	3.6	3.1	6	4

Figure 11: Usefulness of Facetedpedia and Castanet for controlled queries.

description to the user, and asked the user to explore two interfaces pre-generated by Facetedpedia and Castanet, respectively. At the end of each query, the user was asked to provide response to 3 questions, namely $R1$-$R3$ in Figure 10. The available choices for $R1$ and $R2$ are ratings from 1:"useless" to 5:"very useful". The choices for $R3$ are "Facetedpedia" and "Castanet". The same process iterated through the 5 queries in the group assigned to the user. After the 5 queries were done, the user was also provided opportunity to try arbitrary open queries on Facetedpedia, and provided answers to questions $R4$-$R6$ in Figure 10. The available choices are ratings from 1:"strongly disagree" to 5:"strongly agree". The same open query study, however, was not possible for Castanet because the implementation we obtained from the authors takes about 5 minutes to process each query and therefore could not be used for dynamic queries. The reason is that it checks WordNet for each word in constructing category hierarchy. (Remember it was designed for static collection of short texts.)

In Figure 11, column 2 and column 3 records average user ratings per query on questions $R1$ and $R2$ respectively. Column 4 and 5 represent user's absolute preference on one system over the other. Clearly, from the results, Facetedpedia receives much stronger feedback than Castanet on $R1$ and $R2$. Also, for absolute preference, user prefers Facetedpedia over Castanet almost unanimously. Figure 12 records average user ratings per group for $R4$, $R5$ and $R6$. As it can be seen, majority of the groups provide strong positive opinion about usefulness of facets and the interface generated by Facetedpedia and they believe Facetedpedia interface is effective for exploration purposes.

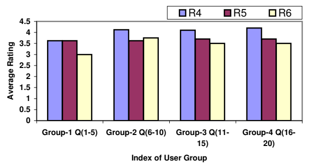


Figure 12: User experience with Facetedpedia for open queries.

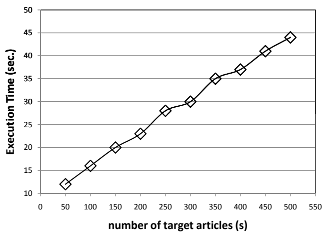


Figure 13: Execution time of Facetedpedia vs. number of target articles

	Coverage	average width	average height	average pair-wise similarity
Random-k	72.3%	53.8	8.6	0.108
Top-k	73.9%	10.2	5.5	0.187
Hill-climbing	68.9%	9.8	5.7	0.072

Figure 14: Comparison of the quality of various k-facet interfaces.

6.4 Characteristics of Generated Facets

Our experiments compare the efficiency of three algorithms: the hill-climbing based algorithm (Algorithm 4), top-k facets by single-facet ranking (Algorithm 2), and randomly choosing k facets. Figure 14 shows the average characteristics of these faceted interfaces generated by these methods. Although hill-climbing algorithm has a slightly worse target article coverage than the other two(5% less), it does outperform them in pair-wise similarity which means the k facets selected have smaller overlapp on navigational paths. The detailed tracing results show that hill-climbing algorithm starts from picking up top-k facets and gradually replacing similar facets with less similar ones. The final top-k facets selected by hill-climbing usually still stand in the top 30%, while the ones selected by randomly choosing k algorithm are equally distributed among these single facet ranking results. The average width and height of these three algorithms are relatively the same, despite of the random choosing k algorithm, which occasionally picks up some much wider facets. Their average width is usually around 10 and average height is usually around 6, which means the expected fanout of each internal nodes and navigational path length are within a reasonable range for the users. In all, the hill-climbing algorithm helps us winnow overlapping facets from top-k single facets without losing much coverage of target articles.

6.5 Efficiency Evaluation

We evaluate the scalability of our approach by measuring the average execution time of discovering k=10 facets for varying number of target articles s from 50 to 500. As can be seen from Figure 13, Facetedpedia scales well as the execution time increases linearly by the number of target articles. The figure also shows that Facetedpedia already achieved fairly fast response time without much performance optimization. In average it took 12 seconds to discover the facets for 50 target articles, and 23 seconds for 200 target articles. From our experiments we observed that 80% of the execution time was spent on querying the aforementioned MySQL database. The queries consists in retrieving the *pagelinks.sql* table to get the attribute articles from the target articles, joining article and category tables (both are from *page.sql*) to get the categories of the attribute articles, and further recursively self-joining *categorylinks.sql* to get the relevant category hierarchy $\mathcal{RCH}$. The running time can be significantly reduced by using in-memory data structure instead of relational tables, which is in total 1.2GB, in order to make the faceted interface a real time Web application.

7. CONCLUSION

In this paper we proposed Facetedpedia, a faceted retrieval system for information discovery and exploration over Wikipedia. This system provides a dynamic and automated faceted search interface for users to browse and navigate articles that are retrieved as a result of a keyword query. Given the sheer size and complexity of Wikipedia and the large space of possible faceted interfaces, we propose metrics for ranking faceted interfaces as well as efficient algorithms to discover them. Our experimental evaluation and user study verify the effectiveness of our methods in generating useful faceted interfaces.

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