International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

COPY RIGHT

IJIEMR Transactions, online available on 17 April 2019.

Link : http://www.ijiemr.org

Title:- Enhancing the Faceted Product Search Engines Using Dynamic Facet Ordering.

Volume 08, Issue 04, Pages: 192 - 197.

Paper Authors

AKULA SAI MADHAVI , K.N.VENKATESWARA RAO.

Department of MCA, SKBR PG College.

USE THIS BARCODE TO ACCESS YOUR ONLINE PAPER

To Secure Your Paper As Per UGC Approvals We Are Providing A Electronic Bar Code

International Journal for Innovative Engineering and Management Research

PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL

www.ijiemr.org

ENHANCING THE FACETED PRODUCT SEARCH ENGINES USING DYNAMIC FACET ORDERING

[1]AKULA SAI MADHAVI , [2]K.N.VENKATESWARA RAO

[1]PG Scholar, Department of MCA, SKBR PG College, Amalapuram

[2]Assistant Professor, Department of MCA, SKBR PG College, Amalapuram

ABSTRACT: Faceted browsing is widely used in Web shops and product comparison sites. In these cases, a fixed ordered list of facets is often employed. This approach suffers from two main issues. First, one needs to invest a significant amount of time to devise an effective list. Second, with a fixed list of facets, it can happen that a facet becomes useless if all products that match the query are associated to that particular facet. In this work, we present a framework for dynamic facet ordering in e-commerce. Based on measures for specificity and dispersion of facet values, the fully automated algorithm ranks those properties and facets on top that lead to a quick drill-down for any possible target product. In contrast to existing solutions, the framework addresses e-commerce specific aspects, such as the possibility of multiple clicks, the grouping of facets by their corresponding properties, and the abundance of numeric facets. In a large-scale simulation and user study, our approach was, in general, favorably compared to a facet list created by domain experts, a greedy approach as baseline, and a state-of-the-art entropy-based solution.

KEY WORDS: Facet ordering, product search, user interfaces

I.INTRODUCTION

Studies from the past have shown that other factors than the price play a role when a consumer decides to choose where to buy a product online [1]. Therefore, online retailers pay special attention to the usability and efficiency of their Web shop user interfaces. Nowadays, many Web shops make use of the so-called faceted navigation user interface [2], which is in literature also sometimes referred to as ‘faceted search’ [3]. Facets are used by some users as a search tool, while others use it as a navigation and/or browsing tool [4], [5]. One of the reasons why faceted search is popular among Web shops is that users find it intuitive [6], [7]. The term ‘facet’ has a rather ambiguous interpretation, as there are different types of facets. In this work, we refer to facets as the combination of a property and its value, such as WiFi: true or Lowest price:64.00.

Furthermore, facets are usually grouped by their property in user interfaces, in order to prevent them from being scattered around, and, thereby, confusing the user. In other words, the facet properties, such as Color, are shown first, and each property presents the actual values (e.g., Red, Green, and Blue). Fig. 1 shows an example of a faceted search user interface, where the same concepts apply (e.g., the ‘Featured Brands’ property with its values ‘Samsung’, ‘Motorola’, ‘Nokia’, etc.). Faceted search is primarily helpful in situations where the exact required result is not known in advance. As opposed to product search using keyword-based queries, facets enable the user to progressively narrow down the search results

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

in a number of steps by choosing from a list of query refinements. However, one of the difficulties with faceted search, especially in e-commerce, is that a large number of facets are available. Displaying all facets may be a solution when a small number of facets is involved, but it can overwhelm the user for larger sets of facets [9].

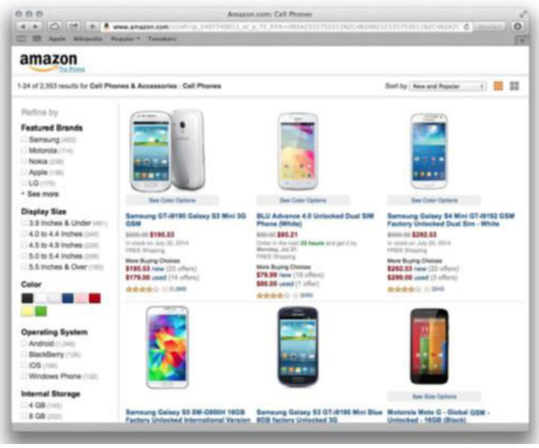

Fig. 1: An Example of a Faceted Search User Interface

Currently, most commercial applications that use faceted search have a manual, 'expert-based' selection procedure for facets [10], [11], or a relatively static facet list [8]. However, selecting and ordering facets manually requires a significant amount of manual effort. Furthermore, faceted search allows for interactive query refinement, in which the importance of specific facets and properties may change during the search session. Therefore, it is likely that a predefined list of facets might not be optimal in terms of the number of clicks needed to find the desired product. In order to deal with this problem, we propose an approach for dynamic facet ordering in the e-commerce domain. The focus of our approach is to handle domains with sufficient amount of complexity in terms of product attributes and values. Consumer electronics (in this work 'mobile phones') is one good example of such a domain. As part of our solution, we devise an algorithm that ranks properties by their importance and also sorts the values within each property.

For property ordering, we identify specific properties whose facets match many products (i.e., with a high impurity). The proposed approach is based on a facet impurity measure, regarding qualitative facets in a similar way as classes, and on a measure of dispersion for numeric facets. The property values are ordered descending on the number of corresponding products. Furthermore, a weighting scheme is introduced in order to favor facets that match many products over the ones that match only a few products, taking into account the importance of facets. Similar to existing recommender system approaches [12], our solution aims to learn the user interests based on the user interaction with the search engine

II. RELATED WORK

We can find approaches in the literature that focus on personalized faceted search [13], [14], [15]. However, we do not discuss these, as, unlike our approach, they require some sort of explicit user ratings. Therefore, we only consider related work that does not require any explicit user input other than the query. The faceted search system proposed in [16] focuses on both textual and structured content. Given a keyword query, the proposed system aims to find the interesting attributes, which is based on how surprising the aggregated value is, given the expectation. The main contribution of this work is the navigational expectation, which is, according to the authors, a novel interestingness measure achieved through judicious application of p-values. This method is likely not to be suitable for the domain of e-commerce, where also small data sets occur and statistically deriving interesting attributes is not possible.

In [17], a framework for general-domain facet selection is proposed, with the aim to maximize the rank promotion of desired documents. There are many aspects in the proposed approach that make it not applicable in an e-commerce environment. First, two main assumptions are made: (1) the search process is initiated using a keyword-based query, and (2) the result is a ranked list of documents. These are serious limitations, as many Web shop users start with a facet selection instead of a keyword-based search, and product ranking is often not supported. Therefore, the framework we propose does not use these two assumptions. Second, the proposed solution does not consider multiple iterations of the search process (i.e., multiple drill-downs). Third, the authors do not differentiate between facet types. Consequently, numeric facets are treated in the same way as qualitative facets (discussed in Section 3), thereby losing their ordinal nature. Fourth, the authors assume that a user can only perform a drill-down using only conjunctive semantics. In our study, we use the common disjunctive semantics for values and conjunctive semantics for properties and take into account the possibility of drill-ups.

This means that result set sizes are expected to both increase and decrease during the search session, either by deselecting a facet or choosing an addition facet in a property (e.g., selecting 'Samsung' when 'Apple' is already selected). Fifth and last, the authors do not distinguish in their approach between values (e.g., Samsung) and properties (e.g., Brand), instead, they only consider the combination of values and properties. In [18] the approach of [17] was extended and improved with a focus on product search. Using additional user assumptions and the same theoretic approach as [17], two new methods for facet sorting were developed. Even though this approach improves upon the original algorithm, it still suffers from the same issues discussed above.

A more recent approach provides another method for facet selection [19], or 'dynamic categorization' as the authors refer to it. The selection process is based on ontological data from a Semantic Web environment. However, due to a limited usage of rich ontological relationships, the algorithms can also be applied to semi-structured data, as also suggested in the paper. The study is an extension of earlier work of the authors, which was based on the idea of selecting more descriptive facets using an entropy-based measure. Similar to [17], [18], this approach does not consider numeric facets and the use of disjunctive semantics for values. Summarizing, most of the related approaches that have been proposed, with the exception of [18], do not explicitly focus on the e-commerce domain [14], [17], [19]. Furthermore, these solutions often assume that there is a ranking of the results, based on a preceding keyword-based query or external data, which is often not the case for e-commerce. Also, our approach ranks properties and facets, unlike existing algorithms [14], [17], [18], [19], which filter (or select) properties and facets. Last, none of the approaches from the literature that we discussed emphasize the performance aspect of the proposed algorithms. However, in order to be useful in practice, for most Web shops, it is important that the proposed solutions are responsive.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

III. PROPOSED SYSTEM

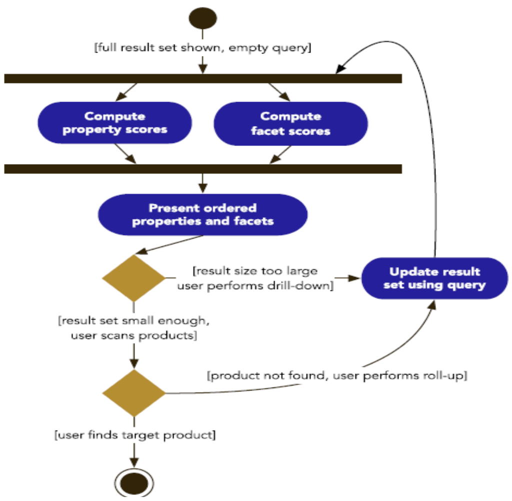

fig. 2: proposed system

The proposed approach which is shown in figure (2) which dynamic facet is ordering in the e-commerce domain. The outcome of the property scores is used to first sort the properties, after which the facet scores, discussed in the next section, are used to sort the values within each property. Consumer electronics (in this work „mobile phones") is one good example of such a domain. As part of our solution, we devise an algorithm that ranks properties by their importance and also sorts the values within each property. For property ordering, we identify specific properties whose facets match many products (i.e., with a high impurity). The proposed approach is based on a facet impurity measure, regarding qualitative facets in a similar way as classes, and on a measure of dispersion for numeric facets. The property values are ordered descending on the number of corresponding products. Furthermore, a weighting scheme is introduced in order to favor facets that match many products over the ones that match only a few products, taking into account the importance of facets. The solution aims to learn the user interests based on the user interaction with the search engine.

When creating facets from source data (e.g., tabular data), every unique property-value combination is converted into a facet. For numeric facets, the same process is applied. However, numeric values can be widely dispersed, especially in large data sets. For facets, however, that would lead to a list of possibly hundreds of different values. One way to deal with that is to create predefined, fixed ranges of values and use these as facets. However, it is never certain whether the predefined ranges will match the user's preferences. Furthermore, fixed ranges can become useless when a result set has only products that fall into one predefined range. For our approach, we have chosen to let the user define custom ranges of values to select. In a product search engine, such custom ranges can be represented using a slider widget. From a technical point of view, however, these custom ranges are considered as selecting a set of facets in one click, i.e., each numeric value is still represented as a separate facet.

The approach we propose aims to order properties and facets in such a way that any individual product could be found quickly and effectively. We put the leading emphasis on property ordering, as we expect that it has the largest impact on the user effort. A straightforward way to order properties would be by presenting those properties on top that feature equal-sized facet counts for the facets of that property, which is an effect that is for instance visible in the entropy-based approach of [18]. However, this would still require many clicks in total, possibly leading to long search times. Our approach aims to rank more specific properties higher. The reason behind is that we

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

believe that users are to a limited extent, and possibly unconsciously, aware that selecting more unique features of the target product will result in a faster drill-down. However, our approach also sorts the values within each property in order to reduce the value scanning effort. This is in contrast to for instance the approach, which considers property ranking but disregards facets ranking. For numeric properties, value ordering is neglected, as these are often represented with a slider widget in user interfaces.

TABLE .1: Results for the Best Facet Drill-Down Model

	Ordering Scheme			
	Expert-Based	Greedy Count	Kim et al.	Our approach
user effort:				
# clicks (X_c)	30.7	62.9	59.8	18.8
# clicks std dev	20.05	27.98	20.01	9.77
prop scan effort (X_p)	0.1220	0.1681	0.1524	0.2268
prop scan effort std dev	0.0232	0.0255	0.0297	0.0261
facet scan effort (X_f)	0.3904	0.4842	0.5443	0.3075
facet scan effort std dev	0.0599	0.1100	0.0325	0.0308
other measures:				
computation time (ms)	16	118, 155	113, 336	2, 843
computation time std dev	12.6	72, 772.1	53, 871.0	2, 094.0
# rollups mean	10.7	10.0	16.6	6.2
successful sessions (%)	90.96%	64.00%	79.53%	99.07%

IV. CONCLUSION

In this work, we proposed an approach that automatically orders facets such that the user finds its desired product with the least amount of effort. The main idea of our solution is to sort properties based on their facets and then, additionally, also sort the facets themselves. We use different types of metrics to score qualitative and numerical properties. For property ordering we want to rank properties descending on their impurity, promoting more selective facets that will lead to a quick drill-down of the results. Furthermore, we employ a weighting scheme based on the number of matching products to adequately handle missing values and take into account the property product coverage.

V. REFERENCES

[1] H. Zo and K. Ramamurthy, "Consumer selection of E-commerce websites in a B2C environment: A discrete decision choice model," IEEE Trans. Syst. Man Cybern. Part A: Syst. Humans, vol. 39, no. 4, pp. 819–839, Jul. 2009.

[2] M. Hearst, "Design recommendations for hierarchical faceted search interfaces," in Proc. 29th Annu. Int. Conf. Res. Develop. Inf. Retrieval, 2006, pp. 1–5.

[3] D. Tunkelang, "Faceted search," Synthesis Lectures Inf. Concepts Retrieval Services, vol. 1, no. 1, pp. 1–80, 2009.

[4] K.-P. Yee, K. Swearingen, K. Li, and M. Hearst, "Faceted metadata for image search and browsing," in Proc. SIGCHI Conf. Human Factors Comput. Syst., 2003, pp. 401–408.

[5] J. C. Fagan, "Usability studies of faceted browsing: A literature review," Inf. Technol. Libraries, vol. 29, no. 2, 2010, Art. no. 58.

[6] M. Hearst, A. Elliott, J. English, R. Sinha, K. Swearingen, and K.-P. Yee, "Finding the flow in Web site search," Commun. ACM, vol. 45, no. 9, pp. 42–49, 2002.

[7] B. Kules, R. Capra, M. Banta, and T. Sierra, "What do exploratory searchers look at in a faceted search interface?" in Proc. 9th ACM/ IEEE-CS Joint Conf. Digit. Libraries, 2009, pp. 313–322.

[8] Amazon.com, "Large US-based online retailer," 2014. [Online]. Available: http://www.amazon.com

[9] V. Sinha and D. R. Karger, "Magnet: Supporting navigation in semi-structured data environments," in Proc. 24th ACM SIGMOD Int. Conf. Manage. Data, 2005, pp. 97–106.

[10] Kieskeurig.nl, "Major Dutch price comparison engine with detailed product descriptions," 2014. [Online]. Available: http://

www.kieskeurig.nl
[11] Tweakers.net, "Dutch IT-community with a dedicated price comparison department," 2014. [Online]. Available: http://www. tweakers.net
[12] Q. Liu, E. Chen, H. Xiong, C. H. Ding, and J. Chen, "Enhancing collaborative filtering by user interest expansion via personalized ranking," IEEE Trans. Syst. Man Cybern. Part B: Cybern., vol. 42, no. 1, pp. 218–233, Feb. 2012.
[13] J. L. Herlocker, J. A. Konstan, A. Borchers, and J. Riedl, "An algorithmic framework for performing collaborative filtering," in Proc. 22nd Annu. Int. Conf. Res. Develop. Inf. Retrieval, 1999, pp. 230–237.
[14] J. Koren, Y. Zhang, and X. Liu, "Personalized interactive faceted search," in Proc. 17th Int. Conf. World Wide Web, 2008, pp. 477–486.
[15] G. M. Sacco and Y. Tzitzikas, Dynamic Taxonomies and Faceted Search, vol. 25. Berlin, Germany: Springer, 2009.