Building User Groups Based on a Structural Representation of User Search Sessions

Wilko van Hoek and Zeljko Carevic(✉)

GESIS – Leibniz Institute for the Social Sciences,
Unter Sachsenhausen 6–8, 50667 Cologne, Germany
{wilko.hoek,zeljko.carevic}@gesis.org

Abstract. Identifying user groups is an important task in order to personalise search results. In Digital Libraries, visited resources and the sequential search patterns are often used to measure user similarity. Whereas visited resources help to understand what users want, they do not reveal how users prefer to search. In contrast, sequential patterns allow to decode the way in which users search, but they are very strict and do not allow changes in the order of the search. A third alternative and compromise could be the analysis of the structure of a search session. In this paper, we aim to obtain some insights into the potential of analysing search sessions on a structural basis. Therefore, we will investigate a structural representation of search sessions based on tree graphs. We will present a novel method to merge multiple session trees into a combined tree. Based on combined tree taken from similar sessions, we will build archetypical trees for different user groups.

Keywords: Retrieval sessions · User behaviour · Session trees · Exploratory search

1 Introduction

To improve the user experience in information retrieval systems, understanding user needs has become more and more important. Methods in information retrieval have ventured from strictly text based models like TF-IDF and language models [13] to learning models based on user behaviour [1]. Along this process, personalisation has become an ever growing field [7]. The more user information is collected and evaluated, the better search results can be tailored to a specific user or user group. Therefore, it is important to understand the users' search behaviour. The methodologies to analyse search behaviour range from descriptive counts and user feedback (e.g. [19]), qualitative feedback and interviews (e.g. [2]), gaze-data (e.g. [12]) to mixed-methods (e.g. [18]). The goal is to identify specific signals in the usage behaviour that indicate the users' needs. In live systems, most systems rely on measurable signals, like click through rates, search terms, the set of visited resources, or sequential patterns.

Sequential pattern analysis has proven to be a very useful approach in personalisation [7,16]. It can be used to measure the similarity between different users [15].

J. Kamps et al. (Eds.): TPDL 2017, LNCS 10450, pp. 459–470, 2017.
DOI: 10.1007/978-3-319-67008-9_36

An important advantage of sequential patterns is the ability to keep the temporal order in which user activity has been executed. This helps to understand if there is a relevance to whether an action or information should be presented before or after another. Sequential pattern analysis stands opposite to bag-of-words-like approaches, where user activities are treated irrespectively of the order in which they were conducted. Using such approaches, user similarity can be measured, based on the objects the users have visited [7].

However, there is another aspect of user activity which is the structure of the user behaviour. Instead of analysing which objects have been visited in which order, the question would be, how have the objects been accessed? A structural representation shows the connections between various objects regardless of the order in which they have been accessed. It is less detailed than a sequential and more detailed than a bag-of-words representation. In this paper, we will investigate a structural representation of search sessions based on tree graphs. We will present a novel method to merge multiple session trees into a combined tree. Based on the combined tree of session groups, we will build archetypical trees for different user groups. We exemplify our approach based on the results of a user study with 32 participants performing an exploratory search task in a digital library. Our goal is to look if we can discover groups that show (a) economic, (b) exhaustive-active and (c) exhaustive-passive behaviour similar to the groups described in [4].

2 Related Work

In [14], a study was conducted in which the search intention given by the participants could be identified automatically. The authors found evidence that there was a connection between search pattern and task type. [6] were able to distinguish between low-level tasks, based on the activity patterns and introduce a novel technique that allowed to detect aspects of tasks. Going beyond the connection between patterns and tasks, [4] found that the user's task influences the result page examination behaviour. They analysed queries, clicks, mouse cursor movement, scrolling, and text highlighting that was collected from the usage of the Bing search engine during a time period of 13 days. By using a set of features derived from the logged data, they were able to derive six clusters. By clustering only data from non-navigational tasks, they were able to distinguish three types of search engine result pages (SERPs) examiners: the economic, the exhaustive-active and the exhaustive-passive user. While economic users do not spend much time on SERPs, show more mouse movements, and abandon SERPs more often, users from the exhaustive groups investigate their SERPs more intensely.

Similar groups have been found in [3]. Here a lab study with 28 participants was conducted. Based on the eye tracking data, specific examination patterns were identified and manually clustered into the two groups economic and exhaustive evaluation styles. For both groups significant differences in the search behaviour could be found. White and Drucker [17] also focus on patterns in the search behaviour. They collected five months of live data from 3290 users and extracted the users' search trails. Based on those trails, they identified differences in the interaction patterns, which led to two identifiable user groups, navigators and explorers. Navigators showed more consistent interaction patterns. They showed few deviations in their behaviour, tackled problems sequentially and revisited former pages more often. In contrast, explorers used a variety of different patterns, they branched frequently, submitted more queries and visited new websites more often. Only one of the studies mentioned above investigated the search session on a structural level. In [17], the search sessions were transferred into a web graph representation, which allowed to identify structural aspects of the user sessions. However, as the authors were interested in other aspects of the user behaviour, they derived sequential patterns from the graph representation and then analysed the sequences instead of the structural information.

In other fields, we can find research on the benefit of analysing structural information. In biology for example, structural information is used to detect common cell developments. The cells are represented as trees. By measuring pairwise similarities of those trees, similar groups of cell developments can be found. In [9], an overview is given on different approaches utilising structural analysis of trees in the field of biology.

3 Merging User Sessions

In this section, we will introduce our data set which we took from a user study on exploratory search. Furthermore, we will explain how to create a structural representation of a user's search session as a tree. At last, we will show how this representation can be used to merge multiple user sessions into a combined tree.

3.1 User Study

The user study involved 32 participants from the social sciences – 16 postdoctoral researchers and 16 students – who were asked to search for related work to a given topic. All participants started with the same document titled *Ethnical education inequality at start of school* and had a limit of ten minutes to solve the task. Having to use Sowiport [11] for their literature search, the participants had access to about 9 million social scientific documents. The seed document (see Fig. 1) was published by two authors, had five keywords and one classification and was published in a German journal for sociology and social psychology. All metadata fields could be utilised for further exploration within the system via a hyperlink. Additionally, participants could browse through citations, references or read the abstract or the full text. Besides this information, the participants were provided with ten recommended documents. Five documents of these were provided using the SOLR *more like this function* and the remaining five were documents published in the same journal. The system comprised 18 different databases and thus duplicates could have been recommended.

A more detailed description of the user study and the procedure can be found in [5]. In this paper, we only focus on the participants' activities and will therefore not go into any more detail regarding the study procedure.

(a) Seed document

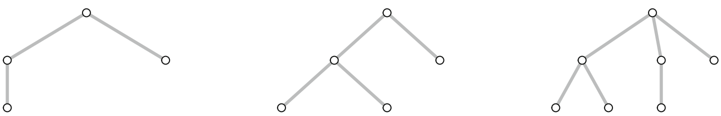
(b) Citation tab

(c) Reference tab

Fig. 1. Seed document for the user study.

3.2 Tree Representation of Search Sessions

We use the screen casts and the notes taken during the experiments to create a tree representation of the user behaviour and transformed them into a JSON format. To illustrate how we create such session trees, Fig. 2 shows three fictitious examples of session trees and the corresponding search patterns. In the first session, starting from the seed document, the document's citation list was clicked and one of the cited documents visited. This is represented by the left two nodes in Fig. 2a. The user then returned to the citation list and to the seed document. This user activity only involved already visited pages. Thus, it did not result in additional nodes. Finally, the search conducted at the session's end accounts for the right node in the tree. The other trees are created accordingly.



(a) Session 1 (b) Session 2 (c) Session 3

Session 1: $doc_{seed} \rightarrow citation \rightarrow doc_1 \rightarrow citation \rightarrow doc_{seed} \rightarrow search$
Session 2: $doc_{seed} \rightarrow journal \rightarrow doc_{seed} \rightarrow author \rightarrow doc_1 \rightarrow author \rightarrow doc_2$
Session 3: $doc_{seed} \rightarrow search \rightarrow doc_1 \rightarrow search \rightarrow doc_2 \rightarrow search \rightarrow doc_{seed} \rightarrow journal \rightarrow doc_{seed} \rightarrow citation \rightarrow doc_3$

Fig. 2. Session trees (a–c) for three example search sessions (1–3)

For this representation we ignore the type of user activity. Whether a node represents a document, a search, or a citation list is discarded. Furthermore, we discard the order of the activities. Instead, we sort the tree by subtree size from left to right. On one level, nodes with more subnodes are sorted further to the left than those with less subnodes. This can be observed in Fig. 2b. The author search happens after the journal search, but the corresponding nodes are on the left side, because there are more subsequential actions involved.

To extend the analysis from individual sessions to session groups, we need a way to combine multiple session trees into one conjoint tree[1]. Instead of combining all trees at once, we merge pairs of trees iteratively. We start with an empty tree and merge it with the first session tree. The resulting tree is then merged with the next tree and so forth. Figure 3a shows the merged tree of the example session tree 1 (cf. Fig. 2a) and 2 (cf. Fig. 2b). When two nodes are merged, the weights of their edges are summed up. After merging session tree 1 and 2, we merge the result with the tree of session 3 (cf. Fig. 2c), shown in Fig. 3b.

(a) Session 1 and 2 merged

(b) Session 1, 2, and 3 merged

Fig. 3. Combined session trees of the example sessions from Fig. 2.

When merging two trees, one has to decide which nodes are merged. As each node and its child nodes can be interpreted as an individual tree, this decision can be made recursively for each node. We create all possible combinations of subtrees for each pair of nodes and select the best combination along two conditions: First, the number of nodes in the resulting subtree has to be minimal. Second, the weight distribution of the subtree has to be optimised.

For the second condition we needed to define what a weight of a subtree is and what an optimum for the subtree weight is. We define the subtree weight $W(p)$ as follows.

Definition 1. *Let $p \in N_T$ be a node in the tree T, $w(p)$ be the weight of the edge leading to the node p, and C_p the set of child nodes of p. The weight $W(p)$ of the subtree with the root node p is then defined as:*

$$W(p) = \begin{cases} \lg(2 \cdot w(p)) & \textit{if } C_p = \emptyset \\ \lg(\sum_{q \in C_p} w(q) \cdot W(q)) & \textit{else} \end{cases}$$

[1] The Java and R based tool is available under: https://github.com/wilkovanhoek/amur-session-graph/tree/tpdl2017.

We sum the product of the weights of the edges leading to child nodes and the subtree weight of those nodes and calculate the logarithm of this sum. We use the logarithm only to keep the subtree weight from increasing exponentially, as we only need it to compare the subtrees, not to assess an actual summed subtree weight. After defining the subtree weight, we need to define what an optimal subtree weighting is. Because we want the weight of the resulting subtrees to increase from left to right and we do not want the weight to be distributed equally, we favour building maximal heavy subtrees. Therefore, the merged nodes with the heaviest subtree is considered to be optimal.

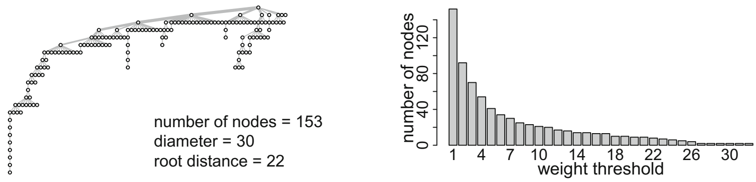
Following the described procedure, we receive exactly one resulting tree, when combining two session trees. However, when merging multiple trees iteratively, the resulting tree depends on the order in which the trees are merged. To find the optimal merging order, we would need to calculate all possible permutations in which the session trees could be merged. This would result in $32! \approx 2,63 \times 10^{35}$ merging orders for the complete set of trees in our study. As this exceeded our computational capacities for this paper, we decided to use another approach. Before merging the trees, we have sorted the session trees in ascending order with respect to their root node's subtree weight. Now, when merging them, the resulting tree of each merge slowly increases in weight (in general trees with a smaller subtree weight tend to be more compact trees). In this way, common structures that exist in many trees are merged very early, whereas outliers are merged later. Note that the sorting does not guarantee an optimal merging order. However, it ensures that there is only one resulting tree for a set of trees and that all combined trees are created with the same procedure.

3.3 Building Subtrees

Figure 4a shows the combined session tree for all participants. In most sessions, starting from the root node, at least three different actions were conducted. In addition, a larger group of users followed a longer trail of multiple consecutive actions (cf. trail of nodes on the left). Overall, the combined session tree is not very compact. There is a certain density within the first two levels, but behind that, only a few longer trails exist in the tree. Instead, there are many edges that are introduced by a few intense sessions. We consider this to be noise, because it inflates the combined session tree. Therefore, we will introduce a way to reduce this noise, without removing the session trees that are responsible for the noise.

Edges with a low weight as displayed in Fig. 4a represent an activity that has happened in a minority of sessions. Figure 4b illustrates how many nodes would remain in the tree, if we remove all edges (and their nodes) below an increasing weight threshold. After the strong decline in the beginning we can see a first 'plateau' where no bigger drop in the number of remaining nodes for the threshold of 6 and onwards is observed. At a threshold of 11 we can observe a similar development.

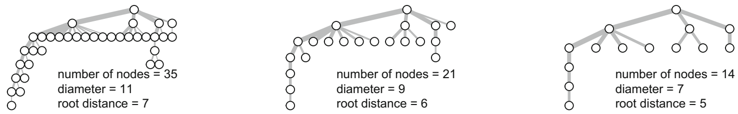
Figure 5 shows three subtrees with different thresholds, extracted from the combined session tree in Fig. 4a. Figures 5a and b show the subtrees for the thresholds of 6 and 11. In addition, we include the tree for a threshold of 17



(a) Combined session tree for all participants.

(b) Distribution of the number of nodes in the combined tree, after removing all nodes with a weight below a given threshold value.

Fig. 4. Combined session tree for all participants (a) and thresholds of graph nodes (b).



(a) Threshold 6

(b) Threshold 11

(c) Threshold 17

Fig. 5. Subtrees extracted from the combined session tree (cf. Fig. 4). Each tree is created by removing all edges (and nodes) with a weight below the specified threshold.

which represents all nodes that appear at least in half of all session trees. In Fig. 5c we can now see our former observation more clearly. Most users start at least three independent activities from the root document and follow at least one longer trail. Comparing all three subtrees in Fig. 5, we can observe that with an increasing threshold mainly the number of nodes per level decreases, whereas the overall structure does not change decisively.

4 Grouping the User Behaviour

Based on the session trees, we tried to divide the user sessions into groups. We grouped similar session trees. We did this based on our visual impression and aspects like the number of nodes on the same level, the number of parallel subtrees, the overall depth of the tree, the number of subtrees with a similar depth, and the branchiness (how often single nodes are followed by multiple nodes).

Figures 6 and 7 show sessions with very intense activity in which many actions have been conducted. The sessions in Fig. 6, however, nearly exclusively show activity close to the seed document. This activity represents SERPs that are closely examined. We characterise this as an highly exhaustive behaviour with a focus on breadth. In contrast, the sessions displayed in Fig. 7, show more activity venturing away from the seed document. It seems as if a trail is being followed. The participants investigated deeper into a specific direction. We characterise this as an exhaustive behaviour with focus on depth.

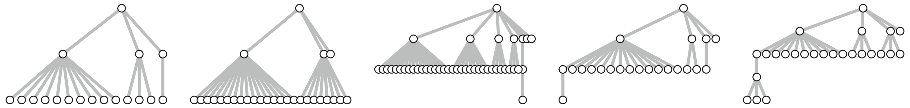


Fig. 6. Exhaustive breadth group

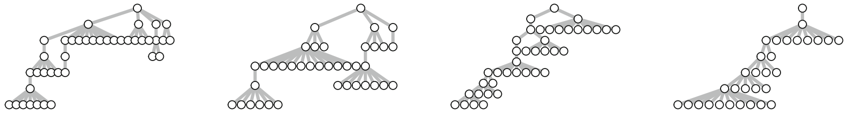


Fig. 7. Exhaustive depth group

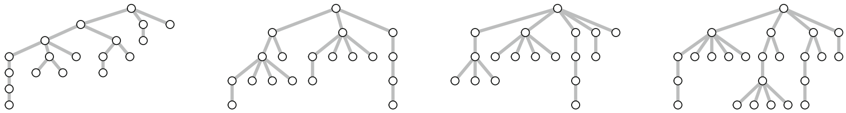


Fig. 8. Economic breadth group

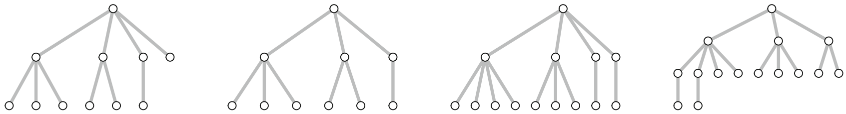
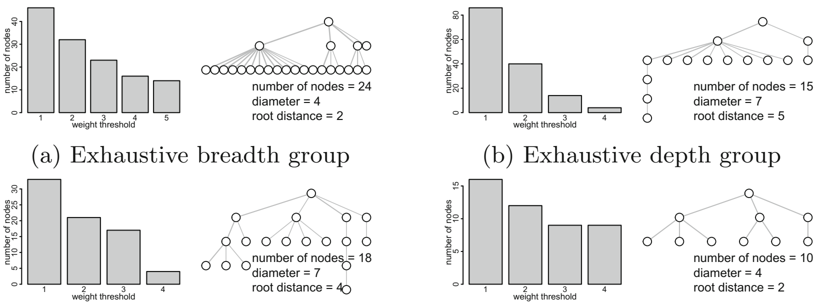


Fig. 9. System support group

Figures 8 and 9 display sessions with a lower number of actions. The trees are less dense and appear more balanced. In Fig. 8, different trails are followed which are inspected to some extend, but not very deeply. It appears to be a more swift examination of the area around the seed document. We characterise this as an economic behaviour with focus on breadth. The sessions in Fig. 9 display a very particular behaviour. When building this group, we realised, that they have strong familiarities with the subtree of the complete data set for a threshold of 17 (Fig. 5c). Structurally speaking, these sessions are similar to a common behaviour in the majority of sessions. To understand this, we watched the sessions' screen casts again. We could see that the participants almost solely relied on information that was provided by the system (recommendations, references and citations) and rarely conducted own searches. We characterise this group as behaviour with a focus on system support. However, we don't know in how far the study task and situation has triggered this behaviour. Possibly, these participants could not identify with the task.

5 Building Archetypical Session Trees per Group

Now that we have four different groups of behaviour, the next step is to build archetypical trees for each group. We will use the method described in Sect. 3.3. At first, we will merge all session trees within each individual group into one combined tree. After that, we will create subtrees based on a suitable edge weight threshold. We will define the resulting subtree as the archetypical tree for the different groups. Figure 10a shows the results for the group of sessions with exhaustive behaviour focused on breadth. We can see that with an increased threshold, the number of remaining nodes decreases constantly. However, for a threshold of 3, still half of the nodes are left in the subtree. Therefore, this subtree represents behaviour that is shared by at least three participants. Looking at the resulting subtree, it seems that this tree does represent the group. We feel that this is a reasonable threshold for creating an archetypical session tree.



(a) Exhaustive breadth group (b) Exhaustive depth group

(c) Economic breadth group (d) System support group

Fig. 10. Distribution of number of nodes and combined session trees for the four different groups

Using the same method to create an archetypical session tree for the exhaustive depth group leads to bad results. The decline of number of nodes left in the subtree, when increasing the weight threshold is a lot faster than with the previous group (cf. Fig. 10b). In addition, the resulting subtree for a threshold of 3 does not look similar to any of the group's individual sessions. Only around one fifth of the combined tree's nodes remain in the subtree. It seems that our method cannot create a suitable archetypical session tree for this group. Although this tree does not represent the underlying group sufficiently we will keep it for further analysis as a negative example.

The results seem to be more sound with respect to the economic breadth group. In Fig. 10c, we can see that a subtree for a threshold of 3 contains more than half of the nodes. Only, when we raise the threshold up to 4 we see a strong decrease in the number of nodes. When comparing the resulting subtree and the group's individual session trees, strong similarities can be observed. For the last group, (system support) our method works best. Figure 10d shows that the number of nodes remaining in all subtrees stay on a higher level than for the other groups. Also, the subtree for threshold 3 resembles the group's session trees reasonably. Analogous to our previous observation, this group's archetype has a strong resemblance to the threshold 17 subtree created from the combination of all 32 session trees (cf. Fig. 5).

Based on the results of our method on creating subtrees for groups of session trees, we propose a following definition of an archetype of a group:

Definition 2. *For a group of session trees $G = \{t_1, t_2, \ldots, t_n\}$, their combined tree t_{comb} and the set of its subtrees $G_{t_{comb}} = \{sub_{t_{comb},1}, sub_{t_{comb},2}, ..., sub_{t_{comb},n}\}$, an archetypical session tree t_{arch} is the session tree, that satisfies the following conditions:*

- *it is included in the set of subtrees of the combined tree: $t_{arch} \in G_{t_{comb}}$*
- *the number of nodes is higher than half of the number of nodes in the combined tree: $|t_{arch}| > |t_{comb}|/2$*
- *the weight of each node is higher than half the number of sessions in the group: $\forall n \in t_{arch} : w(n) > n/2$*

For all groups except the exhaustive depth group, the subtrees for threshold 3 are archetypical session trees. Our approach was not able to merge the trees in the exhaustive depth group very well. As a result, we cannot derive an archetypical tree from this group.

6 Discussion

Utilising our approach based on a tree representation of user activity, we were able to visually identify similar structural patterns. By merging the similar sessions, we created a combined tree per group. By removing edges, with a low edge weight, we created a subtree of the combined tree that represents nodes that exist in most of the individual trees. This has led to the idea that there could be an archetypical tree for each group of users. We proposed a Definition 2 for such an archetypical tree. We applied this method to individual sessions of different users. However, this could also be done for multiple sessions of a user to create a user specific graph. Comparing and merging multiple user specific graphs could then be used to derive user groups in a live system. This could be achieved by merging a user specific tree with different archetypes and measure the number of unmatched nodes. A more rigid version of Definition 2 is imaginable but should be based on a larger data set. Especially the weighting constraint should be investigated more closely in future work. Also, we have not investigated the 15 user session that were not grouped. As future work we plan to assess the most suitable archetypes of those sessions.

So far, we have ignored the types of search activities and objects. It remains unclear how the present approach performs when only edges or nodes of the same type are merged. Untyped trees do not allow us to identify different search tactics. A group of users that frequently utilises a specific tactic, like a journal run, cannot be identified in this way. However, this would require a significantly larger data set. One promising study that involves a larger data set can be found in [10] and could be suitable for future work.

Another aspect we disregarded is the time spent on a specific object. Thus, there is no information about the intensity with which activities are followed. A user who only inspects the list of citations briefly is treated equally to a user that inspects the list in more detail. This could be addressed by including the action duration per node. However, we lack a suitable way to include time into the merging method. In addition, further effort should be invested in evaluating our approach with respect to more profound models in information seeking behaviour like the model by Ellis [8]. One example could be to investigate whether the present approach is capable of identifying the different stages (e.g. *Starting*, *Chaining*) of information seeking.

7 Conclusion

In this paper, we have discussed the structural analysis of patterns in user search behaviour based on a tree representation of the user sessions. We divided the different user sessions manually into groups similar to those in [4]. When grouping, we considered the graphs visual resemblance and graph attributes like the number of nodes. We proposed a novel method to merge multiple user session into one combined tree. We merged the sessions for each of our groups individually and could see that for most groups a relatively high number of nodes can be merged in a combined tree. Furthermore, we defined criteria to derive an archetypical tree from a combined tree. In this way, our method could potentially be used to assign user groups for new users of a system, based on the way in which they perform their searches. By comparing different user sessions, it could also help to identify different search strategies.

Acknowledgments. This work was partly funded by DFG, grant no. MA 3964/5-1; the AMUR project at GESIS. We thank all participants of our user study and Maria Lusky.

References

1. Agichtein, E., Brill, E., Dumais, S., Ragno, R.: Learning user interaction models for predicting web search result preferences. In: Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 3–10. ACM (2006)
2. Athukorala, K., Hoggan, E., Lehtiö, A., Ruotsalo, T., Jacucci, G.: Information-seeking behaviors of computer scientists: challenges for electronic literature search tools. Proc. Am. Soc. Inf. Sci. Technol. **50**(1), 1–11 (2013)
3. Aula, A., Majaranta, P., Räihä, K.-J.: Eye-tracking reveals the personal styles for search result evaluation. In: Costabile, M.F., Paternò, F. (eds.) INTERACT 2005. LNCS, vol. 3585, pp. 1058–1061. Springer, Heidelberg (2005). doi:10.1007/11555261_104

4. Buscher, G., White, R.W., Dumais, S., Huang, J.: Large-scale analysis of individual and task differences in search result page examination strategies. In: Proceedings of the Fifth ACM International Conference on Web Search and Data Mining, WSDM 2012, pp. 373–382. ACM, New York (2012)
5. Carevic, Z., Lusky, M., Van Hoek, W., Mayr, P.: Investigating exploratory search activities based on the stratagem level in digital libraries. Int. J. Dig. Libr. **18**(1), 1–3 (2017). https://arxiv.org/abs/1706.06410
6. Cole, M.J., Hendahewa, C., Belkin, N.J., Shah, C.: User activity patterns during information search. ACM Trans. Inf. Syst. (TOIS) **33**(1), 1 (2015)
7. Eirinaki, M., Vazirgiannis, M.: Web mining for web personalization. ACM Trans. Int. Technol. (TOIT) **3**(1), 1–27 (2003)
8. Ellis, D.: A behavioural approach to information retrieval system design. J. Documentation **45**(3), 171–212 (1989)
9. Fangerau, J.: Interactive Similarity Analysis for 3D+t Cell Trajectory Data. Ph.D. thesis (2015)
10. Hagen, M., Potthast, M., Völske, M., Gomoll, J., Stein, B.: How writers search: analyzing the search and writing logs of non-fictional essays. In: Proceedings of the 2016 ACM on Conference on Human Information Interaction and Retrieval, pp. 193–202. ACM (2016)
11. Hienert, D., Sawitzki, F., Mayr, P.: Digital library research in action: supporting information retrieval in sowiport. D-Lib Mag. **21**(3), 8 (2015)
12. Kules, B., Capra, R., Banta, M., Sierra, T.: What do exploratory searchers look at in a faceted search interface?. In: Proceedings of the 9th ACM/IEEE-CS Joint Conference on Digital Libraries, pp. 313–322. ACM (2009)
13. Manning, C.D., Raghavan, P., Schütze, H., et al.: Introduction to information retrieval, vol. 1. Cambridge University Press, Cambridge (2008)
14. Mitsui, M., Shah, C., Belkin, N.J.: Extracting information seeking intentions for web search sessions. In: Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2016, pp. 841–844. ACM, New York (2016)
15. Mobasher, B., Cooley, R., Srivastava, J.: Automatic personalization based on web usage mining. Commun. ACM **43**(8), 142–151 (2000)
16. Srivastava, J., Cooley, R., Deshpande, M., Tan, P.N.: Web usage mining: discovery and applications of usage patterns from web data. ACM SIGKDD Explor. Newsletter **1**(2), 12–23 (2000)
17. White, R.W., Drucker, S.M.: Investigating behavioral variability in web search. In: Proceedings of the 16th International Conference on World Wide Web, WWW 2007, pp. 21–30. ACM, New York (2007)
18. Wildemuth, B.M.: The effects of domain knowledge on search tactic formulation. J. Am. Soc. Inf. Sci. Technol. **55**(3), 246–258 (2004)
19. Wilson, M.L., Schraefel, M.: A longitudinal study of exploratory and keyword search. In: Proceedings of the 8th ACM/IEEE-CS Joint Conference on Digital Libraries, JCDL 2008, pp. 52–56. ACM, New York (2008)