Visualizing Searcher Gaze Patterns*

Mustafa Abualsaud
School of Computer Science
University of Waterloo

Mark D. Smucker
Department of Management Sciences
University of Waterloo

Charles L. A. Clarke
School of Computer Science
University of Waterloo

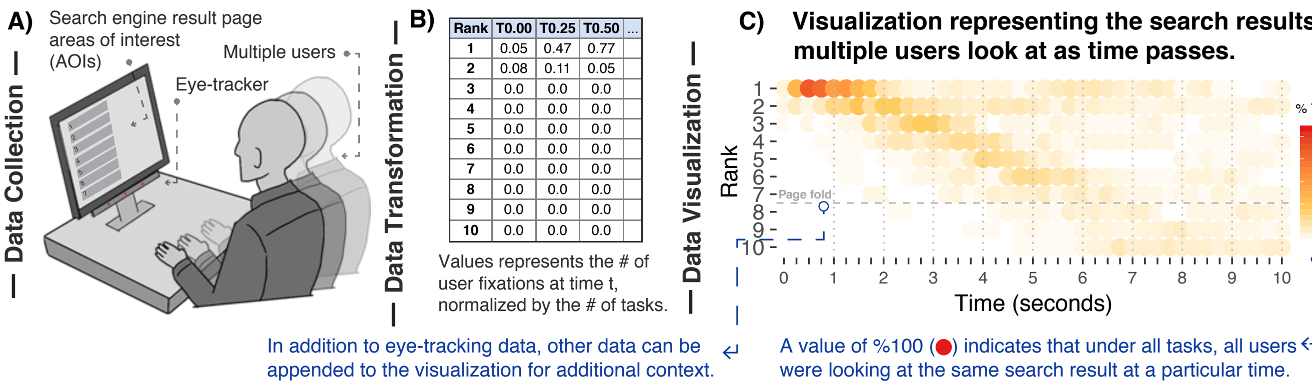


Figure 1: Overview and an example of the method used to visualize eye-tracking data of search engines result pages.

ABSTRACT

Information retrieval researchers often use eye-tracking to gain insights into searchers' decision making processes. In this paper, we present a visualizing method for summarizing the gaze patterns of multiple searchers on search engine result pages (SERPs). Unlike traditional eye-tracking heat maps, this method includes timing information as part of the visualization, providing additional clarity about searcher fixations as time passes. We demonstrate the visualization technique using eye-tracking data collected as part of a previously published search engine user study and show its value in communicating different patterns of searchers' gaze behavior under different user types and query types. We include a code sample in R to facilitate adoption of the method.

ACM Reference Format:

Mustafa Abualsaud, Mark D. Smucker, and Charles L. A. Clarke. 2021. Visualizing Searcher Gaze Patterns. In *Proceedings of the 2021 ACM SIGIR Conference on Human Information Interaction and Retrieval (CHIIR '21), March 14–19, 2021, Canberra, ACT, Australia.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3406522.3446041

*Due to color variation in the visualizations, this paper is best viewed in full color on paper or on a high definition screen.

CHIIR '21, March 14–19, 2021, Canberra, ACT, Australia

ACM ISBN 978-1-4503-8055-3/21/03…$15.00
https://doi.org/10.1145/3406522.3446041

1 INTRODUCTION

Eye-tracking is an important tool for understanding and analyzing searcher behavior [6–10]. Eye-trackers report to the researcher the gaze location of a computer user, called a "fixation". Even short experimental sessions generate a large stream of data, e.g. number of fixations, fixation duration, fixation location, etc. Data visualization allows for the quick summarization of these complex data streams and facilitates exploratory data analysis [5], which is critical to generating new hypotheses about user behavior and decision-making.

The spatio-temporal structure of gazing data allows for different and unique visualization techniques. In this paper, we review some of the existing visualization techniques and then show a visualization for temporal and Area of Interest (AOI)-based gaze data that is suitable for the typical "10 blue links" search engine interface. Our visualization is suitable for scenarios where AOIs are built in a linear (or somewhat linear) ordering and where the fixation locations within the AOI are not needed. Unlike some existing techniques, the visualization we propose allows us to combine data from multiple searchers and include timing information, while avoiding unnecessary visual clutter. We compare the method of visualization with eye-tracking attention heatmaps, and show the value of the proposed method of visualization in understanding user behavior and in communicating different patterns of searchers' gaze behavior.

2 RELATED WORK

Eye-tracking heatmaps overlaid on thumbnail images of SERPS are widely used to visualize searcher gaze patterns. Often these heatmaps only show fixations for individual searchers and do not provide timing information. For example, Dumais et al. [7] use heatmaps (see Figure 1 in that paper) to illustrate individual differences in gaze patterns. Both Liu et al. [9] and Wang et al. [15] use heatmaps to provide examples of individual searchers interacting with search verticals, such as images, news, shopping and maps. Similarly, the heatmaps in Wang et al. [16] illustrate whole-page interactions of individual searchers, including verticals and other elements. Balatsoukas and Ruthven [4] overlay SERPs with fixations and other information, similar to heatmaps.

In addition to providing specific examples of searcher behavior for illustrative purposes, heatmaps can be used to summarize outcomes from an experiment by overlaying fixations from multiple searchers. For example, Buscher et al. [6] use a heat map to display fixations from 20 participants in their experiments. Papoutsaki et al. [12] use heatmaps both to provide examples of individual interactions and to summarize the interactions of many searchers. Al-Wabil et al. [2] used heatmaps to examine visual attention of dyslexic and non-dyslexic Web users searching for information within websites. Although heatmaps provide an overall understanding of gaze patterns, they do not provide timing information.

Raschke et al. [14] visualization technique can be used to display a visual scan path of multiple users while incorporating time into the visualization, as shown in Figure 2. The y-axis indicates time, and the x-axis indicates the list of areas of interest (AOIs) being investigated. Different users are indicated by different line colors in the plot. The scan path of the user changes as time passes. The duration of the fixation at each AOI is indicated by the vertical length of the line. While this visualization is useful for visualizing the scan paths of few searchers, a larger number of searchers increases the number of scan paths, introducing visual clutter.

Räihä et al. [13] proposed a static technique for visualizing gaze data from single users while incorporating timing elements. An example of their technique is shown in Figure 3. With the AOIs displayed on the left as the y-coordinate, and the x-coordinate denoting a relative point in time, the points in the plot indicate the fixation length and the visiting order of the AOIs. This visualization works best when AOIs occur in linear order. This technique is useful for visualizing data from a single searcher, but can result in visual clutter as more searchers are added to the visualization.

Like Räihä et al. [13], the visualization method in this paper is designed to either combine eye-tracking data from many people or to show individual sessions, while incorporating time. In the following sections, we explain the process of generating the visualization and provide examples of the visualization demonstrating different patterns of gazing behavior from a previous search engine user study. We base these visualizations on data from Abualsaud and Smucker [1]. While the statistical analysis reported in that paper confirmed the differences between the searcher and query types illustrated by our visualizations, the visualizations themselves provide additional insights into the scope and nature of the differences.

3 VISUALIZATION METHOD OVERVIEW

A typical data collection process in an IR eye-tracking study involves using an eye-tracker to track users' eye fixations within a monitor screen while they interact with a search engine interface and complete some search task. For the visualization, we assume a typical search bar and ranked list of results presented linearly. While today's SERPs contain a variety of components such as ads, verticals, and knowledge graphs that may not be linearly ordered, many user studies still employ the typical "10 blue links" search

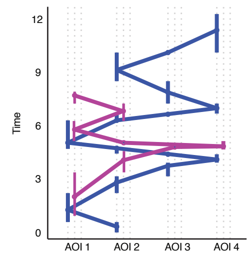


Figure 2: Example of two users AOIs examining behaviors. Y-axis indicates time. Based on Raschke et al. [14]

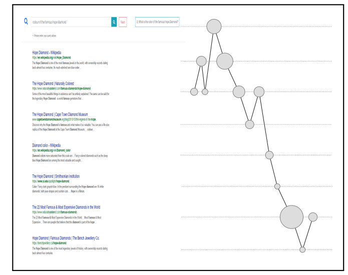


Figure 3: An example visualization of single user examining behaviour on a SERP. X-axis indicates time. Based on Räihä et al. [13]

engine interface to study different aspect of the search process. We believe this visualization method would still be applicable and useful for researchers.

As an abstraction method, we built AOIs around each search result to determine when and if a user examined a search result at a specific rank. Figure 1A shows an example of this eye-tracking data collection process. Using the eye-tracking data, we abstract the data into multiple interaction periods, each starting from the moment a SERP is presented to the user, to the time the user makes their first action, e.g., a click or an abandonment of the search result. With time being a key variable, we can determine how many users were looking at a specific rank at a particular point of time during their interaction period.

We normalize the values based on the number of search tasks in the data, such that a value of 100% would indicate that all users under all tasks in the group were looking at the same rank during a particular time period. Figure 1B shows an example of the transformed data resulted from the abstraction steps.

The visual encoding design is based on the values in the transformed data. The x-axis indicates time, and the Y-axis indicates the rank of the search result. The color encoding of data points was chosen to indicate intensity while adhering to perceptual ordering, an important element in the color theory of information visualization [11, Chapter 10.3.2].

We then use R's `ggplot2` library to implement the visual encoding and execute the visualization technique. We provide the R code for researchers to experiment with and generate visualizations from their own eye-tracking data[1]. Figure 1C shows an example of the final output of the visual encoding.

The visualization can be useful in understanding gaze patterns of searchers, communicating how far down the ranking people examine and how quickly they examine the results. It also allows for the inclusion of other relevant data, such as the location of the "page fold" where the searcher was required to scroll. Such information embedded in the visualization can provide additional context that can be useful to increase our understanding of the data.

[1] `https://gist.github.com/ammsa/dd935ce5133ff9c06a9ec21d6d2348b9`

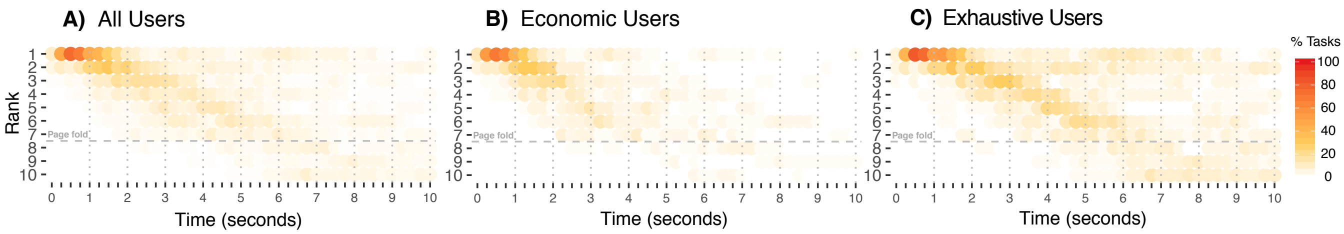


Figure 4: Example of our visualization using eye-tracking data from Abualsaud and Smucker [1] during search tasks where the only relevant document is below the fold (rank 8, 9, or 10), or when there is no relevant documents in the list.

4 STUDY DATA

We base our visualizations on the data from Abualsaud and Smucker [1]. In that work, eye-tracking data was collected to study query abandonment in web search — the behavior of abandoning search results without any clicks — while controlling different qualities of SERPs. In each task in their study, participants were asked to use a search engine interface to find an answer to a simple factoid question (e.g. "How many chapters are in the art of war book by Sun Tzu?"). The interface was designed to appear similar to commercial web search engines and returned 10 search results per query with no pagination. The page fold in the interface occurs after the 7th search result. This is the location where searchers would need to scroll down the page to view the rest of the search results.

In total, 24 users completed 12 tasks in a balanced order. In 11 of the tasks, the results of the searcher's first query were manipulated to include either one relevant result, containing the answer to the question, placed at ranks 1 to 10, or no relevant results at all. The 12th task returned the non-manipulated search results from the Bing API as a control. The set of non-relevant and relevant documents for each factoid question were chosen prior to the study. This data was then analyzed to determine factors affecting the examination and abandonment of search results.

This eye-tracking data includes information on the task type (i.e., where the relevant result is ranked or if it exists in the search results), the time the user issued their query, the time and duration of each fixation, and 10 Boolean variables indicating whether the fixation is within one of AOI representing the 10 search results.

In addition to eye-tracking data, the data also includes information on the user type, i.e. whether they are considered an *economic* or *exhaustive* user, and the type of each query (*weak* or *strong*). In Abualsaud and Smucker [1] this user type was determined from the distribution of the average total number of fixations by users during their search tasks. This definition of economic vs. exhaustive users follows prior literature, where economic users are those that typically make their decisions (e.g. to click or to requery) "faster and based on less information than exhaustive" users [3].

To label queries by type, two assessors were hired to judge the queries submitted by the searchers for each question to indicate whether they should be considered as ambiguous or under-specified queries (which were labeled as "weak") or queries that more specific to the question (labeled as "strong").

Abualsaud and Smucker [1] should be consulted for more information on user and query types, study design and data labeling procedure.

5 RESULTS AND DISCUSSION

One question to investigate is the willingness of people to scroll beyond the page fold to view more search results. Using only data from tasks where the relevant result is placed below the fold or when there are no relevant results in the list, we plotted the visualization to see if and when people examine these low ranking search results.

Figure 4A shows the visualization of all searchers under such tasks. We notice that people start to examine results below the fold (area below the horizontal dashed gray line) after about 5 seconds. Prior literature [3] indicates that economic searchers tend to process results and make their actions faster than exhaustive searchers. Figure 4B&C show the visualization under the two types of searchers. Here, we see examination of low ranking results is mostly done by exhaustive searchers, whereas economic searchers take their next action without examining results below the fold.

We also explored the gaze patterns of searchers under different query types. *Strong queries* are those that are more specific, unambiguously defining the searcher's information need. *Weak queries* are less specific and more ambiguous.

Figure 5 shows the visualizations under each group. For comparison, Figure 6 provides the same visualizations using traditional heatmaps. From Figure 5, we notice how gazing behavior changes under the four groups. When economic searchers submit a weak query, they examine fewer search results than if they issued a stronger query, as shown in the top-left part of the visualization. In contrast, exhaustive searchers keep examining results and even scroll below the fold. Economic searchers stop once they reach the fold. Another apparent difference is in the behaviour between economic and exhaustive searchers, can be seen where exhaustive searchers fill the upper diagonal of the visualization more than economic users and appear to spend more time examining each result. For example, when comparing Figure 5A and 5B, we see that exhaustive searchers spend more time scanning down the ranked list than economic searchers. While heatmaps (e.g. Figure 6) can be useful, such timing information cannot be deduced from the heatmap figures alone. This is one example where the method of visualization can useful for researcher, and can compliment heatmaps.

6 CONCLUSION

We presented a method for visualizing searcher's gaze patterns from eye-tracking data. The visualization can be useful in communicating differences between searchers' gaze patterns. For example, Figures 4 and 5 enable us to quickly and easily visualize gaze patterns and investigate differences in gazing behavior between different types

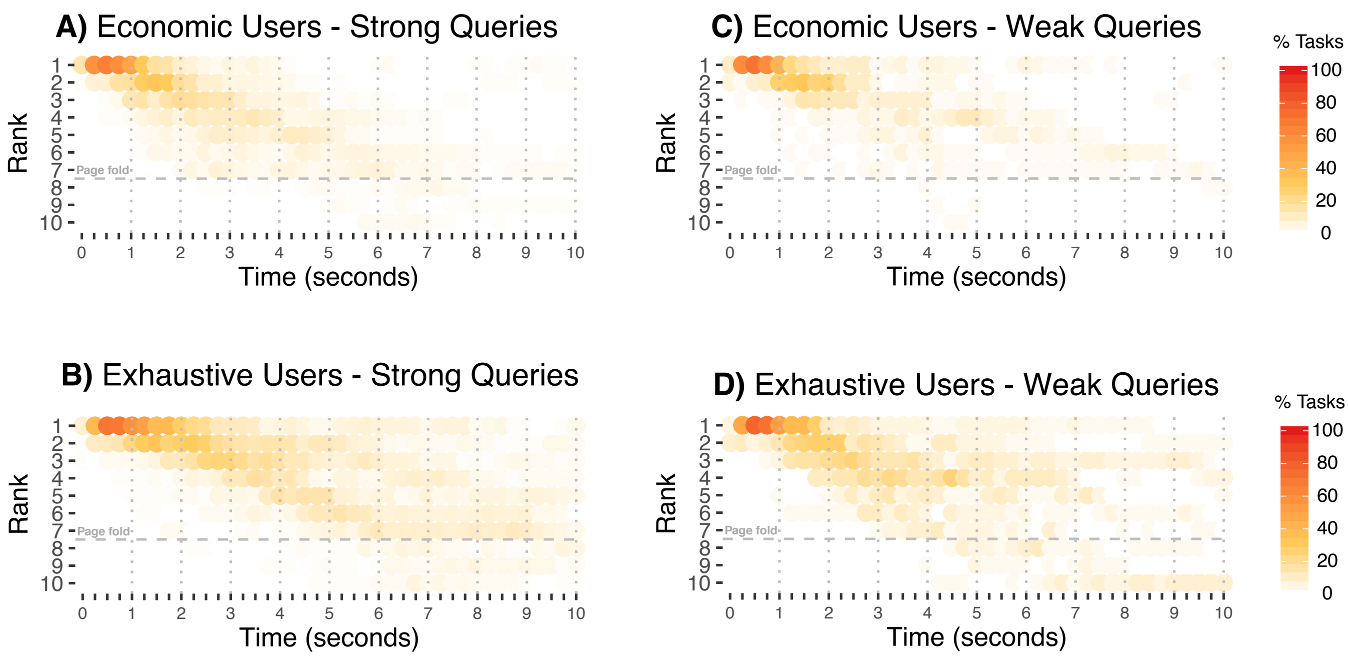
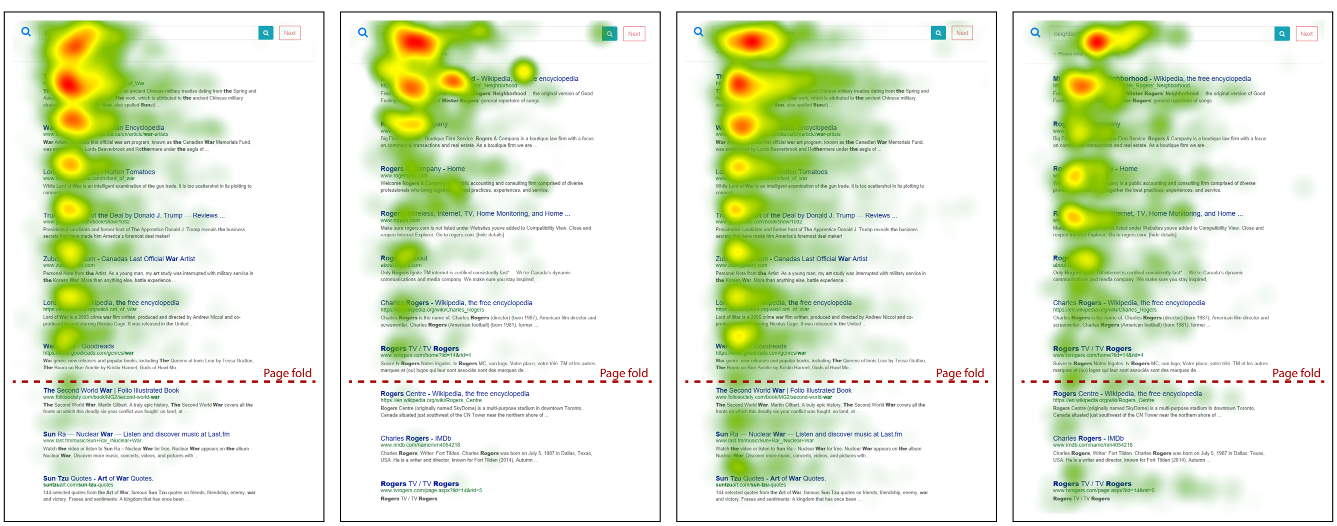


Figure 5: Our visualizations for different types of users under different quality of queries.



(a) Eco. users on strong queries **(b) Eco. users on weak queries** **(c) Exh. users on strong queries** **(d) Exh. users on weak queries**

Figure 6: Traditional visualizations using relative duration attention heatmaps generated by the eye-tracking software using default settings. These may be compared with the corresponding visualization in Figure 5.

of searchers and queries. We believe the visualization is useful in other experiments as well, such as gaze patterns while searching for answers to factoid vs. complex questions, or gaze patterns when including other SERP components such as knowledge boxes or images.

ACKNOWLEDGMENTS

This work was supported in part by the Natural Sciences and Engineering Research Council of Canada (RGPIN-2020-04665).

REFERENCES

[1] Mustafa Abualsaud and Mark D. Smucker. 2019. Patterns of Search Result Examination: Query to First Action. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19)*. Association for Computing Machinery, New York, NY, USA, 1833–1842. https://doi.org/10.1145/3357384.3358041

[2] A. Al-Wabil, P. Zaphiris, and S. Wilson. 2008. Examining visual attention of dyslexics on web navigation structures with eye tracking. In *2008 International Conference on Innovations in Information Technology*. 717–721. https://doi.org/10.1109/INNOVATIONS.2008.4781673

[3] Anne Aula, Päivi Majaranta, and Kari-Jouko Räihä. 2005. Eye-tracking reveals the personal styles for search result evaluation. In *IFIP conference on human-computer interaction*. Springer, 1058–1061.

[4] Panos Balatsoukas and Ian Ruthven. 2012. An eye-tracking approach to the analysis of relevance judgments on the Web: The case of Google search engine. *Journal of the American Society for Information Science and Technology* 63, 9 (September 2012), 1728–1746.

[5] T. Blascheck, K. Kurzhals, M. Raschke, M. Burch, D. Weiskopf, and T. Ertl. 2017. Visualization of Eye Tracking Data: A Taxonomy and Survey. *Computer Graphics Forum* 36, 8 (2017), 260–284. https://doi.org/10.1111/cgf.13079 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/cgf.13079

[6] Georg Buscher, Edward Cutrell, and Meredith Ringel Morris. 2009. What Do You See When You're Surfing? Using Eye Tracking to Predict Salient Regions of Web Pages. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. Association for Computing Machinery, New York, NY, USA, 21–30. https://doi.org/10.1145/1518701.1518705

[7] Susan T. Dumais, Georg Buscher, and Edward Cutrell. 2010. Individual Differences in Gaze Patterns for Web Search. In *Proceedings of the Third Symposium on Information Interaction in Context (IIiX '10)*. Association for Computing Machinery, New York, NY, USA, 185–194. https://doi.org/10.1145/1840784.1840812

[8] Joseph H. Goldberg, Mark J. Stimson, Marion Lewenstein, Neil Scott, and Anna M. Wichansky. 2002. Eye Tracking in Web Search Tasks: Design Implications. In *Proceedings of the 2002 Symposium on Eye Tracking Research & Applications (ETRA '02)*. Association for Computing Machinery, New York, NY, USA, 51–58. https://doi.org/10.1145/507072.507082

[9] Zeyang Liu, Yiqun Liu, Ke Zhou, Min Zhang, and Shaoping Ma. 2015. Influence of Vertical Result in Web Search Examination. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '15)*. Association for Computing Machinery, New York, NY, USA, 193–202. https://doi.org/10.1145/2766462.2767714

[10] Andrew MacFarlane, George Buchanan, Areej Al-Wabil, Gennady Andrienko, and Natalia Andrienko. 2017. Visual Analysis of Dyslexia on Search. In *Proceedings of the 2017 Conference on Conference Human Information Interaction and Retrieval (CHIIR '17)*. Association for Computing Machinery, New York, NY, USA, 285–288. https://doi.org/10.1145/3020165.3022134

[11] Tamara Munzner. 2014. Visualization Analysis and Design. In *A.K. Peters visualization series*.

[12] Alexandra Papoutsaki, James Laskey, and Jeff Huang. 2017. SearchGazer: Webcam Eye Tracking for Remote Studies of Web Search. In *Proceedings of the 2017 Conference on Conference Human Information Interaction and Retrieval (CHIIR '17)*. Association for Computing Machinery, New York, NY, USA, 17–26. https://doi.org/10.1145/3020165.3020170

[13] Kari-Jouko Räihä, Anne Aula, Päivi Majaranta, Harri Rantala, and Kimmo Koivunen. 2005. Static visualization of temporal eye-tracking data. In *IFIP Conference on Human-Computer Interaction*. Springer, 946–949. https://doi.org/10.1007/11555261_76

[14] Michael Raschke, Xuemei Chen, and Thomas Ertl. 2012. Parallel Scan-Path Visualization. In *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '12)*. Association for Computing Machinery, New York, NY, USA, 165–168. https://doi.org/10.1145/2168556.2168583

[15] Chao Wang, Yiqun Liu, and Shaoping Ma. 2016. Building a click model: From idea to practice. *CAAI Transactions on Intelligence Technology* 1, 4 (2016), 313 – 322. https://doi.org/10.1016/j.trit.2016.12.003

[16] Yue Wang, Dawei Yin, Luo Jie, Pengyuan Wang, Makoto Yamada, Yi Chang, and Qiaozhu Mei. 2016. Beyond Ranking: Optimizing Whole-Page Presentation. In *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining (WSDM '16)*. Association for Computing Machinery, New York, NY, USA, 103–112. https://doi.org/10.1145/2835776.2835824