Continuous Click Behavior in Academic Search Environment

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ABSTRACT

Research on user interactive behavior of search engine result page (SERP) has been proven to effectively improve the performance of click-through feedback. In scenarios such as the academic search environment, there are a large number of users who encounter multiple clicks and browses in the SERP in a search session, which may result in multiple downloads after a period of time. Aiming at the unique click result dwell time distribution of this continuous click behavior, this work proposes a modified mapping function based on server-side real log data. Experimental results show that this method can effectively improve the user dwell time fitting results in continuous search behavior in Academic search environment.

KEYWORDS

User Behavior; Log Analysis; Dwell Time;

1. Introduction

Modern search engines record users' actions such as clicking, browsing and downloading on SERP pages. Research about users' interactive behavior on SERP pages have been applied into the improvement of click-through rate (CTR), Web search ranking, and so on.

The breadth-first strategy refers to that users perform a series of browsing actions before clicking on their favorite query results[1]. Such a search strategy is common in general search engines, in particular, under time pressure, users tend to take shorter time to browse through most SERP results [8]. This search behavior is particularly striking in the academic search environment. When a user clicks on a SERP in a retrieval session, there may be multiple downloads after a period of time[16]. Therefore, users click on a small range of results that they think might be relevant, and then download the clicked results after a more detailed browse, which we call continuous click behavior.

As regard this continuous click behavior, we believe it will have a significant impact on dwell time. Previous research [7] has shown that the longer dwell time a user spends on a certain clicked result, the more likely they are to have a preference for it. At the same time, due to the sever-side log record, the interactive behavior of users will cause the sever-side dwell time to deviate from the real dwell time [11]. Therefore, as for the use of data about users' behavior recorded in the sever-side log, the continuous click behavior naturally has a significant impact on the dwell time mapping.

Our paper mainly studies the following two aspects:

• For the phenomenon of continuous click behavior in academic search environment, the retrieval patterns are analyzed and summarized on real scene data sets.

• The estimate of dwell time was revised based on the continuous click behavior.

2. Related Work

2.1 Academic Search Behavior

Li[16] found that in the behavior pattern of downloading caused by academic retrieval, the proportion of directly downloading related literature by input retrieval is the highest. And the research shows that when a user clicks on a SERP in a retrieval session, there may be multiple downloads after a period of time. Therefore, it can be concluded that the search strategy in academic search environment is dominated by the breadth-first

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strategy, and the behavior of continuous clicking in a small range of results is common.

2.2 Click Dwell Time

Dwell Time, as a measure of how long a user's search behavior takes to return SERP, is often recorded by search engines after a user clicks on a page. By analyzing the general search engine data sets, Clarke [10] found that user satisfaction was proportional to dwell Time. Fox [9] conducted detailed research into the relationship between dwell time and user satisfaction and proposed the liner function method to evaluate user satisfaction. However, existing studies on the mapping function of dwell time have ignored the continuous click behavior of users.

Based on the above studies, though, it is possible to predict users' click-level satisfaction with dwell time. The present study also confirms that different data sources have an impact on the Dwell Time mapping approach and learning, and the most appropriate mapping function method needs to be chosen according to the scenario.

3. Continuous Click Behavior Modeling

We obtain some Sever-side log data from the document retrieval system of Information Institute of Jiangsu Province. This data is mainly based on the query subjects of academic users.

3.1Continuous Click Behavior

Our statistical analysis of user Dwell time in the server-side search log finds that the proportion of User Dwell time less than 20s is significantly higher than other values, which is similar to the User Dwell time distribution in [14].

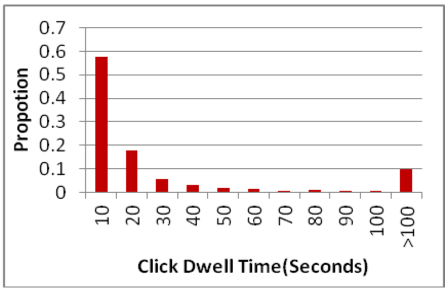

Fig. 1 Distribution of User Dwell time in server-side log

When counting the distribution of d clicks in continuous click behavior, this study finds that it is rare that all results of a SERP page are clicked (a SERP contains 15 results), thereby excluding the possibility of illegal access. In addition, the proportion of users who click on only one page to browse is still the main, and about 40% of users still have continuous click behavior that user doesn't click more than 5 times .

In the Academic search environment, when a user who browses in the SERP during a search session clicks multiple pages, the user may have multiple download actions after a period of time [16]. Similarly, in our search log , users are more inclined to click more pages to check to meet the literature needs of their scientific activities.

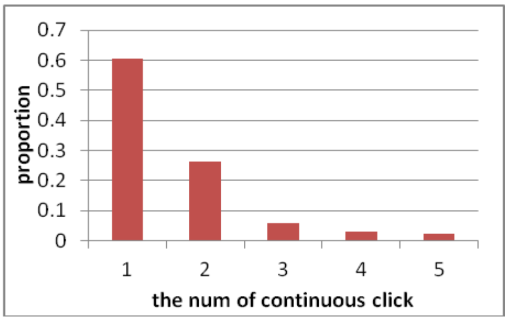

Fig. 2 Distribution of clicks in continuous click behavior

Our statistics of Distance between two consecutively clicked pages find that the distribution of the click distance difference within 10s of the user is basically within 6 pages downward and within 2 pages upward. After a user clicks on a document page, they are attracted by the next adjacent document page to create a temporary click behavior. This behavior is called continuous click behavior.

Fig. 3 Distribution of the distance between two continuous click in 10s

3.2 Modified Mapping Function

In the user's continuous click behavior, the general mapping function which representing the user's dwell time by the Sever-side log data will produce differences. Due to the user's continuous click behavior, These differences makes the server-side perception time less than the actual dwell time..

We believe that the dwell time between the two clicks of the user has an impact on the two clicks. The last clicked Sever-side dwell time contains the examination time of the next clicked document page. Generally, this time will be less than 10s. Therefore, we propose a modified mapping function:

$$W = 1 - \frac{\min(\textit{Previous Dwell Time}, 10)}{10} \quad (1)$$

$$R(DT) = \min(DT, 30) * (1 - W) + W * \min(\max(DT, 10), 10) \quad (2)$$

$$F(DT) = \left(\frac{R(DT)}{40}\right)^2 \quad (3)$$

In the above formula, the previous dwell time represents the dwell time of the previous result. DT indicates the dwell time of the user's click current result. Among them, R(DT) represents the dwell time correction for the user, which means that when two clicks with time difference less than 10s may be continuous click behavior, the dwell time of the user in this result needs to be reduced; If it is not continuous click behavior, the mapping function is same to the Linear mapping function.

4. Experiment

4.1 Experiment Setup

Liu [14] et al proposed a click model TACM that includes the user's non-sequential browsing situation and incorporates the user's dwell time feature. We will apply the Modified mapping function proposed in this paper to the TACM model. In order to ensure that the TACM with Modified mapping function used in our experiments still has a good effect compared with other click models, we will conduct a pre-experiment to compare the performance of TACM on our dataset. Due to the lack of relevant tags for user satisfaction with click results, we will use Perplexity as the evaluation of experimental results.

4.2 Click Model

We use UBM, DBN, and DCM [2,3,4] click models as the base control group. The purpose is to compare the performance of click models modeled using the depth-first strategy hypothesis on our academic retrieval dataset. In addition, the PSCM [13] containing Non-sequential Behavior is used as the main comparison object, and the purpose is to compare the performance of the click model modeled by the depth-first strategy on the data set. Among them, TACM uses the default mapping function.

As the query topics in our data set are relatively scattered, in order to exclude the results of scattered user topics, we will randomly sample the user's click data to simulate the retrieval of multi-user query topic sets.

Table 1 Click perplexity of each model for different query frequencies

Model	(0, 5]	(5, 10]
DBN	1.997265	1.400714
UBM	1.56332	1.360947
DCM	1.620372	1.470992
PSCM	**1.339041**	1.327873
TACM	1.373327	**1.309871**

The experimental results show that the performance of PSCM and TACM are better than the general control group. When the user's query subject is concentrated (the query frequency is greater than 5), TACM has a better effect. However, on query data sets with scattered topics, PSCM performs better than TACM's model. Therefore, we think that the comparison of the two data sets is also needed on the mapping function.

4.3 Time Mapping Function

In order to test whether the Modified mapping function can improve the click effect of the model, we will choose to use the currently known linear mapping function, quadratic mapping function, exponential mapping function and Rayleigh mapping function for comparison.

Table 2 Click perplexity of TACM with each mapping function for different query frequencies

mapping function	(0, 5]	(5, 10]
Linear	1.4604117	1.322669
Exponential	1.4006041	1.319801
Quadratic	1.3733267	1.309871
Rayleigh	**1.3393338**	1.323938
Modified	1.3569666	**1.300651**

When the user's query is more concentrated, TACM model with Modified mapping has a good performance. Although the performance of TACM model with Modified mapping is worse than that of TACM model with Rayleigh mapping on query with relatively scattered topics, the improvement of TACM with Modified mapping function is more obvious on datasets with topic sets. In addition, the Rayleigh mapping function and the Exponential mapping function are related to the dwell time distribution of the data set and are not universal. Therefore, we believe that the Modified mapping function is more worthy of promotion.

5. Conclusion

Based on the analysis of the clicking behavior of users via the real data set in academic search environment, the present study found that the continuous click behavior with the breadth-first strategy was much preferred in users' clicking behavior and it accounted for about 40% of the total users' clicking Behavior.

We also found that although users can not click on SERP in succession more than 5 results, the rank difference of jump click SERP in the document page is no more than 6. This pattern has a certain universality and regularity. On this basis, aiming at modeling continuous click behavior, we propose a new function mapping to fit the dwell time of the user in the real-world log. The experimental results show that our modified mapping function performs better than other mapping functions on the perplexity index. In academic search environment, the modified mapping function can reflect real users' dwell time and predict users' satisfaction through server-side log. This result provides an effective mapping function method for the study of user interaction behavior in retrieval scenarios with continuous click behavior. Future, based on better data sets, we will study the performance of the proposed mapping function method in the estimation of the similarity between query and document.

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REFERENCES

[1] Klöckner, K., Wirschum, N., & Jameson, A. (2004, April). Depth-and breadth-first processing of search result lists. In CHI'04 extended abstracts on Human factors in computing systems (pp. 1539-1539).

[2] Dupret, G. E., & Piwowarski, B. (2008, July). A user browsing model to predict search engine click data from past observations. In Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval (pp. 331-338).

[3] Chapelle, O., & Zhang, Y. (2009, April). A dynamic bayesian network click model for web search ranking. In Proceedings of the 18th international conference on World wide web (pp. 1-10).

[4] Guo, F., Liu, C., & Wang, Y. M. (2009, February). Efficient multiple-click models in web search. In Proceedings of the second acm international conference on web search and data mining (pp. 124-131).

[5] Lorigo, L., Pan, B., Hembrooke, H., Joachims, T., Granka, L., & Gay, G. (2006). The influence of task and gender on search and evaluation behavior using Google. Information Processing & Management, 42(4), 1123-1131.

[6] Dupret, G., & Liao, C. (2010, February). A model to estimate intrinsic document relevance from the clickthrough logs of a web search engine. In Proceedings of the third ACM international conference on Web search and data mining (pp. 181-190).

[7] Kim, Y., Hassan, A., White, R. W., & Zitouni, I. (2014, February). Modeling dwell time to predict click-level satisfaction. In Proceedings of the 7th ACM international conference on Web search and data mining (pp. 193-202).

[8] Crescenzi, A., Kelly, D., & Azzopardi, L. (2015, August). Time pressure and system delays in information search. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 767-770).

[9] Fox, S., Karnawat, K., Mydland, M., Dumais, S., & White, T. (2005). Evaluating implicit measures to improve web search. ACM Transactions on Information Systems (TOIS), 23(2), 147-168.

[10] Smucker, M. D., & Clarke, C. L. (2012, August). Time-based calibration of effectiveness measures. In Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval (pp. 95-104).

[11] Kim, Y., Hassan, A., White, R. W., & Zitouni, I. (2014, July). Comparing client and server dwell time estimates for click-level satisfaction prediction. In Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval (pp. 895-898).

[12] Craswell, N., Zoeter, O., Taylor, M., & Ramsey, B. (2008, February). An experimental comparison of click position-bias models. In Proceedings of the 2008 international conference on web search and data mining (pp. 87-94).

[13] Wang, C., Liu, Y., Wang, M., Zhou, K., Nie, J. Y., & Ma, S. (2015, August). Incorporating non-sequential behavior into click models. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 283-292).

[14] Liu, Y., Xie, X., Wang, C., Nie, J. Y., Zhang, M., & Ma, S. (2016). Time-aware click model. ACM Transactions on Information Systems (TOIS), 35(3), 1-24.

[15] Liu, C., White, R. W., & Dumais, S. (2010, July). Understanding web browsing behaviors through Weibull analysis of dwell time. In Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval (pp. 379-386).

[16] Li, X., & de Rijke, M. (2019). Characterizing and predicting downloads in academic search. Information Processing & Management, 56(3), 394-407.