Exploiting Interaction Features in User Intent Understanding

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Abstract. Understanding user intent during a web navigation session is a challenging topic, which is drawing the attention of many researchers in this area. The achievements of such research goals would have a great impact on many internet-based applications. For instance, if a search engine had the capability of capturing user intents, it could better suite the order of search results to user needs. In this context, the research has mainly focused on the analysis of user interactions with Search Engine Result Pages (SERPs) resulting from a web query, but most methods ignore the behavior of the user during the exploration of web pages associated to the links of the SERP s/he decides to visit. In this paper we propose a novel model that analyzes user interactions on such pages, in addition to the information considered by other mentioned approaches. In particular, captured user interactions are translated into features that are part of the input of a classification algorithm aiming to determine user informational, navigational, and transactional intents. Experimental results highlight the effectiveness of the proposed model, showing how the additional analysis it performs on visited web pages contributes to enhance user intent understanding.

Keywords: user intent understanding, interaction features, web search.

1 Introduction

The success of internet applications is bound to the capability of search engines to provide users with information meeting their expectations. This cannot be guaranteed by merely analyzing the web structure as several existing search engines do. Thus, nowadays, search engines need to incorporate the capability of predicting user intents in order to adapt the order of search results so as to meet their expectation. For this reason, user intention understanding (UIU) has recently become an important research area.

Some approaches to user behavior analysis in web navigation have highlighted the importance of analyzing user interactions with web pages in order to infer their interest and satisfaction with respect to the visited contents [1–3]. Other studies have investigated how user interactions with *Search Engine Result Pages* (SERPs) can be exploited to infer user intent [4–9]. However, such methods

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for UIU limit their analysis to the results contained in a SERP, ignoring many important interactions and contents visited from such results. On the contrary, the aim of this paper is to show that UIU can be considerably improved by performing additional analysis of user interactions on the web pages of a SERP that the user decides to visit. In particular, we define a new model for UIU that incorporates interactions analyzed in the context of SERP results and of the web pages visited starting from them. The interaction features considered in the model are not global page-level statistics, rather they are finer-grained and refer to portions of web pages. This is motivated on the basis of the results of literature studies, performed with eye-trackers, revealing that although a user might focus on many sections composing a web page, s/he will tend to overlook portions of low interest [10]. Thus, capturing interaction features on specific portions of web pages potentially conveys a better accuracy in the evaluation of the user actions. These and other features are evaluated in our approach by means of a classification algorithm to understand user intents. In particular, to simplify the classification process, we use a common taxonomy that defines three types of queries: *informational*, *navigational*, and *transational* [11].

Experimental results highlight the efficiency of the proposed model in query classification, showing how the interaction features extracted from visited web pages contribute to enhance user understanding. In particular, the proposed set of features has been evaluated with three different classification algorithms, namely Support Vector Machine (SVM) [12], Conditional Random Fields (CRF) [13], and Latent Dynamic Conditional Random Fields (LDCRF) [14]. The achieved results have been compared with those achieved with other subsets of features and demonstrate that the proposed model outperforms them in terms of query classification. Moreover, a further analysis highlights the effectiveness of the proposed features for the classification of transactional queries.

The rest of this paper is organized as follows. In Section 2, we provide a short review of related work. Then, we present the model exploiting interaction features for UIU in Section 3. Section 4 describes experimental results. Finally, conclusions are given in Section 5.

2 Related Work

A pioneer study by Carmel *et al.* [15] in the early 90s focusses on the analysis of hypertext. In particular, the study highlights three navigation strategies: *scan browsing*, aiming to inquire and evaluate information contained in the hypertext based on interest, *review browsing*, aiming to integrate information contained in the user mental context, and *search-oriented browsing*, aiming to look for new information based on specific goals, and integrating them with information collected in successive scans.

A further interesting study by Morrison *et al.* [16] aimed to classify types of queries based on search intents. Such taxonomies are defined as formalizations of three basic questions that the user asks him/herself before starting a search session: *why*, *how*, and *what* to search. The taxonomy that is closest to user intent understanding is the one used in the context of a research called (*method taxonomy*), which aims to detect the following types of search activities: *explore*, *monitor*, *find*, and *collect*. By monitoring user search activities, Sellen *et al.* extend previously defined taxonomies, introducing transactional search types [17], defined as *transacting*, and finalized to search purposes and to the use of web services on which it is possible to better exploit user experiences while performing search activities. In this context, the goal of the search is not to find information, rather services of information manipulation: hence, the search engine becomes a means to migrate towards a web service. Successively, new approaches to user intent understanding have highlighted the necessity to introduce a clear classification of search queries based on user intents. To this end, one of the former studies by Broder *et al.* [11] refers to a simple taxonomy of search queries based on three distinct categories: *navigational queries* to search for a particular web site, *informational queries* to collect information from one or more web pages, and *transactional queries* to reach a web site on which further interactions are expected.

In the last decade, all existing approaches have aimed at applying taxonomies in a recognition and automatic classification context. One of the former methodologies by Kang *et al.* [4] aims at two types of search activities: *topic relevance*, that is, searching documents for a given topic, of informational type, and *homepage finding*, aiming to search main pages of several types of navigational web sites. Starting from common information used by Information Retrieval (IR) systems, such as web page content, hyperlinks, and URLs, the model proposes methods to classify queries based on the two categories mentioned above.

The analysis and the comprehension of user interaction models during web navigation is the basis of a predictive model on real case studies, proposed by Agichtein *et al.* [6]. The model tries to elicit and understand user navigation behaviors by analyzing several activities, such as clicks, scrolls, and dwell times, aiming to predict user intention during web page navigation. The features this study proposes to analyze are used to characterize the complex system of interactions following the click on a result. Successively, a study by Guo *et al.* [9] starts from the hypothesis that such interactions can help accurately inferring two particular tightly correlated intents: search and purchase of products, a two phase activity defined as *search-purchase*.

Starting from experimental studies on real user navigation strategies, Lee *et al.* propose a model for the automatic identification of search goals based on features, and restricted to navigational and informational queries [5]. These studies have primarily revealed that most queries can be effectively associated to one of two categories defined within the taxonomy, making it possible the construction of an automatic identification system. Moreover, most queries that are not effectively associable to a category are related to few topics, such as proper nouns or names of software systems. This makes it possible to use *ad-hoc* systems of features for all those unpredictable cases. The model proposes two features: *past user-click behavior* that infers user intent from the way s/he has interacted with the results in the past, and *anchor-link distribution*, which uses possible targets of links having the same text of the query.

The strategies for user intent understanding described so far aim to classify search queries exclusively using features modeled to describe several aspects of search queries. A study by Tamine *et al.* proposes to analyze search activities that the user has previously performed in the same context, aiming to derive data useful for inferring the type of the current query [8]. The set of queries already performed represents the *query profile*.

3 The Proposed Model

In this section we describe the proposed model and the features used for the classification process.

3.1 Search Model: Session, Search, Interaction

Several approaches and models have been proposed to provide solutions to the user intention understanding problem, but all of them mainly focus on the interaction between users and the SERP. Additional interactions originating from SERP's contents, such as browsing, reading, and multimedia content fruition are not considered by the research community.

The proposed model aims to extend existing models, by analyzing user interactions between users and web pages during a search session. Our aim is to analyze not only the interactions between users and SERP, but also between users and web pages reached by clicking on SERP's results. We believe that data about interactions between users and web pages may be very useful to clarify the intent of the user, because these interactions are driven by the same motivation behind the initial search query. All user interactions with web pages could be reduced to three main categories, which are the same we consider in our model: *session*, *search*, and *interaction*.

Session. A *session* is a sequence of search activities aimed at achieving a goal. When the first query does not provide the desired result, the user tries to gradually approach the target, refining or changing search terms and keywords. All these research activities constitute a session.

Search. A *search* activity is the combination of the following user actions: submission of a query to a search engine, analysis of search results, navigation on one or more web pages inside them. During a search activity a user has a specific goal, generally described by the query itself. This goal is classifiable in a taxonomy, as defined by previous studies [11, 18].

Interaction. *Interaction* is the navigation of a web page using a wide range of interactions that include mouse clicks, page scrolling, pointer movements, and text selection. Starting from these interactions, combined with features such as dwell time, reading rate, and scrolling rate, it is possible to derive an implicit feedback of users about web pages [2]. Moreover, several studies have proven the usefulness of user interactions to assess the relevance of web pages [1, 3, 19, 20], to classify queries, and to determine the intent of search sessions [9, 21].

The proposed model introduces a new methodology for tracing interactions between users and web pages. In particular, user interaction analysis is restricted to a smaller portion of a web page: the *subpages*. Indeed, a web page consists of several blocks of text, graphics, multimedia, and can have a variable length. As shown by studies using eye-tracking [10], the user frequently adopts a *E or F reading pattern* during browsing, excluding areas of little interest. Compared to a global analysis of the entire page, the introduction of *subpage-level* analysis gives higher accuracy in the assessment of the interaction.

3.2 Features

Interaction data extracted from user web navigation have been encoded into features that characterize user behavior. We organize the set of features into the following categories: *query*, *search*, *interaction*, and *context*.

Query. These features are derived from characteristics of a search query such as keywords, the number of keywords, the semantic relations between them, and other characteristics of a search or an interaction.

Search. These features act on the data from search activities such as: results, time spent on SERP, and number of results considered by the user. The *DwellTime* is measured from the start of the search session until the end of the last interaction originated by the same search session. The reaction time, *TimeToFirstInteraction,* is the time elapsed from the start of the search session and the complete loading of the first selected page. Other features dedicated to interactions with the results are *ClicksCount*, which is the number of visited results, and *FirstResultClickedRank*, determining the position of the first clicked result.

Interaction. These features act on the data collected from interactions with web pages and subpages, taking into account the absolute dwell time, the effective dwell time, all the scrolling activities, search and reading activities. The *DwellRate* measures the effectiveness of the permanence of a user on a web page, while the reading rate *ReadingRate*, measures the amount of reading of a web page [2]. Additional interactional features are: *ViewedWords*, the number of words considered during the browsing, *UrlContainsTransactionalTerms*, which verifies if the URL of the page contains transactional terms (download, software, video, watch, pics, images, audio, etc.), *AjaxRequestsCount*, which represents the number of AJAX requests originated during browsing.

Context. These features act on the relationship between the search activities performed in a session, such as the position of a query in the sequence of search requests for a session.

4 Experiments

In this section we describe the dataset constructed for evaluating the proposed approach and the results achieved with different classification algorithms.

In particular, after an overview on the evaluation metrics used and on the subsets of features taken into consideration, experimental results are presented.

4.1 Experiments Configuration

The goal of this experimentation is to evaluate the effectiveness of the proposed model for inferring user intention in web searches. In particular, we analyze the performances of the model for classifying queries, based on the query taxonomy: informational, navigational, and transactional.

Search activities have been accomplished by a pool of thirteen subjects (seven men and six women), whose age ranges from 24 to 37 years old. Sixth subjects had a master degree (5 in computer science and 1 in linguistics), 3 a bachelor degree (1 in computer science, 1 in political science, and 1 in chemistry), and 4 a high school degree in accounting. The average experience in web browsing was of 9.6 years.

Dataset. The dataset has been constructed by the thirteen participants to the test. In particular, all the subjects were requested to perform a series of search activities related to various topics and with different intentions. Each subject was asked to determine his/her own goal in advance. After starting the session, subjects performed a series of searches using the Google search engine, without any limitation as to time or the results to visit. By following this protocol, we had 129 sessions and 353 web searches, which were subsequently manually classified by relying on the intent of the user. Starting from web searches, 490 web pages and 2136 sub pages were visited. All interactions were detected by the YAR plug-in for Google Chrome/Chromium [2].

Evaluation Metrics. In order to evaluate the effectiveness of the proposed model, we adopted the classical evaluation metrics of Information Retrieval: *precision*, *recall*, and *F1-measure*. They are defined as follows:

$$\mathbf{Precision} = \sum_{Category(i)} \frac{\#correctly\ classified\ queries}{\#classified\ queries} \times \frac{\#category\ queries}{\#total\ queries}$$

$$\mathbf{Recall} = \frac{\#correctly\ classified\ queries}{\#total\ queries}$$

$$\mathbf{F1-measure} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Feature Subsets. In order to verify the effectiveness of the proposed features in different combinations, we have grouped them into several subsets:

– ***All***: subset of all the proposed features *query*, *search*, *interaction*, and *context*;

- ***Query***: subset of all the features related to *queries*;
- ***Search***: subset of all the features related to *search* and *context*;
- ***Interaction***: subset of all the features related to *interactions*;
- ***Query+Search***: subset of the features derived as union from *Query* and *Search*. The goal is to evaluate the effectiveness of query classification by using the features considered in other studies [3, 6, 9];
- ***Transactional***: subset of all the features related to interactions over transactional queries *ViewWords*, *AjaxRequestsCount*, *ScrollingDistance*, *ScrollingCount*, and *UrlContainsTransactionalTerms*. The goal here is to evaluate the classification of transactional queries by adopting more specific features;
- ***All−Transactional***: subset derived by the exclusion of the transactional features from the set *All*. The goal here is to evaluate the effectiveness of the classification of transactional queries by comparing results achieved with all features to those achieved by excluding transactional features.

Classifiers. We considered three classifiers to evaluate the proposed feature model: SVM [12], CRF[13], and LDCRF[14]. Support Vector Machine (SVM) is a discriminative model, based on the structural risk minimization principle from statistical learning theory [12], widely used in binary classification problems. In particular, SVM maps the input data in a higher dimensional feature space, and splits the data into two classes by computing a hyperplane that separates them. CRF is a discriminative probabilistic model used for labeling sequential data [13]. The model utilizes inter-dependent features to select the most probable label sequence for one observation LDCRF extends CRF by incorporating hidden state variables which model the sub-structure of input sequences [14]. It is able to learn the transitions between input elements by modeling a continuous stream of class labels, and the internal sub-structure by using intermediate hidden states.

In the context of query classification, SVM assumes that the queries in a user session are independent, Conditional Random Field (CRF) considers the sequential information between the queries, and LatentDynamic Conditional Random Fields (LDCRF) models the sub-structure of user sessions by assigning a disjoint set of hidden state variables to each class label. They have been configured as follows:

1. **SVM**. We used MSVMpack [22] as the SVM toolbox for model training and testing. The SVM model is trained using a linear kernel and the parameter C has been determined by cross-validation.
2. **CRF**. We used the HCRF library[1] as the tool to train and test the CRF model. For the experiments we used a single chain structured model and the regularization term for the CRF model was validated with values 10^k with $k = -1 \dots 3$.
3. **LDCRF**. We used the HCRF library for training and testing LDCRF model. In particular, the model was trained with 3 hidden states per label, and the regularization term was determined by cross-validation to achieve the best performance.

[1] http://sourceforge.net/projects/hcrf/

4.2 Results

In order to simulate an operating environment, the set of queries made by users was separated into two subsets, which included 60% and 40% of web searches, and were used for training and testing the classifiers, respectively.

Taking into account informational queries (see Figure 1), it could be found that best classifications were achieved by using the CRF classifier with the *All* set of features, whereas worst performances were achieved by considering the subsets of features *Query* and *Search*. Similar considerations hold for *Search+Query*. These initial observations demonstrate the importance of the subset of interactional features, which alone are able to achieve classification performances close to those achieved by the *All* set of all features.

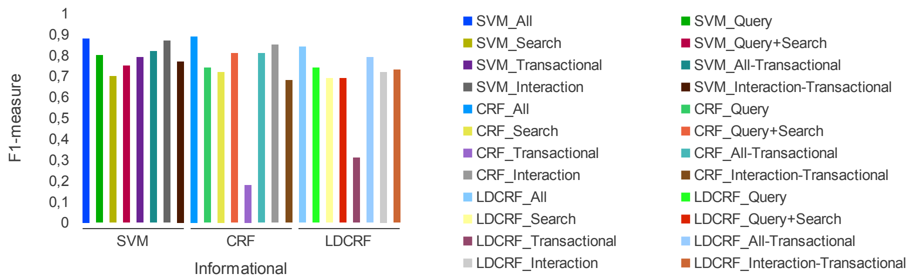

Fig. 1. Performances of the considered feature subsets for informational queries

Among the interactional set of features proposed above, there is a subset, named *Transactional*, which was introduced to improve the classification of transactional queries. The experimental results highlight that these features also improve the classification of informational queries. In fact, the *Search+Query* subset achieves performances that are closer to the subset *All−Transactional*, as shown in Figure 1. This means that the subset of interactional features, which are not part of *Transactional*, are not effective for the classification of informational queries. The relevance of transactional features in this type of query is confirmed by two other important experimental results. The first one regards the application of the single subset *Transactional*, which is able to achieve performances equivalent to the *Search+Query* and *All−Transactional* subsets. The second one is the performance degradation of the *Interaction−Transactional* features, which achieve results by far lower than the ones achieved through the application of all the interactional features, and any other subset of features considered individually.

Turning to navigational query results shown in Figure 2, there may be some surprising findings. First of all, the set *All* of all the features does not provide the best performances, which are instead provided by the subset *All−Transactional*. This highlights the problem of classifying navigational and transactional queries due to their similarity. Even if slightly, performances of the model improve by excluding transactional features. The inefficiency of these features can also be

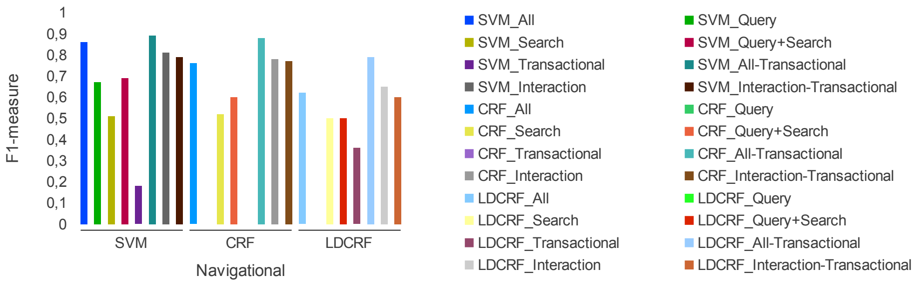

Fig. 2. Performances of the considered feature subsets for navigational queries

seen by considering the subset *Transactional*, which provides performances worse than with other subsets. Poor results were also achieved from subsets of features considered individually, except for *Interaction*, which provides acceptable performances.

Finally, let us analyze performances related to transactional queries (Figure 3). In this context, the set *All* confirms to be more effective than the other subsets. What we want to highlight here is the efficacy of transactional features. The subset *Transactional*, in terms of performances, is second only to the subset of all features, but it is close to it. By excluding such features in the subset *All−Transactional*, performances degrade providing results comparable to *Query+Search*. The inefficiency of pure interactional features with respect to transactional ones also arises by a direct comparison: The subset *Interaction* achieves performances comparable to *Transactional*, but far better than *Interaction−Transactional*, which excludes transactional features from Interaction.

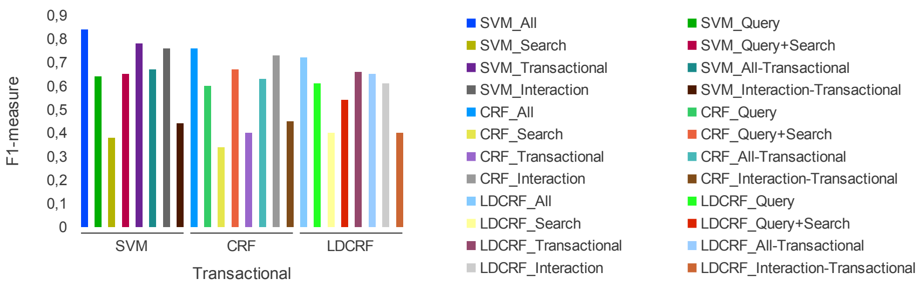

Fig. 3. Performances of the considered feature subsets for transactional queries

An Analysis of Transactional Features. A substantial limit of traditional approaches described in the literature is represented by the classification of *transactional queries*. In this paper we propose some features that aim to characterize transactional queries by analyzing scrolling behaviors, ajax requests, read text, and presence of transactional terms in queries or URLs. The goal here is to compare the effectiveness of query classification by applying all the features (*All*) with respect to applying a subset of them that excludes the transactional features (*All−Transactional*). Referring to transactional queries, Table 1 shows that there is a conspicuous improvement of the set *All*, especially when using SVM. To be noted the precision value of 0.93, by far higher than the precision measured through all the classifiers for the subset *All−Transactional*.

Table 1. Precision, Recall, and F1-measure of the classification of transactional queries with the feature sets *All* and *All−Transactional*

Class_Model	Precision	Recall	F1-measure
SVM_All	0.93	0.76	0.84
SVM_All−Transactional	0.72	0.62	0.67
CRF_All	0.78	0.74	0.76
CRF_All−Transactional	0.85	0.50	0.63
LDCRF_All	0.77	0.68	0.72
LDCRF_All−Transactional	0.65	0.65	0.65

Moreover, transactional features are also useful to improve the quality of the classification process of informational queries (Table 2), whereas they have no effect on navigational ones (Table 3).

Table 2. Precision, Recall, and F1-measure of the classification of informational queries with the feature sets *All* and *All−Transactional*

Class_Model	Precision	Recall	F1-measure
SVM_All	0.83	0.90	0.88
SVM_All−Transactional	0.80	0.84	0.82
CRF_All	0.86	0.92	0.89
CRF_All−Transactional	0.76	0.87	0.81
LDCRF_All	0.84	0.83	0.84
LDCRF_All−Transactional	0.80	0.78	0.79

Table 3. Precision, Recall, and F1-measure of the classification of navigational queries with the feature sets *All* and *All−Transactional*

Class_Model	Precision	Recall	F1-measure
SVM_All	0.82	0.90	0.86
SVM_All−Transactional	0.87	0.90	0.89
CRF_All	0.84	0.70	0.76
CRF_All−Transactional	0.90	0.87	0.88
LDCRF_All	0.59	0.67	0.62
LDCRF_All−Transactional	0.77	0.80	0.79

5 Conclusions

In this paper we have proposed a new model for user intent understanding in web search. Assuming that the interactions of the user with the web pages returned by a search engine in response to a query can be highly useful, in this research we aimed at defining a new model, based on the results returned by the search engine, on the interactions of the user with them, and with the web pages visited by exploring them. By examining these interactions, we have produced a set of features that are suitable for determining the intent of the user. Each feature involves a different level of interaction between the user and the "system": query, search, and web pages (interaction). To simplify and make the process of classification more efficient, we also adopt a simple one level taxonomy: *informational*, *navigational*, and *transactional*. In addition to the set of all the proposed features, during the testing phase we also considered some subsets corresponding to features of individual interactional contexts and to their union or difference, in order to evaluate the effectiveness of the classification with respect to traditional models, and to interactional, or transactional features.

Experimental results have highlighted the effectiveness of query classification when applying both features representing interactions on web pages and those representing interactions in the context of queries and results. This also arise in the classification of transactional queries, further highlighting the effectiveness of interactional features, and more important, of transactional features.

References

1. Agichtein, E., Brill, E., Dumais, S.: Improving web search ranking by incorporating user behavior information. In: Proceedings of the International Conference on Research and Development in Information Retrieval, SIGIR 2006, pp. 19–26. ACM (2006)
2. Deufemia, V., Giordano, M., Polese, G., Tortora, G.: Inferring web page relevance from human-computer interaction logging. In: Proceedings of the International Conference on Web Information Systems and Technologies, WEBIST 2012, pp. 653–662 (2012)
3. Guo, Q., Agichtein, E.: Beyond dwell time: estimating document relevance from cursor movements and other post-click searcher behavior. In: Proceedings of the International Conference on World Wide Web, WWW 2012, pp. 569–578. ACM (2012)
4. Kang, I., Kim, G.: Query type classification for web document retrieval. In: Proceedings of the Conference on Research and Development in Informaion Retrieval, SIGIR 2003, pp. 64–71. ACM (2003)
5. Lee, U., Liu, Z., Cho, J.: Automatic identification of user goals in web search. In: Proceedings of the International Conference on World Wide Web, WWW 2005, pp. 391–400. ACM (2005)
6. Agichtein, E., Brill, E., Dumais, S., Ragno, R.: Learning user interaction models for predicting web search result preferences. In: Proceedings of the International Conference on Research and Development in Information Retrieval, SIGIR 2006, pp. 3–10. ACM (2006)

7. Jansen, B.J., Booth, D.L., Spink, A.: Determining the user intent of web search engine queries. In: Proceedings of the International Conference on World Wide Web, WWW 2007, pp. 1149–1150. ACM (2007)
8. Tamine, L., Daoud, M., Dinh, B., Boughanem, M.: Contextual query classification in web search. In: Proceedings of International Workshop on Information Retrieval Learning, Knowledge and Adaptability, LWA 2008, pp. 65–68 (2008)
9. Guo, Q., Agichtein, E.: Ready to buy or just browsing? detecting web searcher goals from interaction data. In: Proceedings of the International Conference on Research and Development in Information Retrieval, SIGIR 2010, pp. 130–137. ACM (2010)
10. Nielsen, J.: F-shaped pattern for reading web content (2006), http://www.useit.com/articles/f-shaped-pattern-reading-web-content/
11. Broder, A.: A taxonomy of web search. SIGIR Forum 36, 3–10 (2002)
12. Cortes, C., Vapnik, V.: Support-vector networks. Mach. Learn. 20, 273–297 (1995)
13. Lafferty, J.D., McCallum, A., Pereira, F.C.N.: Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In: Proceedings of the International Conference on Machine Learning, ICML 2001, pp. 282–289 (2001)
14. Morency, L.P., Quattoni, A., Darrell, T.: Latent-dynamic discriminative models for continuous gesture recognition. In: Proceedings of IEEE Conference Computer Vision and Pattern Recognition, CVPR 2007, pp. 1–8 (2007)
15. Carmel, E., Crawford, S., Chen, H.: Browsing in hypertext: a cognitive study. IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans 22, 865–884 (1992)
16. Morrison, J., Pirolli, P., Card, S.K.: A taxonomic analysis of what world wide web activities significantly impact people's decisions and actions. In: Extended Abstracts on Human Factors in Computing Systems, CHI EA 2001. pp. 163–164. ACM (2001)
17. Sellen, A., Murphy, R., Shaw, K.: How knowledge workers use the web. In: Extended Abstracts on Human Factors in Computing Systems, CHI 2002, pp. 227–234. ACM (2002)
18. Rose, D., Levinson, D.: Understanding user goals in web search. In: Proceedings of the International Conference on World Wide Web, WWW 2004, pp. 13–19. ACM (2004)
19. Guo, Q., Agichtein, E.: Towards predicting web searcher gaze position from mouse movements. In: Proceedings of the International Conference on Human Factors in Computing Systems, CHI EA 2010, pp. 3601–3606. ACM (2010)
20. Kelly, D., Teevan, J.: Implicit feedback for inferring user preference: a bibliography. SIGIR Forum 37, 18–28 (2003)
21. Guo, Q., Agichtein, E.: Exploring mouse movements for inferring query intent. In: Proceedings of the International Conference on Research and Development in Information Retrieval, pp. 707–708. ACM (2008)
22. Lauer, F., Guermeur, Y.: MSVMpack: a multi-class support vector machine package. Journal of Machine Learning Research 12, 2269–2272 (2011)