# Leveraging User Inspiration with Microblogging-Driven Exploratory Search

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**Abstract.** In creative tasks, the user expects to acquire holistic information, to explore the space of available information and to come up with diverse views before converging to a solution for the creative task. We hypothesize that the implicit use of social chatter in information seeking activities can enhance the potential for novel, diverse and unexpected encounters which can in turn inspire users. We present an interactive exploratory search tool that combines diversification of content and sources with a user interface design that visualises cues from the social chatter generated with microblogging services such as Twitter and lets users interactively explore the available information space. A task-based user study comparing our system to a query-based baseline indicates that our system significantly improves inspirational discoveries by providing access to more interesting, novel and unexpected information.

**Keywords:** Exploratory search, inspirational systems.

## 1 Introduction

Creativity is the process of generating new ideas and concepts or making connections between ideas into producing new ones, which previously did not exist [1]. Among the most important enablers of creativity is the capability to be inspired. Inspiration requires among others an environment that offers space for exploration, cognitive stimuli and accessibility to information resources [2]. Our work is based on the observation that social recommendations through e.g., social media feeds, already provide an everyday inspirational channel to people. Many users already use social media such as Twitter for exchanging links to web pages that are of interest to them. Such links, although not necessarily relevant to an explicitly expressed need, have the potential to inspire.

We aim to examine how to extract inspirational cues from social chatter and use them to assist users in finding inspirational information during creative tasks. To do so, we follow the approach of funnelling social chatter into an information seeking service that enables users to indirectly consume streams of information, not by reading them explicitly, but by utilizing information embedded in them in order to expand

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their search queries. Social chatter may contain valuable information that can inspire, though it is difficult for the user to process each nugget of information manually. Moreover, the inspiration potential of each informational resource may increase if combined with other cues and used to enhance a targeted search initiated by the user. For example, [3] showed that focusing search on the referrals of the users' friends can return highly serendipitous results, albeit with lower relevance to the query.

We formulate the following research questions: (1) How to extract and present to the user cues from the social chatter in order to stimulate the user's ability to identify and combine important aspects pertaining her search quest? (2) How to use social media information to form novel search paths for exploring available search spaces? (3) How to boost diversity of content, media and resources in order to enhance the ability to discover serendipitous resources with high inspiration potential? The paper proceeds as follows. Section 2 presents previous work related to our research questions. Section 3 provides the overview of our approach, which is instantiated in a tool called CRUISE, whereas Section 4 shows how the tool is used with a walkthrough scenario. Section 5 describes the detailed design of the building blocks of our tool. The results of a pilot study and a focused experiment which were used to evaluate our tool are presented in Section 6. Finally, we conclude in Section 7 with our main findings and suggestions for further research.

## 2 Related Work

We distinguish three areas which are related to our three research questions: information extraction from social media, interactive information exploration and diversity-aware search.

Tweetspiration is a search application which displays filtered tweet results through a word cloud visualization [4]. Bernstein et al. [5] proposed a Topic Based Browsing interface for the categorization of tweets and guided exploration using NLP in order to produce a list of nouns as a representative of each tweet, which is then used by the system to perform queries over an external search engine. SLANT [3] is a tool that automatically mines a user's email and Twitter feeds and populates four personalized search indices that are used to augment regular web search. In [6], users browse in order to explore popular bookmarks, browse other people's collections and find people with specific expertise. Chen et al. [7] provide interesting URL recommendations from Twitter by combining popular tweets and the notion of followees of the followees.

Contrary to typical information retrieval systems that direct users to specific information resources, interactive information exploration systems are designed to reveal latent, alternative directions in the information space in order to enable user orientation and engagement [8], [9]. To this end, researchers have proposed a variety of techniques involving rich user interface support with learning algorithms to assist users to comprehend the results and the existing information space [10], and visualizing and summarizing the resulting information to enable faster relevance judgment of the quality of the information returned by the search engine [11]. Głowacka et al. [12] developed an interactive information retrieval system that combines Reinforcement

Learning techniques along with a user interface design that allows active engagement of users in directing the search. Devendorf et al. [13] proposed a novel interactive interface for guided exploration through topics visualization over a large corpus. TweetMotif [14] extracts a set of topics from Twitter in order to provide a faceted search interface. Finally, several works have focused on the exploration of image and other rich media resources, see e.g. [15].

Diversity-aware search systems [16] have been proposed to cope with the uncertainty of query ambiguity [17], aiming at revealing multiple aspects of a query. Related approaches focus on reducing information redundancy comparing the documents of the result set with each other [18] while others consider documents independent from each other and compare their relevance to each aspect of a query providing results proportionally to their probability to belong to each query aspect [19]. In order to diversify the set of the documents displayed by their exploratory search application, Glowaca et al. [12] sample the results retrieved by the search engine using the Dirichlet Sampling Algorithm. Content metadata have been used to diversify based on categorical distance by making use of the Open Directory Project Taxonomy [19]. xQuAD [20] models an ambiguous query as a set of sub-queries and computes the relevance of search results comparing them not to each other, but to each sub-query instead. The OptSelect algorithm [21] identifies the different intents that appear in the query refinements of most users' query sessions and calculates the probability distributions in order to ensure that they are covered proportionally to the associated probabilities. The Max-Min algorithm [22] maximizes the minimum relevance (to the topic) and dissimilarity (between two results) of the selected set, whereas the Max-Sum algorithm maximizes the sum of relevance and dissimilarity of the selected set.

## 3 Creative User Centric Inspirational Search

We developed CReative User centric Inspirational SEarch (CRUISE) with the main objective to support search for inspirational resources during creative tasks. The tool couples techniques inspired from social search with information visualization and diversification. In this section we briefly describe how the tool interface design addresses our three research questions.

*Extracting and visualizing cues:* CRUISE utilises information from Twitter to support users explore available search spaces. The exploration starts with the users entering a set of terms as an initial entry point to their exploration. The tool uses the exploration terms and queries Twitter for the most recent popular tweets. Then it constructs a word cloud of high frequency terms found in recent popular tweets. Unlike existing trending topic interfaces like Twitter's trending topics, CRUISE identifies emerging terms even if only a single user on Twitter tweets about it. Moreover, CRUISE offers the ability of injecting into the word cloud terms which are derived from tweets by specific users or hashtag streams which are relevant to a particular context or scenario. Terms derived from their tweets are promoted and presented alongside terms derived from the Twitter stream and are represented in a different colour so that the user can discern between them.

*Exploring the search space:* Users can browse through available search spaces by making multiple selections of terms appearing on the word cloud. This interaction results in new terms appearing on the cloud as well as a new set of resources presented to the user. Using a slider, the user is able to adjust the depth of the search space, which is directly related to the terms' popularity; they can drill down into the word cloud to reveal terms, previously hidden due to their low frequency in relation to other terms.

*Querying external search engines and diversifying results:* Whilst exploring the word cloud, users are able to add any of the terms into their 'search path'. Search paths function as queries to external information sources which may be public such as Bing, Flickr or Google scholar or private information found in a company's intranet, such as portals, intranets, etc. Users are presented with diversified results and are provided with the capability to restrict their search paths by selecting more terms from the cloud or relaxing them by removing terms.

## 4 Walkthrough

We present a simple example which explains the functionality of the tool and the interaction design that accompanies an exploratory search task. Consider a concept developer working with a food company as a client. The developer aims at investigating future challenges of the food industry and coming up with new product concepts addressing them. The developer starts an exploration using the query 'food company'.

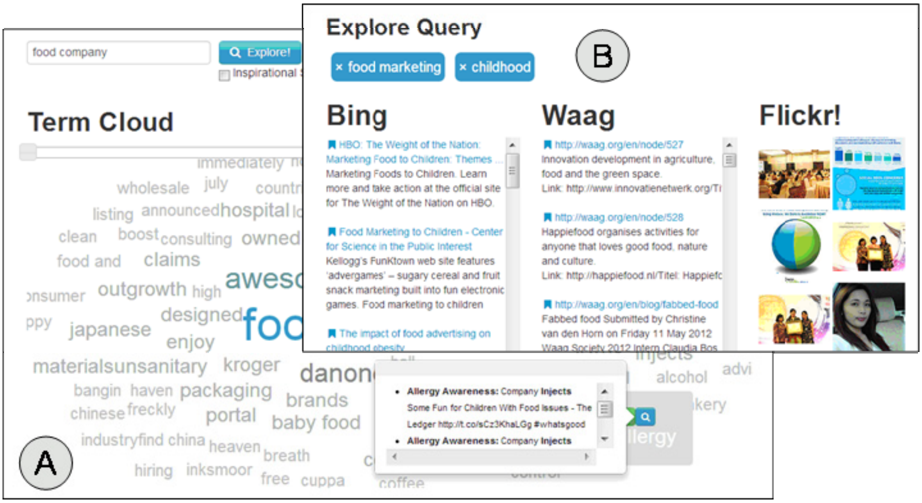


**Fig. 1.** CRUISE funnels social chatter into an information seeking service that enables users to indirectly consume streams of information– not by reading them explicitly, but by utilizing information embedded in them in order to expand their search directions

A word cloud is created with terms that are extracted from the most popular tweets relevant to the query. Terms such as 'allergy', 'baby-food', 'toxic over-eating' appear in the word cloud (Figure 1.A). The concept developer goes through these terms to see how they are related to children. She finds tweets about 'Bio-tech industries that slip propaganda into school text-books' and also tweets about the 'relation of food marketing to children obesity, referring to the influence of the industry on the nutritional behaviour of children. She continues by clicking on the terms 'food marketing' and 'childhood' (Figure 1.B). This initiates a new search to the available search spaces, having as a query the triplet {food marketing childhood}. She skims the results and she observes a Bing result about 'the impact of food advertising to childhood obesity', which decides to bookmark. A result coming from her company site ('Waag' in Figure 1.B) on 'injecting fun in food' reminds her of a workshop she attended one year ago, where, together with clients, they created fabbed food with the use of 3D printing. (With 3D printing one can print food in the desired shape and flavour) She finds the idea new and interesting and she is inspired to start investigating the idea further; she continues using CRUISE over a new iteration, making a focus-shift with the goal to investigate how 3D printing for child food can affect children's nutritional behaviour.

# 5 Tool Design

There are three main building blocks associated with the three research foci: one is responsible for the extraction of cues from the social chatter, another one for exploration of the search space and a third one for results retrieval and diversification. The initial set of terms is extracted, processed and displayed through the Term Retrieval, Processing and Visualization module. The explicit user feedback is sent to the Search Path Exploration and the Resource Diversification modules. The result set changes in each iteration with the Resource Diversification module determining the set and order of resources that are passed onto the user interface.

## 5.1 Term Retrieval, Processing and Visualization

We use a folksonomy based model to generate the word cloud. It includes the identification of most frequent words, as well as most frequent co-locations in the corpus. Specifically, we first retrieve the top 100 highest frequency words contained in the tweet-results returned for each query using the Twitter Search API. We then apply a custom filter to the results using lucene.apache.org API in order to filter out redundant words that exist in tweets. We also apply rules for data cleansing such as the exclusion of usernames, of terms with repeating characters (i.e. 'boooh', 'loool' etc), links removal as well as cleaning of words that include special characters. To derive a weighting for the words, we adapt the typical formula of TF-IDF which is

$$tfidf(t,c,N) = tf(t,c) * idf(t,N) \tag{1}$$

by considering *tf(t,c)* as being the number of times *t* the word *c* appears in the results, not in every tweet, because words typically appear just once or twice in the 140 characters of tweets. Term frequency is multiplied by $\mathrm{idf}(\mathrm{t}, \mathrm{N}) = \log\frac{\mathrm{N}}{\mathrm{dft}}$, where *N* the total number of tweets and *dft* the number of tweets the word appears in. Note that we could have just used as weighting factor the number of times a word appears in the results but by applying IDF we strike a balance between the few frequent words, which typically dominate in the results set, and less frequent words which nevertheless should be visible in the cloud because they may reveal interesting cues. Next, we generate bigrams, which typically are n-grams for n=2 (for example, a sentence such as ‘Leave me now.’ would result in tokenized strings like ‘Leave me’, ‘me now’). The key idea behind is to capture words that co-occur more than once in the “corpus of documents” and avoid splitting and scattering them around the cloud. This way, we enable users to foster associations between words, which may in turn instigate further explorations.

**N-grams generation pseudocode**

```
T=set of tweets (t) in the index
n=minGram
N=maxGram
NGrams{} → Ø // hash to store ngrams and their numberofoccurrences
fort_i in Tdo
words[] ← Split(t_i)
    for i=n to N do
        forj = 0 to length(words) – i do
ngram = ‘’
            fork = j toi do
ngram = Concat(ngram, words[k])
            end for
            if ngram in NGrams
NGrams[ngram] += 1
            Else
NGrams[ngram] = 1
        end for
    end for
end for
RemoveSingleOccurences(NGrams) //removes ngarms that occur only once
NgramFilter(NGrams) //filters ngrams according to regular expressions
returnNGrams
```

**Fig. 2.** N-grams algorithm implementation

The pseudo-code listed in Figure 2 describes the algorithm for the extraction of n-grams. The algorithm loops over each tweet that belongs to the initial result set, splits the words contained in the tweet and then generates n-grams by concatenating consecutive words. In our case, minGram and maxGram are set to the value of two because we are looking to get only bi-grams. In case, e.g., we feed the method with minGram=2 and maxGram=3, then we would get bi-grams and 3-grams. The RemoveSingleOccurences method continues with checking the frequency of n-grams eliminating those that occur only once in the corpus. Finally, the method NgramFilter is called in order to filter and clean the n-grams as also happened in the case of single terms. If one term of the n-gram is unacceptable due to filtering rules then the n-gram is eliminated from the list, too.

### 5.2 Search Path Exploration

Hovering over terms appearing in the cloud displays a preview of the tweets that include the term (see Figure 1.A). This enables users to see how the term relates to the initial query. We enable end users to interact with the words not only by exploring what people post but also by using them to form search paths. Selecting (or deselecting) terms gives users the capability to form (or modify) search paths which are used as queries to the available search spaces. We utilize the APIs of public search engines such as Bing as well as custom search engines for querying private spaces. The tool provides immediate feedback to the user by refreshing the screen with results from search spaces and allows for further interactions by modifying search paths. With this, we aim to enable users to recognize or create associations between cues and information that may lead to serendipitous discoveries.

### 5.3 Resource Diversification

Diversity examined from several aspects [16] can be a supporter of serendipitous encounters. In CRUISE, we have exploited this principle and attempted to inject visual and content diversity by including several sources of information such as Twitter, Bing and Flickr. Considering that a) the user capability to diverge is mostly based on her perception that the environment and the pieces of information are diverse and b) the typical user checks the top ten to fifteen results before proceeding to the reformulation of her query, we apply post processing to the search engines results: We diversify the results using an algorithm that re-ranks results with a goal to reveal content that is related to all the possible aspects of the query in the top ten results. For this purpose, we use the canonical version of Maximal Marginal Relevance (MMR) framework [18]:

$$MMR = Arg\max_{Di\in\mathcal{R}\setminus S}[\lambda Sim(D_i, \mathrm{Q}) - (1-\lambda)\max_{\mathrm{Dj}\in S} Sim(D_i, \mathrm{D}_j)] \tag{2}$$

where $Sim(\mathrm{Di, Q})$is the similarity of the document with respect to the query Q, and $Sim(\mathrm{Di, Dj})$ is the similarity between the current document and a document in previous ranks and $\lambda$ is a parameter that optimizes a linear combination of the criteria of relevance and diversity. When λ=1 then the standard relevance-ranked list is produced, whereas when λ=0 a maximal-diversity list of documents is generated We consider as document the snippet of each Bing result, title for Flickr and web-page content for the case of company's portal results.

Since we rely on public search APIs and hence cannot be aware of the actual similarity scores of the results with respect to the query, we compute them by exploiting the documents' positions in the list as follows [23]:

$$Sim(Di, Q) = \frac{N - Pos(Di)}{N} \tag{3}$$

Where $Pos$(Di) is the position of document d in the query result list returned by the search engine and $N$ is the size of the list. The document ranked first gets a value of $Sim(\mathrm{Di, Q})$= 1 while the last one gets a value of $Sim(\mathrm{Di, Q})$= 1/N.

In order to compute the similarity between the documents in the result set *R* we use cosine similarity:

$$Sim(\mathrm{Di},\mathrm{Dj}) = \cos(\theta) = \frac{Di\,Dj}{||Di\,||\,||Dj||} \tag{4}$$

where $\theta$ is the angle between the vectors of documents. We use the Vector Space Model (VSM) to represent each document as a vector, the components of which represent the importance of a term using TF-IDF metrics, given a bag of words that derive from the documents in *R*. For the lexicographic analysis (tokenization, stop words removal and stemming) of the documents in *R*, we use the Apache Lucene Standard analyser.

```
MMR Implementation
Input: S = set of documents (D) returned by the search engine, Q=query
Output: Final Ranked list = re-ranked documents
FinalRank{} → Ø
Temp{} → Ø // List that holds the candidate documents
for the next rank
forDi in Sdo
Calculate TF*IDF vector
Calculate Sim(Di, Q)
end for
while |FinalRank|<|S| do
    fordi in S do
            for djin FinalRankdo
Scorei← Similarity(Di, Dj)
            end for
Scorei← 0,1*Sim(Di, Q) – 0,9* Scorei
Temp ← {di, Scorei}
    end for
maxScoreDoc← Call FindMaxScore(Temp)
FinalRank{} ← {maxScoreDoc}
end while
returnFinalRank
```

**Fig. 3.** Diversification algorithm implementation

Figure 3 shows in more detail the implementation of MMR in CRUISE. The algorithm starts with the representation of each document as a vector of all words included in the index and the calculation of the similarity of each document with the query. It then proceeds with applying MMR that starts by placing the first document in the final list of documents, which will be the diversified bucket of documents. It iterates through the remaining documents and for each one calculates the MMR score summing its similarities with each of the documents that are already in the final bucket. The document with the maximum Maximal Marginal Relevance will occupy the place of the next element in the final bucket of documents. The process continues until all documents are placed in the bucket.

## 6 Evaluation

We conducted a pilot study and a focused experiment to evaluate our tool[1]. A team of professional concept developers from the Waag[2] Society institute for art, science and technology, have performed search tasks with the purpose of getting inspired in the context of their actual work assignments. Once the participants completed the tasks, they filled a questionnaire to provide their subjective usability and perceived usefulness assessment. To this end, we adapted the standard System Usability Scale [24] and the ResQue evaluation framework [25]. Moreover, we employed a think-aloud methodology and recorded qualitative user comments to gain additional insights.

In addition to the pilot study, we ran a laboratory study in order to evaluate the specific research objectives of CRUISE and whether CRUISE is subjectively better for leveraging inspiration than standard query-based interfaces. Thus, the baseline system was a typical query–based retrieval system, which used neither social chatter-based term extraction and visualization, nor search path exploration and resource diversification. The search spaces and search engines were the same in both systems. In the baseline, users could express their information need only through typing queries and the results were presented as a list of resources.

We recruited 20 CS researchers from our university to participate in the laboratory study. Their task was to formulate an outline for a short-term research proposal, e.g., a diploma thesis, in cloud computing. We limited the time available to complete the task to 15 minutes to make sure that the participants were actively searching during the experiment and had equal time to complete the task. Half of the participants performed the task using CRUISE and the other half using the baseline system. Participants were asked to evaluate the top 10 results of each exploration for novelty (whether a given resource was showing a new aspect), interestingness (whether this resource is interesting yet neither relevant nor directly related) and unexpectedness (whether this resource was relevant to the assignment yet not directly related and not expected to be found).

After the completion of the experiment we asked two professors to assess the quality of the thesis outlines based on the perceived relatedness to cloud computing research and their originality. Moreover, professors provided feedback on the theses fluency which refers how detailed theses were. We hypothesized that users who had access to inspiring resources would be able to formulate their ideas better.

In the pilot study, the overall impression from the concept developers' comments was positive. One developer stated that CRUISE provides a solid basis for "a very powerful inspiration tool". Many commented that with CRUISE they could "reach inspiring information from search engines and the company's portal faster", nevertheless a messy arrangement of sources and additional media types would be more inspiring for "visual people" as concept developers are. Another noted that "those red-coloured words that appeared to be really interesting" referring to the terms that came from design platforms that concept developers followed in Twitter and which were fed to CRUISE. Another developer suggested that the user should get feedback about

[1] Please visit `http://imu.ntua.gr/software/cruise` for a url pointing to CRUISE

[2] `http://waag.org`

the origin of the related tweet. The diversity of sources was appreciated because they "didn't always get common results in the top ranks". However, the cloud formation by exploiting just one social source was considered very restricting in terms of the variety of viewpoints they could get.

**Table 1.** Overview of the average, standard deviation and mode for our post pilot study questionnaire based on a five point Likert scale from 1, strongly disagree to 5, strongly agree

| Aspect | Mean | Std | Mode |
|---|---|---|---|
| Quality of Results (Novel, Interesting, Ser/pitous, Diverse) | 4.2 | 0.8 | 4 |
| Interaction Adequacy (to express, revise needs) | 4 | 0.7 | 4 |
| Interface Adequacy (attractive, adequate layout) | 4 | 0.7 | 4 |
| Perceived Ease of Use (familiarity with the tool) | 4.8 | 0.4 | 5 |
| Perceived Usefulness (supported in exploring) | 4.7 | 0.5 | 5 |
| Control/Transparency (control to express preferences) | 4.2 | 0.6 | 4 |
| Attitudes (confidence of getting inspired) | 4.8 | 0.4 | 5 |
| Behavioral Intention (use again, tell my friends) | 4.8 | 0.4 | 5 |

The quantitative results from the post laboratory study (see also Table 1) favoured CRUISE in terms of its adequacy to support users into expressing their needs (m=5 std=0.7) and getting familiar with it (m=4.7 std=0.4). With respect to quality of content, the users tended to agree that CRUISE offers valuable, novel and unexpected content (m=4.2 std=0.8) with strong confidence that it could inspire them (m=4.7 std=0.4). Data logged from the interactions with CRUISE and baseline system including details of the articles displayed, terms displayed by the system, manipulated terms, queries typed by the participants and user ratings of results revealed that with CRUISE users performed more queries (m=1.8) than using the baseline (m=1.14). The difference was statistically significant ($p < 0.05$). Moreover, with CRUISE users found more unexpected and valuable results than in the baseline (see Table 2).

**Table 2.** Overview of the ratings of results for CRUISE and baseline

| Type of results | Mean per session |
|---|---|
| Novel | Cruise: 0.23 Baseline: 0.2 |
| Valuable | Cruise: 0.20 Baseline: 0.15 |
| Unexpected | Cruise: 0.26 Baseline: 0.061 |

Considering the professors' assessment of the creative outcomes, we ascertained that our approach had some effect with respect to fluency (p-value: 0.05 and quality (p-value: 0.01) (See Table 3) which indicates that users who had access to resources with CRUISE were able to formulate their ideas better than those who didn't. A possible explanation for this finding could be that with CRUISE users could access diverse resources and could identify content of better quality than in the baseline. Moreover, CRUISE guides users towards more targeted searches that may help into finding novel ideas.

**Table 3.** Analysis of research thesis proposals

| | CRUISE | Baseline |
|---|---|---|
| **Fluency mean** | 3.8 | 2.7 |
| **Fluency STD** | 1.4 | 0.9 |
| **Quality mean** | 3.8 | 2.4 |
| **Quality STD** | 0.6 | 1.2 |

# 7 Conclusions

We presented an interactive, exploratory search system that combines diversity of content and information sources with a novel user interface design to allow the social chatter generated with micro-blogging services such as Twitter to actively help users in exploring the information space. Users can direct their search by manipulating terms extracted from online chatter and formulate new search paths. A task-based user study comparing our system to a query-based baseline indicated that our system improves inspirational discoveries by providing access to more interesting, novel and unexpected information. Our results are encouraging, providing evidence that the implicit use of social chatter in information seeking activities can enhance the potential for novel, diverse and serendipitous encounters which can in turn inspire users. We plan to conduct further empirical studies to understand the effect of each of our three research constituents and to enhance CRUISE with social and team-oriented features that will e.g., allow team members to view relevant searches of colleagues, as well as with user profiling capabilities that will enable personalization of user interaction by taking into account the user social network.

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# References

1. Amabile, T.M.: Creativity and innovation in organizations, pp. 1–15. Harvard Business School (1996)
2. Woodman, R.W., Sawyer, J.E., Griffin, R.W.: Toward a theory of organizational creativity. Academy of Management Review, 293–321 (1993)
3. Nagpal, A., Hangal, S., Joyee, R.R., Lam, M.S.: Friends, romans, countrymen: lend me your URLs. using social chatter to personalize web search. In: Proc. CSCW 2012, pp. 461–470. ACM Press (2012)
4. Herring, S.R., Poon, C.M., Balasi, G.A., Bailey, B.P.: TweetSpiration: leveraging social media for design inspiration. In: Proc. CHI 2011, pp. 2311–2316. ACM Press (2011)
5. Bernstein, M.S., Suh, B., Hong, L., Chen, J., Kairam, S., Chi, E.H.: Eddi: Interactive topic-based browsing of social status streams. In: Proc. UIST 2010, pp. 303–312. ACM Press (2010)
6. Millen, D., Yang, M., Whittaker, S., Feinberg, J.: Social bookmarking and exploratory search. In: Proc. ECSCW 2007, pp. 21–40 (2007)

7. Chen, J., Nairn, R., Nelson, L., Bernstein, M., Chi, E.: Short and tweet: Experiments on recommending content from information streams. In: Proc. CHI 2010, pp. 1185–1194. ACM Press (2010)
8. Marchionini, G.: Exploratory search: From finding to understanding. Communications of the ACM 49(4), 41–46 (2006)
9. Teevan, J., Alvarado, C., Ackerman, M.S., Karger, D.R.: The perfect search engine is not enough: A study of orienteering behavior in directed search. In: Proc. of SIGCHI 2004, pp. 415–422 (2004)
10. Baldonado, M., Winograd, T.: Sensemaker: An information-exploration interface supporting the contextual evolution of a user's interests. In: Proc. SIGCHI 1997, pp. 11–18 (1997)
11. Havre, S., Hetzler, E., Perrine, K., Jurrus, E., Miller, N.: Interactive visualization of multiple query results. In: Proc. IEEE Symposium on Information Visualization 2001, p. 105 (2001)
12. Glowacka, D., Ruotsalo, T., Konuyshkova, K., Kaski, S., Jacucci, G.: Directing exploratory search: Reinforcement learning from user interactions with keywords. In: Proc. IUI 2013, pp. 117–128. ACM Press (2013)
13. Devendorf, L., O'Donovan, J., Hollerer, T.: TopicLens: An Interactive Recommender System based on Topical and Social Connections. In: Proc. RecSys 2012, p. 41 (2012)
14. O'Connor, B., Krieger, M., Ahn, D.: TweetMotif: Exploratory Search and Topic Summarization for Twitter. In: Proc. ICWSM (2010)
15. Waitelonis, J., Sack, H.: Towards exploratory video search using linked data. Multimedia Tools and Applications 59(2), 645–672 (2012)
16. Denecke, K.: Diversity-Aware Search: New Possibilities and Challenges for Web Search. Library and Information Science 4, 139–162 (2012)
17. Vallet, D., Castells, P.: Personalized diversification of search results. In: Proc. SIGIR 2012, pp. 841–850. ACM Press (2012)
18. Carbonell, J., Goldstein, J.: The use of MMR, diversity-based reranking for reordering documents and producing summaries. In: Proc. SIGIR 1998, pp. 335–336. ACM Press (1998)
19. Agrawal, R., Gollapudi, S., Halverson, A., Ieong, S.: Diversifying search results. In: Proc. WSDM 2009, pp. 5–14. ACM Press (2009)
20. Santos, R.L., Macdonald, C., Ounis, I.: Exploiting query reformulations for web search result diversification. In: Proc. WWW 2010, pp. 881–890. ACM Press (2010)
21. Capannini, G., Nardini, F.M., Perego, R., Silvestri, F.: Efficient diversification of web search results. VLDB Endowment 4(7), 451–459 (2011)
22. Gollapudi, S., Sharma, A.: An axiomatic approach for result diversification. In: Proc. WWW 2009, pp. 381–390. ACM Press (2009)
23. Bordogna, G., Campi, A., Psaila, G., Ronchi, S.: Disambiguated query suggestions and personalized content-similarity and novelty ranking of clustered results to optimize web searches. Information Processing & Management 48(3), 419–437 (2012)
24. Brooke, J.: Susa quick and dirty usability scale. Usability Evaluation in Industry 189, 194 (1996)
25. Pu, P., Chen, L., Hu, R.: A user-centric evaluation framework for recommender systems. In: Proc. RecSys 2011, pp. 157–164 (2011)