SearchLens: Composing and Capturing Complex User Interests for Exploratory Search

Leave Authors Anonymous
for Submission
City, Country
e-mail address

Leave Authors Anonymous
for Submission
City, Country
e-mail address

Leave Authors Anonymous
for Submission
City, Country
e-mail address

ABSTRACT

Whether figuring out where to eat in an unfamiliar city or deciding which college to attend, large collections of consumer generated data (i.e. reviews and forum posts) are an important influence in online decision making. To make sense of these rich repositories of diverse opinions, users need to sift through a large number of items to learn common attributes, what the important features are, and determine how those match with their personal preferences. We introduce a novel system, SearchLens, which allows the user to build up "lenses" that enable them to evolve representations of their interests in a way that matches how their interests are instantiated in the data. SearchLens goes beyond previous approaches such as faceted browsing, user intent models, and personalized search by introducing the idea that each lens can match part of a users' latent interests and concepts, and that these lenses can be composed together to match a user's particular context (e.g., searching for restaurants with outdoor spaces and that serve alcohol and aren't too crowded). Across a lab and field study we find that users find benefits in the SearchLens approach, including being able to transfer and reuse lenses across contexts, find and capture "honest signals" of their concepts in the data, transparency and explainability, and working at multiple levels of specificity and hierarchy.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; See http://acm.org/about/class/1998/ for the full list of ACM classifiers. This section is required.

Author Keywords

Exploratory Search Interfaces; Sensemaking; Visualization

INTRODUCTION

Whether figuring out where to eat in an unfamiliar city or deciding which college to attend, people often rely on reading online reviews and forum posts to make predictions about how well different options might match their personal interests and needs. With the proliferation of online reviews, people now have instant access to millions of online reviews from people with different perspectives and interests. It was estimated that in 2013 Amazon provided shoppers access to more than one million reviews for just their electronics section [32], and in 2016 Yelp provided around 250,000 reviews for over 6,000 restaurants for the city of Toronto alone [25]. Having access to this rich repository of diverse perspectives based on the past experiences of others has the potential to empower consumers to understand their choices thoroughly and make better decisions for themselves without being overly influenced by marketing and branding [13].

However, the rapid growth of online reviews can make it overwhelming to search through and understand how the experiences of others meet one's own interests and goals. To understand the prevalence of this issue, we conducted a pilot survey with 50 participants recruited from Amazon Mechanical Turk (age between 21 and 63, M=37.0, SD=11.7, 52% male, and 48% female, mostly from the US), focusing on their experiences when researching restaurants online. We chose restaurant search as our main topic due to its subjective natural and that people often have very diverse and nuance interests or criteria when picking restaurants. Almost all of our participants self-reported that they use services that provide reviews and ratings to look for restaurant information online. At the same time, 60% of the participants agreed that restaurants they like do not always have high average ratings. Participants also agreed that when searching for restaurants online, they had encountered restaurants with bad average ratings but were mostly about things that they did not care about (62%), and that it is time consuming to sift through reviews to find ones that were of interest to them (60%). This suggests that even though modern search engines can return a list of options in split seconds, searchers often still need to spend a lot of time and effort carefully examining each result to find parts that are relevant to them.

Doing so is challenging in part because the interests and goals of an individual are poorly described by simple computational representations such as keywords or term vectors. Consider for example an individual interested in Indian food – this may be true at a high level, but perhaps that person prefers North Indian cuisine, and has particular specific favorites, such as pani puri or samosas. Or perhaps they are trying to look for outdoor restaurants that have space for kids to run around but also serve alcohol and are not too crowded. Some of these needs (such as the particular types of drinks they like, such as bourbon and hoppy beers but definitely not tequila)

CHI'16, May 07–12, 2016, San Jose, CA, USA

ISBN 123-4567-24-567/08/06. . . $15.00

DOI: http://dx.doi.org/10.475/123_4

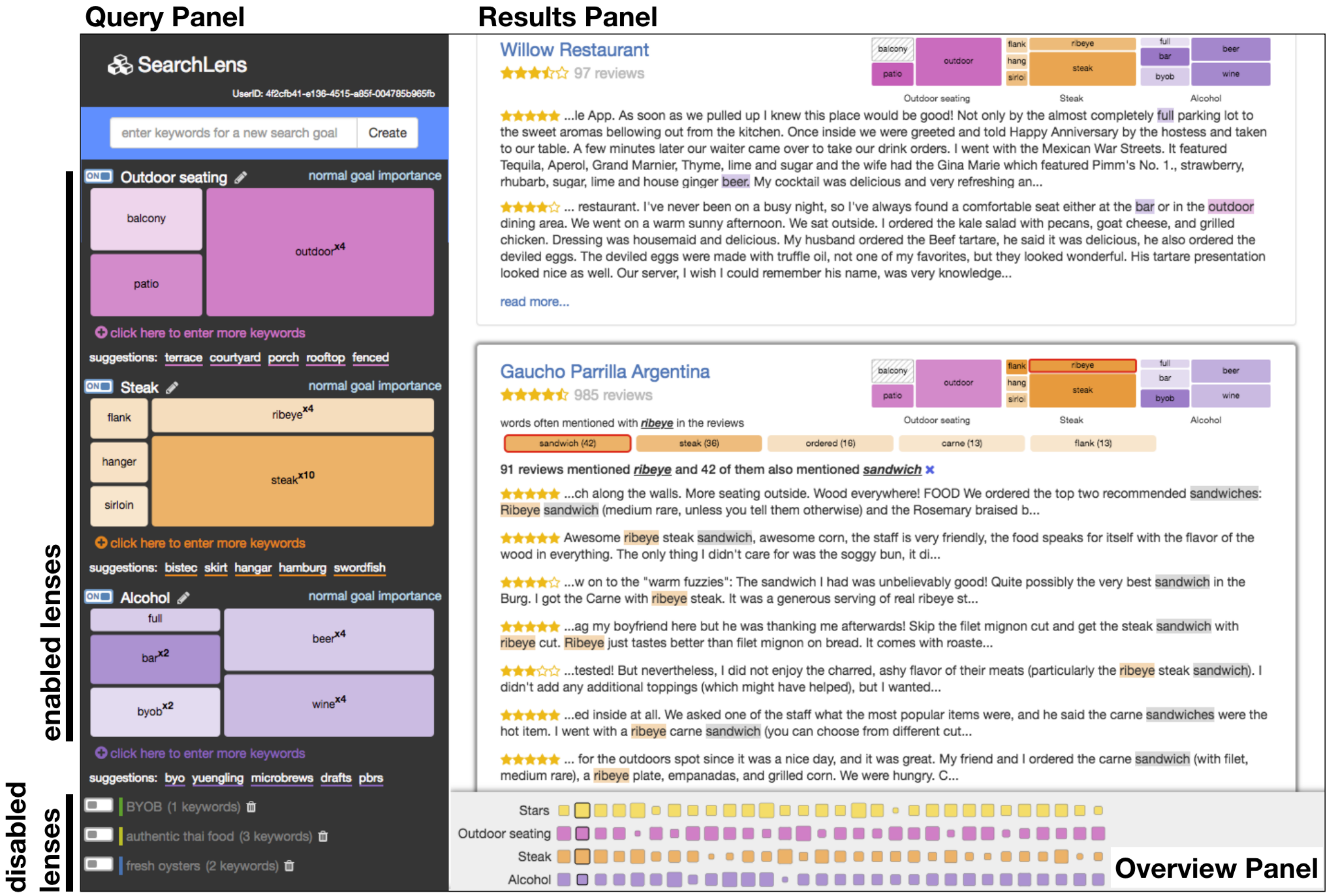

Figure 1. An overview of the SearchLens system. The Query Panel on the left allows users to specify search topics, or Search Lenses, with keywords of different importance visualized by colored treemaps. Search Lenses can be freely disabled or enabled for different scenarios. The Results Panel on the right shows a ranked list of search results that best match the enabled Lenses from the searcher. The same visualization for specifying query now are used for explaining how each result matches with users interests and mental model, and also serve as an interactive navigation for filtering mentions of specific keywords. The Overview Panel at the bottom shows a collapsed version of the treemaps that allows for quick comparison between restaurants.

might be relevant for other situations as well such as going out for drinks with friends or on a date night. Finally, some of the terms that might seem to be good at first might in fact not be very discriminatory (e.g., “great”, “delicious”) versus less obvious terms that act as more "honest signals" (e.g., the use of the word “bone” for ramen that is simmered in bone broth for days). In summary, we suggest that capturing and supporting individuals’ complex interests requires providing them with the ability to generate, visualize, and manipulate representations that are rich, hierarchical, and composable.

In this paper we explore a novel interface that allows users to specify and maintain their multifarious and idiosyncratic search goals with structured queries that we call Search Lenses, and gradually construct an interactive search interface based on their own interests and past activities. The instantiation of this approach is a prototype system called SearchLens, which allows users to progressively and persistently build up a repository of “Search Lenses” that can be used to reflect their topics of interests and mental model. Users construct Search Lenses by specifying keywords and weights, and the system visualizes the importance and frequency of each keyword in the results for comparison. Besides specifying keywords from prior knowledge, SearchLens also provides a mechanism for users to discover and collect keywords as they look at the search results. In addition, the system provides suggested keywords for each Search Lens using a semantic word vector model. The Search Lenses that users create persist across sessions, allowing users to freely enable and disable different sets of Lenses for different occasions. For example, enabling their Search Lenses for “kids friendly”, “easy parking”, and “home cooking” to explore restaurant options for a big family dinner, and enabling their Search Lenses for “cozy and intimate”, “easy parking”, and “good wine selection” to explore restaurant options for date night. These Lenses in turn allow the system to present each result based on the current interests of the users, and allow them to explore each of the results by revealing mentions of different query terms. We conducted a lab study with 29 participants, and a field study with 5 participants conducting their own tasks over 3 days. Results show that our prototype system SearchLens a) allows users to fluidly capture, build, and refine Lenses to reflect their interests and needs, b) allows users to interpret, explore, and discover desired results using the interactive interfaces, and

c) that the user-generated interfaces can be reused over time and transfer across contexts. In addition, we also show that standard information retrieval systems (i.e., document search engines) can be easily adapted to support these interactions with high efficiency and scale.

RELATED WORK

Unlike simple and objective information seeking scenarios, such as finding the address of a restaurant or checking the weather, scenarios where people share and search for reviews are often multifarious and subjective in nature – each review includes the subjective values of its posters, but at the same time, different searchers also have varying interests and criteria that do not always match with the reviews [29, 13]. For example, restaurants might receive negative reviews for its simple decor and lack of good ambiance, but some searchers might value more the authenticity of the food and whether vegan options were available on the menu. Traditional search interfaces that only allow users to specify bag-of-word queries and show short summaries with highlighted search terms provides little support for searching and presenting results for users with multiple topics and goals, and the sheer amount of diverse information online can be overwhelming to the users, making it difficult to make confident and informed decisions. In many case like this, searchers would have to look past the average review ratings, and sift through the reviews of each result to find ones that mentioned aspects of interest in order to make confident decisions.

Despite their ubiquity, operations for searching with multiple topics of interest as described above are poorly supported by modern approaches. Search engines have optimized for providing information as quickly as possible [44], such as knowledge cards in which an answer is surfaced directly on a search results page or visual carousels of possible options that a user can quickly click through [57, 4]. These approaches excel at finding answers to objective, factual questions, but notably fail to address activities involved in complex, personalized search tasks, such as specifying multiple goals and criteria, explaining search results based on personal interests, and allowing for deeper exploration of different options for comparison [30, 49, 50]. The bag-of-words search fields provide no structure for users to express their multifarious search goals and criteria, and the returned short summaries provide little support for personalized interpretation results beyond highlighted query terms in the short summaries. Even if users listed keywords of many different topics at once, the linear result list also provides little information about each result beyond their overall relevance ranking. As a result, the search result list can become increasingly difficult to interpret as the user adds more keywords to their query, raising questions like how different keywords influenced the ranking, and whether each result matches with their different topics of interests. Further, in order to explore deeper to get a better understanding of their options, users would need to leave the search result list page and visit each result independently and manually extract parts that are relevant to their goals, often with the in-page keyword matching provided by the browser.

A variety of approaches to collecting and modeling users' interests and intents have been developed to address some of the problems with search listed above. Our work builds on a diversity of literature which have attempted to address different aspects of this problem.

Modeling Interests and Intents

A significant topic of research has been interfaces that can collect, explicitly or implicitly, the personal interests of users as they search for information and modify their viewing of content correspondingly. While there is extensive literature on doing so in the context of personalized search and reranking of search results (e.g., [43, 41, 6, 7]), we focus here on work that enables more interactivity and transparency of users' interests to support more complex searching. One such thread lies in the collection of users' interests through keywords or interest vectors into an agent or user interest or intent model. This includes seminal work such as WebMate [9], which built up an agent composed of sets of TF-IDF [52] vectors to represent the user's different interests. Similar to WebMate, we aim to build collections of terms that represent the user's interests, but focus on explicit user selection of those sets, and making them explainable and composable. Interestingly, WebMate's "Trigger Pair Model" which looked at co-occurrence of words within a sliding window across a set of documents can be seen as a precursor to the word vector model that we use for keyword suggestions. More recent work in this vein includes user modeling of concepts, such as AdaptiveVIBE [1] and Intent Radar [37], which include two dimensional visualizations of documents and their relation to the user's inferred interests. Our work builds upon these but aims at increasing the richness of the structure, nuance, and specificity of the user's expression of interests. Specifically, our lenses, composed of multiple keywords that can capture multiple levels of specificity, can be themselves composed into more complex expressions and reused across different contexts and tasks. We also focus on supporting users in the discovery process of building good terms that are discriminatory and explanatory.

Exploratory Search Interfaces

Another thread of work that we draw on includes novel personalized search interfaces such as faceted navigation [18], semantic web interfaces [51], or computational approaches such as automatic or interactive result clustering [12]. Several exploratory search interfaces have been developed in order to help searchers orient themselves in the information space, review and explore the different subtopics, and keep track of their overall progress [19, 31, 35, 46, 34]. Two closely related studies include Topic-Relevance Map and Exploration Wall, which explored ways to provide overviews of search results of academic papers using document keywords and entities and easily choose keywords to build up subsequent queries [36, 27]. When metadata is available, faceted search is perhaps the most commonly used search interface, in which users can filter results by selecting or deselecting categories or "facets" (e.g., products on an online shopping site). Although originally designed to help searchers efficiently narrow down on relevant sources and exclude irrelevant sources from their search results, researchers have also found faceted search interfaces to benefit exploratory scenarios, where searchers are less certain about their information needs [20, 56]. However, these expert structures are typically designed for navigation or filtering, whereas SearchLens instead use a novel interactive visualization that allowed searchers to specified and refine their personal and idiosyncratic search topics in a composable and dynamic way.

Automatically Identifying Structure

Meanwhile, computationally inferring task-specific fine-grained facets (e.g., day trip destinations) remains a challenge [5, 45]. Researchers have long explored ways to extract structure by clustering search results using machine learning [58, 59, 22], lexical and HTML patterns [28], crowdsourcing [17, 8, 10], or interaction techniques [22, 23, 23]. The Scatter/Gather system in particular, allowed users to navigate and explore large collections of documents using an interactive hierarchical clustering paradigm [22]. However, a number of papers [21, 11, 8] point to the fact that automatically techniques can often produce incoherent structures that are difficult to comprehend by users. Further, the automatically generated structures were designed to reflect the characteristics of data for exploration, and does not take into account the interests of the users when trying to infer structures. While they may be effective for exploration and navigation, they typically provide little support for allowing users to externalize idiosyncratic search goals, and do not present data in ways that reflects the interests of the users. In SearchLens, we allowed the users to explicitly express their idiosyncratic search goals using structured queries we call Search Lenses. The system provided a novel interactive visualization that allowed users to both refine their query structures, and also help them interpret the results based on their interests. As such it also has roots in degree of interest (DOI) functions used in the visualization literature, which drive human attention to areas of the information that have high expected utility for a user's expressed or inferred goals [16, 47], and suggest a bottom-up and iterative, user-driven process of searching in which the user is continually updating the expected utility function.

SEARCHLENS

The key motivating concept behind SearchLens was providing users with a way to externalize the complex mental models of their interests in a way that could be useful for themselves in understanding their information space immediately and in the future. We aimed to make the interface simple and transparent but also powerful enough to express hierarchy and support multiple concepts and levels of specificity. To do this we introduced the idea of "Lenses": reusable collections of weighted keywords that contain "honest signals" of a user's interests that can be composed in different configurations to match a user's current needs. The Lenses that are enabled in a particular configuration drive various visualization and explanation elements to help the user understand how the information space meets their needs, and also whether they need to fix or reformulate their Lenses.

A typical use case is as follows. A user just moved to Pittsburgh and wants to go out to eat ramen. She starts by pulling up a restaurant she knows she likes from Toronto and goes through some of the reviews, noticing that the reviews of her favorite tonkatsu ramen mention interesting signals such as "bone" and "umami" and adds them to her ramen lens along with other useful words such as "tonkatsu", "ramen", "bowl", etc. Checking to see that her lens is bringing up other restaurants that serve ramen she likes in Toronto and adding a few of their terms to her lens, she switches to Pittsburgh and looks for how her lens is being used. She also activates her drinks lens, which she's built up over the years to incorporate her particular interests in unfiltered sakes as well as hoppy beers.

In this section we describe SearchLens, an interactive search interface. As an overview of the system, Figure 1 shows an example use case of SearchLens, which addresses the issues in the following way:

- **Query specification** The query panel on the left allowed users to specify structured queries, or Search Lenses, that reflect their different search goals. A treemap [42] is presented for each search lens that illustrate the set of user-specified keywords (cells) and corresponding importance (sizes of each cell). The overall frequencies of query term in the results (shading of each cell) is also presented to show how the results reflect the expectations of the users.
- **User-generated interface** Search Lenses are persisted between visits to the system. As users perform more searches, they gradually build up a repository of their personal Lenses that reflects their different interests and goals. The users can freely enabled or disabled different sets of Lenses for different or recurring scenarios
- **Explanation** The user-specified Search Lenses are also used for providing an overview for each search result. The same treemap visualization shows the frequencies of each query terms within each search result to help users interpret each result efficiently using the familiar visualization that they created when specifying their search goals. A collapsed version of the treemaps are shown in the bottom panel for overview and quick comparison.
- **Exploration** The user-specified Search Lenses are also used for navigation for deeper exploration. User can click on their query terms to see their mentions for each search result in real-time. SearchLens also show frequently co-occurring terms in cases where a lot of mentions exist.

In the following subsections, we describe in detail the domain and data source we used, the design and implementation of each component, and a scalable backend ranking method that powers the interactions.

Domain and Data Source

To test our prototype system in a realistic and manageable setting, we focused on the domain of restaurant reviews where personalization and searching with multiple goals is especially important. We used a subset of the dataset from the Yelp challenge [25], which, in total, contains information about local business in 11 metropolitan areas across 4 countries which contains 48,485 restaurants and 2,577,298 reviews. We focused on all restaurant reviews from both Montreal (Canada) and Pittsburgh (USA), which contains 75,537 reviews for 2,957 restaurants, and 100,765 reviews for 1,990 restaurants, respectively. This allows us to explore how user-specified Search Lenses can be composed and reused for different scenarios, as well as for the same scenario across different cities. On the other hand, to generate lens-specific query term suggestions, we trained a word2vector model using the entire Yelp dataset.

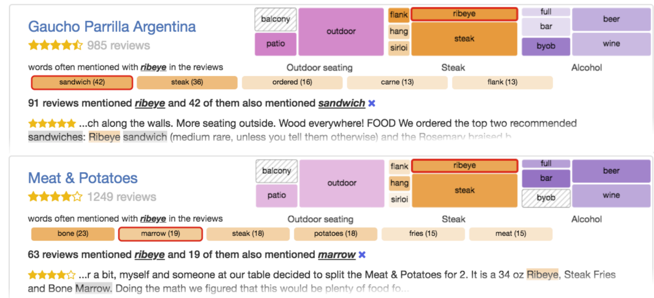

Figure 2. Treemaps for each results allows comparison at different levels of granularity using a familiar interface what was used for specifying queries - at the Search Lens level, at the keyword level, or at the mentions and co-occurring terms level.

Expressing Interests with Search Lenses

SearchLens allows users to specify sets of keywords that describe different topics of interests we call Search Lenses, and supports searching with multiple Lenses at the same time (similar to [23]). Users can create a new search lens by specifying a set of keywords using the text field in the Query Panel on the left. Once created, the new search lens will be assigned a unique color, and its treemap visualization will be added to the Query Panel, where each cell in represents the different user-specified keywords. Using the interactive treemaps, users can refine their their Lenses by adding or removing keywords, and also by adjusting the weights of each keywords. The Results Panel on the right will update in real-time to reflect those changes.

Users can refine their Lenses by adding new keywords using three different approaches, each for a different scenario. Firstly, users can click on the plus icon under each Lenses to enter new keywords based on their prior knowledge using a lens specific text field. Secondly, as users read the reviews, they may discover more indicative keywords or new topics of interests. In this case, they can highlight the keywords using the standard text selection method and use the context menu to add them to a existing search lens or to create a new search lens. Finally, a list of lens-specific keyword suggestions are listed under each lens. The users can hover over each suggestion to see example mentions, and click on the keyword include it. This allows users to assess the usefulness of the suggestions, such as to avoid ambiguous terms. The lens-specific suggestions were computed based on the existing keywords of the search lens and a word semantic model. We describe this below in in the Backend and Ranking subsections. To remove a keyword, users can click on its cell and select remove keyword in the context menu.

SearchLens also allows users to specify the importance of each query term using the treemap visualization to better reflect the users' mental representation of each topic. The size of each cell illustrates the importance of each keyword as specified by the users. To adjust the importance of a keyword, a user can click on it and select a different level of importance in a context menu, and the treemap will resize the cells accordingly. The importance levels (x1, x2, x4, and x10) directly correspond to the keyword and lens weight in the backend ranking function, which will be described in detail in a later subsection. The shade of each cell shows the overall frequency of each keyword in the top 30 search results. This allows the user to get a sense of how items in the corpus reflect their mental representation of each topic. For example, a large cell with very light shade represents a concept that the users deemed as an important feature of the topic, but was rarely found in the results. Surfacing this information ensures user are aware of how useful each of their keywords are, and refine their Lenses to include more indicative keywords if needed.

Building a Repository of Search Lenses

The user-generated Lenses can be freely disabled and re-enabled and are persisted across different visits to the SearchLens interface. Disabled Lenses are listed at the bottom of the Query Panel. As a user performed more searches using SearchLens, a repository of Search Lenses that reflects their personal interests gradually builds up over time. The users can enable different sets of Lenses for different occasions. For example, a user might enable their personalized Lenses for cozy and intimate, vegan, and easy parking for date night, and their Lenses for fast casual, vegan, and easy parking for weekday lunches. Alternatively, users can use a single lens to create curated list of recurring criterias. For example, creating a lens for top ramen shops to try with keywords such as ramen, broth, savory, authentic, tonkotsu, and japanese. Although in this case the search lens would become less composable as it includes multiple topics. In our study, we observed different behavior from different participants and under different conditions. We will present detailed results in later sections.

Explanation and Exploration

Presenting search results in an easy-to-interpret way is especially important for searches with multiple topics and keywords, as it can be difficult for the users to understand which topics and keywords were associated with each result. SearchLens allows users to express their multiple topics of interest separately, enabling the system to distinguish between keywords of different topics. This opens the possibility of visualizing each result according to users' interests in easy-to-interpret ways. One obvious approach to explaining items in the search results is to surface mentions and statistical information, such as mention frequencies, at the topic level. For example, [24] visualized the overall frequency of different search terms in different topics for each search result, and [23] in addition visualized the mention locations of different topics within each document. Visualizing at the topic level allowed these systems to provide mechanisms for specifying many topics and keywords, while at the same time visualized deeper information about each result in a way that matches the mental model of the searchers. However, visualizing at the topic level can also be prohibitive for keyword-level operations. Such as query reformulation and assigning importance levels to different keywords based on their frequencies. We instead visualized each results at both the topic level and at the keyword level using the same treemap visualization technique we used for specifying queries. By using identical colors and layouts of each Search Lenses, and showing result-specific keyword frequencies, users can quickly interpret how each result matches with their different interests at both the topic and at the keyword level using a familiar visualization. In addition to acting as an overview of each results, the treemaps also act as a navigation tool for deep exploration at the keyword level. Users can explore mentions of different keywords by clicking on its corresponding cell and the summary will update in real-time to show a list of its mentions. When more than 10 reviews contain the selected keyword, the SearchLens also shows the top 9 words that frequently mentioned near the selected keyword, a strategy that was shown to be useful for exploratory scenarios [14, 15, 36]. As an example, Figure 2 shows the how SearchLens allowed users to explore and compare options at different levels of granularity. At the highest level, users can use the shading of different treemaps to see that the *Outdoor Seating* lens has more mentions in the first restaurant (Figure 2). Searchers can use the shading of individual cells to compare options at the keyword level. For example, the term "BYOB" was frequently mentioned in reviews for the first restaurant, but did not show up in reviews for the second restaurant. Finally, clicking on the individual cells allowed users to explore mentions of its corresponding keywords and words that were frequently mentioned together. For example, when exploring mention of the work "ribeye" for both restaurants, SearchLens showed that there were many mentions of "sandwich" near the word "ribeye" for the first restaurant, and many mentions of "bone marrow" near "ribeye" for the second restaurant (Figure 2). Finally, to provide an overview of all restaurants in the search results for comparison between items, SearchLens collapsed each treemap into a single cell similar to [24] and uses the size of each cell to show the overall frequencies of keywords in different Search Lenses for each result (Figure 1). This allows users to first get a quick overview of restaurants in the search results, and compare different options at the topic level using the Overview Panel at the bottom.

Backend

Indexing and Ranking Restaurants

The backend of SearchLens works similarly to common document retrieval engines. In the indexing phase, text in each review is lowercased, tokenized, and stemmed using the Word Punkt Tokenizer [26] and the Porter Stemmer [48]. Stop words are filtered out. An inverted index that records the document and the offsets of the mentions of each word stems is computed and stored in a relational database. At runtime, we used a modified version of the standard Okapi BM25 ranking function for document retrieval [39], which by default considers both term frequency and document frequency to rank documents similar to TF-IDF ranking function, but also adjust for the length of each documents.

We modify the Okapi BM25 ranking function to account for the importance levels specified by the users in the following ways. By default, Okapi BM25 use the inverse document frequencies to weight each keywords, and the motivation is that words that appeared in many documents tend to be less important. Since in SearchLens users can specify keyword importance using the interactive treemaps, we instead weight each keyword according to their user-specified importance level. By default, SearchLens assume each lens is equally important, and normalizes the weights of keyword q in a Search Lenses ℓ in proportion to the user-specified importance level of all keywords $\acute{q}$ in search lens ℓ:

$$weight(q) = \frac{importance(q)}{\sum_{\acute{q}\in\ell} importance(\acute{q})}$$

SearchLens then uses the normalized keyword weights in place of the inverse document frequency term in the Okapi BM25 ranking function, and the score of each document D in the corpus for a set of Lenses L is therefore:

$$score(D,L) = \sum_{\substack{\ell\in L\\ q\in\ell}} \frac{weight(q) * tf(D,q) * (k+1)}{tf(D,q) + k * (1 - b + b * |D|/avgDL)}$$

where ℓ is the different user-specified Search Lenses, q is the different keywords in each lens ℓ, $tf(D,q)$ is the term frequency of keyword q in document D, $|D|$ is length of the document D, and the constant $avgDL$ is the average document length in the corpus. Finally, we used the default parameters $k = 1.2, b = 0.75$ for Okapi BM25. This modified version of the the Okapi BM25 function, and can be easily translated to SQL queries for standard relational databases, or as a custom ranking function for the popular open sourced document retrieval engine Apache Lucene. This allows the SearchLens interface to be easily implemented to using readily available tools that were already optimized for scaling and computational efficiency.

Keyword Suggestions

Having the user-search Search Lenses allowed the system to know which query term belong to the same topic, which allowed SearchLens to generate lens-specific topical keyword suggestions. To do so, we trained a Word2Vec model [33] with 300 dimensions using the entire Yelp dataset with 2,577,298 reviews. The trained word semantic model can project words onto a semantically meaningful vector space, which in turn allows for measuring semantic similarity between words. Alternatively, it can also be used to find a set of words that were semantically similar to a given term by searching in the semantic vector space for nearby words. To generate lens-specific keyword suggestions, we first project all its keywords in a lens onto the vector space and calculate the average vector to obtain a list of semantically similar terms around the average vector. To further increase the chance of presenting useful and discriminatory search terms, we only used terms that appeared more than 50 times in the corpus, were mentioned in reviews

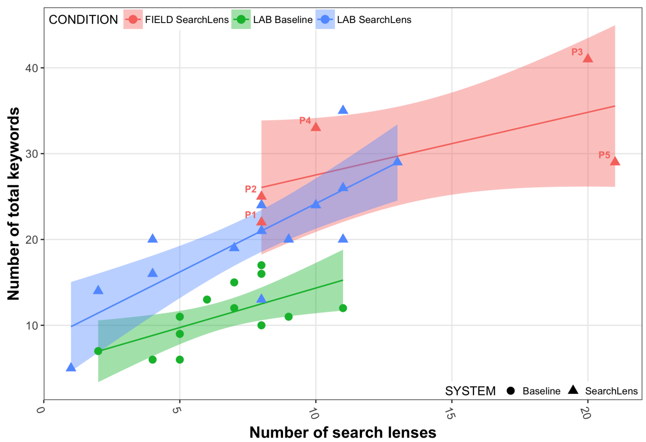

Figure 3. **Number of Search Lenses and keywords specified by participants under different conditions. In the lab study with predefined search tasks, participants using SearchLens (blue) created a similar number of Lenses but used more keywords than the baseline condition (green). Participants in the field study (red) using SearchLens for their own needs used more Lenses.**

of more than three restaurants, and were mentioned in less than 40% of all restaurants.

Implementation Notes

The backend of SearchLens was implemented in Python, using the NLTK toolkit [3] and the gensim toolkit [38] for indexing and word semantic model, respectively. PostgreSQL relational database is used for storing and accessing the inverted index, and the Flask Python framework was used for our HTTP server. We implemented front-end of the SearchLens prototype as a web-based system using Javascript (ES6) and the ReactJS GUI framework, and the interactive visualizations are implemented using the D3.js library. User-specified Search Lenses were stored on client-side using browser cookies, so that they are persistent for the searchers between multiple visits.

EVALUATION

We evaluated SearchLens by conducting a lab study with 29 participants, and a field study with 5 participants. The studies aimed at assessing both the usefulness of the interface, and how searchers utilizes the different novel features and query paradigm. For the lab study, participants were given three predefined search tasks and personas, where we observe their strategies and behaviors on building and reusing the Lenses. For the field study, participants were conducted their own search tasks outside the lab, so we can test SearchLens in real-life scenarios. During the studies, we logged the user interactions for further analysis. In the following subsections, we will describe the two studies in detail.

Lab Study

For the lab study, we recruited 29 participants from a local participant pool, where 14 participants tested the SearchLens interface with three predefined search tasks (N=14, Age=18-61, M=28.1, SD=12.7, 7 male, 6 female, and 1 other/not listed), and 15 participants tested a Baseline interface with the same search tasks (Figure 4, N=15, Age=18-54, M=28.1, SD=10.7, 7 male, 7 female, and 1 other/not listed). The study

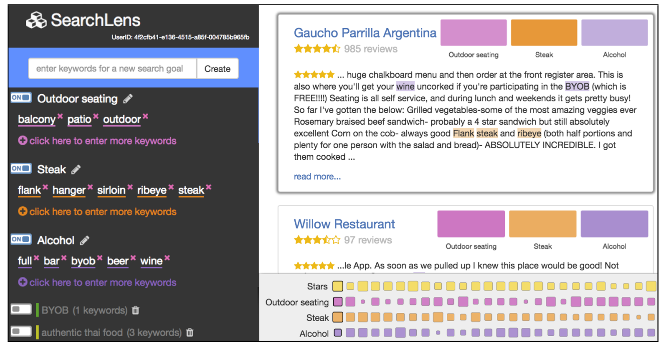

Figure 4. A Baseline system with collapsed treemaps inspired by the TileBars and HotMaps systems.

took about 60 minutes to complete, and each participant was paid 10 USD. The three predefined search task scenarios were as follows:

- **Scenario 1**: Stanley is in Pittsburgh, USA visiting some friends and he is in charge of finding a few good restaurants for the group. They are interested in Japanese restaurants. They're not familiar with Japanese food or the different types of Japanese restaurants, so it is up to you to find Japanese restaurants based on reading the reviews and your personal preferences. The restaurants should have a nice decor and good atmosphere. Some of his friends like to have a few drinks with their meal, so if the place has a bar that serves beer or wine it would also be great. Since its pretty nice out, it would also be nice if the restaurants has outdoor seating or a patio, too.
- **Scenario 2**: John is looking for good seafood restaurants in Pittsburgh, USA, particularly places that serves fresh oysters and has a bar that serves beer, cocktails or wine. Decor or atmosphere are not important, but big plus if they offer outdoor seating, for example, a patio. Some of his friends are allergic to seafood, so the place must also have non-seafood options, preferably steak.
- **Scenario 3**: (Same as Scenario 1 but for finding restaurants in Montreal, Canada instead of in Pittsburgh, USA.)

The first scenario is design to have both clear criteria (nice decor and good atmosphere and serves beer or wine), and a exploratory criteria (find a specific type of Japanese restaurant based on your own preferences). Scenario 2 and 3 are designed to explore whether users would reuse their Search Lenses for different context. Scenario 2 had overlapping criteria to Scenario 1 (serves beer, cocktails, or wine), and Scenario 3 was to perform Scenario 1 in a different city.

Baseline System

We compared the behaviors of participants using the SearchLens system to participants using a baseline system as a between subject condition. The Baseline system, as shown in Figure 4 is inspired by the TileBars and the HotMap systems [23, 24], where we collapse the treemaps and visualized the results at the topic level. Keyword-level features that were not supported by the two prior systems were also disabled, such as keyword suggestions and keyword-based exploration. Since

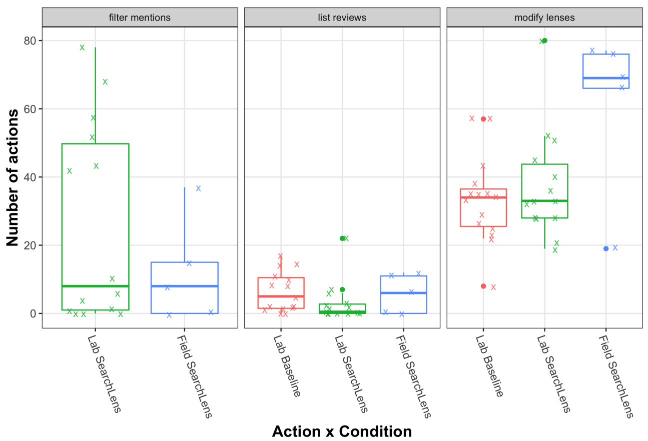

Figure 5. Number of different action participants performed under different conditions. Participants in Baseline relied on reading full reviews to understand results, whereas participants SearchLens frequently used the interactive treemaps to see keyword mentions. Participants conducting their own tasks in the Field study tend to refine their Search Lenses often.

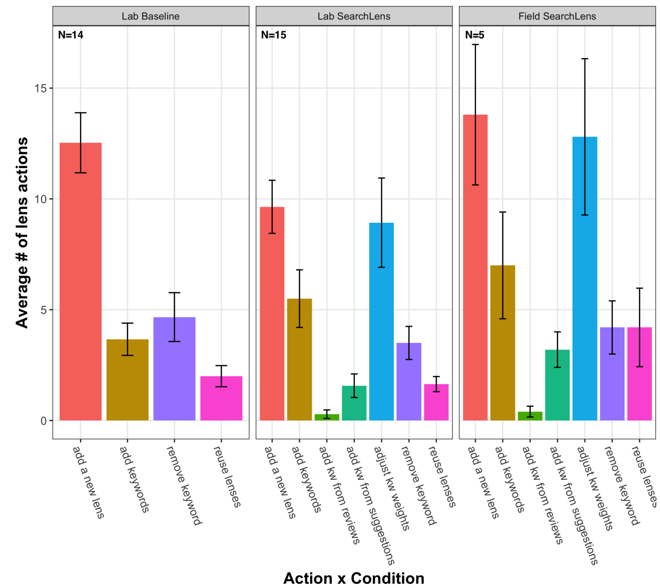

Figure 6. Average number of lens editing actions performed by participants under different conditions. Notice keyword specific features are not available in the Baseline condition.

searchers can not assign importance levels for each keyword, the Baseline system uses the Okapi BM25 ranking function with keywords in the Lenses to retrieve the results [39].

Results

At the end of the Lab study, participants build up a small repository of keywords and Lenses from conducting the three predefined search tasks. Using the behavior logs, we examine how the size of their search lens repositories. Figure 3 shows the number of Lenses and keywords each participants under different conditions collected during the study. In general, participants in either condition generated similar number of Lenses. This is expected since the predefined scenarios had many clearly defined criteria. However, results suggest that participants in the SearchLens condition ware able to collect and manage larger number of keywords for their Lenses.

Figure 5 shows the number of actions participants performed under different conditions. In general, participants in the Baseline condition examined the full review lists of different restaurant more frequently then participants in the SearchLens conditions. On the other hand, participants in the SearchLens condition frequently used of the interactive treemaps to filter out mentions of different keywords, which was not available to the participants in the Baseline condition. This suggests that participants in the Baseline condition relied on listing and reading full reviews in order to understand the search results, whereas participants in the SearchLens condition frequently used the interactive treemaps to see mentions of their different keywords in the reviews directly on the search results page. Participants under the two conditions performed similar number of lens modifying actions. Figure 6 shows the average number of detailed lens modifying actions. More than 70% of the participants in either condition reused their Search Lenses across condition (with 11 out of 15 participants for the Baseline condition, and 10 out of 14 participants out of the SearchLens condition). Participants under the SearchLens condition used keywords from prior knowledge by creating Lenses and adding keywords to them, but also found keywords in the reviews and used the suggested keywords. In the Field Study, we examined in more detail on how searchers utilizes different SearchLens features to refine their Lenses.

Field Study

Five participants were recruited from the first study based on their self-reported high interests in researching restaurants online in a short post-study survey (N=5, Age=18, 20, 22, 23, and 25, 4 male, and 1 others/not listed). The goal of the field study is to investigate how people use SearchLens for their own tasks without given any predefined search goals. The participants were given access to the SearchLens system via the internet, and were asked to use the system for at least 60 minutes in total over a three day period and at the time and place of their convenience. Although they were free to choose from any of the 11 cities in the dataset for this study, all five participants conducted the study for restaurant in the city that they lived in. Finally, they finish a survey with mostly free-formed questions that takes about 45 minutes, and finally return to the lab for a 15 minute interview. The participants were paid 40 USD each for finishing the study.

Participants and Use Cases

Below is a summary of the five participants. In the next subsections, we list common use cases and strategies as reported by the participants in the interviews, as well as observed from the behavior logs:

- **P1** lived in the city for the past 4 years, Created 8 Lenses with 22 keywords in total for more than 5 tasks across in 3 search sessions. Used SearchLens mainly to explore different types of restaurants in the city.
- **P2** lived in the city for the past 4 years. Created 8 Lenses with 25 keywords in total for the 2 tasks. Used SearchLens

to find Mexican restaurants with vegan options and also places that have bubble tea.

- **P3** lived in the city for the past 4 years. Created 20 Lenses with 41 keywords in total to explore the city and also to find restaurants that have Chicago deep dish pizza.
- **P4** lived in the city for the past 3 years. Created 10 Search Lenses with 33 keywords in total for more than 5 different tasks. Similar to P1 used SearchLens to explore different types of restaurants in the city in multiple search sessions.
- **P5** lived in the city for almost 1 years. Created 21 Lenses with 29 keywords for more than 5 search tasks across multiple search sessions. Used SearchLens to explore the city, but also to check for new vegan restaurants.

Behavior Logging

We recorded the behavior of our participants while using the SearchLens interface. Figure 3 shows the number of Lenses and keywords each participants under different conditions collected during the study, and Figure 5 and 6 shows the number of action participants performed under different conditions. In general, participants in the Field Study conducting their own tasks generated more Lenses and keywords, and also performed operation on refining their Lenses. However, they were performing different search tasks and spending more time on the system than participants in the Lab Study.

Reusing Lenses: Combinations and Task Resumption

All five participants reused their Search Lenses that were previously created. Their strategies can be broken down into two non-exclusive categories. The first use case we observed was task resumption between multiple search sessions (P1, P3, P4). Participants described having the ability to switch to a different sets of Lenses yet still keep the original Lenses for the future being useful (P3). One participant (P1) searched with a single lens most of the time, but still cited that being able to re-enable Lenses from past sessions and to continue work on previous tasks and refined restaurants being useful. For the second use case, participants mentioned reusing Lenses in combination with other Lenses (P2, P3, P5). When asked about which of their Search Lenses were used in combination with different other Lenses, participants reported Lenses that concerned style and environment (*Cute and Quirky* (P5), *Atmosphere and Vibe* (P2, P5), *Friendly Staff* (P3)), price (*Inexpensive* (P2, P3), *Large Portion* (P3)), and some food-related but not for a general genre (*Fresh* (P2), *Fast Casual* (P2), *Vegan Options* (P2, P5), *Strong Beer* (P3)).

Refining Lenses

While participants reported that most keywords used were based on prior knowledge (i.e., included when the Lenses were created), all five participants also reported learning to refine their Lenses throughout the process. For awareness, that the shaded cells of the treemaps helped them quickly noticed some keywords were too uncommon, and that an important concept of interest was missing from the search results (P1, P2, P5). For refining, more participants mentioned discovering, or replacing existing keywords from the suggestions (P1, P2, P3, P5) than from the reviews (P1, P2), which is consistent with the behavior logging data (Figure 6). Alternatively, one also mentioned noticing and removing ambiguous keywords when using the mention filtering features (P4).

General vs Specific

Participants created both general and more specific Search Lenses. P4 specifically mentioned that it was useful being able to search for different genre (i.e., American, Mexican, or Indian restaurants) and very specific dishes (i.e., cheese steak sandwich made with chicken) at the same time, and still being able to see how each results match with different things. Citing that "more specific things are hard to search for on Yelp." Alternatively, P3 presented an interesting use case for deeper exploration of a specific genre, by first creating an more general Indian Food lens, and then creating multiple more specific Lenses describing specific dishes from different regions of India, generating an overview of different styles of Indian restaurants in the city. This suggests that some users may want to create higher level groups of Lenses

Usefulness and Other Scenarios

We also asked participants if they actually found useful information or interesting restaurant from using SearchLens, and also asked them to imagine other scenarios or domains that SearchLens would be useful for. Three participants reported that they saved some of the restaurants that they found using SearchLens, and intent to visit those restaurant in the near future (P1, P3, P4). P1 in particular went to one of the restaurants the was discovered using SearchLens and was happy about the discovery, and P3 used SearchLens to complete a previous task, saying "I wanted to try deep dish pizza for some time since I moved to US. Finally found one near the city. Kudos!" When asked about what future scenario would SearchLens be useful for them many cited they have multiple interests and criteria. P2 particularly pointed to scenarios where he needed to "find a place for many people that may want different things", and mentioned that his family will be visiting soon for his graduation. Other participants also pointed to scenarios for searching in other domains, such as shopping (P2, P3), trip planning (P2, P5), house hunting (P2), and job hunting (P4).

LIMITATIONS AND FUTURE WORK

One limitation of the current implementation of SearchLens is its lack of ability to filter restaurants using their metadata, such as geographic location. We intentionally did not expose these information to our participants so we can focus our studies on allowing them to build personalized Search Lenses. However, practical systems would likely combine both paradigms to maximize efficiency, and the interactions between the two paradigms would require further studies.

Another obvious limitation of SearchLens it that it required more user effort upfront in order to receive the benefits provided by the system, such as reuse, explanation, and exploration. On a 7-point Likert scale, most participants from our lab study responded favorably to this trade-off with 64% agreed or strongly agreed that SearchLens is an improvement to the traditional search interfaces, and another 21% somewhat agreed with the statement, however, the long-term effect remained to be seen. One way to extend SearchLens is to combine machine learning and information retrieval approaches to reduce the effort of building Lenses, such as building interest profiles automatically, or using collaborative filtering and query expansion for expanding or inferring Search Lenses automatically [2, 40, 53], or word-sense disambiguation techniques for resolving ambiguous keywords [55].

Alternatively, we could also ways to allow users to share their Search Lenses or reuse Lenses that were built by previous users through explicit or implicit collaborations. For example, one participant mentioned "It would be nice if I can see what Search Lenses a local person would use if I'm traveling, because I always try to ask the locals about where I should eat." Allowing access to Lenses created by previous users or expert users could potentially enable expertise transfer and accumulation through continuing refinement of a set of Search Lenses. For example, locals and past travelers could iteratively curate a set of Search Lenses that leads to a interactively and explorable list of local specialties for future travelers.

Many other interesting future directions present itself. A promising direction is to explore deeper the idea of user-generated interest profiles and the different ways they could dynamically influence the different interfaces accessible to the users or interacting with users in more proactive ways. Since we asked the field study participants to use SearchLens for their own tasks, most participants searched for restaurants in the city they lived in. Some participants that conducted more targeted search tasks (P2, P3, P5) mentioned that they were already familiar with most of the options in the city that fits their goals, but would still occasionally search online to see if there were new restaurants that match their interests (P2, P5). As users continue to use SearchLens, the system will accumulate more understanding of what the users is interested in, and can potentially detect and notify the users of new information that might be of interests with high accuracy [54]. Alternatively, existing users may use their repository of Lenses to explore or curate the restaurants in an unfamiliar city. More fundamentally, having access to interactive information interfaces that were based on transparent and user-controlled interest profiles can potentially empower users to be more aware and to regain control of their online information diet. For example being able to control what to read from your social media news feed, while at the same time, being more aware of how the information was selected and hidden.

CONCLUSION

In this paper we introduced SearchLens, a novel search interface for specifying and maintaining users' multifarious and idiosyncratic interests. This in turn allowed SearchLens to shape an interactive interface for sensemaking during exploratory search by presenting new information in ways that reflect the interests of the users and allowing them to perform deep exploratory and comparison efficiently. Across a lab and field study we observed that users find benefits in the SearchLens approach, including being able to transfer and reuse their Search Lenses across contexts, being able to interpret new information that reflects their own personal interests with transparency, and working at multiple levels of specificity and hierarchy. We believe SearchLens represents a first step towards a transparent and user-centered approach to addressing subjective and fragmented nature of information today.

REFERENCES

1. Jae-wook Ahn and Peter Brusilovsky. 2009. Adaptive visualization of search results: Bringing user models to visual analytics. *Information Visualization* 8, 3 (2009), 167–179.

2. Jae-wook Ahn, Peter Brusilovsky, Jonathan Grady, Daqing He, and Sue Yeon Syn. 2007. Open user profiles for adaptive news systems: help or harm?. In *Proceedings of the 16th international conference on World Wide Web*. ACM, 11–20.

3. Steven Bird and Edward Loper. 2004. NLTK: the natural language toolkit. In *Proceedings of the ACL 2004 on Interactive poster and demonstration sessions*. Association for Computational Linguistics, 31.

4. Horatiu Bota, Ke Zhou, and Joemon M Jose. 2016. Playing your cards right: The effect of entity cards on search behaviour and workload. In *Proceedings of the 2016 ACM on Conference on Human Information Interaction and Retrieval*. ACM, 131–140.

5. Christine Susan Bruce. 1999. Workplace experiences of information literacy. *International journal of information management* 19, 1 (1999), 33–47.

6. Chris Burges, Tal Shaked, Erin Renshaw, Ari Lazier, Matt Deeds, Nicole Hamilton, and Greg Hullender. 2005. Learning to rank using gradient descent. In *Proceedings of the 22nd international conference on Machine learning*. ACM, 89–96.

7. Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. 2007. Learning to rank: from pairwise approach to listwise approach. In *Proceedings of the 24th international conference on Machine learning*. ACM, 129–136.

8. Joseph Chee Chang, Aniket Kittur, and Nathan Hahn. 2016. Alloy: Clustering with crowds and computation. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 3180–3191.

9. Liren Chen and Katia Sycara. 1998. WebMate: A personal agent for browsing and searching. In *Proceedings of the second international conference on Autonomous agents*. ACM, 132–139.

10. Lydia B Chilton, Greg Little, Darren Edge, Daniel S Weld, and James A Landay. 2013. Cascade: Crowdsourcing taxonomy creation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1999–2008.

11. Jason Chuang, Daniel Ramage, Christopher Manning, and Jeffrey Heer. 2012. Interpretation and trust: Designing model-driven visualizations for text analysis. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 443–452.

12. Douglass R Cutting, David R Karger, Jan O Pedersen, and John W Tukey. 2017. Scatter/gather: A cluster-based approach to browsing large document collections. In *ACM SIGIR Forum*, Vol. 51. ACM, 148–159.

13. Bart De Langhe, Philip M Fernbach, and Donald R Lichtenstein. 2015. Navigating by the stars: Investigating the actual and perceived validity of online user ratings. *Journal of Consumer Research* 42, 6 (2015), 817–833.

14. Cecilia di Sciascio, Peter Brusilovsky, and Eduardo Veas. 2018. A Study on User-Controllable Social Exploratory Search. In *23rd International Conference on Intelligent User Interfaces*. ACM, 353–364.

15. Cecilia di Sciascio, Vedran Sabol, and Eduardo E Veas. 2016. Rank as you go: User-driven exploration of search results. In *Proceedings of the 21st International Conference on Intelligent User Interfaces*. ACM, 118–129.

16. G. W. Furnas. 1986. Generalized Fisheye Views. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '86)*. ACM, New York, NY, USA, 16–23. DOI: **http://dx.doi.org/10.1145/22627.22342**

17. Nathan Hahn, Joseph Chang, Ji Eun Kim, and Aniket Kittur. 2016. The Knowledge Accelerator: Big picture thinking in small pieces. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 2258–2270.

18. Marti Hearst. 2006a. Design recommendations for hierarchical faceted search interfaces. In *ACM SIGIR workshop on faceted search*. Seattle, WA, 1–5.

19. Marti Hearst. 2009. *Search user interfaces*. Cambridge University Press.

20. Marti Hearst, Ame Elliott, Jennifer English, Rashmi Sinha, Kirsten Swearingen, and Ka-Ping Yee. 2002. Finding the flow in web site search. *Commun. ACM* 45, 9 (2002), 42–49.

21. Marti A Hearst. 2006b. Clustering versus faceted categories for information exploration. *Commun. ACM* 49, 4 (2006), 59–61.

22. Marti A Hearst and Jan O Pedersen. 1996a. Reexamining the cluster hypothesis: scatter/gather on retrieval results. In *Proceedings of the 19th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 76–84.

23. Marti A Hearst and Jan O Pedersen. 1996b. Visualizing information retrieval results: a demonstration of the TileBar interface. In *Conference Companion on Human Factors in Computing Systems*. ACM, 394–395.

24. Orland Hoeber and Xue Dong Yang. 2006. A comparative user study of web search interfaces: HotMap, Concept Highlighter, and Google. In *Web Intelligence, 2006. WI 2006. IEEE/WIC/ACM International Conference on*. IEEE, 866–874.

25. Yelp Inc. 2016. The Yelp Dataset Challenge: Discover what insights lie hidden in our data. https://www.yelp.com/dataset/challenge. (2016). Accessed: 2017-09-10.

26. Bryan Jurish and Kay-Michael Würzner. 2013. Word and Sentence Tokenization with Hidden Markov Models. *JLCL* 28, 2 (2013), 61–83.

27. Khalil Klouche, Tuukka Ruotsalo, Diogo Cabral, Salvatore Andolina, Andrea Bellucci, and Giulio Jacucci. 2015. Designing for exploratory search on touch devices. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 4189–4198.

28. Weize Kong and James Allan. 2014. Extending faceted search to the general web. In *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management*. ACM, 839–848.

29. Gary Marchionini. 2006a. Exploratory search: from finding to understanding. *Commun. ACM* 49, 4 (2006), 41–46.

30. Gary Marchionini. 2006b. Exploratory search: from finding to understanding. *Commun. ACM* 49, 4 (2006), 41–46.

31. Gary J Marchionini, Gary Geisler, and Ben Brunk. 2000. Agileviews. In *Proceedings of the ASIST Annual Meeting*, Vol. 37. 271–280.

32. Julian McAuley and Jure Leskovec. 2013. Hidden factors and hidden topics: understanding rating dimensions with review text. In *Proceedings of the 7th ACM conference on Recommender systems*. ACM, 165–172.

33. Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781* (2013).

34. Dan Morris, Meredith Ringel Morris, and Gina Venolia. 2008. SearchBar: a search-centric web history for task resumption and information re-finding. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1207–1216.

35. Emily S Patterson, Emilie M Roth, and David D Woods. 2001. Predicting vulnerabilities in computer-supported inferential analysis under data overload. *Cognition, Technology & Work* 3, 4 (2001), 224–237.

36. Jaakko Peltonen, Kseniia Belorustceva, and Tuukka Ruotsalo. 2017a. Topic-Relevance Map: Visualization for Improving Search Result Comprehension. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces*. ACM, 611–622.

37. Jaakko Peltonen, Jonathan Strahl, and Patrik Floréen. 2017b. Negative Relevance Feedback for Exploratory Search with Visual Interactive Intent Modeling. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces*. ACM, 149–159.

38. Radim Řehůřek and Petr Sojka. 2010. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*. ELRA, Valletta, Malta, 45–50. http://is.muni.cz/publication/884893/en.

39. Stephen Robertson, Hugo Zaragoza, and others. 2009. The probabilistic relevance framework: BM25 and beyond. *Foundations and Trends® in Information Retrieval* 3, 4 (2009), 333–389.

40. Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on World Wide Web*. ACM, 285–295.

41. Xuehua Shen, Bin Tan, and ChengXiang Zhai. 2005. Implicit user modeling for personalized search. In *Proceedings of the 14th ACM international conference on Information and knowledge management*. ACM, 824–831.

42. Ben Shneiderman and Martin Wattenberg. 2001. Ordered treemap layouts. In *Information Visualization, 2001. INFOVIS 2001. IEEE Symposium on*. IEEE, 73–78.

43. Mirco Speretta and Susan Gauch. 2005. Personalized search based on user search histories. In *Web Intelligence, 2005. Proceedings. The 2005 IEEE/WIC/ACM International Conference on*. IEEE, 622–628.

44. Jaime Teevan, Kevyn Collins-Thompson, Ryen W White, Susan T Dumais, and Yubin Kim. 2013. Slow search: Information retrieval without time constraints. In *Proceedings of the Symposium on Human-Computer Interaction and Information Retrieval*. ACM, 1.

45. Jaime Teevan, Susan T Dumais, and Zachary Gutt. 2008. Challenges for supporting faceted search in large, heterogeneous corpora like the web. *Proceedings of HCIR* 2008 (2008), 87.

46. Simon Tretter, Gene Golovchinsky, and Pernilla Qvarfordt. 2013. SearchPanel: A Browser Extension for Managing Search Activity.. In *EuroHCIR*. 51–54.

47. Frank Van Ham and Adam Perer. 2009. âĂIJSearch, show context, expand on demandâĂİ: supporting large graph exploration with degree-of-interest. *IEEE Transactions on Visualization and Computer Graphics* 15, 6 (2009).

48. Cornelis J Van Rijsbergen, Stephen Edward Robertson, and Martin F Porter. 1980. *New models in probabilistic information retrieval*. British Library Research and Development Department London.

49. Ryen W White, Bill Kules, Steven M Drucker, and others. 2006. Supporting exploratory search, introduction, special issue, communications of the ACM. *Commun. ACM* 49, 4 (2006), 36–39.

50. Ryen W White and Resa A Roth. 2009. Exploratory search: Beyond the query-response paradigm. *Synthesis lectures on information concepts, retrieval, and services* 1, 1 (2009), 1–98.

51. Max Wilson, Alistair Russell, Daniel A Smith, and others. 2006. mSpace: improving information access to multimedia domains with multimodal exploratory search. *Commun. ACM* 49, 4 (2006), 47–49.

52. Ho Chung Wu, Robert Wing Pong Luk, Kam Fai Wong, and Kui Lam Kwok. 2008. Interpreting tf-idf term weights as making relevance decisions. *ACM Transactions on Information Systems (TOIS)* 26, 3 (2008), 13.

53. Jinxi Xu and W Bruce Croft. 1996. Query expansion using local and global document analysis. In *Proceedings of the 19th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 4–11.

54. Beverly Yang and Glen Jeh. 2006. Retroactive answering of search queries. In *Proceedings of the 15th international conference on World Wide Web*. ACM, 457–466.

55. David Yarowsky. 1995. Unsupervised word sense disambiguation rivaling supervised methods. In *Proceedings of the 33rd annual meeting on Association for Computational Linguistics*. Association for Computational Linguistics, 189–196.

56. Ka-Ping Yee, Kirsten Swearingen, Kevin Li, and Marti Hearst. 2003. Faceted metadata for image search and browsing. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM, 401–408.

57. Xing Yi, Hema Raghavan, and Chris Leggetter. 2009. Discovering users' specific geo intention in web search. In *Proceedings of the 18th international conference on World wide web*. ACM, 481–490.

58. Oren Zamir and Oren Etzioni. 1999. Grouper: a dynamic clustering interface to Web search results. *Computer Networks* 31, 11 (1999), 1361–1374.

59. Hua-Jun Zeng, Qi-Cai He, Zheng Chen, Wei-Ying Ma, and Jinwen Ma. 2004. Learning to cluster web search results. In *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 210–217.