Exploring Knowledge Graphs for Exploratory Search

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ABSTRACT

In order to provide the user with more support in performing exploratory activities, recent research has been focused on identifying the types of tasks users perform, and understanding the nature of these tasks. However, most of the proposed models focus on either traditional document retrieval or the use of linked data for finding relevant information. We believe neither of these two types of information resources can offer sufficient support for complex search tasks on their own. We propose that a hybrid approach that combines the coherent content of text with the organized structure of graphs should be taken to better support information finding and sense making.

Currently, there is limited insight into the types of information seeking activities performed when a knowledge graph is combined with document retrieval to support exploratory search. This paper describes a general framework that provides the first step towards examining users' exploratory search behaviour when interacting with knowledge graphs and their corresponding documents. We conducted a user study that suggests searchers perform different information seeking activities for a complex search task compared with a simple search task. These findings provide insights that can be used to inform the design of a new search framework, which enables more effective information finding and analysis.

Categories and Subject Descriptors: H.3.3 Information Search and Retrieval

General Terms: Experimentation, Human Factors

Keywords

Exploratory Search, Knowledge Graph, Information Discovery, Complex Search Tasks, Information Extraction

1. INTRODUCTION

There is a growing realization in the IR community that the current paradigm of retrieving a ranked list of documents is inadequate in solving complex information needs [2]. Examples of exploratory search tasks include: learning about a new domain (e.g., "astronomy 101") or finding hidden connections between two events or concepts (e.g., "impacts of WWI on economy"). It can be argued that current search engines are generally sufficient when the need is well-defined in the searcher's mind. However, when information is sought to address broad curiosities, for learning and other complex mental activities, retrieval is necessary but not sufficient [18].

In order to bridge the gap between what search engines currently offer with the support needed for more complex search activities, different extensions have been proposed (Section 2). These solutions focus on retrieving information as opposed to documents to address the user's information need. A dominant technique towards automatic retrieval of information is Information Extraction. IE aims at (semi)automatic collection of triples from textual corpora of given domain (e.g., <Napoleon, invaded, Russia> is extracted from "Napoleon invaded Russia."). These triples indicate the relationship between two entities. The outcome can be represented as a Knowledge Graph, that is a network of some domain knowledge represented by labelled nodes and labelled links between them. When these maps are available, they can provide a useful structure for understanding new documents, and the new documents can provide useful context to the knowledge models. [17]

Knowledge Graphs (also referred to as Concept Maps or repositories of Linked Data) have been widely used to promote meaningful learning as well as browsing knowledge and navigation. As observed by Carnot et al. [4] the structure of Concept Maps that are carefully constructed may assist learners in finding information more quickly.

The problem of automatically generating knowledge graphs and databases of linked data from the web has been well studied. However, there is limited insight into how these graphs can be utilized by searchers to aid with locating relevant information and making sense of them. Indeed, better integration of structured and unstructured information to seamlessly meet a user's information needs is a promising, but underdeveloped area of exploration [2].

There has been some efforts (e.g., [7]) for utilizing Linked Data to enable user-oriented exploratory search systems. However, we believe these graphs, when applied in isolation, are not sufficient for an effective information finding and sense making, particularly for more complex search tasks. That is, a hybrid approach that combines the coherent content of text with the organized structure of graphs should be taken to better support complex tasks. Therefore, we aim

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at exploring a new search framework (Section 3) and observe how the provided Knowledge Graphs and their mappings to corresponding documents will be utilized by different searchers to complete both simple and exploratory search tasks. In this paper we focus on the interplay between each document and its corresponding graph to gain insight into how this coupling can support finding and analyzing information. Investigating how people make sense of information by utilizing this new framework can help us design an interaction model that facilitates comprehension, analysis and insight.

The main goal of this paper is to develop a better understanding of how users search for relevant information using a new design based on Knowledge Graphs that are derived from text. We conducted a user study which is exploratory and observational in nature and provides the opportunity to document and analyze interesting interaction patterns (Section 4). We also identified frequent interaction patterns performed during an information seeking session (Section 4.4). Further investigation of the similarities and differences observed between simple and complex search tasks can be utilized to understand the reasons behind the lack of support from the current search engines for complex search tasks. Finally, we examined the obstacles and challenges faced by the participants during their exploration and propose future directions that can lead to better understanding of the requirements of a new search model that supports information seeking activities (Section 5).

2. RELATED WORK

The recognition that there is more to search than basic Information Retrieval has led to many extensions and alternatives to the keyword search paradigm. These extensions aimed at supporting users by providing "information" and not documents and also involving users more actively in the search process. Information Extraction (IE), Question Answering (QA) and Summarization all generate a focused response to a user's information need in the form of entities, sentences or text snippets. Summarization systems generate shorter versions of documents that contain the most important parts presented in a concise and coherent way. When compared with QA, these summaries provide more context and coherent text and thus offer better support for search tasks that require learning and understanding in order to generate answers to more broad questions. These systems leverage IE to improve their effectiveness by finding key entities and the relationships between them to generate candidate answers.

One main limitation of traditional QA and Summarizarion systems is that they exclude users from the process of finding answers. However, there is a growing realization that search in the real world is inherently interactive and the users thus have to be at the heart of the search process. Since the SWIRL[2] workshop identified a huge gap between the study of users and the study of IR algorithms, there has been widespread acknowledgement that the understanding of users is essential for improving IR systems. Currently, researchers have developed numerous theoretical models of how people go about doing search tasks. The vast majority of these models represent information seeking as an interactive, evolving and learning behaviour. Next, we review the studies that aimed at understanding users' information seeking behaviour. The final subsection focuses on the related work that utilized graphs for search.

2.1 Interactive User Modeling

The primary observation is that supporting a user during his interaction with the information space requires a more advanced design than the classic ranked list of documents provided by current search engines. Numerous studies have been made of people engaged in the search process, and the results can help guide the design of search interfaces. Hearst [9] provides a thorough review of information-seeking user interfaces and their evaluation.

There is a body of work that focuses on observing users' behaviour and identifying the challenges searchers face during their search session, common information seeking activities among them and gaining insight into how to support these activities. A taxonomy of search result visualization techniques is proposed by Wilson et al. [20]. They identify two main classes of approaches: (1) Using annotations or classifications to organize results into groups (e.g. faceted search which uses a hierarchy structure to enable users to browse information by choosing from a pre-determined set of categories). (2) Result organization which visualizes a result set to help users find the specific results they are looking for. Our design can fit into the latter as it provides alternative or complementary representations of results.

Diriye et al. [8] employed qualitative and quantitative data gathering methods to investigate the interplay between the interface features, the user and the search tasks. The results suggest that "searching is more effective when supported by an interface that is tailored towards the search activities of the task". Alhenshiri et al. [1] present the results of a study to explore the difficulties users experience during Web information gathering tasks. They identified a set of activities performed by searchers, their frequencies and the reasons behind the most and least frequent activities. Our work is more similar to [3] that proposes a subjunctive exploratory search interface to support media studies research. They use the statistics of maximal interaction patterns to compare their design with a baseline.

2.2 Utilizing Graphs for Search

The models most similar to our work are those which make use of entities and the relations between them to support search. Dimitrova et al. [7] designed a semantic data browser based on external Linked Data resources to support exploratory tasks. Yogev et al. [21] describe an extended faceted search solution that allows to index, search and browse rich Entity-Relationship (ER) data. The output of the search system is a ranked list of entities that are distributed over different facets. These facets can be used by the user to focus the search on a specific entity type or to explore another direction by navigating to another related entity in the ER graph. With the introduction of the so-called "Knowledge Graph", Google has made a significant paradigm shift towards "things, not strings" [16]. Entities covered by their graph include landmarks, celebrities, buildings and more. The "Knowledge Graph" enhances Google's search in three main ways: query disambiguation, providing a summary of related facts to the user's query, and exploratory search suggestions (based on what other users explored next).

The main distinctions between our work and these related work are as follows: (1) Approaches based on faceted search and linked data are mainly limited to named entities and basic relations (simple predicates or hierarchical) between them. However, we extract a broader set of entities and concepts and we identify semantic relations based on dependencies between them. These relations are not limited to a predefined set of predicates and provide context for understanding the connections between entities. (2) We generate graphs automatically using the documents collection retrieved for the user's query. Our knowledge graphs thus are derived from the same information space that the searcher is interested to explore. This is beneficial because first, the graphs contain the information related to the user's information need and second, it provides an interplay between the text and the graph which can support "comprehension" through discourse relations [11] which is not preserved in linked data.

3. ENABLING A NEW SEARCH PARADIGM

We propose a new search framework that takes advantage of knowledge graphs to mitigate the problem of information overload by providing a semantic organization of the information space. We also argue that knowledge graphs cannot enable an effective framework for supporting complex search tasks if applied in isolation. In the following subsections we provide an outline of our general framework and we describe how this new framework can be employed to support searchers during information seeking activities.

3.1 The Proposed Framework

With the current document retrieval paradigm, searchers need to make sense of the long lists of ranked results provided by search engines. In fact, the lack of effective overviews challenges users who seek to understand these results. We envision the following qualities that Knowledge Graphs can offer to minimize this challenge:
(1) They provide a fine grained representation of articles and enable searchers to retrieve relevant pieces of information (rather than documents) for their query; (2) They visualize how different entities and concepts are connected in a domain; (3) They provide an overview (i.e., the big picture) of the information space related to the user's topic of interest; (4) They demonstrate the salient entities related to a topic.

Although Knowledge Graphs could be powerful tools to support navigation and learning for exploratory search, they cannot replace the document search and retrieval for searchers. Each document represents facts (described in sentences) in a particular order, which is coherent and meaningful. This ordering helps with identifying the connections between different facts, which are not preserved in the graph representation. When we extract information from text and restructure it as a knowledge graph to visualize semantic relations between concepts, we lose discourse relations (i.e., information on how two segments of discourse are logically connected to one another) which are crucial for comprehension and inference from a text.

Hence, there should be an interconnection between the documents and their corresponding graphs in order to overcome the shortcomings of each search mode in isolation. We hypothesise that a hybrid approach, which combines the structure of graphs and the coherent context of text, should be used to better aid information seeking activities. We believe such a framework can engage users more fully in the search process. As the searcher explores, each graph provides a graphical summary for each document. They could be considered as advanced tables of content that point to the more interesting parts of a possibly long article and help with getting the big picture at a glance. In order to design a framework which supports a seamless interaction between documents and their corresponding graphs, we identified different types of edges and connections:

`Connecting each document to its corresponding graph`: In each document, only the sentences containing an extracted triple (entity1, relation, entity2) are linked to their corresponding part of the graph and vice versa. Therefore, when the user skims a document these sentences are highlighted and linked to the graph. So the user can switch to browsing the graph to explore a particular entity (most commonly, a named entity), the related entities and how it connects to the other parts of the article.

`Connecting the graphs:` Documents fetched for the user's query may discuss different aspects of the same topic or provide different perspectives. Therefore, the corresponding graphs are not independent of one another. The same domain terms and entities appear in these graphs and they have to either be represented as a single node in the aggregated graph, or mapped through a set of inter-graph links to preserve these connections. These links indicate how different parts of different documents are related to each other. These links can also be helpful when a user is analyzing the documents in a sequence. The user can start with the first document and take advantage of the corresponding graph as a structured summary, which guides him through understanding this document. Then he moves on to a new document and extends the current graph to represent both documents. This way, the user can keep track of the facts "he already knows" and the ones which are covered in the new document. He can also identify the common facts covered by both documents. He can build on this graph by incrementally adding a document to his collection.

3.1.1 A Sample Search Scenario

Consider the following scenario: while reading an article about "Napoleon's invasion of Russia", the user comes across the entity "Treaty of Tilsit". By traversing to this node in the graph, he analyzes a set of related facts, which includes:
- Which countries first signed this treaty? Which countries followed later?
- When was this initially signed and why?
- What were the terms of this agreement?

The user can then go back to the article and resume reading (while he now has a better understanding of this topic) or navigate through the graph and explore a different part of the article based on where the graph takes him. The nodes and facts in the graphs are also linked to their corresponding text in the documents. Therefore, the readers can clarify the interesting facts they observe in the graph. They can also navigate to the sections of the texts that are more appealing to them without needing to read through an article in a linear fashion.

Also, consider a scenario in which a searcher is trying to find out the "impacts of WWI on economy". The following two facts are extracted from an article: "many of America's men were serving overseas in the war" and "companies allowed women to work in previously male only jobs". While these two facts are located in close proximity, they are positioned at two disconnected parts of the graph. By traversing the graph only, the searcher cannot discover any connection between these two seemingly unrelated facts. Hence, there should be an interplay between the graph and the document in an effective search paradigm.

3.2 Evaluating the New Framework

In the previous section we hypothesized that coupling a set of retrieved documents with their corresponding knowledge graph, which represents the salient entities and underlying relations in a domain of interest, can provide a more effective search experience for the user, especially when investigating more complex search tasks. In this paper we focus on the interplay between each document and its corresponding graph to gain insight into how this coupling can support information seeking. Therefore, we do not investigate the effects of connecting different documents through knowledge graphs and the incremental extension of a graph in this work. We formulated a list of research questions to investigate our hypothesis:

1. How is this framework used for finding relevant information?
   (a) Which features of the graphs are used more frequently by the participants?
   (b) Is there a difference in this usage across two different types of search tasks?
   (c) What is the most common starting point for the searchers? The graph side or the document side?
   (d) Is the starting point affected by the complexity of the search task?
   (e) What are the common activities across the searchers who start their exploration from the same side?
2. How does this framework provide support for locating relevant information?
   (a) What are the most common interaction patterns that correspond to finding relevant information?
   (b) Are these patterns affected by the complexity of the search tasks?
   (c) To what extent do the graphs contribute to locating relevant information?
   (d) Do nodes and edges in the graphs provide different types of support for finding relevant information?
   (e) Does the complexity of the search task affect the effectiveness of the graphs (and in turn nodes and edges) in locating relevant information?

In order to find answers to these questions we designed a user study in three steps: (1) Extracting Knowledge Graphs from Text, (2) Mapping Graphs and Documents and (3) Employing search tasks with different levels of complexity. The following subsections discuss these steps.

3.2.1 Generating Knowledge Graphs and Mappings

We designed an Open Information Extraction system that processes a text collection and generates (entity-relation-entity) triples [15]. This module is implemented in four phases. During the first phase we create the input corpus by collecting retrieved documents based on a given query. Next, we extract entities from text using state-of-the-art entity taggers. We then select the sentences that contain at least two entities in them and parse them using Stanford Dependency Parser. For each sentence, we extract meaningful relations between the entities by finding the shortest path in the corresponding parse tree. We constructed a set of patterns based on dependency triples that lead to semantically meaningful relations. In the final phase we generate labels for the extracted relations and rank them based on relevance to the query and the informativeness of the extraction. Since we are investigating the effectiveness of employing knowledge graphs to provide support for exploratory search tasks, we assure the generated graphs are accurate. Therefore, some minor errors that were caused by ER extraction and label generation modules were revised by an export.

For each document in our result list, we created a corresponding knowledge graph and mapped all entities and relations to their corresponding parts of text. All nodes and edges in the graphs as well as their mentions in text are clickable. These mappings provide an interplay between text and graphs and are made possible because our graphs are derived from the same set of documents. This is one key advantage of this framework as compared with systems that employ external resources such as DBPedia to aid information seeking.

3.2.2 Simple and Complex Search Tasks

People's day-to-day search activities can vary greatly in their motivations, objectives, and outcomes. These search activities can be broadly classified into two groups: "Simple" and "Complex". Simple search tasks are similar to "known-item" search tasks and usually involve looking up some discrete, well-structured information object: for example numbers, names and facts [12]. Complex search tasks, on the other hand, are seen to be more exploratory and involve investigating, learning and synthesis of information [19]. There are two activities which mediate the exploration process: information foraging theory [13] describes how searchers collect relevant pieces of information; sense making [6] describes the process through which people assimilate new knowledge into their existing understanding.

What really differentiates simple and exploratory search tasks is the clarity of the information need, the familiarity the searcher has with the task domain, and the analysis and understanding involved [18]. These factors invariably affect how searchers interact with information, and how they search and browse. In this paper we investigate (1) how the complexity level of a given search task affect the searchers' information seeking behaviour and (2) how well the designed framework supports these two search tasks.

4. DESIGNING THE EXPERIMENTS

We designed a within-subject study in which each participant needed to complete two search tasks using the same interface. We conducted our experiments within the framework provided by the TREC 2007 Question Answering track. We followed the guidelines from QA and CiQA tracks [5] to design a "simple" task and a more complex and open ended search scenario ("complex" task).

For the "complex" task, the searchers were required to find as many relevant sentences as possible within a 10 minute time limit. They were given the following task description: "What is the position of [California] with respect to [stem cell research]? – "The analyst wishes to know if Californians generally support stem cell research and what actions they are taking to accomplish the research." For the "simple" task, the searchers were given the topic "Lyme disease" and a short list of questions (e.g., "what organism causes Lyme disease?") and they were required to find answers to these questions by providing the corresponding sentence and document number from the given list based on a fixed query.

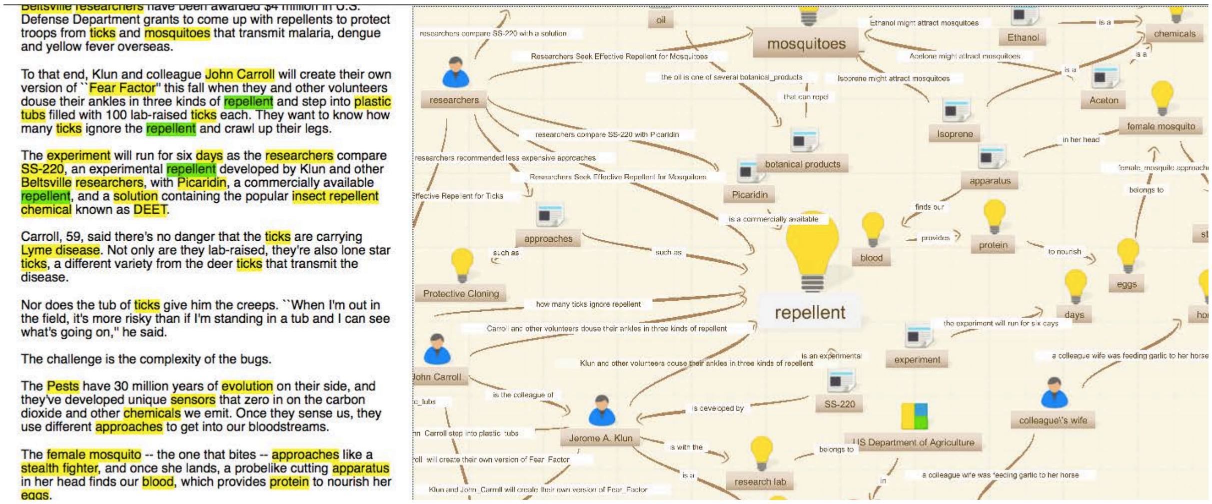

Figure 1: A sample coupling of a document and its corresponding knowledge graph in the designed interface

4.1 Construction of Results Lists

We created a list of 10 documents for each search task. In order to investigate the contribution of the graphs in identifying "relevant" documents we used different procedures to construct "artificial" result lists. For the "complex" task we were interested to see how many "nuggets" (i.e., a piece of text containing relevant information) would be found by the searchers. Therefore, we retrieved all documents related to the given topic and ordered them based on the number of nuggets they contained (as identified by NIST assessors). We then created our list by selecting the top 10 documents and shuffling them so they are not placed in that order.

For the "simple" task we constructed a list by adding a mix of relevant documents that contained nuggets (answers to the factoid / list questions) and the ones that did not. We refer to them as "good" and "bad" documents respectively. We distributed the "good" documents evenly throughout the list. This will assure the participants will have to explore the entire list to be able to find all the answers. Hence, we are able to investigate if the graphs can be used to identify "good" documents faster, while they can also be used for locating "relevant" sentences inside each document.

4.2 Experiment Setup

We recruited 20 (6 female) participants from a very diverse pool for this study, all of whom use the Internet on a regular basis to search for information. They ranged from students to senior engineers and faculty members. Their study area covered many major areas of Computer Science, Architecture, Chemistry, Biology and Physics.

The participants were given 10 minutes to complete each task. They also needed to complete two post-task questionnaires that would assess their familiarity with the topic and the experience they just had. We used questionnaires provided by TREC-9 Interactive Searching track[1] and modified them to fit into our experiment design. Two of the participants did not finish the experiment so we excluded their data from our analysis. In order to control for order effects, we rotated the order in which the tasks were assigned to the participants. That is, participants were randomly divided into two groups of equal size and one group started with the "simple" task while the other group started with the "complex" task. By the end of both tasks, the participants were asked to share their feedback about the effectiveness of the search interface and knowledge graphs for search by responding to a more detailed questionnaire. Participants were also monitored during the search sessions and the computer screen was captured for a later review.

[1] www-nlpir.nist.gov/projects/t9i/qforms.html

4.3 Search Interface

We utilized a search interface implemented by the InsightNG company based on our design for conducting the user study. This interface has two panes (Figure 1). The left pane resembles the Google Search Engine which provides a list of 10 documents along with their titles and text snippets. Clicking on each of these items would load the full document on the left and the corresponding graph on the right side. On the document side, all terms with corresponding nodes in the graph were highlighted in yellow while the parts of the text corresponding to an edge (i.e., relationship) were highlighted in grey. The user could explore the article by either browsing the graph or reading through the documents. We implemented mappings between corresponding elements of the text and the graph such that clicking on one would highlight the other. For example, clicking on a node in the graph will highlight all corresponding terms in the text in green. Besides, clicking on an "entity" or "relation" from the text would center and zoom on that element in the graph.

4.4 Results and Observations

While finding relevant information is the goal of all information seeking systems, we cannot successfully design an effective approach unless we learn about searcher's information seeking patterns. By testing the designed interface we were mainly interested to learn how people go about finding information. For example, will they navigate through the graphs to find an answer to their question? Or will they make use of the graphs to locate where to read in the text. By looking through the data collected by questionnaires and observing the participants using the designed search interface, we gained interesting insight into the common user behaviour during information foraging activities.

GCN	Clicking on a node in the graph
GCE	Clicking on an edge in the graph
DCN	Clicking on an entity mention in the document
DCE	Clicking on a relationship mention in the document
SfG	Starting from the Graph side
SfT	Starting from the Document side
B2G	Switching to the Graph side
B2T	Switching to the Document side
RM	reading the mention of an entity/relation in text
RF	exploring an entity in the graph by looking at related nodes and connection of this entity
DC	dragging the canvas around
DR	reading the document text
GR	reading the node/edges labels in the graph
CP	Copy-Paste an answer to the answer sheet
SD | SU	Scrolling down / up the text
B2R	going back to the SERP

Table 1: Actions and their notations

We defined a set of actions by observing the activities performed by different participants over the course of their interaction with the system. Table 2 lists the more prominent actions. For each participant 2 sequences of actions (one per search task) were generated by using the logs of screen videos and observing the users' interaction with the system during the experiment. For each search task we calculated the frequency of all subsequences of length 1 to 5. We call each of these subsequences an "interaction pattern" (or "pattern" in short). We filtered out the patterns with a frequency below 5. Since none of the patterns of length 5 passed this threshold we did not consider the patterns of length more than 4 in our analysis. The following subsections discuss frequent patterns observed during each search task and how participants exhibited different behaviour during four main activities: (1) switching between the graph and the text mode; (2) taking advantage of nodes and edges to locate relevant information and (3) getting started with the exploration; (4) in the end, we investigate the common patterns that led to locating an answer and compare them across two tasks. We examined the statistical significance of our observations using a paired t-test. Also, for all the tables Simple and Complex tasks are denoted by **SP** and **CX** respectively.

4.4.1 General Characteristics of Interaction Patterns in Simple and Complex Tasks

In this work, we are interested to identify the "interaction patterns" that are common in both search tasks and the ones that are more pertinent to one of the tasks. We hypothesise that identifying these similarities and differences can help us understand the characteristics of simple and complex search tasks and how this will affect searchers interaction behaviour.

Table 2 lists the top five frequent patterns of length 1 to 4. As can be seen in this table the pattern B2T→RM (i.e., switch from the graph to the text and read the mentions of the recently clicked node / edge) was the most frequent pattern of length 2 for both tasks. This pattern corresponds to making use of the graphs to highlight the areas in the text that user is interested to read. Also, we can see that patterns starting with a GCN (i.e., clicking on a node in the graph) are the next top two frequent patterns of length 2 for the simple task. These patterns correspond to clicking on a node in the graph and then either going back to text (GCN→B2T) or exploring the related entities and the connection to the current entity (GCN→RF).

Among the longer patterns we observe clicking on a node, switching back to the text and reading the mentions is the most frequent pattern of length 3 for the simple task. This pattern repeats followed by a CP (i.e., locating an answer) as the top frequent pattern of length 4 for this task. Interestingly, a similar pattern occurs for the Complex task with one distinction: while clicking on a node is the most likely pattern to end in locating an answer for the simple task (i.e., GCN→B2T→RM→CP), clicking on an edge is more effective for the Complex task (i.e., GCE→B2T→RM→CP). We will discuss these patterns in Section 4.4.5.

We also looked at the distribution of main activities between two tasks (Table 3). For each pattern we report its conditional probability followed by its frequency (accumulated over all 18 participants). We calculated the conditional probability of (A→ B) by applying Equation 1. For example, the action B2G was observed 123 times in total during the simple task and it was followed by the action DC in 27% of the cases (33 out of 123). Please note that the same equation is used for calculating the percentages in Tables 4 to 6. Also, in all these tables the frequency of patterns are reported in parentheses and the shaded rows indicate the frequency of the preceding action (i.e, A in A→ B).

$$P(B|A) = \frac{freq(A \rightarrow\ B)}{freq(A)} \quad (1)$$

These results indicate:
(1) *Switching between Graphs and Documents:* overall, switching back and forth between two sides was done similarly in both tasks ($\rho > 0.1$);
(2) *Click patterns: Nodes v.s. Edges:* In both tasks participants tended to click on nodes more than the edges. This trend was strongly significant for the simple task ($\rho < 0.001$)
(3) *Click patterns: Simple v.s. Complex:* on the other hand, the edges were used more frequently during the Complex task than the Simple task ($\rho < 0.1$);
(4) *Starting the exploration: Graphs v.s Text as a starting point:* finally, while participants started their search from the graph more than the text, it was a strongly significant trend for the simple task ($\rho < 0.001$). Also, starting from text was done significantly more for the Complex task than the simple task ($\rho < 0.05$).

4.4.2 Switching between Graphs and Documents

As we discussed in Section 3.1 Graphs and Documents both provide different types of support for users who are searching for information. We were interested to identify the main activities that led the participants switch from the text to the graph or vice versa. To this end, we analyzed the frequent patterns starting with a "B2G" (switching from text to graph) or a "B2T" (switching from graph to text).

As indicated in Table 4 (1) for both tasks clicking on a node (GCN) and dragging the canvas (DC) were the most frequent actions taken by the participants right after switching to the Graph side; (2) while learning about an entity (RF) was the third frequent action for the simple task, going back to the document again (B2T) came third for the

	Length of the Pattern							
	1		2		3		4	
	pattern	freq	pattern	freq	pattern	freq	pattern	freq
SP	GCN	190	$B2T \rightarrow RM$	93	$GCN \rightarrow B2T \rightarrow RM$	61	$GCN \rightarrow B2T \rightarrow RM \rightarrow CP$	20
	B2T	151	$GCN \rightarrow B2T$	70	$B2T \rightarrow RM \rightarrow CP$	34	$B2T \rightarrow RM \rightarrow CP \rightarrow B2G$	17
	B2G	123	$GCN \rightarrow RF$	52	$SFG \rightarrow GCN \rightarrow RF$	26	$DC \rightarrow GCN \rightarrow B2T \rightarrow RM$	14
	DC	117	$SFG \rightarrow GCN$	49	$RM \rightarrow CP \rightarrow B2G$	18	$GCN \rightarrow B2T \rightarrow RM \rightarrow B2G$	13
	RM	115	$RM \rightarrow CP$	42	$GCE \rightarrow B2T \rightarrow RM$	16	$GCN \rightarrow B2T \rightarrow RM \rightarrow B2R$	10
CX	B2T	135	$B2T \rightarrow RM$	76	$B2T \rightarrow RM \rightarrow CP$	42	$GCE \rightarrow B2T \rightarrow RM \rightarrow CP$	24
	CP	129	$RM \rightarrow CP$	65	$GCN \rightarrow B2T \rightarrow RM$	39	$B2T \rightarrow RM \rightarrow CP \rightarrow B2G$	17
	GCN	122	$GCN \rightarrow B2T$	48	$GCE \rightarrow B2T \rightarrow RM$	32	$GCN \rightarrow B2T \rightarrow RM \rightarrow CP$	16
	RM	110	$CP \rightarrow B2R$	38	$RM \rightarrow CP \rightarrow B2G$	18	$GCN \rightarrow B2T \rightarrow RM \rightarrow B2G$	10
	B2G	98	$GCE \rightarrow B2T$	37	$B2T \rightarrow RM \rightarrow B2G$	17	$SFG \rightarrow GCN \rightarrow B2T \rightarrow RM$	9

Table 2: Top 5 frequent "interaction patterns" of length 1 to 4

	Switch Sides		**Clicks**				**Starts**		
	B2G	B2T	GCN	GCE	DCN	DCE	SfT	SfG	Total
SP	8% (123)	10% (151)	12% (190)	2% (31)	3% (43)	0.3% (5)	2% (30)	5% (78)	1531
CX	7% (98)	10% (135)	9% (122)	3% (47)	3% (46)	1% (11)	3% (43)	4% (57)	1347

Table 3: Distribution of Actions between Tasks

	action	%	action	%
SP	$B2G \rightarrow DC$	27% (33)	$B2T \rightarrow RM$	62% (93)
	$B2G \rightarrow GCN$	27% (33)	$B2T \rightarrow DR$	8% (12)
	$B2G \rightarrow RF$	15% (19)	$B2T \rightarrow DCN$	6% (9)
	B2G	(123)	B2T	(151)
CX	$B2G \rightarrow DC$	29% (28)	$B2T \rightarrow RM$	56% (76)
	$B2G \rightarrow GCN$	23% (23)	$B2T \rightarrow DR$	10% (13)
	$B2G \rightarrow B2T$	13% (13)	$B2T \rightarrow DCN$	8% (11)
	$B2G \rightarrow RF$	8% (8)	$B2T \rightarrow CP$	6% (8)
	$B2G \rightarrow GCE$	7% (7)	$B2T \rightarrow SD$	7% (9)
	B2G	(98)	B2T	(135)

Table 4: Reasons for Switching to Graph / Text

	action	%	action	%
SP	$GCE \rightarrow B2T$	74% (23)	$GCN \rightarrow B2T$	37% (70)
	$GCE \rightarrow B2T \rightarrow RM$	52% (16)	$GCN \rightarrow RF$	27% (52)
			$GCN \rightarrow GCN$	8% (15)
			$GCN \rightarrow DC$	12% (22)
	GCE	(31)	GCN	(190)
CX	$GCE \rightarrow B2T$	79% (37)	$GCN \rightarrow B2T$	39% (48)
	$GCE \rightarrow B2T \rightarrow RM$	68% (32)	$GCN \rightarrow RF$	25% (31)
			$GCN \rightarrow GCN$	11% (14)
			$GCN \rightarrow DC$	7% (8)
	GCE	(47)	GCN	(122)

Table 5: The most likely actions after a Click

Complex task. This distinction is significant ($\rho < 0.01$). That could be an indicator of the fact that after switching to the graph the participant was not sure where to start from or where to go next. Therefore, they decided to go back to the text again; (3) one interesting observation is that the top three main activities after going back to the text were similar for both tasks, with similar likelihood. Furthermore, RM (i.e., "reading a mention") was by far the most dominant activity once the participants switched to the document side ($\rho < 0.001$). This corresponds to making use of nodes or edges in the graph to find out where to read in the text.

4.4.3 Click Patterns: Node v.s Edges

This user study revealed that different searchers take advantage of the provided graph in a variety of ways: while some participants found the edges more effective to locate relevant pieces of information, others made use of the mappings between nodes and text to find important terms more quickly in text. We used the click patterns to investigate if nodes and edges are used differently across two tasks. Overall, we observed similar patterns for clicking on nodes and edges for both tasks.

As can be seen in Table 5, most of the clicks are followed by reading a mention. This action is by far the dominant action performed after clicking on an edge ($\frac{16}{31}$ and $\frac{32}{47}$) and no other frequent pattern starting with a GCE is observed. However, reading the mentions of a node is not as dominant ($\rho > 0.1$) and it is followed closely by exploring an entity by reading its connections to other nodes (i.e., GCN->RF). The only noticeable difference observed between the two tasks is that reading the mentions of an edge was done more frequently for the Complex task ($\rho < 0.05$).

4.4.4 Starting the Exploration

We also identified the common activities performed by the group who start their exploration from the Graph side (SfG) as compared with the group who start from the Document side (SfT). Table 6 lists the most frequent patterns starting with a SfG and the ones starting with a SfT.

By analyzing these patterns, we observed that clicking on an entity was the very first action taken by participants regardless of their starting point (graph or text) and the task ($\rho < 0.001$). However, for the group who started their exploration from the graph side, clicking on an entity was by far the most dominant action (around 60% for both tasks). Whereas, for the group who started from the document side, the top two patterns (i.e., clicking on an entity in text (DCN) and reading the text (DR)) were not significant ($\rho > 0.1$).

In fact, "query nodes" was identified as the main starting point for exploring the graph. One should note that since the participants did not submit a query to the system, we refer to the main entities in the task description as "query

	action	%	action	%
SP	$SFG \rightarrow GCN$	63% (49)	$SFT \rightarrow DCN$	43% (13)
	$SFG \rightarrow DC$	9% (7)	$SFT \rightarrow DR$	27% (8)
	$SFG \rightarrow GCE$	4% (3)		
	SFG	(78)	SFT	(30)
CX	$SFG \rightarrow GCN$	60% (34)	$SFT \rightarrow DCN$	33% (14)
	$SFG \rightarrow GR$	14% (8)	$SFT \rightarrow DR$	26% (11)
	$SFG \rightarrow DC$	11% (6)	$SFT \rightarrow CP$	23% (10)
			$SFT \rightarrow DCE$	7% (3)
	SFG	(57)	SFT	(43)

Table 6: Starting from the Graph v.s. Starting from the Document

nodes". While for the complex task "California" and "Stem-cell*" nodes were clicked in 72% of the cases, "Lyme*" nodes were selected in 63% of the cases once participants started their search from the graph side.

Another observation for the group who started from the graph was that exploring the graph (corresponding to DC and GR activities) was done more frequently for the complex task (25% as compared with 9% for the simple task and the difference was significant ($\rho < 0.05$)).

4.4.5 Common Patterns for Finding Answers

The conducted user study clearly indicated that the current stage of the new interface provided different levels of support for different types of tasks. Out of 18 participants, 9 found the availability of a knowledge graph very useful for the simple task, while they preferred the text view for the Complex task. However, 4 found the graphs more useful for the complex task and 4 mentioned the graphs were useful for both tasks. One participant preferred the text for both tasks. As commented by most participants, the graphs were the most effective when the searchers were clear about what information they were looking for (e.g., an answer to a specific QA question). While, when the nature of task was complex (e.g., CiQA topics), they were not sure how to navigate in the graphs and would mostly go through the text to find relevant information (Table 7).

In this paper we assume the Rationality Principle [14] holds. That is, the searchers' behaviour is purposeful and hence they carry out a sequence of actions to achieve some goal. As mentioned, the participants interacted with our system in order to find a set of "answers" for two different tasks within a 10 minute time limit. These answers were evaluated by using NIST judgements provided by TREC. For the QA task, participants found 2.42 correct answers on average to the 5 factoid question. For the CiQA topic, there was a total of 2 vital and 13 okay nuggets present in the 10 listed documents, out of which the participants were able to retrieve 0.63 vital and 2.0 okay nuggets on average.

One of the most interesting outcomes of analyzing the interaction patterns was to identify the ones that led to locating an "answer". While for the simple task an answer is a known factoid (mostly an entity), for the Complex task an answer is a snippet of text that contains some evidence or support for a given statement. We created state diagrams that illustrate the patterns that led to locating an answer.

As depicted in Figures 2 and 3, blue states (circles) correspond to the Graph's contribution and green states (octagons) correspond to the Document's contribution in finding an answer. The state RM could belong to either of these two groups based on the preceding nodes in this state diagram. Links labels indicate the probability of transition from the source state to the destination state regardless of other states in this graph. This is the conditional probability calculated using Equation 1. Also, each state contains a weight that indicates the probability of getting to an answer by starting from this state. That is, traversing the state diagram starting from this node and ending at CP. Since for some states there are multiple paths leading to CP, we select the path with the maximum probability and record this path as the best candidate pattern for leading to an answer. We calculated these probabilities using Equation 2.

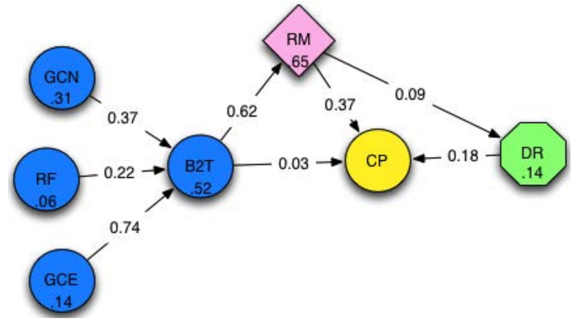

Figure 2: State Diagram for Frequent Patterns that Led to an Answer - Simple task

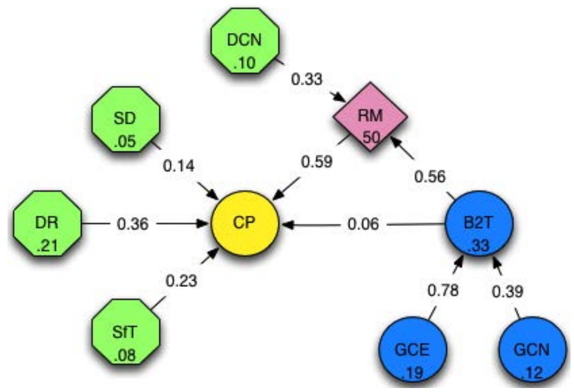

Figure 3: State Diagram for Frequent Patterns that Led to an Answer - Complex task

$$P(state_i) = \frac{\max(freq(state_i \rightarrow ... \rightarrow state_{CP}))}{freq(state_{CP})} \qquad (2)$$

Where $\max(freq(state_i \rightarrow ... \rightarrow state_{CP}))$ indicates the frequency of the most repeating patterns that starts from $state_i$ and ends at CP; $freq(state_{CP})$ indicates the total number of paths that lead to CP. That is, the sum of all maximal patterns ending in CP. For example, in Figure 2, starting from B2T there are three paths that lead to CP:
(a) B2T→CP with a probability of 0.08
(b) B2T→RM→CP with a probability of 0.52
(c) B2T→RM→DR→CP with a probability of 0.06
Therefore, we consider path (b) as the most successful path that starts from going back to text and ends at locating an answer. We removed the less likely patterns from these diagrams for the sake of clarity. Therefore, the probabilities of

edges exiting from a state do not sum to 1 in these figures.

We made the following key observations:

(1) Overall, there are more distinct paths (i.e. maximal repeating patterns) that lead to an answer for the complex task (129 paths) than the simple task (65 paths). This resulted in a more complex structure depicted in Figure 3.

(2) Graphs were more likely to initiate a path to an answer for the simple task than the Complex task (0.52 v.s. 0.33 respectively ; $\rho < 0.05$);

(3) In the cases that using the Graph led to finding an answer, nodes are more likely to be the contributing factor for the simple task (0.31 v.s. 0.14 ; $\rho < 0.05$). However, clicking on an edge was significantly more beneficial for locating an answer in the Complex task than the Simple one (0.14 v.s. 0.19 ; $\rho < 0.05$);

(4) The paths starting from RM were the most likely paths that ended in CP. These patterns correspond to finding the answers by going through the mentions of entities and relations in text.

Discussion.

The more complex structure of the diagram in Figure 3 indicates that searchers take a more diverse set of paths to an answer. This observation can justify why the complex search tasks are not well supported by the current search engines. In fact, different searchers exhibit different information seeking behaviour in order to locate the relevant pieces of information in retrieved documents. A better understanding of the common interaction patterns can help the search engines to identify and facilitate these activities.

The second observation was also stated by the participants in the provided questionnaires. They found the graphs are more helpful for the simple task as they had a better idea of what they were looking for.

The third observation is intuitive. Since the answers for the simple task are entities, nodes should be more helpful to locate the factoid information in text. On the other hand, relevant evidence supporting the "position of California w.r.t Stemcell research" is expressed by sentences / text snippets and more context is required to judge and identify these answers by the searchers. Therefore, edges provide more support for locating more complex information. This finding was also observed in Table 2 as the "interaction pattern" of length 4, denoted by [GCE→B2T→RM→CP] was more frequent as compared with its counterpart [GCN→B2T→RM→CP] for the Complex task and the opposite was true for the simple task.

Overall, applying IE techniques to highlight the mentions of key entities and the relations connecting them in text were proved beneficial for locating relevant information. This is illustrated in the state diagrams as the probability of starting from RM and ending at CP.

4.4.6 *Summary of Findings*

In this section we revisit our research questions from Section 3.2 and discuss our findings.

1 (a-b). Overall, the participants clicked on nodes more than the edges in both tasks. This trend was strongly significant for simple task, while edges were clicked more during the complex task.

1 (c-d). Overall, the participants started their exploration from the graphs more than the documents. However, this trend was significantly stronger for the simple task. Also, they started their exploration from the documents for the complex task significantly more than the simple one.

1 (e). While clicking on an entity was the main activity done by the group who started from the graphs, it was strongly significant for the simple task. On the other hand, exploring the graph was a significant pattern for this group during the complex task.

2 (a-b) Figures 2 and 3 depicted the most frequent patterns that involved finding an answer by the participants. While there are similar patterns observed across two tasks, the set of patterns for the complex task was more diverse.

2 (c-d-e) Overall, the graphs provided more support for the simple task as compared with the complex task. Also, nodes were proved more useful in locating an answer for the simple task, while edges appeared more frequently in that paths that led to an answer during the complex task.

Types of documents the graph is useful for	Longer documents	11
	with a lot of names	10
	more technical	8
Main benefits of using graph	Locate certain pieces of information	12
	Get the big picture / overview of document	11
	Connecting pieces of information	11
Switching from document to graph	To explore related entities	14
	To look at the big picture	8
	To locate a more interesting part of text to jump to	8
Switching from graph to document	To Further read about a fact	11
	To learn more about the current element of graph	11
	To understand a label in graph	8

Table 7: Summary of Searchers Preferences

5. CONCLUSION AND FUTURE WORK

This paper reported the results of an initial user study conducted to develop a better understanding of searchers during information finding and analysis activities. We gained valuable insights by observing different information finding patterns and searchers' exploration within a new search paradigm. We conclude that utilizing graphs of concepts and relationships, which are derived from documents, can be effective for finding relevant information when the information need is well defined. Our findings also demonstrate that providing meaningful relations that explain how different entities of a domain are connected are crucial for supporting more complex search task. We envision two main directions to pursue in order to extend the current framework and provide more support for exploratory tasks.

Ranking and Suggestion Generation.

We identified a major barrier to effective application of automatically generated knowledge graphs to complex search scenarios. As noted by many searchers, for the larger graphs, it was not clear where to start and where to go next in the graph. This was the main reason mentioned by the participants who preferred the document text where the nature of the search task was complex. Since the users of exploratory search systems are usually engaged in complex search scenarios it is easy for them to get lost or frustrated in the middle of a search session and just abandon their exploration. It is also very difficult for them to keep track what they have browsed so far and what is there to explore further.

Hence, we are seeking approaches to provide suggestions for the searchers automatically to guide the navigation and exploration process. We are investigating different ranking methods based on interestingness and graph-based measure to suggest a list of candidate subtrees of the graph to be explored next. We need to identify an optimal set of parameters to these ranking algorithms including the current node, the paths traversed in the graph so far, the past click logs, etc. We also need to address the problem of extracting meaningful subgraphs (e.g., [10])

Finally, as we monitored the searchers finding relevant information about a topic they were not very familiar with (e.g., "Stemcell research"), we realized they were making use of the graphs to learn basic facts (e.g., "Stemcells are undifferentiated biological cells") about the salient entities or the query terms. However, since documents mostly lack this basic information the corresponding graphs would not contain such nodes or links either. Therefore, these basic facts can also be suggested to the searchers by leveraging external knowledge sets such as DBpedia that contain these triples.

Connecting the Documents.

One of the main challenges for conducting an effective exploratory search is to fight the information overload. That is, where there are many documents retrieved for a query, (1) how can the searcher select the "right" documents to read and (2) how each of these documents is related to the other documents in that collection. To this end, we are investigating methods for automatically mapping the graphs and providing a structured, easy way to navigate within a new topic and discover hidden connections. This is our main focus for extending this work and we would like to address the following research question: "Does coupling the graph and the document browsing modes help with "sense making" and "learning" by highlighting the underlying connections between different documents retrieved for the user's query?"

As identified by many participants, the poor visibility of labels for the large graphs was the main barrier for utilizing the graphs for exploration and information finding. Moving from a single document to a collection of retrieved documents can exacerbate this problem. Some of the participants mentioned they would like to see only those parts of the graph that are related to the node they are currently viewing. They found partially visible graphs less confusing to explore. Therefore, presenting graphs with different levels of granularity and generating summary graphs will also need to be investigated.

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