Collaborative Information Access: A Conversational Search Approach

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Abstract. Knowledge and user generated content is proliferating on the web in scientific publications, information portals and online social media. This knowledge explosion has continued to outpace technological innovation in efficient information access technologies. In this paper, we describe the methods and technologies for 'Conversational Search' as an innovative solution to facilitate easier information access and reduce the information overload for users. Conversational Search is an interactive and collaborative information finding interaction. The participants in this interaction engage in social conversations aided with an intelligent information agent (Cobot) that provides contextually relevant search recommendations. The collaborative and conversational search activity helps users make faster and more informed search and discovery. It also helps the agent learn about conversations with interactions and social feedback to make better recommendations. Conversational search leveragesthe social discovery process by integrating web information retrieval along with the social interactions.

1 Introduction

Socially enabled online information search (social search) is a new phenomenon facilitated by recent Web technologies. This collaborative social search involves finding specific people in your network who have the knowledge you're looking for or finding relevant information based on one's social network. Social psychologists have experimentally validated that the act of social discussions have facilitated cognitive performance[1]. People in social groups can provide solutions (answers to questions)[2], pointers to databases or other people (meta-knowledge)[2][3] , validation and legitimation of ideas[2][4], can serve as memory aids[5] and help with problem reformulation[2]. Guided participation[6] is a process in which people co-construct knowledge in concert with peers in their community[7]. Information seeking is mostly a solitary activity on the web today. Some recent work on collaborative search reports several interesting findings and the potential of this technology for better information access. [8] [9] [10] [11]

We are building a system called Cobot [1] to address these challenges. Cobot introduces a conversational environment that provides social search through conversations integrated with intelligent semantic meta-search from the web. Users

[1] We use the term Cobot for Cobot system as well as Cobot agent interchangeably

want to simplify their experience when performing an information finding task. Conversational Search is about letting users collaboratively search and find in natural language, leaving the task of user intent comprehension on the system. The participating agent interacts with users proving recommendations that the users can accept, reject, like, dislike or suggest.

Figure 1 captures the online search space divided into web search and social search on one axis and aggregated, personalized and semantic search on the other axis. Cobot falls in the space of Social and Semantic Search space. It is social because it uses the user's social graph to find socially relevant results. It is semantic because it understands the queries (to some extent), concepts, relationships and indexes terms by their enclosing semantic types.

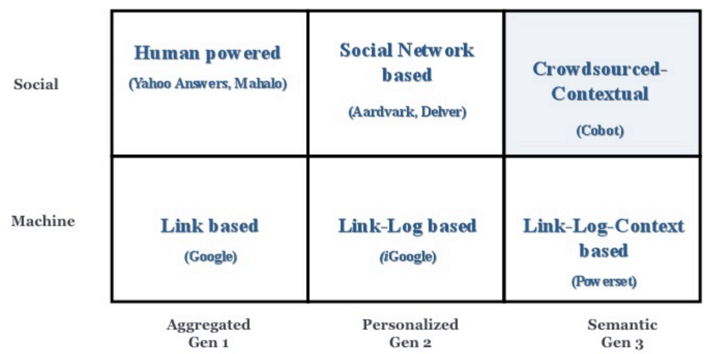

Fig. 1. Web Search Space

2 The Problem

The need to make the world wide web information universally accessible has accelerated research and development in Information Retrieval (IR) systems. Most web search systems are based on general Information Retrieval (IR) principles. Many of these IR systems are general purpose search systems that index millions, if not billions of pages and use state of the art advanced statistical modeling techniques to make them findable using keyword based matching. Google, for example, models webpages using link cardinality on the hypertext web graph to calculate the relative importance of webpages. They use several other parameters like proximity, anchor text and cardinality to build their full text search index. One of the design goals of the initial Google system was to handle the common case of queries well, topical information and under-specified queries. Even today, these popular search engines are not able to find precise, specific and non topical information efficiently.

Conversational Search differs from traditional search paradigms in some ways. The focus is user centric collaborative information access from the web; it is not acceptable to return hundreds of results matching a few keywords even if two or three of the top ten are relevant. Unlike traditional information retrieval, the problem requires synthesis of information and interaction, the system along with the users of the system must analyze the results collectively to create an effective solution.

3 Proposed Solution

3.1 Conversational Search

Conversational Search(CS) is an interactive and collaborative information finding interaction. The participants engage in a conversation and perform a social search activity that is aided by an intelligent agent. The collaborative search activity helps the agent learn about conversations with interactions and feedback from participants.

It uses the power of semantics with natural language understanding to provide the users with faster and relevant search results without being overwhelmed by information. It moves search from being a solitary activity to being more participatory activity for the user. The search agent performs multiple tasks of finding relevant information and connecting the users together; participants provide feedback to the agent during the conversations that allows the agent to perform better.

CS is different from Information Retrieval (IR) [12] or Question Answering (QA) [13]. The focus of IR systems is on retrieving relevant documents from a large document collection in response to a query. If the user's information need is complex, browsing through retrieved results to find solutions to problem queries is time consuming and inefficient. Moreover, IR generally does not deal with the process of understanding the meaning of queries when posed in natural language e.g. in the form of a question or paraphrases.

In Question Answering (QA), researchers are developing different algorithms and techniques to obtain effective responses for specic information requests. The solution is generally present in a paragraph, sentence, or phrase. These snippets of information contain possible answers to the posed questions. While QA deals with understanding the meaning of natural language queries, it does not involve a back and forth interaction to continuously adapt the results and find out more and explore in continuum about some information or questions.

CS involves a continuous exchange of information between the sender and recipients; allowing for mutual learning and benefit. Fusion of IR and QA can be imagined to be a part of the CS approach. It is an intelligent problem solving AI technique applied to address the problem of search differently. There are several hard problems and challenges involved in CS besides the inherent problems in IR and QA. Some of the additional problems in CS are as follows:

– *How to model CS as a collaborative information finding activity?* The process of modeling an artifact involves giving it structure and organization for representing its intension and extension. The challenge lies in modeling it such that it can lend itself naturally for carrying out tasks for which it needs to be modeled. CS brings relevant information and people to the participants.

These recommendations are generated in progression with users' social interactions. Taking these functionalities into account, modeling CS involves creating dynamic data structures that are socially aware of the participants of the conversation and its content.

- *How do we use the model as a basis for providing recommendations?* The socio-semantic models of conversations along with the user models, case index of conversations and the semantically searchable document index act as different levels of memory structures for the system. Users' interactions and social feedback are registered in the system to bring in suitable recommendations and also improve contextual relevance of the data being generated.
- *How do we dynamically connect cohorts based on the conversations?* The system is aware of the users' social network along with the users who are online in the system. The user models consist of an aggregate of user's knowledge as a result of his past interactions. We dynamically connect cohorts by overlaying the user models with the social network taking into account the users that are online in the system.
- *How does the agent find relevant information to insert in the conversation besides providing relevant recommendations?* Besides providing the recommendations for the conversations, the agent's goal is to insert possible answers to questions directly into the conversation. The "Text Analysis and Processing Engine(TAPE)" analyzes the conversation and the recommendations to identify possible answers for the natural language questions.

The approach we have taken to address CS problems is by developing dynamic data structures that model it. We call this structure the "Socio-Semantic Conversation Net" - these conversation nets maintain in memory models of the conversation, participants, participants' immediate social connections, concepts, relationships and information flow.

3.2 Socio-Semantic Conversation Model

"The core problem that context-sensitive asynchronous memory addresses is how to get the information an agent needs when it doesnt know how to ask the right question and doesnt have the time to exhaustively search all information available to it. The key to this solution is to interleave remembering with thinking and doing, thus making the context of thought and action available to guide remembering."[14]

The Socio-Semantic Conversation Model that we are developing is a dynamic memory data structure based on principles of experience based agent architecture. [15] It supports interleaved retrieval of information by applying different memory retrieval algorithms such as PageRank or Spreading Activation. The model maintains the user's social graph, the conversation graph with the extracted semantic net for the conversation.

Some essential properties of the model are as follows:

- The model should be socially aware of the participant and his social network's availability (to aid with Cohort Matching)

- The model should provide bi-directional recommendation and feedback.
- The model should understand domain terminology and be able to find semantic relationships amongst concepts extracted from conversations.
- The model should be aware of user's basic profile (such as interests) for the agent to be able to use that information if needed.

The Socio-Semantic Model aims to provide storage and memory based retrieval for dynamic representation, update and reuse of users' knowledge and experiences. Figure 2 depicts the user-centric domain information modeling approach to jointly model the information context from users' perspective.

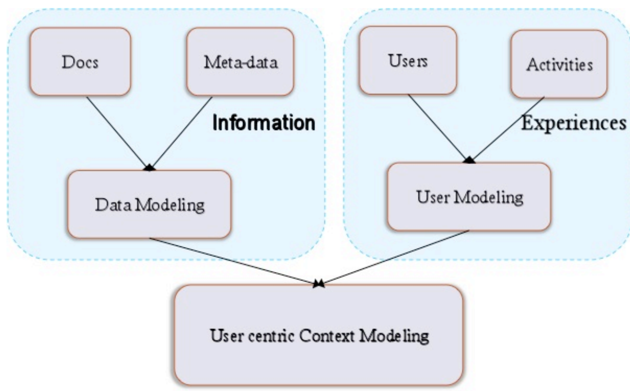

Fig. 2. User-centric Domain Information Modeling

4 Cobot System Prototype Design

Cobot is an intelligent agent platform that connects users through real-time and offline conversations. Cobot lives in a community, has a limited understanding of domains through ontologies and brings relevant information to the users by participating in the conversations. Cobot's 'conversation engine' monitors user conversations with other users in the community and provides/receives recommendations (links and snippets) based on the conversation to the participants. Cobot's community engine' models conversations to capture user-user and user-information interactions.

The following design goals are being adhered while developing the Cobot system.

1. Near real time conversational agent
2. Personalized recommendations
3. Agent learns with interaction
4. Uses a structured internal organization of content
5. Connects conversations to people.

Figure 3 depicts the high level architecture of the Cobot system. The Conversational Agent uses different modules for conversation analysis (TAPE), search and recommendation and maintains a short-term conversation memory for each conversation. The socio-semantic index is analogous to the agent's long term memory model where it stores all processed information about users, conversations, activities and content descriptors.

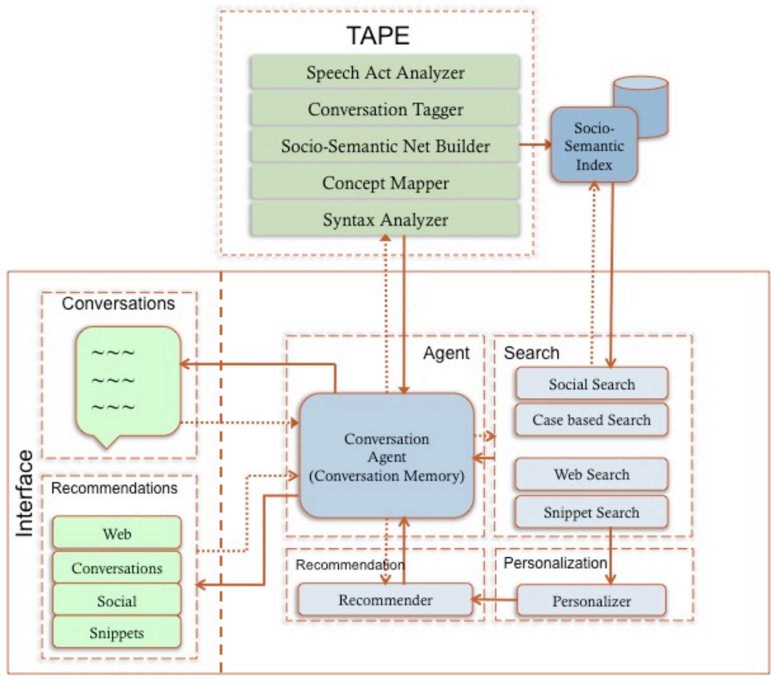

Fig. 3. System Architecture

Figure 4 shows one screenshot of the initial system prototype. This prototype is fine tuned for health related searches by incorporating medical ontologies in order to better understand the conversations. Users actively engage in conversations by multi-user chat, rating or adding recommendations. The agent monitors the environment to build user interaction models and to improve search relevance.

5 Key Research Challenges for Conversational Search

Search results are not tailored to the users goals or information need, or to his/her specific situation. Cobot system is agent based and agent assisted. We browse, find and soon forget what we have found. The agent based system builds and maintains user models and finds relevant information from the web or his past interactions, network and experiences.

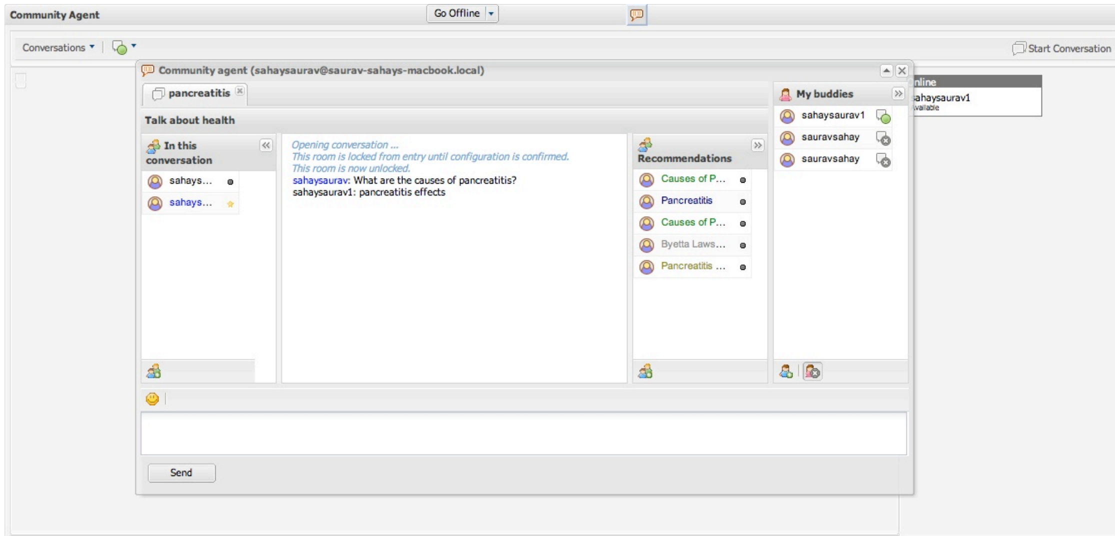

Fig. 4. Prototype Interface

5.1 Precise Search

Identifying relevant documents for a particular user's need without extensive search, in conversational manner is the key objective for precise search. The right search queries need to be figured out with situation assessment from the conversational snippets. It is not desirable to return dozens or hundreds of remotely relevant results, even if some of them will be highly relevant. The aim is to retrieve successive recommendations that try to address the search problem precisely.

5.2 Knowledge Representation and Synthesis

Any form of knowledge that needs to be captured has to be expressed in some representation medium. This representation of knowledge is one of the fundamental intelligence design problems that has been extensively studied in Articial Intelligence research. Textual search based systems work on natural language. Natural language, unlike math or logic, does not intrinsically lend itself to computational reasoning. In order to intelligently reason from text, it needs to be abstracted in a form that becomes amenable to communicating that meaning to any user. Combining the document models with the user models in an integrated representation will lead to development of systems that intrinsically lend their model to user centric personalization efforts. We are developing a graph based representation of our information model that includes data entities as well as user based entities.

5.3 Socio-Semantic Conversation Modeling

Language and interaction creates usable memories, useful for making decisions about what to do, what to retain, or how to plan future moves. Data Modeling is the process of providing some organization and structure to data. Knowledge bases and databases are built by adhering to some data model and populating the model with occurrences of data. We build socio-semantic nets as discussed earlier to model the social behavior of people on the system across the semantic data nets.

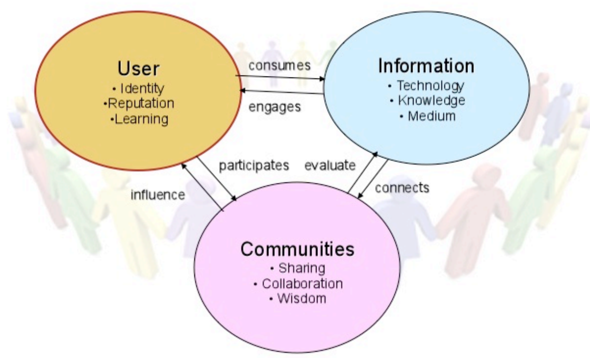

Fig. 5. The Socio-Information Cycle

Figure 5 tries to depict the relationships between the user, information and the communities. Communities are made up of users who are grouped by different information needs into dynamic cohorts. These online communities, through effective sharing and collaboration, increase the utility of systems and help solve individual problems more effectively.

5.4 Case based Reasoning for Longitudinal Search

Case-based reasoning is an artificial intelligence approach, in which past cases are used to solve new problems [16] [17]. The key lies not in running a smarter search engine against a set of documents, but in understanding which documents contain appropriate answers to users' different kinds of queries using his past experiences. While driven by information retrieval techniques, there is a learning component that goes beyond simply matching queries against documents to matching queries against past episodes. Cases are stored in a case library and represent the systems experience or historical record of previous queries and responses.

Conversational Search uses the familiar CBR cycle (retrieve, select, apply, learn) but with the following differences:

– there is a separate acquisition and representation phase which builds the knowledgebase by acquiring information from the web

- these is a social retrieval component that finds people based on their related past conversations; it also retrieves information from the user's social network based on conversations
- retrieve and select require text analytics (in our case, NLP, search), since the knowledgebases and cases are unstructured text instead of traditional AI representations
- the apply phase merges the social and web based recommendations to create a new case for the problem
- learn requires human-in-the-loop relevance feedback and requires storing new cases in the case library

Instead of matching queries against keywords in documents, the system develops a case library of past problem-solving sessions containing previous queries the system has seen and corresponding solutions the system has proposed. More specifically, this approach builds on the following research issues, as can be associated with a CBR system:

- Knowledge Representation: What information does a case contain apart from the given knowledgebase representation? How is this information represented?
  Information is modeled by capturing user-user and user-data interactions for every user so that the system can reason with their experiences. A particular case is associated with the problem as posed by the user and the solution which in turn keeps a record of the suggested and finally chosen solution(s).
- Indexing and Retrieval: How are cases organized to enable relevant cases to be found later? How are cases retrieved in response to a users query? How is the relevance of a case determined?
  Relevance of a case is dependent on the user model in the system along with the experience (feedback) associated with it.
- Learning: How are new cases learned? How are indexes and cases updated through experience?
  For every case that is finally created, there is social feedback associated with it. The system uses such implicit and explicit feedback to learn and update associated user models and also to gauge relevance of cases.

6 Discussion

This paper proposes a collaborative system for conversational search. We are hypothesizing that such a Conversational Search system is more usable for information access as compared to a solitary web search experience. We briefly describe the challenges involved in construction of a Socio-Semantic Conversation Model for Conversational Search. Socio-Semantic Conversation Modeling using Experience-based Agency is a unified approach for solving Conversational Search problem. This approach leverages the individual Social and Semantic Approaches efficiently. The dynamic and self configuring memory structures and the semantic net details enable memory retrieval from the storage. Automatic

Cohort Matching based on Conversations describes a methodology to dynamically pull users for conversations. Unlike users themselves having to find relevant conversations, the conversations find the users using this approach.

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