ABSTRACT

We present APolo, a system that uses a mixed-initiative approach to help people interactively explore and make sense of large network datasets. It combines visualization, rich user interaction and machine learning to engage the user in bottom-up sensemaking to gradually build up an understanding over time by starting small, rather than starting big and drilling down. APolo helps users find relevant information by specifying exemplars, and then using a machine learning method called Belief Propagation to infer which other nodes may be of interest.

We demonstrate APolo’s usage and benefits using a Google Scholar citation graph, consisting of 83,000 articles (nodes) and 150,000 citations relationships. A demo video of APolo is available at http://www.cs.cmu.edu/~dchau/apolo/apolo.mp4.

Categories and Subject Descriptors
H.3.3 [Information Storage and Retrieval]: Relevance feedback; H.5.2 [Information Interfaces and Presentation]: User Interfaces

General Terms
Algorithms, Design, Human Factors

Keywords
Sensemaking, large network, Belief Propagation

1. INTRODUCTION

Extracting useful knowledge from large network datasets has become an increasingly important problem in domains ranging from citation networks of scientific literature; social networks of friends and colleagues; and links between web pages in the World Wide Web. Theories of sensemaking provide a way to characterize and address the challenges faced by people trying to organize and understand large amounts of network-based data. Sensemaking refers to the iterative process of building up a representation or schema of an information space that is useful for achieving the user’s goal [13]. For example, a scientist interested in connecting her work to a new domain must build up a mental representation of the existing literature in the new domain to understand and contribute to it. Much existing work on graph visualization aims to develop “summary views” of graphs, on the assumption that the user knows nothing or very little about the data. However, such approaches often struggle to work when faced with large networks with millions of nodes and edges. Sometimes, the approaches simply cannot scale up to such data size due to computation or space requirements; sometimes, the views created are too overwhelming, showing too many nodes and edges; and more often, there are simply no good canonical views that can be generated for the graphs (e.g., real, large social networks often do not have well-defined clusters).

We have been investigating a different approach where we help the user start with a small subgraph, then incrementally explore and expand, rather than starting big and drilling down. This style of sensemaking can be found in many real-world scenarios. For example, imagine looking for relevant papers for our own research in a citation network; we would often start with papers that we are familiar with, then look at papers that they have cited or being cited by them. We created the APolo system [4] (Figure 1) to support this kind of bottom-up sensemaking to help the user gradually build up an understanding over time. Within APolo, a machine learning algorithm called Belief Propagation (BP) guides the user to explore relevant areas of the graph; in turns, the user specifies the nodes that he is interested in as “exemplars”, and BP compute all other nodes’ relevance and show the most relevant ones in the visualization. APolo provides a number of interaction and visualization features that help people develop and evolve externalized represen-
Figure 2: Screenshot of APOLO showing a user exploring the landscape of the related research areas around the article The Cost Structure of Sensemaking (highlighted in black). The user gives relevance feedback to APOLO as to which papers he is interested in, as exemplars (each with a color dot underneath); and how the exemplars should be categorized (by colors). APOLO incorporates these preferences into BP to find more related nodes, and shows some of the most relevant ones, to avoid overwhelming the user.

We summarize our main contributions as follows:

- We aptly select, adapt, and integrate work in machine learning and graph visualization in a novel way to help users make sense of large graphs using a mixed-initiative approach. APOLO goes beyond just graph exploration, and enables users to externalize, construct, and evolve their mental models of the graph in a bottom-up manner.

- APOLO offers a novel way of leveraging a complex machine learning algorithm, called Belief Propagation (BP) [15], to intuitively support sensemaking tailored to an individual’s goals and experiences; BP was never applied to sensemaking or interactive graph visualization.

2. DEMONSTRATING APOLO

We will demonstrate APOLO’s usage, user interaction and fast algorithm through sensemaking scenarios on a Google Scholar citation network dataset, which contains about 83,000 articles (nodes) and 150,000 citations relationships (edges, each represents either a “citing” or “cited-by” relationships).

Scenario. Here, we illustrate one example scenario, where we try to explore and understand the landscape of the related research areas around a seminal article The Cost Structure of Sensemaking by Russell et al. (Figure 2 shows final results.) This scenario will touch upon the major features of APOLO. We begin with a single source article highlighted in black in the center of the interface (Figure 4a) and the ten most relevant articles as determined by the built-in BP algorithm. Articles are shown as circles with sizes proportional to their citation count. Citation relationships are represented by directed edges.

Figure 3: The Details Panel, shown when mousing over an article, displays article details obtained from Google Scholar. The user has made the article an exemplar the InfoVis group by clicking the group’s label.

After viewing details of an article by mousing over it (Figure 3), the user moves it to a place on the landscape he thinks appropriate, where it remains pinned (as shown by the white dot at the center). The user can also star, annotate, unpin, or hide the node if so desired. After spatially arranging a few articles the user begins to visually infer the presence of two clusters: articles about information visualization (InfoVis) and collaborative search (Colab Search). After creating the labels for these two groups (Figure 4a), the user selects a good example article about InfoVis and clicks the InfoVis label, as shown in Figure 3, which puts the article into that group. A small blue dot (the group’s color) appears below the article to indicate it is now an exemplar of that group. Changing an article’s group membership causes BP to execute and infer the relevance of all other nodes in the network relative to the exemplar.
Figure 4: a) In the beginning, the top 10 most relevant articles (in gray) of our starting paper (in black) are shown. Our user has created two groups: Collab Search and InfoVis (magnified). b-d) Our user first spatially separates the two groups of articles, then assigns them to the groups, making them exemplars and causing Apolo to compute the relevance of all other nodes, which is indicated by color saturation; the more saturated the color, the more likely it belongs to the group. The image sequence shows how the node color changes as more exemplars are added.

Figure 5: a) Pop-up menu shown upon right click; the user can choose to show more articles, add suggested articles for each group, rank sets of nodes in-place within the visualization, etc. b) Newly added neighboring nodes ranked by citation count. c) The same nodes, ranked by their “belongness” to the (blue) InfoVis group; articles whose titles contain “visual” are highlighted with yellow halos.

Figure 6: Two spatial subgroups
probabilities being in each of the group created by the user. A group’s exemplars have high prior probability being in that group, which BP incorporates to perform inference. We implemented BP as described in [10]. The key settings of the algorithm include: (1) a node potential function that represents how likely a node belongs to each group (a value closer to 1 means more likely), e.g., if we have two groups, then we assign (0.99, 0.01) to exemplars of group 1, and (0.5, 0.5) to all other nodes; (2) an edge potential function that governs to what extent an exemplar would convert its neighbors into the same group as the exemplar (a value of 1 means immediate conversion; we used 0.58).

Implementation. The APOLO system is written in Java 1.6. It uses the JUNG library [11] for visualizing the network. The network data is stored in an SQLite\(^1\) embedded database, for its cross-platform portability. One of our goals is to offer APOLO as a sensemaking tool that work on a wide range of network data, so we designed the network database schema independently from the APOLO system, so that APOLO can readily be used on different network datasets that follow the schema.

4. RELATED WORK

APOLO builds on a large body of research aimed at understanding and supporting how people can gain insights through visualization [8]. APOLO adopts a bottom-up sensemaking approach [13] aimed at helping users construct their own landscapes of information. APOLO provides several features to help people create flexible, ad-hoc groups as they explore, which fit with the process of how they would learn and represent concepts [2]. This “human in the loop” approach differs from a lot of research in graph mining that studies how to automatically discover clusters (or groupings) in graphs, e.g., Graphcut [9], METIS [6].

Much work has been done on developing methods to compute relevance between two nodes in a network; many of them belong to the class of spreading-activation [1, 7, 3]. Used by APOLO, Belief Propagation [15] is a message passing algorithm over link structures similar to spreading activation, but it is uniquely suited for graph sensemaking because it offers simultaneous support for: multiple user-specified exemplars (unlike [14]); any number of groups (unlike [1, 5, 14]); linear scalability with the number of edges (best possible for most graph algorithms); and soft clustering, supporting membership in multiple groups (unlike [9]).

Few tools have integrated graph algorithms to interactively help people make sense of network information [5, 12, 14], and they often only support some of the sensemaking features offered by APOLO, e.g., [14] supports one group and a single exemplar.

5. CONCLUSIONS

We present APOLO, a mixed-initiative system for helping users make sense of large network data. Apolo tightly couples large scale machine learning with rich interaction and visualization features to help people explore graphs through constructing personalized information landscapes.

We will demonstrate APOLO’s usage and benefits using a Google Scholar citations graph, consisting of 83,000 articles (nodes) and 150,000 citations relationships. We will invite our audience to try out APOLO, comment on its usability and usefulness, and discuss how APOLO may help with their work.

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7. REFERENCES


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