Using Multipartite Graphs for Recommendation and Discovery

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Abstract. The Smithsonian/NASA Astrophysics Data System exists at the nexus of a dense system of interacting and interlinked information networks. The syntactic and the semantic content of this multipartite graph structure can be combined to provide very specific research recommendations to the scientist/user.

1. Introduction

Modern information systems, such as the ADS (Kurtz, et al. 1993), act as a nexus, linking together many densely interconnected systems of information. These systems can be viewed as systems of interconnecting graphs, an example of a bipartite graph would be the interaction of the set of all papers with the set of all authors, which yields connections between papers and papers (papers are connected if they have the same author) and between authors and authors (co-authorship).

Modern computational techniques permit these rich data sources to be used to solve practical problems. Some techniques use the graph representation to achieve orderings, such as with the Girvan-Newmann algorithm (Girvan and Newmann, 2002) or the Rosvall-Bergstrom algorithm (Rosvall and Bergstrom, 2008). Others use eigenvector techniques on the interconnectivity or influence matrices, either using exact methods (e.g. Thurstone 1934, Ossorio 1965, Kurtz 1993), or approximate methods suitable for huge systems such as PageRank (Brin and Page 1998).

2. A Faceted Browse System

Developing practical solutions to the problem “given my current state of knowledge, and what I am currently trying to do, what would be the best things for me to read” requires an in depth understanding of the properties of the data and the nature of the many different reduction techniques. The data are quite complex; as an example two papers (A and B) can be connected to each other because 1) A cites B; 2) B cites A; 3) A and B cite C; 4) Author X wrote both A and B; 5) Author X wrote a set of papers, at least one of which was cited by both A and B; 6) A and B were read by the same person; 7) A and B have the same key word; 8) A and B refer to the same astronomical object; 9) etc..
A practical example of combining data and techniques would be to build a faceted browse system for current awareness. A possible avenue is: take a set of qualified readers, say persons who read between 80 and 300 papers from the main astronomy journals within the last six months; for each reader find the papers that reader read; for each of these papers find the papers that that paper references; for each of these papers find the keywords assigned to that paper by the journal; next, for each reader create an N-dimensional normalized interest vector, where each dimension is a keyword and the amplitude represents the normalized frequency of occurrence in the papers cited by the papers read. This yields a reader-keyword matrix; one way to view this is that the readers are points in a multidimensional keyword space.

Several things can be done with this matrix, for example if the readers are clustered, by K-means or some other algorithm, one obtains groups of readers with similar interests. These can be used as the basis of a collaborative filter, to find important recent literature of interest, and can be subdivided, to narrow the subject (as defined by people with similar interests). This creates a faceted browse of important recent papers in subjects of current interest. The ADS has sufficient numbers of users to support three levels of facets.

3. A Recommender System

Using similar techniques the ADS is currently implementing a recommender system: given that you are reading a particular article, what other articles might be useful for you to read? The first step in developing a recommender system is to find a set of papers similar to the paper being read. A group of similar articles substantially enhances the signal to noise of the recommender system compared with a single article; the mean downloads per month for a ten year old Astrophysical Journal article, for example, is one. There are three basic steps to this process: first create a system to find similar articles for an arbitrary article; then given an article of interest find those similar articles, and finally use them to find recommended articles. The system must be designed so that the recommended articles can be chosen in real time, once the arbitrary article of interest is selected.

One effective method for finding similar articles is: 1) take the reader-keyword matrix and reduce its dimensionality (to about 50) using SVD; 2) transform all the papers into the reduced dimensionality system by fitting their keyword vectors to the significant SVD vectors; 3) cluster the (50 dimensional) article keyword vectors into many clusters (of about 1000 articles each) using hierarchal clustering techniques; 4) for each of the small clusters of papers perform a new SVD decomposition on the ≈50 dimensional vectors, reducing the dimensionality further (to about 5); 5) for each small cluster of papers transform each paper into the corresponding 5 dimensional subspace. These steps can be done in advance as part of the indexing necessary for a text retrieval system.

Now, to find suggested reading for a new article, say one just released on arXiv, is relatively simple. First the keyword vector must be created for the paper, but note that this is a function of the articles the paper references, the arXiv paper itself need not be keyworded. Next perform the transformations and classifications to put the article into the proper small cluster of papers with its
five dimensional subspace. Then find those n papers (40 is a reasonable number) from the 1000 or so in the cluster which are closest in the 5-dimensional space to the input arXiv article. These 40 articles become the basis for the recommender systems.

We look for recommended papers using second order operators (Kurtz 1992, Kurtz, et al 2005). For three possible recommendations we use the betweeness of the papers in the group of 40; we find the paper which was most read immediately following the reading of a member of the group, the paper most often read immediately before a member of the group, and the paper most often read either before or after (these can be, and often are, different). This inverts the concept of betweenness centrality, we do not find the papers which are most between a set of papers, we find the set of papers for which the group of 40 papers very similar to our input paper are between.

Two additional recommendations can be gotten by finding all the people who read any of the group of 40 papers, and finding the paper they read the most in the last few months, and by finding the most recent paper in the top 100 of this most also read list. The citations can give two more recommendations: the paper which the group of 40 papers cite the most, and the paper which cites the largest number of the group of 40.

Finally a joint query of ADS with SIMBAD (Wenger, et al. 2000) can find the paper which refers to the largest number of astronomical objects which are referred to by the papers in the group of 40 very similar papers to the input paper.
4. Conclusion

Clearly this is not the only way to find recommended papers; like with architecture or civil engineering (there is no best building or bridge design) the problem is too complex to be fully optimized. There are very likely ways of doing this which are better than others, however, and this will be learned over time.

We only used part of the available data here; from the citations we only used in-degree and out-degree from the group of 40. We did not use the author-based relations at all. Instead of clustering the papers based on a hierarchal clustering of the reduced keyword vector (a subject matter technique) we could have clustered them based on the co-citation network, using the Rosvall-Bergstrom algorithm (Kurtz, et al. 2007). We did not use any knowledge about the actual user. Etc.

These methods are not restricted to scientific papers. We are entering an age of very densely interconnected “data” objects; building intelligent systems to guide users in their traversal of these new universes is clearly a branch of knowledge engineering whose time has come.

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References

Brin, S. & Page, L. 1998, Computer Networks and ISDN Systems, 30, 107.
Girvan, M. & Newman, M.E.J. 2002, PNAS 99, 7821.
Kurtz, M.J. 1992, ESO Conference Series 43, 85
Kurtz, M.J. et al 1993, ASP Conference Series 52, 132.
Kurtz, M.J. 1993, ASSL 182, 21.
Kurtz, M.J. et al. 2005 JASIST 56, 36.
Ossorio, P.G. 1965 J. Multivariate Behavioral Research 2, 479.
Rosvall, M. & Bergstrom, C. 2008, PNAS 105, 1118.
Thurstone, L.L. 1934, Psychological Review 41, 1.
Wenger, M. et al. 2000, A&AS 143, 9.