Mining Newsgroups Using Networks Arising From Social Behavior by Rakesh Agrawal et al.

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Motivation

- IR on newsgroups is challenging due to lack of connection among documents
  - Unlike WWW, can not use PageRank to improve the retrieval performance
- An automatically-generated social network within a newsgroup may help IR and text mining applications

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- Assumptions
  - New posts contain opposite comments against parent posts
  - There are only two groups of users with roughly the same size

Newsgroup Threads

Re: combining open office spellchecker with Luce...	David Spencer	9/9/2004 11:01...
Re: combining open office spellchecker with Lu...	Andrzej Bialecki	9/9/2004 11:15...
Re: combining open office spellchecker with...	David Spencer	9/9/2004 11:51...
Re: combining open office spellchecker with Lu...	Doug Cutting	9/9/2004 12:03...
Re: combining open office spellchecker with...	David Spencer	9/9/2004 1:10 ...
Re: combining open office spellchecker ...	Doug Cutting	9/9/2004 10:09...
Re: combining open office spellchecke...	eks dev	3:04 AM
Re: combining open office spellche...	David Spencer	10:05 AM
frequent terms - Re: combining open office ...	David Spencer	7:38 PM
Re: MultiFieldQueryParser seems broken... Fix att...	Doug Cutting	9/9/2004 11:52...
Re: MultiFieldQueryParser seems broken... Fix ...	Daniel Naber	9/9/2004 12:28...
Re: MultiFieldQueryParser seems broken... ...	Doug Cutting	12:50 PM
Re: MultiFieldQueryParser seems broken... Fix ...	Bill Janssen	9/9/2004 2:48 ...
Re: MultiFieldQueryParser seems broken... Fix ...	Bill Janssen	9/9/2004 2:53 ...
Lucene working example.	Mr dharmanand ...	9/9/2004 12:44...
Out of memory in lucene 1.4.1 when re-indexing ...	Daniel Taurat	9/9/2004 12:47...
Re: Out of memory in lucene 1.4.1 when re-ind...	Daniel Naber	9/9/2004 2:30 ...
Re: Out of memory in lucene 1.4.1 when re-i...	Daniel Taurat	7:10 AM

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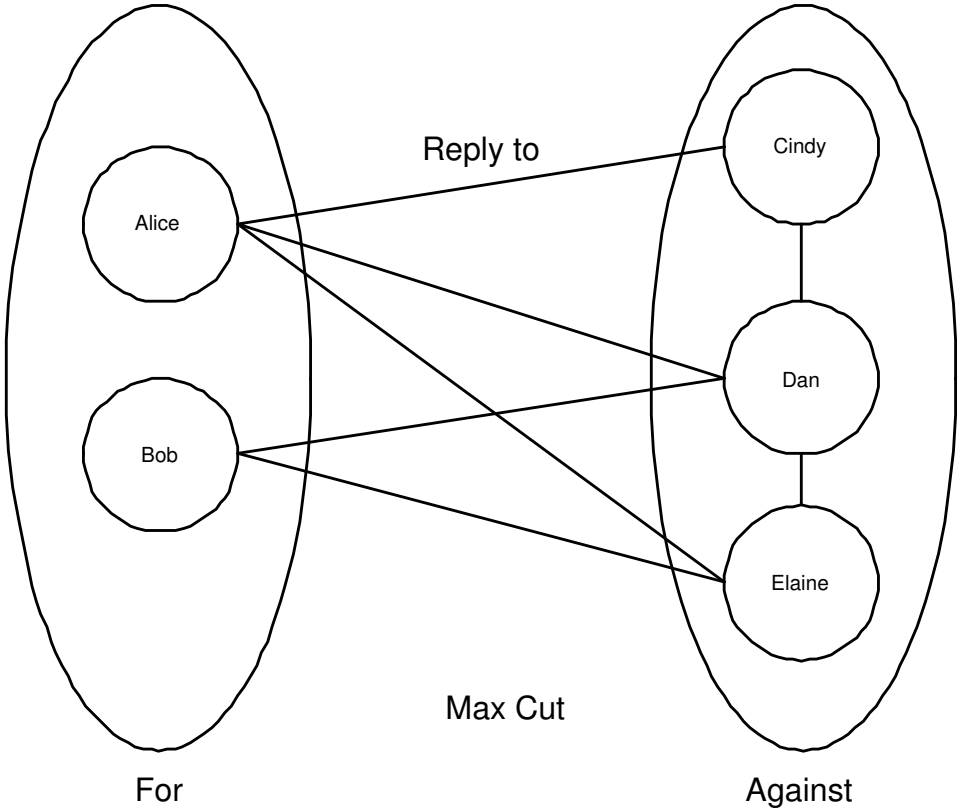
- Uses spectral partitioning for efficiency

Turning Social Behavior Into Graph Problem



Graph Partitioning Methods

1. EV Algorithm

   (a) Co-citation matrix $D = GG^T$ with weighted edge $w = \#$ of people "co-cited" by author u_1 and u_2. Think of D as a similarity matrix for author u_i and u_j.
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iii. Accept $k = N \times \frac{i}{m}$ labels where i = iteration, m = total iterations, and N = number of instances in test data

Evaluation

- Uses three newsgroups – Abortion, Gun Control, and Immigration
- Manually tag 50 random people in the "for" or "against" categories
- Comparing with classic classification algorithms (Naive Bayes & SVM) that work on message content

	Abortion	Gun Control	Immigration
Majority	57%	72%	54%
SVM	55%	42%	55%
Naive Bayes	50%	72%	54%
Iterative	67%	80%	83%
EV/EV+KL	73%/75%	78%/74%	50%/52%
Constrained EV/EV+KL	73%/73%	84%/82%	88%/88%

- Also, sensitivity experiments show more posts = more bias posts = higher accuracy

Contributions / Limitations

- Contributions
  - Apply graph-theoretic algorithms to a new domain
  - Sensitivity analysis on simulated newsgroup data
- Limitations
  - Assume users post against each other, may not be true in some newsgroups (technical ones)
  - Constrained and iterative method still need training data
  - Should justify why the constrained methods perform much better than the unconstrained ones

Discussion Questions

- How does user partitioning help IR?
- In a complex web of discussions within a newsgroup, users may not belong to the same "for" or "against" group for all topics. How can this system be applied on such newsgroup?
- How is this system similar to the PageRank algorithm? Is there any other way to draw connection among the newsgroup postings?