Automatically Building Research Reading Lists

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Recommending Research Papers

Way too many papers to read — need to find the right ones so we can get on to research!

Many papers, many reviewers — who is most qualified to judge the work?

Working on a bibliography or reference list — who should have cited you?

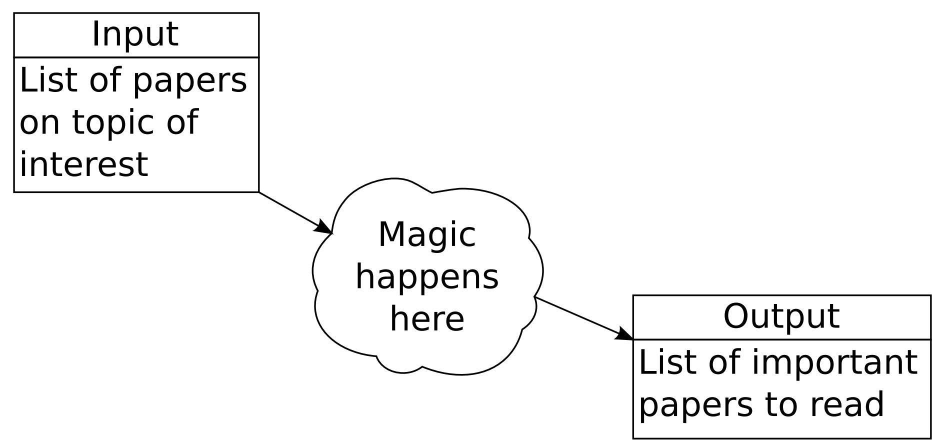
Building a Reading List

Alice is a new grad student who took a class on adaptive web technologies. The professor assigned some readings, and she wants to learn more.

- Herlocker et al. An algorithmic framework for performing collaborative filtering. In *Proc. SIGIR 1999*.
- Hoffman. Latent semantic models for collaborative filtering. In *TOIS*, volume 22, issue 1 (January 2004).
- Guy et al. Personalized recommendation of social software items based on social relations. In *Proc. RecSys 2009*.
- Karypis. Evaluation of Item-Based Top-N Recommendation Algorithms. In *Proc. CIKM 2001*.

How can we find important ones to read?

The *Reading List* Task



Domain Characteristics

Traditional CF methods are blind to item content or relationships.

The citation web has a defined structure.

Can we harness this to improve recommendation?

Questions

- Can we harness domain structure to improve recommendation of research papers?
- What algorithms perform well at building reading lists?
- How can we measure this performance?

Approach

Analyze Task and Domain → Design Candidate Algorithms → Prune Algorithm Pool (offline) → Evaluate Performance (user study)

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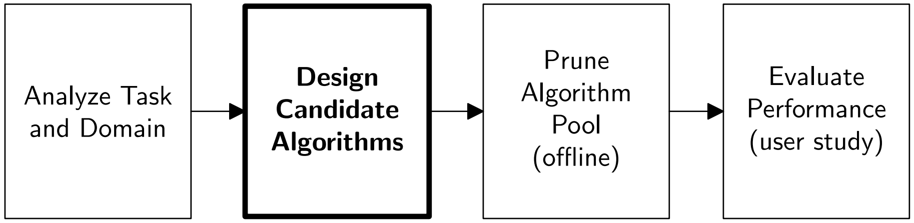
Designing Candidate Algorithms



Algorithms

We adapt and combine off-the-shelf algorithms.

Collaborative filtering (CF)
: Item-item CF over sets of items [Karypis, 2001]

Content-based filtering (CBF)
: Lemur toolkit [Ogilvie and Callan, 2002] in BM25 mode with recommended baseline parameters

Graph ranking

- PageRank [Page et al., 1999]
- HITS authority scores [Kleinberg, 1999]
- SALSA [Lempel and Moran, 2000]
- Relative algorithms [White and Smyth, 2003]
  - Biased HITS
  - k-step Markov importance

Applying Item-Item CF

No users - papers are both users and items [McNee et al., 2002].

	A	B	C
A	✓		✓
B	✓	✓	
C		✓	✓

Becomes a form of co-citation analysis.

Rank-Weighting CF

Inspired by [Karypis, 2001]: user influence in item similarity does not need to be the same!

Karypis's approach: normalize user purchase vectors to unit vectors so users with few purchases influence item similarity more.

Our adaptation: weight citation vectors by graph rank. Highly-ranked papers have more influence.

$$\hat{\mathbf{a}} = r(a)\mathbf{a}$$

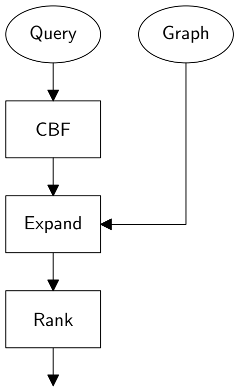
Use weighted citation vectors to compute cited paper similarity.

Using Weights with CBF

Two approaches

Subgraph ranking

Build subgraph from CBF results and rank its nodes.

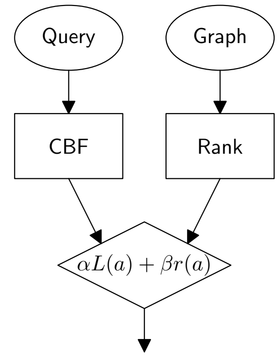


Using Weights with CBF

Two approaches

Linear blending

Blend CBF scores with node weights in the global graph.



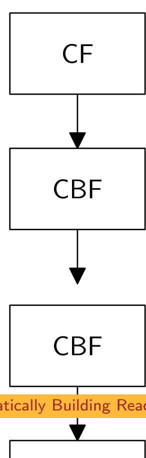
Learned coefficients with multivariate logistic regression (more on this later).

Hybridizing Recommenders [Burke, 2002]

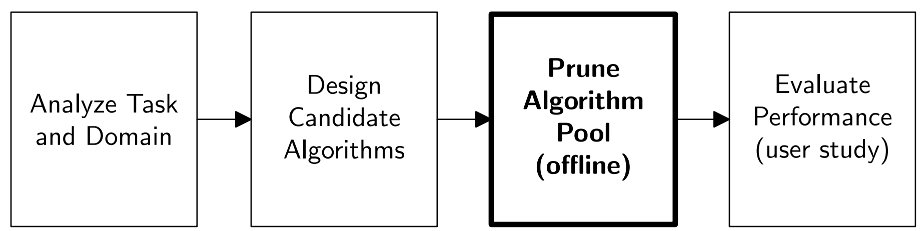
Several ways of blending algorithms

- **Use CF as input to CBF**
- **Use CBF as input to CF**
- **Blend output from CBF and CF to produce result**

Basic algorithms + all hybrids = **177 algorithms**.



Pruning the Algorithm Pool



Designing an Evaluation Strategy

Goal: Measure algorithm performance at supporting a specific task.

Accuracy isn't enough [McNee et al., 2006].

Offline Evaluation

Use metadata from ACM Digital Library.

Simulate introductory reading list with hold-out test on articles in *ACM Computing Surveys*.

- Hold out 5 items from each citation list
- Attempt to recommend back the 5 items
- Skip surveys with less than 15 resolved citations

Result: 220 survey articles for training and testing.

Interlude - Learning CBF Blending Coefficients

Use half the articles to train the CBF blend.

Learned multivariate logistic regression with response of 1 for articles in the holdout set, 0 for other articles.

$$s(a) = \alpha L(a) + \beta r(a)$$

Since we're ranking, intercept and log don't matter.

Offline Evaluation (cont)

Measure using half-life utility metric [Breese et al., 1998]:

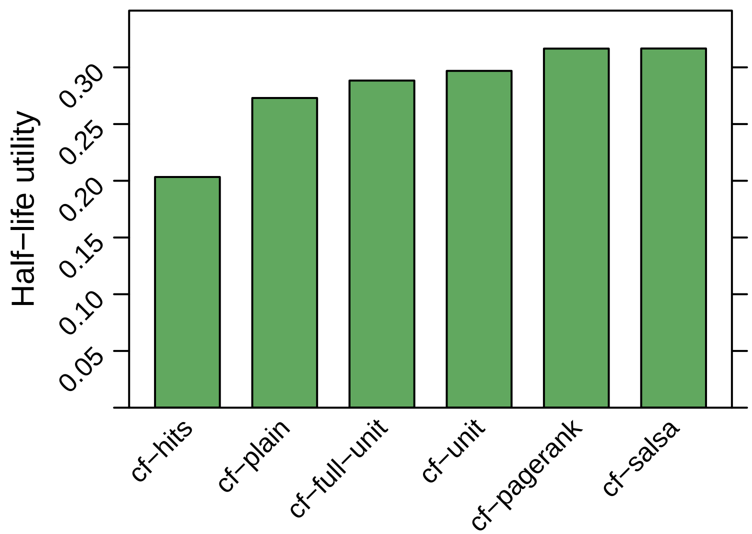
$$R_a = \sum_i \frac{u_{a,i}}{2^{(i-1)/(\alpha-1)}}$$

- $\alpha = 5$, the length of our reading lists
- $u_{a,i} = 1$ if article i is cited by survey a, 0 otherwise

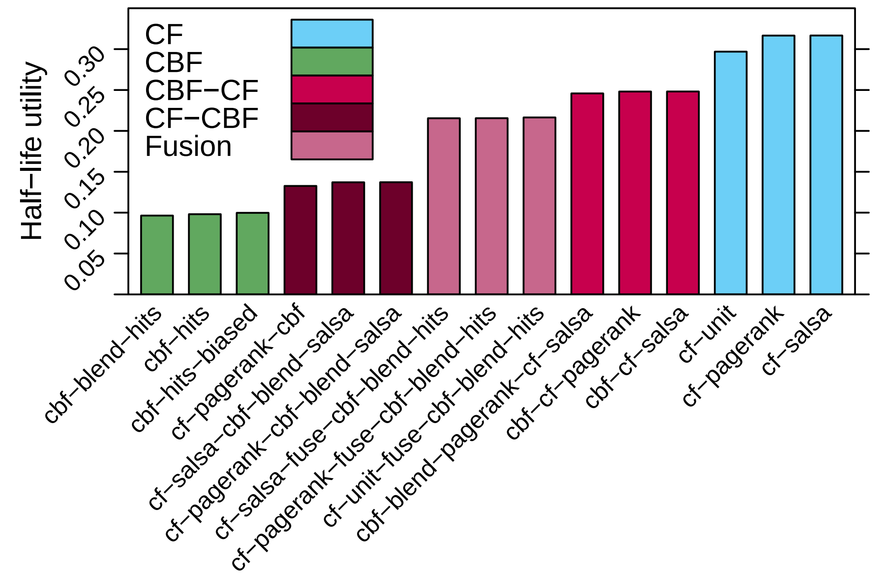
Aggregate to compute *fraction of potential utility achieved* (in range $[0, 1]$).

$$R = \frac{1}{nR_a^{\max}} \sum_a R_a$$

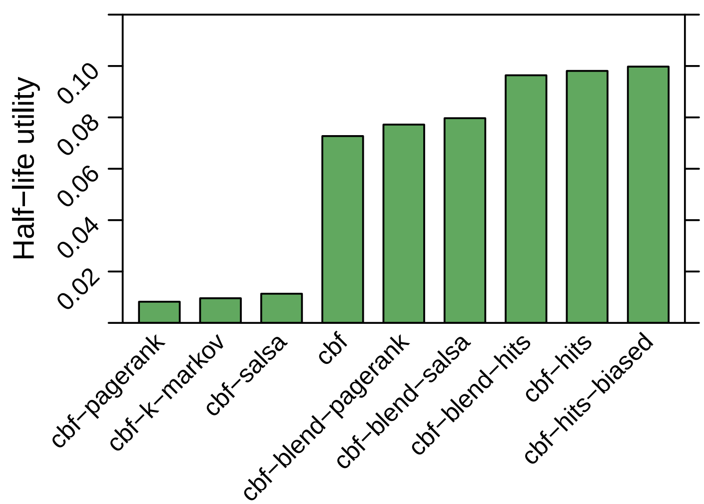
Offline Results — CF



Offline Results



Offline Results — CBF



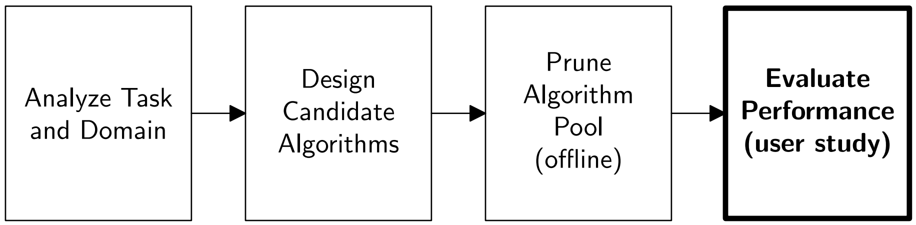
Salsa performs like PageRank

Selected Algorithms

Chose 3 algorithms that performed well but have differing structures.

- CBF with Biased HITS in subgraph ranking configuration
- CBF fed into PageRank-weighted CF
- PageRank-weighted CF

Evaluating Performance

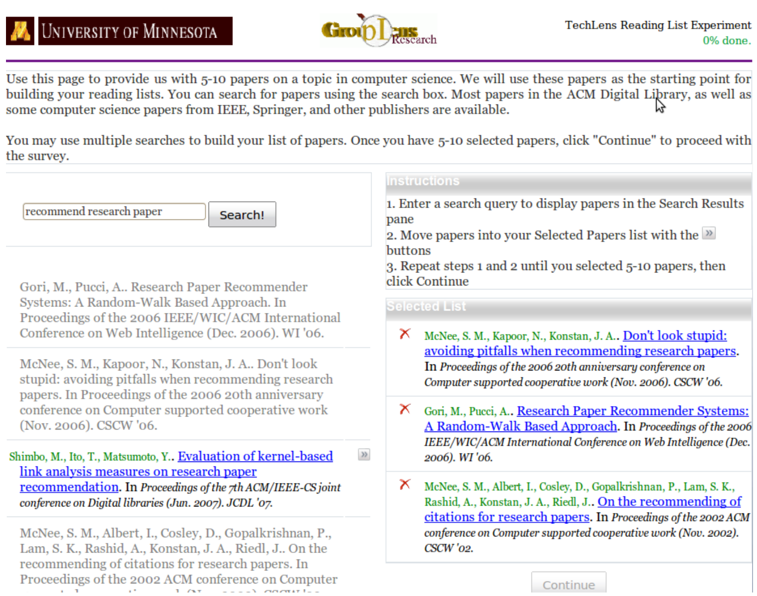


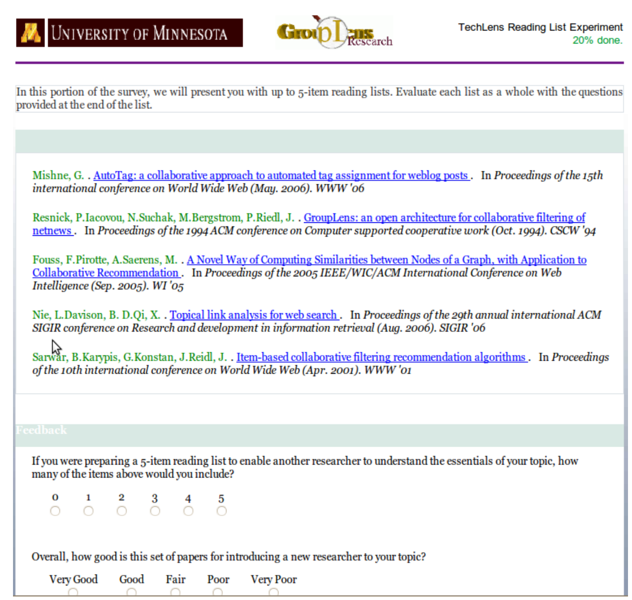
User-Based Evaluation

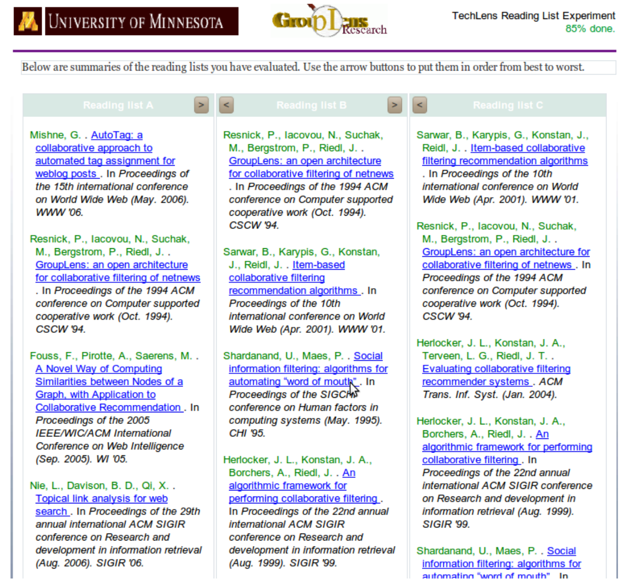
Asked graduate students to provide query sets of 5-10 papers and evaluate 3 5-item reading lists.

- Relevance of individual papers
- Importance of individual papers
- Quality of reading list as a whole
- Relative ranking of reading lists

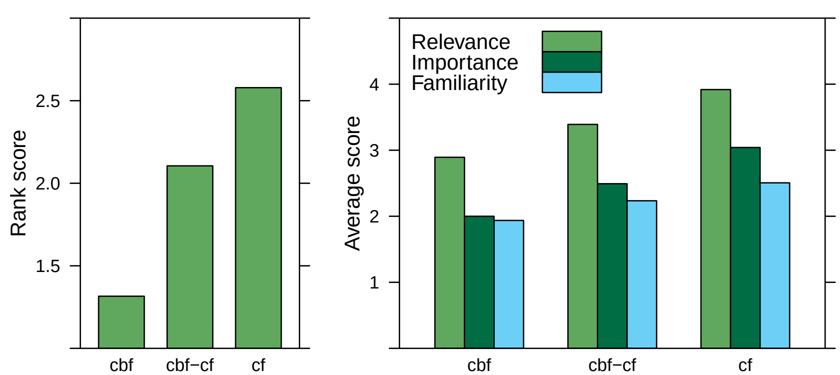
All questions were set in the context of introducing a new researcher to the topic.







User-Based Results



CF performed the best (surprisingly)

Input Query (again)

- Herlocker et al. An algorithmic framework for performing collaborative filtering. In *Proc. SIGIR 1999*.
- Hoffman. Latent semantic models for collaborative filtering. In *TOIS*, volume 22, issue 1 (January 2004).
- Guy et al. Personalized recommendation of social software items based on social relations. In *Proc. RecSys 2009*.
- Karypis. Evaluation of Item-Based Top-N Recommendation Algorithms. In *Proc. CIKM 2001*.

How do we do?

CF's Recommender Systems Recommendations

- Sarwar et al. Item-based collaborative fitlering recommendation algorithms. In *Proc. WWW 2001*.
- Resnick et al. GroupLens: An open architecture for collaborative filtering of netnews. In *Proc. CSCW 1994*.
- Shardanand and Maes. Social information filtering: algorithms for automating "word of mouth". In *Proc. CHI 1995*.
- Deshpande and Karypis. Item-based top-N recommendation algorithms. In *TOIS*, volume 22, issue 1 (January 2004).
- Herlocker et al. Evaluating collaborative filtering recommender systems. In *TOIS*, volume 22, issue 1 (January 2004).

Task-Driven Design and Evaluation

Design recommenders to support human information needs, not just improve prediction error [McNee et al., 2006].

Task and context inform design of both recommenders and evaluation strategies.

Opportunity to harness unique characteristics (or "personalities") of specific algorithms.

Conclusion

Contributions

- Design and evaluation of recommenders for reading lists
- Method for biasing CF with authority metrics
- CF works well for reading lists (surprising)

Open Questions

- How to tell user that they have an important paper?
- How to more accurately operate within topic scope?
- Is SALSA misused?

Questions?

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