COEN 169

Recommendation Systems III

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K Nearest Neighborhood

User-based Collaborative Filtering

"Similar users rate similarly!"

Item-based Collaborative Filtering

"Similar items are rated similarly!"

Centering your data

- Some users have orders of magnitude more ratings than others
- Estimates based on fewer data points tend to be noisier

$$\mathbf{R} = \begin{array}{lccccccc} & A & B & C & D & E & F & \text{User mean} \\ \textit{Alice} & 2 & 5 & 5 & 4 & 3 & 5 & 4 \\ \textit{Bob} & 2 & ? & ? & ? & ? & ? & 2 \\ \textit{Craig} & 3 & 3 & 4 & 3 & ? & 4 & 3.4 \end{array}$$

Hard to trust mean based on one rating

Smoothing may help!

- Linear smoothing

$$\tilde{r}_u = \alpha \cdot r_u + (1 - \alpha) \cdot g$$

where g is the global mean of ratings

- Problem: α is fixed and not depend on the number of u's ratings
- Dirichlet smoothing?

$$\tilde{r}_u = \frac{n_u}{\beta + n_u} \cdot r_u + \frac{\beta}{\beta + n_u} \cdot g$$

where n_u is the number of u's ratings

Previous example

For global mean *g*=3.5 and $\beta = 1$

	A	*B*	*C*	*D*	*E*	*F*	User mean	Shrunk mean
Alice	2	5	5	4	3	5	4	3.94
Bob	2	?	?	?	?	?	2	2.79
Craig	3	3	4	3	?	4	3.4	3.43

The $1 Million Question

Ratings Data

17,700 movies

480,000 users

1	3	4			
	3	5			5
		4	5		5
		3			
		3			
2			2		2
				5	
	2	1			1
	3			3	
1					

Training Data

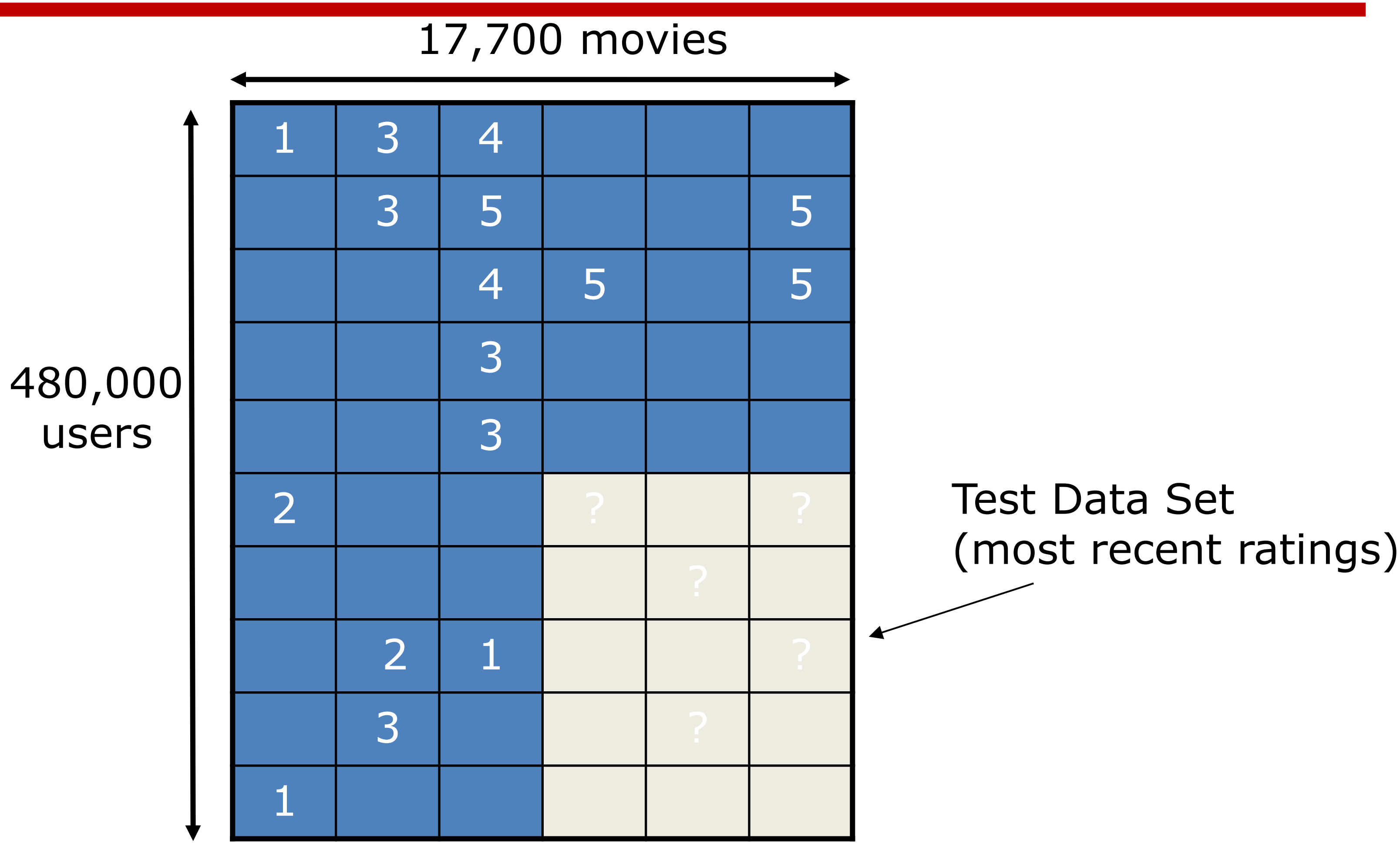
100 million ratings (matrix is 99% sparse)

Rating = [user, movie-id, time-stamp, rating value]

Generated by users between Oct 1998 and Dec 2005

Users were randomly chosen

Ratings Data



Structure of Competition

- Register to enter at Netflix site
- Download training data of 100 million ratings
  - 480k users x 17.7k movies
  - Anonymized
- Submit predictions for 3 million ratings in "test set"
  - True ratings are known only to Netflix
- Can submit multiple times (limit of once/day)
- Prize
  - $1 million dollars if error is 10% lower than Netflix current system
  - Annual progress prize of $50,000 to leading team each year

Scoring

- Minimize root mean square error (RMSE)
- Does not necessarily correlate well with user satisfaction
- But is a widely-used well-understood quantitative measure

RMSE Baseline Scores on Test Data

1.054 - just use the mean user rating for each movie

0.953 - Netflix's own system (Cinematch) as of 2006

0.941 - *k* nearest-neighbor method using Pearson correlation

0.857 - required 10% reduction to win $1 million

Other Aspects of Rules

- Rights
  - Software + non-exclusive license to Netflix
  - Algorithm description to be posted publicly

- Competition not open to entrants in North Korea, Iran, Libya, Cuba….and Quebec of Canada

First Progress Prize, October 2007

Progress prize: $50k annually awarded to leading team provided there is at least 1% improvement over previous year

Oct 2^{nd}	Leaders were BellKor, 8.4% improvement (Yehuda Koren, Bob Bell, Chris Volinksy, AT&T Research)
Oct/Nov	Code and documentation submitted for judging Complicated methods: primarily relying on factor models
Nov 13	Winners officially declared and BellKor documentation published on Netflix Web site

Progress in 2008…

Progress slows down…improvements are incremental

Many of the leading prize contenders publishing their methods and techniques at academic conferences

Much speculation on whether the prize would ever be won – is 10% even attainable?

Many initial participants had dropped out – too much time and effort to seriously compete

But leaderboard and forum still very active

Progress Prize 2008

Oct 2nd   Leading team has 9.4% overall improvement

Oct/Nov   Code/documentation reviewed and judged

Progress prize ($50,000) awarded to BellKor team of 3 AT&T researchers (same as before) plus 2 Austrian graduate students

Key winning strategy: clever "blending" of predictions from models used by both teams

Speculation that 10% would be attained by mid-2009

The End Game

NETFLIX

Netflix Prize

COMPLETED

Home | Rules | Leaderboard | Update | Download

Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace_	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59
11	Opera Solutions	0.8623	9.47	2009-07-24 00:34:07
12	BellKor	0.8624	9.46	2009-07-26 17:19:11
Progress Prize 2008 - RMSE = 0.8627 - Winning Team: BellKor in BigChaos				
13	xiangliang	0.8642	9.27	2009-07-15 14:53:22
14	Gravity	0.8643	9.26	2009-04-22 18:31:32
15	Ces	0.8651	9.18	2009-06-21 19:24:53
16	Invisible Ideas	0.8653	9.15	2009-07-15 15:53:04
17	Just a guy in a garage	0.8662	9.06	2009-05-24 10:02:54
18	J Dennis Su	0.8666	9.02	2009-03-07 17:16:17
19	Craig Carmichael	0.8666	9.02	2009-07-25 16:00:54
20	acmehill	0.8668	9.00	2009-03-21 16:20:50
Progress Prize 2007 - RMSE = 0.8723 - Winning Team: KorBell				

NETFLIX

Netflix Prize

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Million Dollars Awarded Sept 21st 2009

Lessons Learned

Combining results from various methods works surprisingly well!

Why combine models?

- Diversity in Decision Making

- Utility of combining diverse, independent outcomes in human decision-making
  - Expert panels
  - Protective Mechanism
    (e.g. stock portfolio diversity)

Recommendations in industry

- “60 percent of Netflix views are a result of Netflix's personalized recommendations”

- “35 percent of Amazon product sales result from recommendations”

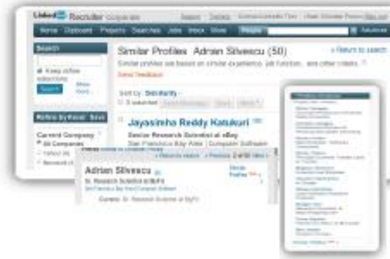
Recommendation Products at LinkedIn

Jobs You May Be Interested In

Talent Match

CAP

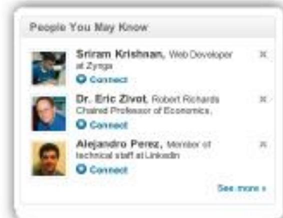
Similar Profiles



Related search

Profile browse maps

Connections



Companies

Recommendations, similar companies search, peer companies, and company browse maps, company products and services browse maps

Network updates

Jobs browse maps

Events You May Be Interested In

Ad matching engine

pCTR = f(member, creative, advertiser, context, inventory, OCTR)

Groups

Recommendations, similar groups search

Similar jobs

Referral Engine

News

Recommendations at LinkedIn

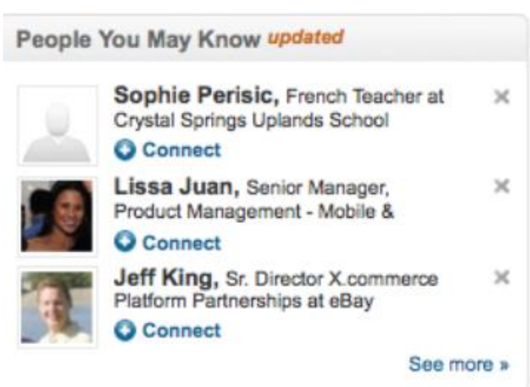
More than 50%

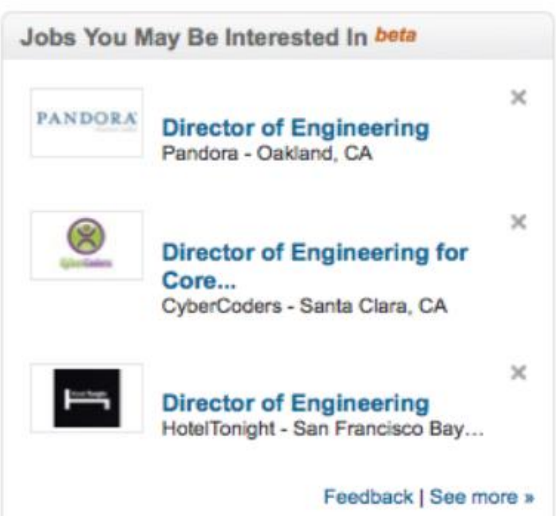
Recommendations drive:

> 50% of connections

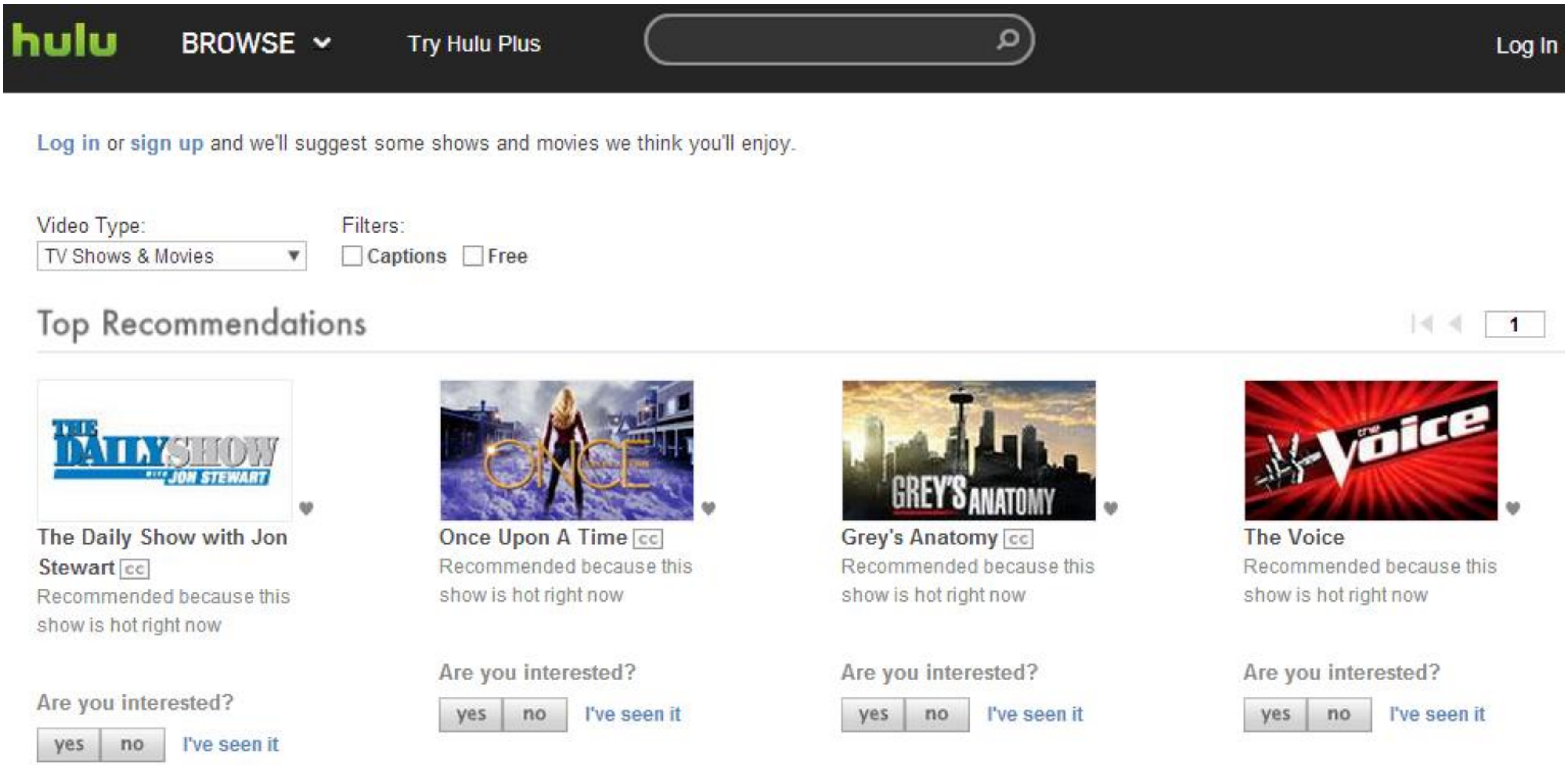
> 50% of job applications

> 50% of group joins





Recommendations at Hulu



Recommendations at Hulu

hulu TV Movies Try Hulu Plus for Free ▸

Hulu Tech Blog

Hulu's Recommendation System

September 19th, 2011 by **Liang Xiang**

As the Internet gets more and more popular, information overload poses an important challenge for a lot of online services. With all of the information pouring out from the web, users can be overwhelmed and confused as to what, exactly, they should be paying attention.

A recommendation system provides a solution when a lot of useful content becomes too much of a good thing. A recommendation engine can help users discover information of interest by analyzing historical behaviors. More and more online companies — including Netflix, Google, Facebook, and many others — are integrating a recommendation system into their services to help users discover and select information that may be of particular interest to them.

Item-based Collaborative Filtering

http://tech.hulu.com/blog/2011/09/19/recommendation-system/

Recommendations at YouTube

Item-based Collaborative Filtering

"The YouTube Video Recommendation System" ACM RecSys 2010.

Recommendations at Digg

"Whenever you Digg a story, the recommendation engine records two things about the action. First, that you liked that story, and second, every user that Dugg the story before you (this includes the submitter). This signals to the recommendation engine that these users like the same content as you, and sometimes they find it before you, so it uses those parameters to recommend to you stories they Digg or submit."

User-based Collaborative Filtering!

http://searchengineland.com/a-comprehensive-look-at-diggs-recommendation-engine-14470

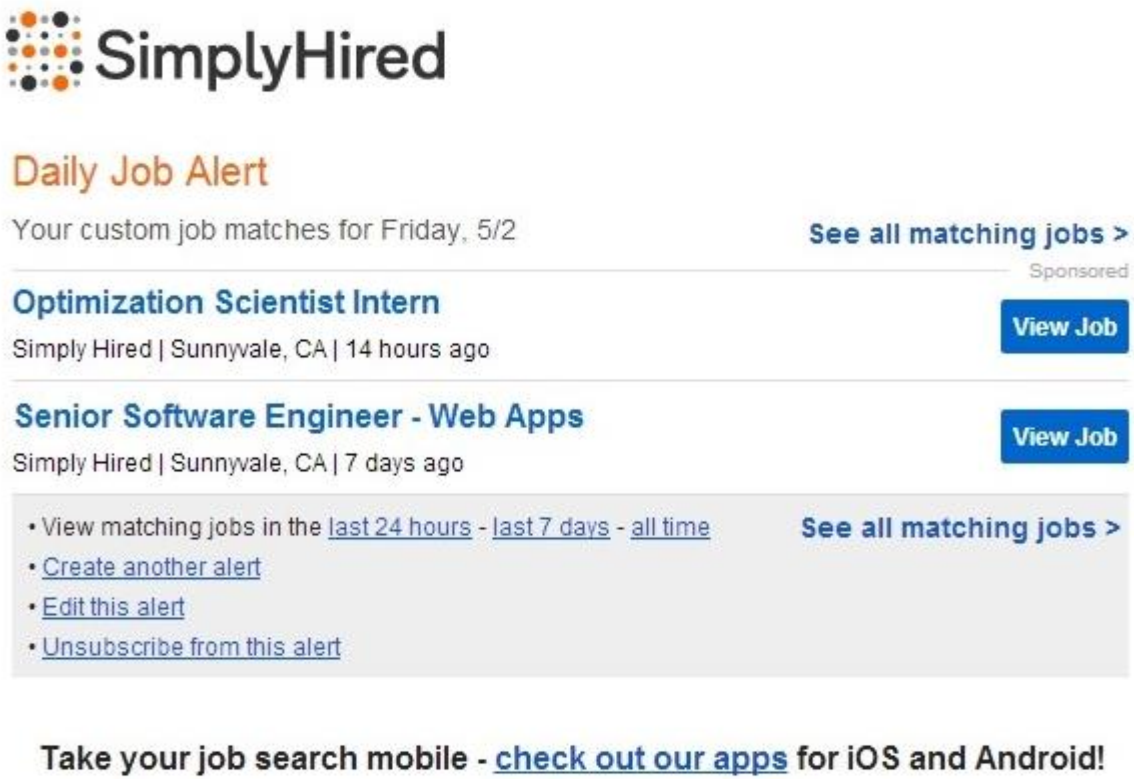
Gift recommendation in *Walmart*

- "Anatomy of a gift recommendation engine powered by social media" SIGMOD 2012
- Exploit social media such as Facebook

  - Infer the interests of the user as well as their friends (e.g., yoga, music, comics)

  - find occasions for gift recommendation (e.g., birthday, wedding anniversary, etc)
- Gifts should be *surprising*!

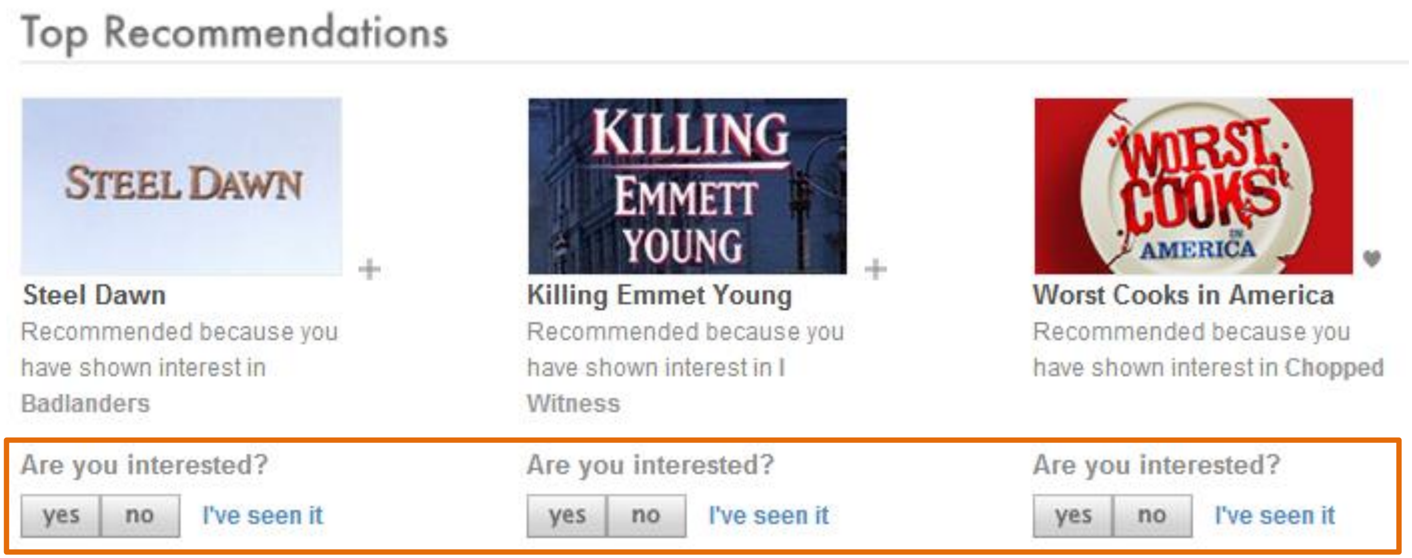
Personalized Job Recommendation



Future Directions

User Satisfaction

- Subjective metric ≠ RMSE
- Measured by user survey or online experiments



Diversity

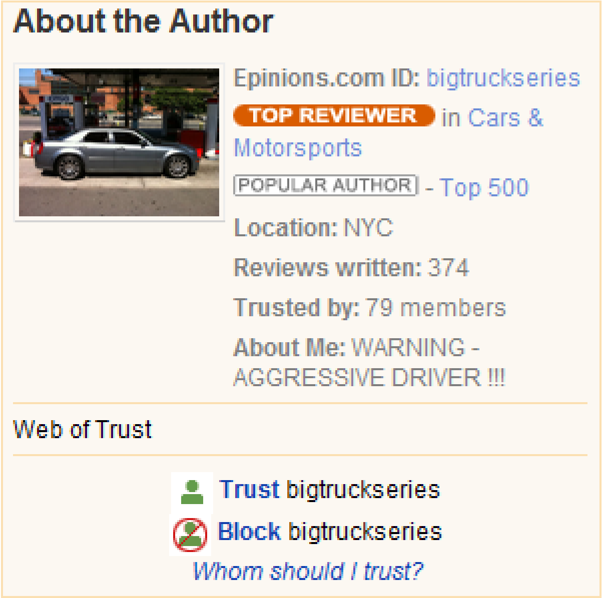
- Measure the ability of recommender system to cover users' different interests
- Recommendation results should not come from single reason
- Improving recommendation lists through topic diversification

Serendipity

- A recommendation result is serendipity if:
  - don’t have strong relation with user’s historical interest, or user do not expect we can recommend it.
  - novelty to user
  - user will find it’s interesting after user views it

Trust

- If user trust recommender system, they will interact with it.
- Ways to improve trust:
  - Transparency
    - Explanation
  - Social
  - Trust System (Epinion)



Robust

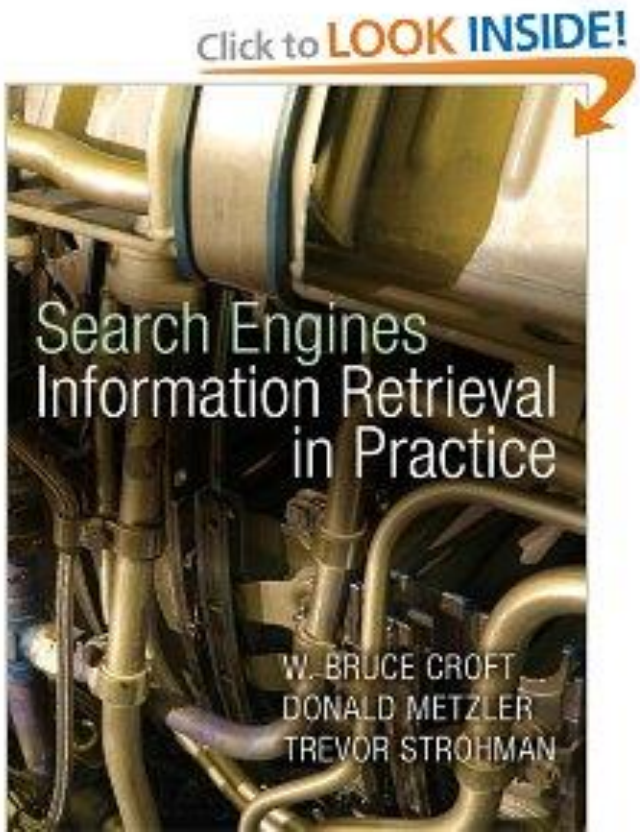
- The ability of recommender system to prevent attack
- Neil Hurley. [Tutorial on Robustness of Recommender System](). ACM RecSys 2011.

Data

- User behaviors data

Behavior	User	Size
Page view	All user	Very Large
Watch video	All user	Large
Favorite	Register user	Middle
Vote	Register user	Middle
Add to playlist	Register user	Small
Facebook like	Register user	Small
Share	Register user	Small
Review	Register user	Small

Book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Search Engines
Information Retrieval
in Practice
W. BRUCE CROFT
DONALD METZLER
TREVOR STROHMAN

Premier Conferences

ACM Conferences

- RecSys (Recommender System): 2007-
- SIGIR: 1971-
- CIKM: 1992-
- WWW: 1994-
- WSDM (Web Search and Data Mining): 2008-

Excellent resources to keep up with the state-of-the-art