Introduction to the Social Web

Recommendation and Mining

Sihem Amer-Yahia

updated by Vincent Leroy

Sihem Amer-Yahia

- Ph.D. in CS, 1999, Univ. of Paris-Orsay & INRIA, France
- Research Scientist, at&t labs: 1999-2006
- Senior Research Scientist, Yahoo! Research: 2006-2011
  – Member of the jury of a young PhD student, *Vincent Leroy*
- Principal Research Scientist, QCRI: 2011-12
- Since Dec 2011: DR1 CNRS@LIG
  – Big Data Management and Query Processing for Search and Recommendation and their application to Social Computing, Large-scale information exploration algorithms
  – Head of the SLIDE team (ScaLable Information Discovery and Exploitation) at LIG (among which …)

Social Content Sites

- **Web destinations that let users:**
  - Consume and produce content
    - Videos / photos / articles /…
    - tags / ratings / reviews /…
  - Engage in social activities with
    - friends / family / colleagues / acquaintances /…
    - people with similar interests / located in the same area /…
- **Two major driving factors:**
  - Social activities improve the attractiveness of traditional content sites
    - the "similar traveler" feature improves user engagement
  - Content is critical to the value of social networking sites
    - a significant amount of user time is spent browsing other people's photos, posts, etc.

Social Content Sites

- **Users engage the system**
  - Contribute content
  - Disclose information about themselves
  - Need help navigating the ever-growing cyber-city maze
- **Ultimate goal**
  - Personalize search and information discovery
  - Predict what a user's interests will be in the future
  - Understand user behavior
- **Many social content sites, collaborative tagging sites are one particular kind**
  - *Flickr*, *YouTube*, *Delicious*, photo tagging in *Facebook*

Recommendation Outline

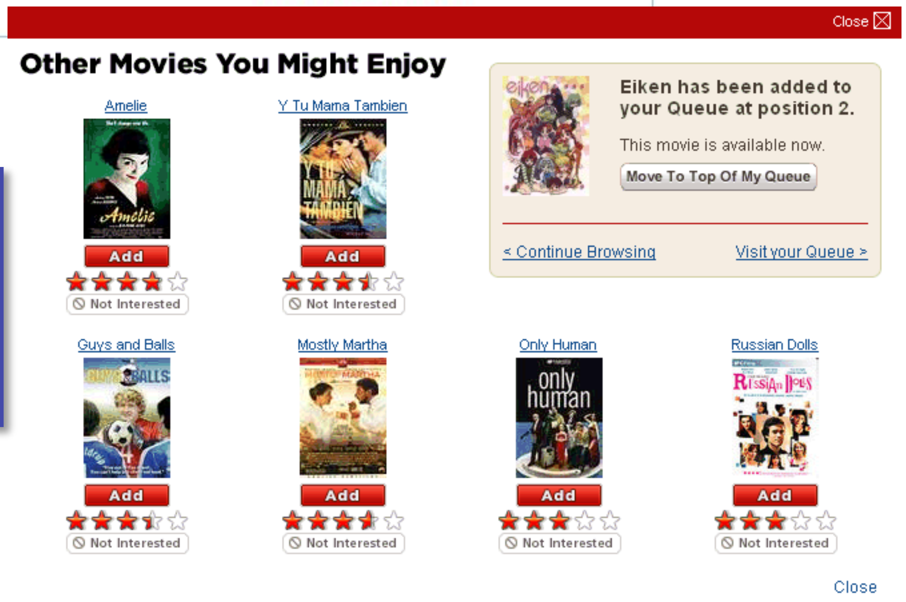
- Recommender Systems
  - **What are recommender systems** and how do they work?
  - Example application: Hotlist Recommendation on Delicious
  - How are recommender systems evaluated?

- Recommendation challenges
  - Well-known challenges
  - Recommendation diversity
  - Group recommendation

Recommender Systems

All are social content sites that thrive on User Generated Content (UGC)!

Recommender System



- *Predict ratings for unrated items*
- *Recommend top-k items*

Motivation

- Amazon makes 20-30% of its sales from recommendations. Only 16% of people go to Amazon with explicit intent to buy something
- Collected data matters more than the algorithm.
  - Amazon's algorithm is essentially a large product-product correlation matrix for the past hour, but it works for them because they collect so much data through user actions
- A lot of types of data can be used: votes, ratings, clicks, page-view time, purchases, tagging…

Academia: An Overview

- **Early days: 3 papers by HCI researchers (1995)**
- **Today: over 1000 papers**
  - ACM RecSys09
    - 203 submissions, thereof 140 long and 63 short papers
    - acceptance rate for long papers of 17% and of 34% overall
  - Fields: CS/IS, marketing, DM/statistics, MS/OR
- **Netflix $1M Prize Competition**
  - Data: ≈18K movies, ≈500K customers, 100M ratings
  - $1M Prize: improve Netflix RMSE rates by 10%
  - ≈ 40K contestants from 179 countries
  - Winners in June 2009: a coalition of four: BellKor's Pragmatic Chaos with statisticians, machine learning experts and computer engineers from America, Austria, Canada and Israel — declared that it had produced a program that improves the accuracy of the predictions by 10.05 percent.

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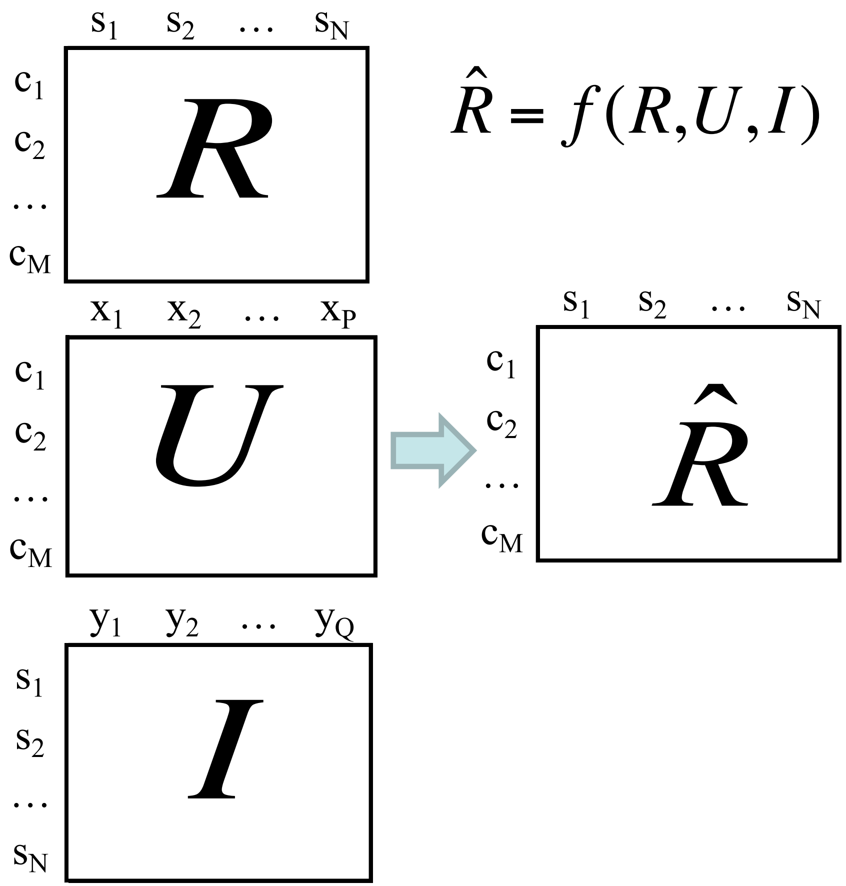
Recommendation Model

- **Input**
  - Rating matrix *R:* r_{ij} – rating user c_i assigns to item s_j (*explicit* Vincent rates Westworld 5/5, or *implicit* Vincent listened to Explosions in the sky 659 times)
  - User attribute matrix *U:* x_{ij} – *attribute* x_j *of user* c_i (e.g. demographic attributes)
  - Item attribute matrix *I:* y_{ij} – *attribute* y_j *of item* s_i (e.g. product category, tags)
- **Output**
  - Predicted new matrix $\hat{R}$

$$\hat{R} = f(R, U, I)$$



Types of Recommendations

- **Content-based**
  - How similar is an item *i* to items *u* has liked in the past?
  - Uses metadata for measuring similarity
  - Works even when no ratings are available on items
  - Requires metadata!

- **Collaborative filtering**
  - Treat items and users as vectors of ratings, compute vector distance

Taxonomy of Traditional Recommendation Methods

- Recommendation approach [Balabanovic & Shoham 1997]
  - Content-based, collaborative filtering
- Nature of the prediction technique
  - Heuristic-based (uses matrix as is), model-based
- Support for rating/transaction data
  - Both, rating-only [R], transaction-only [T]

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		

Content-based, Heuristic-based

- Item similarity methods
  - Information Retrieval (IR) Techniques
  - Treat each item as a document
  - Item similarity computed as document similarity

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		

Similarity Measures

- Use attributes of items to build an item profile
- User profile v_i of user c_i constructed by aggregating profiles of items c_i has experienced
- Ex:
  - Justin Bieber (Pop 723, R&B 428, Canada 109)
  - Selena Gomez (Pop 341, Female Vocalist 156)

  → Similarity = 0.77

$$\hat{r}_{ij} = score(\mathbf{v}_i, \mathbf{y}_j)$$

$$\hat{r}_{ij} = \cos(\mathbf{v}_i, \mathbf{y}_j) = \frac{\mathbf{v}_i \bullet \mathbf{y}_j}{\| \mathbf{v}_i \|_2 \cdot \| \mathbf{y}_j \|_2}$$

TF-IDF: relevance in Information Retrieval

- Some attributes are very frequent (e.g. *rock* or *pop* tags on music)
  - Not able to differentiate items accurately
- *Romantic ballads* is much less frequent
  - Sharing this tag is much more meaningful
- Term Frequency:
  - The more a term is present in a document the more meaningful it is for this document (equivalent to tag frequency for an item)
- Inverse Document Frequency:
  - The fewer documents contain this term, the more meaningful it is (equivalent to a tag only used on a few items is more meaningful than a tag used on all items)

Term Frequency

Variants of TF weight

weighting scheme	TF weight
binary	$0, 1$
raw frequency	$f_{t,d}$
log normalization	$1 + \log(f_{t,d})$
double normalization 0.5	$0.5 + 0.5 \cdot \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$
double normalization K	$K + (1 - K)\frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$

Inverse Document Frequency

Variants of IDF weight

weighting scheme	IDF weight ($n_t = \|\{d \in D : t \in d\}\|$)
unary	1
inverse document frequency	$\log \frac{N}{n_t}$
inverse document frequency smooth	$\log(1 + \frac{N}{n_t})$
inverse document frequency max	$\log\left(1 + \frac{\max_{\{t' \in d\}} n_{t'}}{n_t}\right)$
probabilistic inverse document frequency	$\log \frac{N - n_t}{n_t}$

Item Similarity based on IR

- Account for TF and IDF when building the vector of an item / user
- Item attributes are word occurrences in each document

$$y_{ij} = TF_{ij} \cdot IDF_j$$

- TF_{ij} – term frequency: frequency of word y_j occurring in the description of item s_i;
- IDF_j – inverse document frequency: inverse of the frequency of word y_j occurring in descriptions of all items

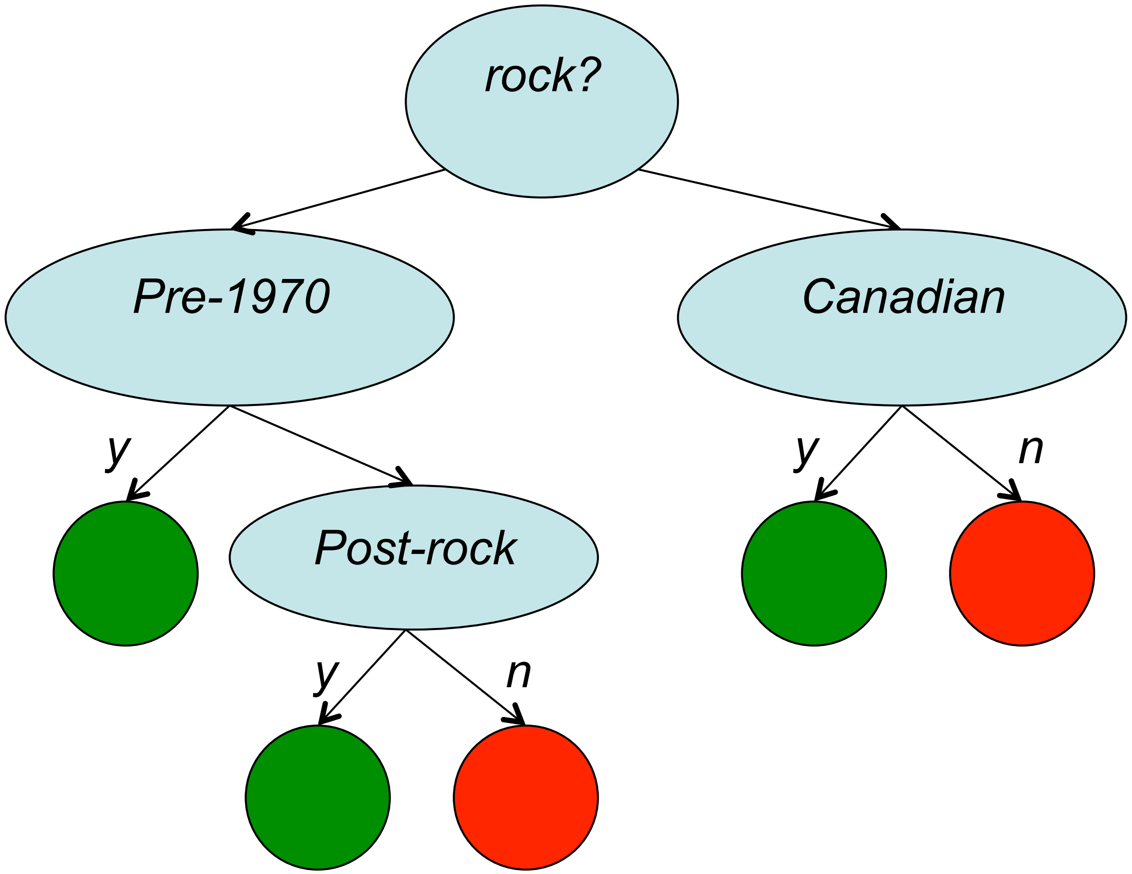
Content-based, Model-based

- Classification models [Pazzani & Billsus 1997; Mooney & Roy 1998]
- One-class Naïve Bayes classifier [Schwab et al. 2000]
- Latent-class generative models [Zhang et al. 2002]

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		

Tree-based classification model

- Train a classifier using attributes to predict 2 classes:
  - Liked
  - Disliked



Collaborative Filtering Algorithms

- Non-Personalized Summary Statistics
- K-Nearest Neighbor
- Dimensionality Reduction
- Content + Collaborative Filtering
- Graph Techniques
- Clustering
- Classifier Learning

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		
Hybrid		

Collaborative Filtering, Heuristic-based

- **Neighborhood methods**
  - User-based algorithm [Breese et al. 1998; Resnick et al. 1994; Sarwar et al. 1998]
  - Item-based algorithm [Deshpande & Karypis 2004; Linden et al. 2003; Sarwar et al. 2001]
  - Similarity fusion [Wang et al. 2006]
  - Weighted-majority [Delgado and Ishii 1999]
  - Matrix reduction methods (SVD, PCA processing) [Goldberg et al. 2001; Sarwar et al. 2000]
- **Association rule mining [Lin et al. 2002]**
- **Graph-based methods [Aggarwal et al. 1999; Huang et al. 2004, 2007]**

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		
Hybrid		

Collaborative Filtering, Heuristic-based (examples from Rajaraman and Ullman book)

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

Jaccard

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

Jaccard(A,B) = 1/5 < 2/4 = Jaccard(A,C)

Cosine

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

, where A_i and B_i are components of vector A and B respectively.

cos(A,B) = 0.380 > 0.322 = cos(A,C)

Normalizing ratings

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	2/3			5/3	-7/3		
B	1/3	1/3	-2/3				
C				-5/3	1/3	4/3	
D		0					0

Replace each rating with its difference with the mean (average) for that user
Low ratings become negative
High ratings are positive

Cosine: users with opposite views on common movies will have vectors in opposite directions and users with similar opinions about movies rated in common will have a small angle.

cos(A,B) = 0.092 > -0.559 = cos(A,C)

K Nearest Neighbors recommendation

- Using Ratings Matrix select *k* most similar users
- Aggregate their ratings to create a ranking of items
  - E.g. 3 users that love the same series as Jon love *Stranger Things*, and I haven't seen it → recommend *Stranger Things* to Jon

Collaborative Filtering, Model-based

- Matrix reduction methods [Takacs et al. 2008; Toscher et al. 2008]
- Latent-class generative model [Hofmann 2004; Kumar et al. 2001; Jin et al. 2006]
- User-profile generative model [Pennock et al. 2000; Yu et al. 2004]
- User-based classifiers [Billsus & Pazzani 1999; Pazzani & Billsus 1997]
- Item dependency (Bayesian) networks [Breese et al. 1998; Heckerman et al. 2000]

	Heuristic-based	Model-based
Content-based		
Collaborative filtering		
Hybrid		

Alternating Least Squares (ALS)

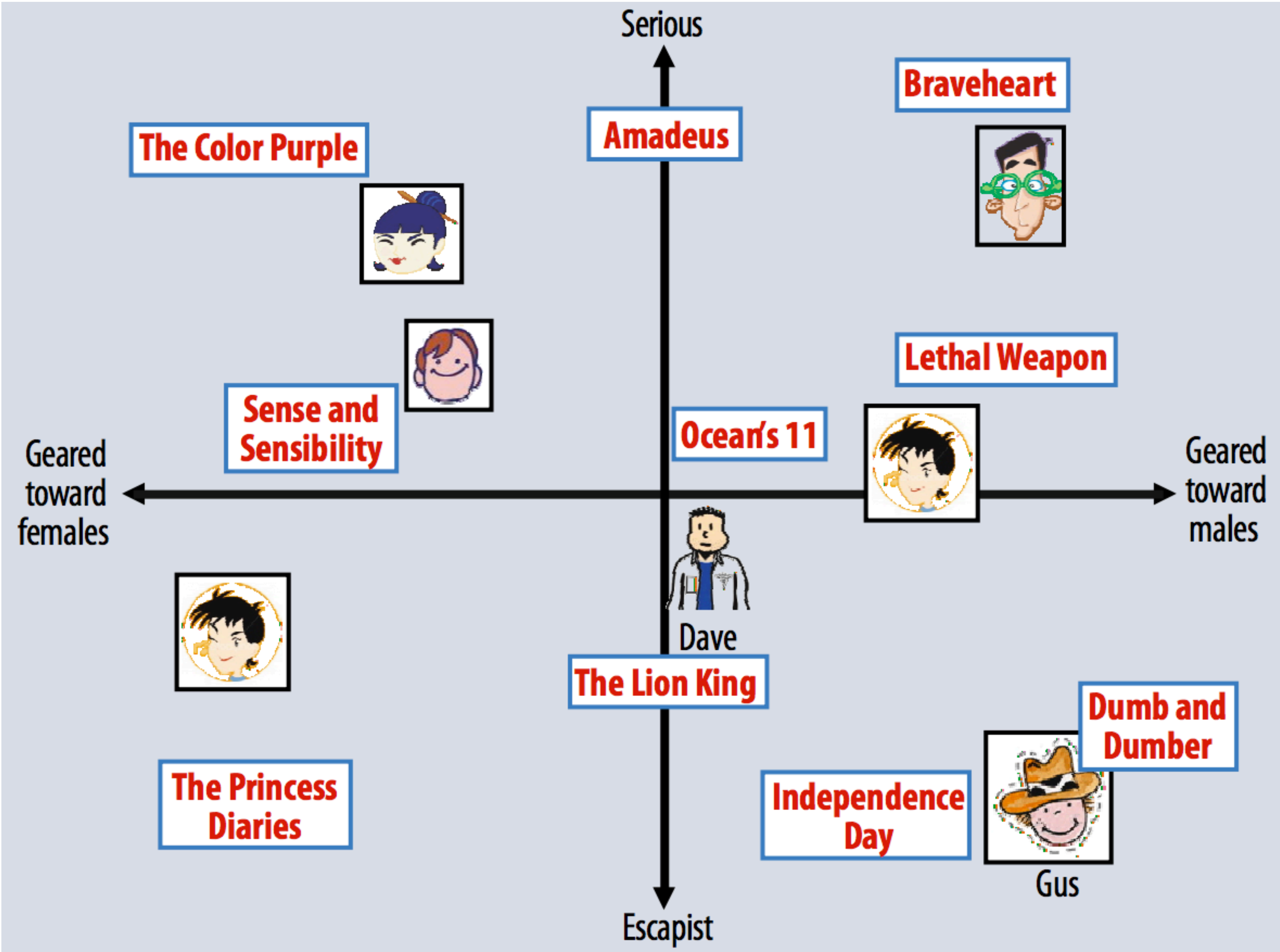
- The type of approach that won the Netflix prize!
- Matrix Factorization method
  - Represent users and items as vectors p_u and q_i
  - Prediction $\hat{r}_{ui} = q_i^T p_u$
- How do you learn these vectors?

$$\min_{q^*,p^*} \sum_{(u,i)\in\kappa} (r_{ui} - q_i^T p_u)^2 + \lambda(\| q_i \|^2 + \| p_u \|^2)$$

  - Minimize prediction error on known ratings (κ) while keeping the model simple (λ) to avoid *overfitting*
  - 2 parameters: number of dimensions of vectors (hidden features, called rank), and regularization parameter λ

Read more: https://goo.gl/6z09EG

ALS on 2 dimensions



Solving ALS

- Fix user vectors
  - Solve equation to find optimal items vectors
- Fix item vector
  - Solve equation to find optimal user vectors
- Execute until convergence (or for *x* iterations)
- There is a Spark implementation of this!
  - Mllib

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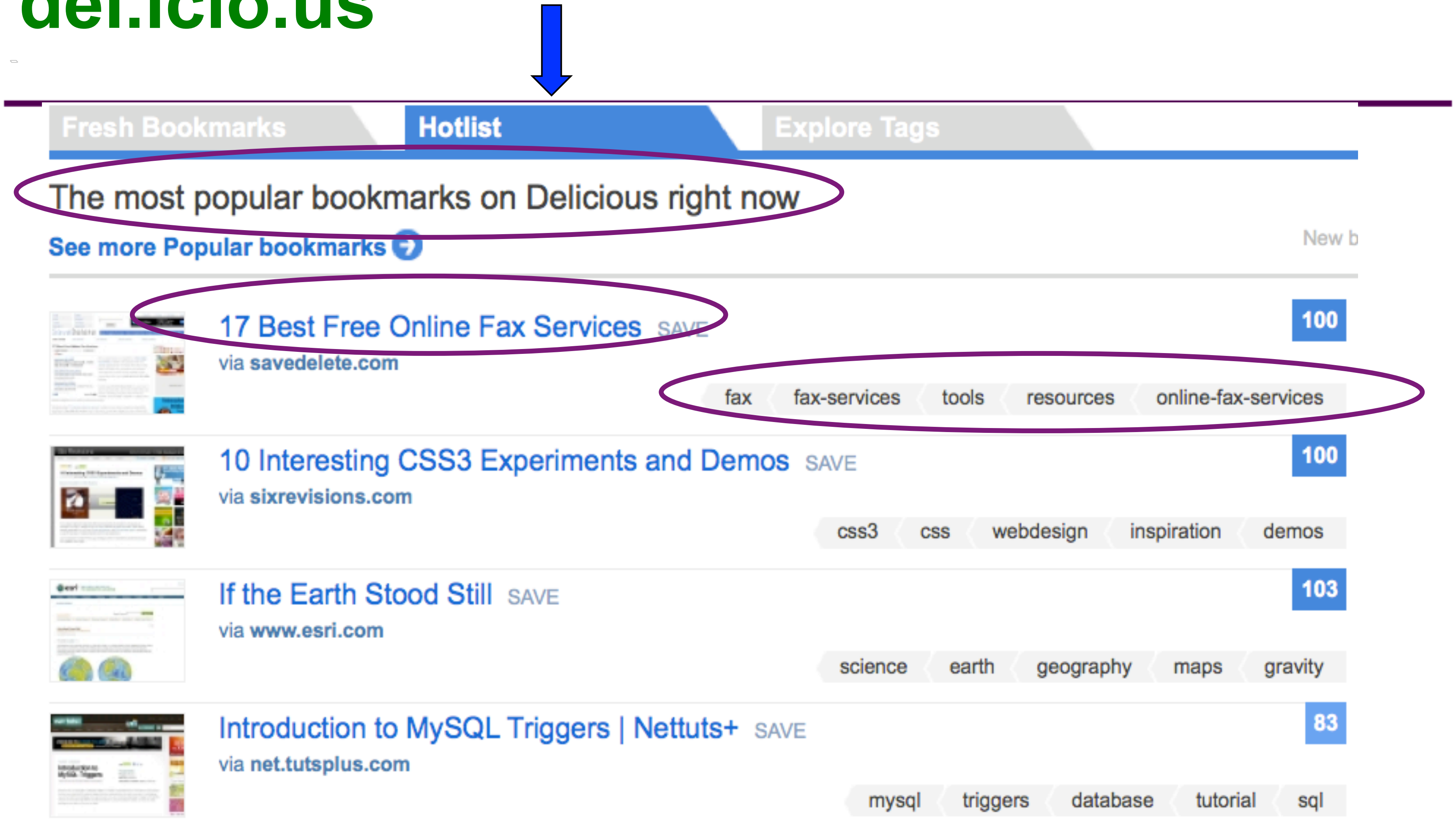
del.icio.us



Fresh Bookmarks
Hotlist
Explore Tags
The most popular bookmarks on Delicious right now
See more Popular bookmarks
New b
17 Best Free Online Fax Services SAVE
via savedelete.com
100
fax
fax-services
tools
resources
online-fax-services
10 Interesting CSS3 Experiments and Demos SAVE
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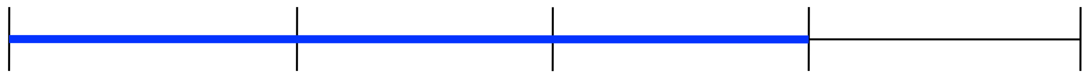
del.icio.us Hotlists Experiment

- **116,177 del.icio.us users**
  - who tagged 175,691 distinct URLs
  - using 903 tags
  - for a total of 2,322,458 tagging actions
  - for 1 month in 2006
- **Evaluate how networks predict user's interest**
  - *J. Stoyanovich, S. Amer-Yahia, C. Yu, C. Marlow: Leveraging Tagging Behavior to Model Users' Interest in del.icio.us (AAAI Workshop on Social Information Processing 2008)*



A/B testing: user behavior in first 3 weeks to predict 4th week

Data Model

- users $u \in U$, tags $t \in T$, items $i \in I$
- *friends(u)* directional

- *tags(u)*
- *items(u)* & *items(u,t)*

- *taggers(i)* & *taggers(i,t)*

Tagging data has a long tail

- we have to clean it for efficiency (relational processing)
- we removed unpopular tags (< 4 uses) & URLs (< 10 uses), reduced to 27% of original size

Global

10 URLs that are tagged most often over-all

Performance

coverage (**`global`**) = 3%

scope (**`global`**) = 100%

Global Top-10

Rank	***URL***	***Votes***
1	*google.com*	*980*
2	*facebook.com*	*820*
3	*iTunes.com*	*729*
4	*twitter.com*	*720*
5	*jonasbrothers.com*	*680*
6	*cnn.com*	*678*
7	*amazon.com*	*620*
8	*yahoo.com*	*525*
9	*youtube.com*	*524*
10	***techcrunch.com***	*492*

Items(Chris)

URL	***Tag***
jars.com	*java*
java.sun.com	*java*
techcrunch.com	*news*
devshed.com	*tutorial*

Items(Ben)

URL	***Tag***
bbc.co.uk	*news*
pbs.org	*news*
tomwaits.com	*music*
nick-cave.com	*music*
loureed.com	*music*

Tag-based

- **If a user tags with *sports*, he is interested in sports-related content**
  – interest(u,t) = |items(u,t)| / |items(u)|

Top-10 for "news"

Rank	*URL*	*Votes*
1	*cnn.com*	*610*
2	*bbc.co.uk*	*503*
3	*npr.org*	*427*
4	*nytimes.com*	*414*
5	*slashdot.org*	*392*
6	*reuters.com*	*330*
7	*news.cnet.com*	*290*
8	*msnbc.msn.com*	*250*
9	*news.yahoo.com*	*180*
10	*digg.com*	*149*

Top-10 for "music"

Rank	*URL*	*Votes*
1	*iTunes.com*	*542*
2	*eMusic.com*	*420*
3	*pandora.com*	*350*
4	*thebeatles.com*	*330*
5	*jonasbrothers.com*	*215*
6	*madonna.com*	*175*
7	*rhapsody.com*	*148*
8	*rollingstones.com*	*133*
9	*lastfm.com*	*120*
10	*beyonce.com*	*107*

Items(Ben)

URL	*Tag*
bbc.co.uk	*news*
pbs.org	*news*
tomwaits.com	*music*
nick-cave.com	*music*
rollingstones.com	*music*

Build one global hotlist per tag, use in one of two ways

- `best_tag`
  hotlist = top-10 for tag for which user has highest interest

- `dominant_tags`
  hotlist is a combination of up to 3 top-10 lists s.t. interest(u,t) $\geq$ 0.3 (user has *strong interest* for these tags)

Performance of Tag-based

`best_tag`

coverage = 9%

***scope* = 100%**

`dominant_tags`

1 tag	coverage = 10%	scope = 32%
2 tags	coverage = 14%	scope = 14%
3 tags	coverage = 18%	scope = 6%

Network-based

Choose 10 most popular URLs from those tagged by a user's friends.

coverage (`friends`) = 43%

scope (`friends`) = 31%

Common Interest Networks: URL-interest

Identify the seed -- a set of users who tag many of the same URLs as the user* u *("agree with* u*"). Hotlist = 10 most popular URLs tagged by users in seed.

$agr(u,f) = |items(u) \cap items(f)| \,/\, |items(u)|$
$U_{scope} = \{u \in U \mid \exists f \in U,\ agr(u, f) > threshold\}$
$U_{seed} = \{f \in U \mid agr(u, f) > threshold\}$

thresh = 0.3	coverage = 61%	scope = 1.2%
thresh = 0.5	coverage = 71%	scope = 0.7%

Common Interest Networks: Tag-URL-Interest

Agreement across the board is rare, let's look at agreement per-tag: may agree with adviser on research, but with mom on cooking.

agr (u,f,t)=|items(u,t) ∩ items(f,t)| / |items(u,t)|

U_{scope}, U_{scope} defined as for `url-interest`, combined as in `dominant-tags`.

scope (`tag-url-interest`) = 7%

Tag/Interest-based Methods: a Comparison

Users in the intersection of `dominant-tags`, `url-interest` and `tag-url-interest`, with a strong interest in 2 tags, all thresholds = 0.3

	$\lvert U_{scope} \rvert$	avg ($\lvert U_{seed} \rvert$)	coverage
`dominant-tags`	1235	26,856	17%
`tag-url-interest`	1235	227	82%
`url-interest`	205	203	85%

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Evaluation Approaches

- **Industry outcome**
  - Add-on sales
  - Click-through rates
- **In research**
  - Offline: To anticipate the above beforehand
    - No actual users are involved and an existing dataset is split into a test and a training set
    - Using the ratings in the training set, predict the ratings in the test set
    - Predicted ratings are compared with ratings in the test set using different measures
    - In K-fold cross validation (a common cross validation technique), the data set is partitioned into K equal-sized subsets: one is retained and used as the test set, the other subsets are used as training set. This process is repeated K times, each time with a different test set.
  - Online: User satisfaction

Evaluation Metrics

- Accuracy Metrics
  - measure how well a user's ratings can be reproduced by the recommender system, and also how well a user's ranked list is predicted
  - 3 kinds of accuracy metrics
    - Predictive
    - Classification
    - Rank
- Other metrics:
  - Coverage, Confidence, Diversity, Novelty and Serendipity

Predictive Metrics

- measure to what extent a recommender system can predict ratings of users.
- useful for systems that display the predicted ratings to their users.
- MAE = (|0|+|1|+|3|+|0|+|− 2| + |0| + |2|)/7 = 1.143

$$MAE = \frac{1}{|B_i|} \sum_{b_k \in B_i} |r_i(b_k) - p_i(b_k)|$$

Also RMSE (Root Mean Squared Errors) as discussed for ALS
→ Several small errors is better than one big errors

	Ranking		Rating	
Item	**User**	**RS**	**User**	**RS**
A	1	1	5	5
B	2	5	4	3
D	3	4	4	4
G	4	6	4	2
E	5	3	3	5
C	6	2	2	5
F	7	7	2	2

Classification Metrics

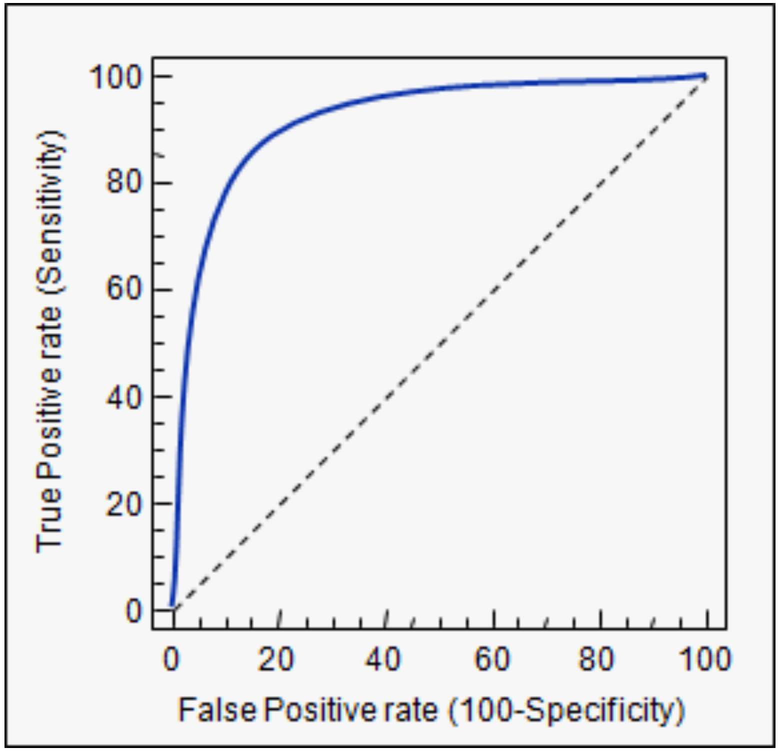
- measure to what extent a RS is able to correctly classify items as interesting or not.
- Ignores rating difference

		Predicted class	
		P	*N*
Actual Class	*P*	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

- *Precision: TP/(TP+FP)*
  - measures proportion of recommended items that are good
- *Recall: TP/(TP+FN)*
  - measures proportion of all good items recommended

ROC curve

- Combine Recall and Precision
- *Imagine a recommender that orders items from the most likely to the least likely*



Rank Metrics
DCG, nDCG for list comparison

- A measure of effectiveness of a web search engine algorithm or related applications
- DCG measures the usefulness, or *gain*, of a document based on its position in the result list
- Two assumptions are made in using DCG:
  - Highly relevant documents are more useful when appearing earlier in a search engine result list (have higher ranks)
  - Highly relevant documents are more useful than marginally relevant documents, which are in turn more useful than irrelevant documents.
- DCG originates from an earlier, more primitive, measure called Cumulative Gain.

Cumulative Gain: CG

It is the sum of the graded relevance values of all results in a search result list.

The CG at a particular rank position p is defined as:
where rel_i is the graded relevance of the result at position i.

$$\mathrm{CG_p} = \sum_{i=1}^{p} rel_i$$

CG Example

$$D_1, D_2, D_3, D_4, D_5, D_6$$

the user provides the following relevance scores:

$$3, 2, 3, 0, 1, 2$$

$$\mathrm{CG_p} = \sum_{i=1}^{p} rel_i = 3 + 2 + 3 + 0 + 1 + 2 = 11$$

does not account for document ordering.

Discounted Cumulative Gain: DCG

DCG is that highly relevant documents appearing lower in a search result list should be penalized as the graded relevance value is reduced logarithmically proportional to the position of the result.
The discounted CG accumulated at a particular rank position is defined as:

$$\mathrm{DCG_p} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i)}$$

No theoretical justification for using a logarithmic reduction factor other than it produces a smooth reduction.
An alternative formulation of DCG places stronger emphasis on retrieving relevant documents:

$$\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

DCG Example

$D_1, D_2, D_3, D_4, D_5, D_6$

the user provides the following relevance scores:

$3, 2, 3, 0, 1, 2$

i	rel_i	$\log_2 i$	$\frac{rel_i}{\log_2 i}$
1	3	0	N/A
2	2	1	2
3	3	1.585	1.892
4	0	2.0	0
5	1	2.322	0.431
6	2	2.584	0.774

So the DCG_6 of this ranking is:

$$\mathrm{DCG_6} = rel_1 + \sum_{i=2}^{6} \frac{rel_i}{\log_2 i} = 3 + (2 + 1.892 + 0 + 0.431 + 0.774) = 8.10$$

Normalized DCG

$$\mathrm{nDCG_p} = \frac{DCG_p}{IDCG_p}$$

Search result lists vary in length depending on the query.

Comparing a search engine's performance from one query to the next cannot be consistently achieved using DCG alone.

The cumulative gain at each position for a chosen value of should be normalized across queries.

Ideal DCG (IDCG) at position is obtained by sorting documents of a result list by relevance, producing the maximum possible DCG till position p.

nDCG Example

$$D_1, D_2, D_3, D_4, D_5, D_6$$

the user provides the following relevance scores:

$$3, 2, 3, 0, 1, 2$$

$$3, 3, 2, 2, 1, 0$$

The DCG of this ideal ordering, or *IDCG*, is then:

$$\mathrm{IDCG}_6 = 8.69$$

And so the nDCG for this query is given as:

$$\mathrm{nDCG}_6 = \frac{DCG_6}{IDCG_6} = \frac{8.10}{8.69} = 0.932$$

Recommendation Outline

- Recommender Systems
  - What are recommender systems and how do they work?
  - Example application: Hotlist Recommendation on Delicious
  - How are recommender systems evaluated?

- **(Some) Recommendation challenges**
  - Well-known challenges
  - Recommendation diversity
  - Group recommendation

Well-Known Challenges

- The new user problem
- The recurring startup problem
- The sparse rating problem
- The scaling problem

The New User Problem

- To be able to make accurate predictions, the system must first learn the user's preferences from the input the user provides (e.g., movie ratings, URL tagging).
- If the system does not show quick progress, a user may lose patience and stop using the system

The Recurring Startup Problem

- New items are added regularly to recommender systems.
- A system that relies solely on users' preferences to make predictions would not be able to make accurate predictions on these items.
- This problem is particularly severe with systems that receive new items regularly, such as an online news article recommendation system.

The Sparse Rating Problem

- In any recommender system, the number of ratings already obtained is very small compared to the number of ratings that need to be predicted.
- Effective generalization from a small number of examples is thus important.
- This problem is particularly severe during the startup phase of the system when the number of users is small.

The Scaling Problem

- Recommender systems are normally implemented as a centralized algorithm and may be used by a very large number of users.
- Sometimes, predictions need to be made in real time and many predictions may potentially be requested at the same time.
- The computational complexity of the algorithms needs to scale well with the number of users and items in the system.

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Diversification

From the pool of relevant items, identify a list of items that are dissimilar to each other and maintain a high cumulative relevance, i.e., strike a good balance between relevance and diversity.

Existing Solutions

- **Attribute-based diversification in 3 steps:**
  - pair-wise item-to-item distance function on item attributes
  - Perform Diversification:
    - Optimize an overall score as a weighted combination of relevance and distance
    - Constrain either relevance or distance, maximizing the other
  - Overhead of retrieving item attributes

- **Explanation-Based Diversification**

Recommendation Strategy

- **Estimate the rating of an unrated item (*i*) by the user (*u*) based on its similarity to items already rated and how *u* rated those items.**

$$\texttt{relevance}(u, i) = \Sigma_{i' \in \mathcal{I}} \texttt{ItemSim}(i, i') \times \texttt{rating}(u, i')$$

- **Similarly, one could define a user-based strategy**

$$\texttt{relevance}(u, i) = \Sigma_{u' \in \mathcal{U}} \texttt{UserSim}(u, u') \times \texttt{rating}(u', i)$$

Explanation

- **Basic Notion**
  - The set of objects because of which a particular item is recommended to the user

- **Explanation for Item-Based Strategies**

$$\mathtt{Expl}(u, i) = \{i' \in \mathcal{I} \mid \mathtt{ItemSim}(i, i') > 0 \;\&\; i' \in \mathtt{Items}(u)\}$$

- **Explanation for User-Based Strategies**

$$\mathtt{Expl}(u, i) = \{u' \in \mathcal{U} \mid \mathtt{UserSim}(u, u') > 0 \;\&\; i \in \mathtt{Items}(u')\}$$

Explanation-Based Diversity

- **Pair-wise diversity distance between two recommended items**
  - Standard similarity measures like *Jaccard similarity* and *cosine similarity*
  - E.g. (Distance based on Jaccard similarity)

$$DD_u^J(i, i') = 1 - \frac{|\mathtt{Expl}_{(u,i)} \cap \mathtt{Expl}_{(u,i')}|}{|\mathtt{Expl}_{(u,i)} \cup \mathtt{Expl}_{(u,i')}|}.$$

- **Diversity for the set of recommended items (*S*)**

$$DD_u(S) = avg\{DD_u(i, i') \mid i, i' \in S\}$$

Diverse Recommendation Problem

Top-K Recommendation with Diversification

Given a user u, find a subset S from the set of candidate items, such that |S| = k and the overall relevance of items in S and the diversity of S are balanced.

Cong Yu, Laks V. S. Lakshmanan, Sihem Amer-Yahia: Recommendation Diversification Using Explanations. ICDE 2009: 1299-1302

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Group Recommendation (motivation)

- How do you decide where to go to dinner with friends?
  - email/text/phone
  - not optimal for reaching consensus
- What if there was a system that knew each user’s preferred list?
- What is the best way to model consensus?
- How to *evaluate* that?
- How to *efficiently* compute *group recommendations*?

Group Recommendation by Example

- **Task: recommend a movie to group G ={u1, u2 ,u3}**
  - predictedRating(u1,"God Father") = 5
  - predictedRating(u2, "God Father") = 1
  - predictedRating(u3, "God Father") = 1

  - predictedRating(u1, "Roman Holiday") = 3
  - predictedRating(u2, "Roman Holiday") = 3
  - predictedRating(u3, "Roman Holiday") = 1

- ***Average Rating*** **and** ***Least Misery*** **fail to distinguish between "God Father" and "Roman Holiday"**

Group Reco Problem Definition

Consensus function *combines* ***relevance*** *(average or least misery) and* ***disagreement*** *(average pair-wise or variance) in the score of a group recommendation*

$\mathcal{F}(\mathcal{G}, i) = w_1 \times \mathtt{rel}(\mathcal{G}, i) + w_2 \times (1 - \mathtt{dis}(\mathcal{G}, i))$, *where* $w_1 + w_2 = 1.0$ *and each specifies the relative importance of relevance and disagreement in the overall recommendation score.*

Problem: Given a user group G (formed on-the-fly) and a consensus function F, find the k best items according to F, such that each item is new to all users in G

S. Amer-Yahia, S. B. Roy, A. Chawla, G. Das, C. Yu: Group Recommendation: Semantics and Efficiency. VLDB 2009.

In practice

- Choose your similarity measure wisely, you will have to try more than one
- Define your goal early with the domain expert to determine how to evaluate your approach
- Build a prototype ASAP
- Use existing tools whenever possible

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- Evaluating recommender systems

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