Recommender Systems

Harnessing the Power of Personalization

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amazon.com

Hello, Kristina. We have recommendations for you.

Kristina's Amazon.com | Today's Deals | Gifts & Wish Lists | Gift Cards

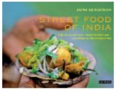
Shop All Departments | Search | All Departments

Your Amazon.com | Your Browsing History | Recommended For You | Rate These Items | Improve Your

Kristina, Welcome to Your Amazon.com

Today's Recommendations For You

Here's a daily sample of items recommended for you. Click here to **see all recommendations**.

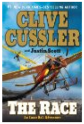


Street Food of India: The 50...
(Hardcover) by Sephi Bergerson
(4) $19.17
Fix this recommendation

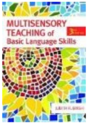
Lavazza Tierra! 100% Arabica Whole Bean Espress...
(38) $34.41
Fix this recommendation

Entourage: The Complete Fou... DVD ~ Adrian Grenier
(44) $16.49
Fix this recommendation

New For You®

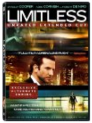


The Race (Isaac Bell)
Clive Cussler, Justin Scott
Hardcover
~~$27.95~~ $14.97
Fix this recommendation

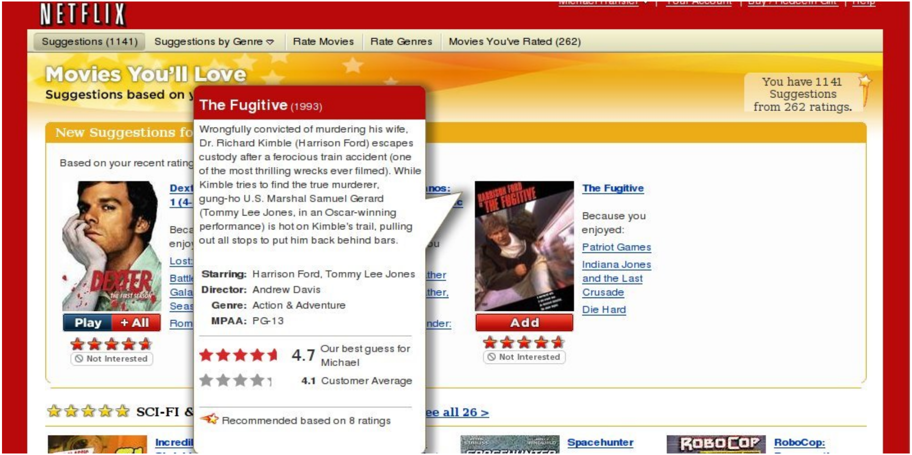


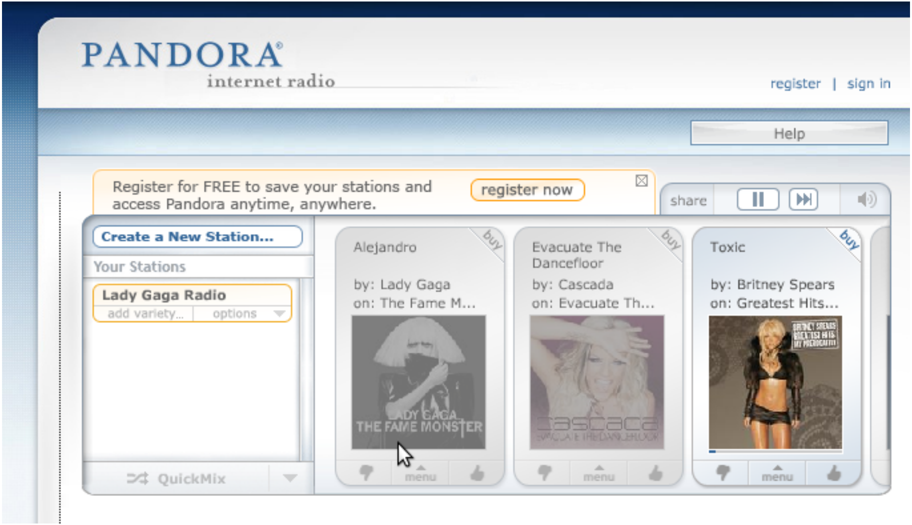
Multisensory Teaching of Basic...
Judith R. Birsh, Sally E. Shaywitz
Hardcover
~~$79.95~~ $44.99
Fix this recommendation

Kill Shot (Mitch Rapp)
Vince Flynn
Hardcover
~~$27.99~~ $16.62
Fix this recommendation



Limitless (Unrated Extended Cut)
Bradley Cooper, Anna Friel, Abbie...
DVD
~~$29.99~~ $15.19
Fix this recommendation


NETFLIX
Suggestions (1141)
Suggestions by Genre
Rate Movies
Rate Genres
Movies You've Rated (262)
Movies You'll Love
Suggestions based on y
You have 1141 Suggestions from 262 ratings.
New Suggestions fo
Based on your recent rating
The Fugitive (1993)
Wrongfully convicted of murdering his wife, Dr. Richard Kimble (Harrison Ford) escapes custody after a ferocious train accident (one of the most thrilling wrecks ever filmed). While Kimble tries to find the true murderer, gung-ho U.S. Marshal Samuel Gerard (Tommy Lee Jones, in an Oscar-winning performance) is hot on Kimble's trail, pulling out all stops to put him back behind bars.
Starring: Harrison Ford, Tommy Lee Jones
Director: Andrew Davis
Genre: Action & Adventure
MPAA: PG-13
4.7 Our best guess for Michael
4.1 Customer Average
Recommended based on 8 ratings
Play
+ All
Not Interested
The Fugitive
Because you enjoyed:
Patriot Games
Indiana Jones and the Last Crusade
Die Hard
Add
Not Interested
SCI-FI &
ee all 26 >
Spacehunter
RoboCop:


PANDORA
internet radio
register | sign in
Help
Register for FREE to save your stations and access Pandora anytime, anywhere.
register now
share
Create a New Station...
Your Stations
Lady Gaga Radio
add variety...
options
QuickMix
Alejandro
by: Lady Gaga
on: The Fame M...
LADY GAGA
THE FAME MONSTER
menu
buy
Evacuate The Dancefloor
by: Cascada
on: Evacuate Th...
menu
buy
Toxic
by: Britney Spears
on: Greatest Hits...
menu
buy

A Great Infographic

Can I recommend anything else?

http://www.columnfivemedia.com/work-items/infographic-can-i-recommend-anything-else

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Recommender Systems

Original Definition

Recommender systems apply statistical and knowledge discovery techniques to the problem of making product recommendations.

Sarwar *et al.* (2000)

Advantages of recommender systems (e.g., Schafer *et al.*, 2001):

- Improve conversion rate: Help customers find a product she/he wants to buy.
- Cross-selling: Suggest additional and more diverse products.
- Up-selling: Suggest premium products.
- Improve customer satisfaction/loyalty: Create a value-added relationship.
- Better understand what users want: Knowledge can be reused.

A More General View of Recommender Systems

A recommender system is a fully automatic system to provide (near) personalized decision support given limited information while optimizing a set of potentially conflicting objective functions.

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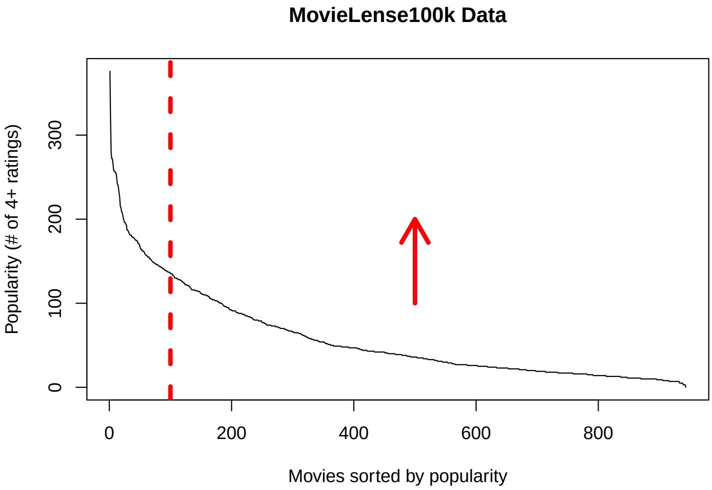
Design Space:

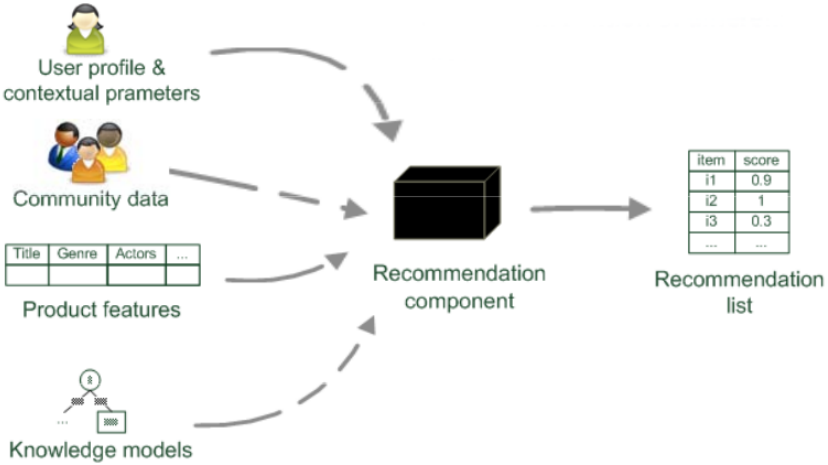
- Domain - What are the recommended items? Products, info, etc.
- Purpose - Why recommendations? Sales, building a community, etc.
- Recommendation context - What is the user doing?
- Whose opinions - Available data, incentives, quality.
- Personalization level - From non-personalized to persistent.
- Privacy and trust - Are the recommendations biased?
- Interfaces - Data collection and presenting recommendations.
- Used algorithms - Quality and speed.

What Items to Recommend?



Increase diversity by recommending less well known items.

Recommender System Architecture



Source: Recommender Systems - An Introduction

Common Approaches

- Non-Personalized recommendations: Recommendations by experts or summary of community ratings.

Personalized Recommendations

- Content-based filtering: Use consumer preferences for product attributes.
- Collaborative filtering: Mimics word-of-mouth based on analysis of rating/usage/sales data from many users.
- Hybrid recommender systems: Incorporate content, collaborative filtering, expert information and contextual information.

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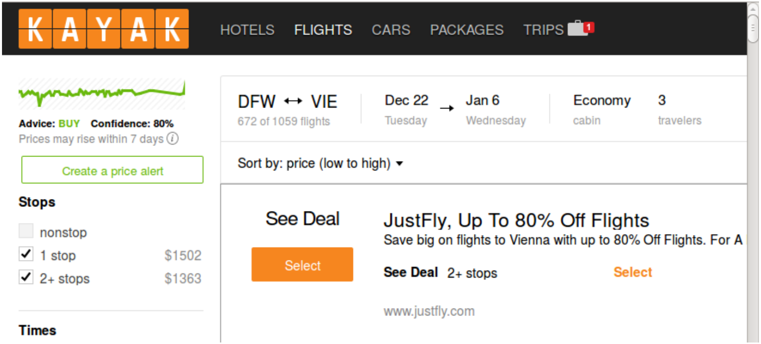
Content-based Approach

1. Analyze the objects (documents, video, music, etc.) and extract attributes/features (e.g., words, phrases, actors, genre).
2. Recommend objects that match the user profile (e.g., with similar attributes to an object the user likes).

"The Music Genome Project is an effort to capture the essence of music at the fundamental level using almost 400 attributes to describe songs and a complex mathematical algorithm to organize them."

http://en.wikipedia.org/wiki/Music_Genome_Project



Content can be dynamic...

An issue with content based filtering?

An issue with content based filtering?

Missing diversity!

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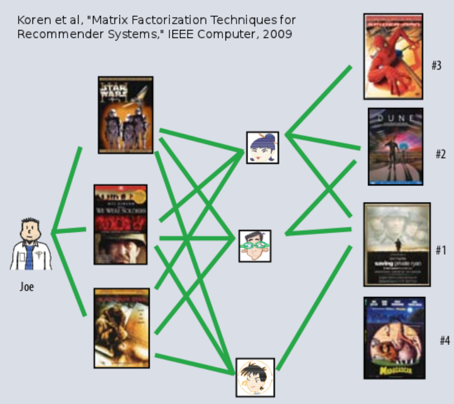
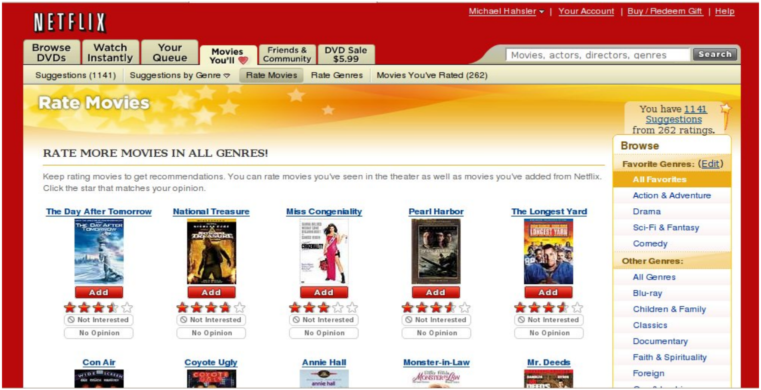
Collaborative Filtering (CF)



Make automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many other users (collaboration).

Assumption: those who agreed in the past tend to agree again in the future.

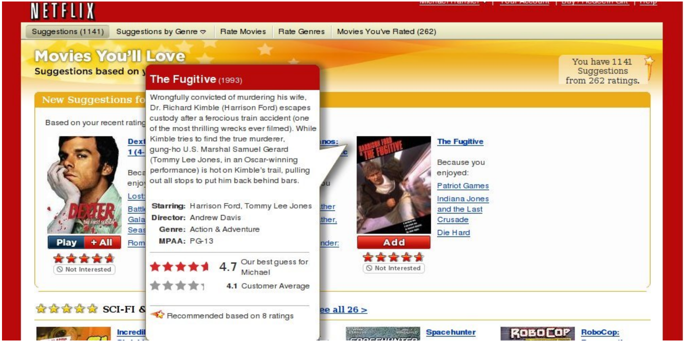
Data Collection



- Explicit: ask the user for ratings, rankings, list of favorites, etc.
- Observed behavior (Implicit): clicks, page impressions, purchase, uses, downloads, posts, tweets, etc.

What is the incentive structure?

Output of a Recommender System



- Predict ratings of unrated movies (Breese *et al.*, 1998).
- Top-N lists of unrated (unknown) movies ordered by predicted rating/score(Deshpande and Karypis, 2004).
- Annotation in context (e.g., in a electronic guide).
- Recommend as sequence or a bundle.

How do you explain the recommendation to the user? → Trust

Types of CF Algorithms

- **Memory-based:** Find similar users (user-based CF) or items (item-based CF) to predict missing ratings.
- **Model-based:** Build a model from the rating data (clustering, latent structure, etc.) and then use this model to predict missing ratings.

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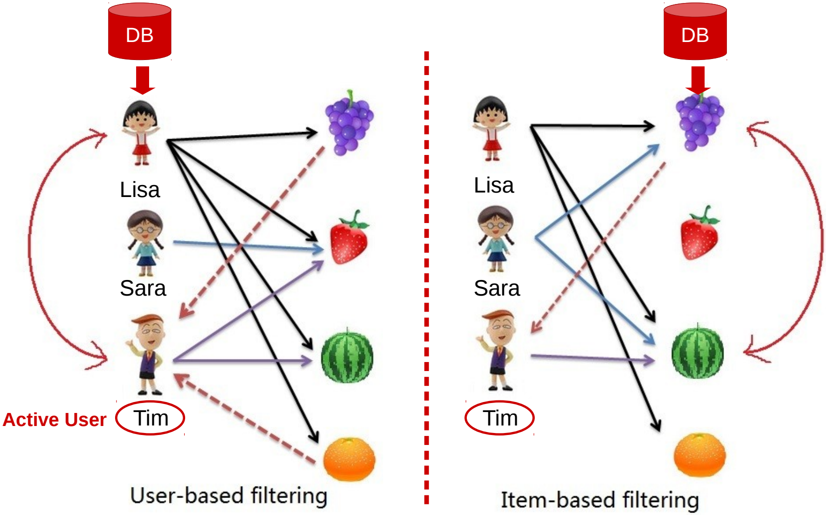
User-based vs. Item-based CF



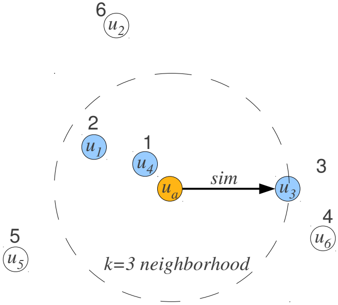
Source: `http://cuihelei.blogspot.com/2012/09/the-difference-among-three.html`

User-based CF

Produce recommendations based on the preferences of similar users (Goldberg *et al.*, 1992; Resnick *et al.*, 1994; Mild and Reutterer, 2001).

	i_1	i_2	i_3	i_4	i_5	i_6
u_a	?	?	4.0	3.0	?	1.0
u_1	?	4.0	4.0	2.0	1.0	2.0
u_2	3.0	?	?	?	5.0	1.0
u_3	3.0	?	?	3.0	2.0	2.0
u_4	4.0	?	?	2.0	1.0	1.0
u_5	1.0	1.0	?	?	?	?
u_6	?	1.0	?	?	1.0	1.0
	3.5	4.0			1.3	

Recommendations: i_2, i_1



1. Find k nearest neighbors for the user in the user-item matrix.
2. Generate recommendation based on the items liked by the k nearest neighbors. E.g., average ratings or use a weighting scheme.

User-based CF II

- Pearson correlation coefficient:

$$\mathrm{sim}_{\mathrm{Pearson}}(\mathbf{x}, \mathbf{y}) = \frac{\sum_{i \in I} x_i y_i - I\bar{\mathbf{x}}\bar{\mathbf{y}}}{(I-1) s_x s_y}$$

- Cosine similarity:

$$\mathrm{sim}_{\mathrm{Cosine}}(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\|_2 \|\mathbf{y}\|_2}$$

- Jaccard index (only binary data):

$$\mathrm{sim}_{\mathrm{Jaccard}}(X, Y) = \frac{|X \cap Y|}{|X \cup Y|}$$

where $\mathbf{x} = b_{u_x,\cdot}$ and $\mathbf{y} = b_{u_y,\cdot}$ represent the user's profile vectors and X and Y are the sets of the items with a 1 in the respective profile.

Problem

Memory-based. Expensive online similarity computation.

Item-based CF

Produce recommendations based on the relationship between items in the user-item matrix (Kitts *et al.*, 2000; Sarwar *et al.*, 2001)

S	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8
i_1	-	0.1	0	**0.3**	**0.2**	**0.4**	0	0.1
i_2	0.1	-	**0.8**	**0.9**	0	**0.2**	0.1	0
i_3	0	**0.8**	-	0	**0.4**	0.1	0.3	**0.5**
i_4	**0.3**	**0.9**	0	-	0	**0.3**	0	0.1
i_5	**0.2**	0	**0.7**	0	-	**0.2**	0.1	0
i_6	**0.4**	**0.2**	0.1	**0.3**	0.1	-	0	0.1
i_7	0	**0.1**	**0.3**	0	0	0	-	0
i_8	**0.1**	0	**0.9**	**0.1**	0	0.1	0	-
	-	0	4.56	2.75	-	2.67	0	-

$k=3$

$u_a=\{i_1, i_5, i_8\}$

$r_{ua}=\{2, ?, ?, ?, 4, ?, ?, 5\}$

Recommendation: i_3

1. Calculate similarities between items and keep for each item only the values for the k most similar items.
2. Use the similarities to calculate a weighted sum of the user's ratings for related items.

$$\hat{r}_{ui} = \sum_{j \in s_i} s_{ij} r_{uj} / \sum_{j \in s_i} |s_{ij}|$$

Regression can also be used to create the prediction.

Item-based CF II

Similarity measures:

- Pearson correlation coefficient, cosine similarity, Jaccard index
- Conditional probability-based similarity (Deshpande and Karypis, 2004):

$$\mathrm{sim}_{\mathrm{Conditional}}(x, y) = \frac{\mathrm{Freq}(xy)}{\mathrm{Freq}(x)} = \hat{P}(y|x)$$

  where x and y are two items, $\mathrm{Freq}(\cdot)$ is the number of users with the given item in their profile.

Properties

- Model (reduced similarity matrix) is relatively small ($N \times k$) and can be fully precomputed.
- Item-based CF was reported to only produce slightly inferior results compared to user-based CF (Deshpande and Karypis, 2004).
- Higher order models which take the joint distribution of sets of items into account are possible (Deshpande and Karypis, 2004).
- Successful application in large scale systems (e.g., Amazon.com)

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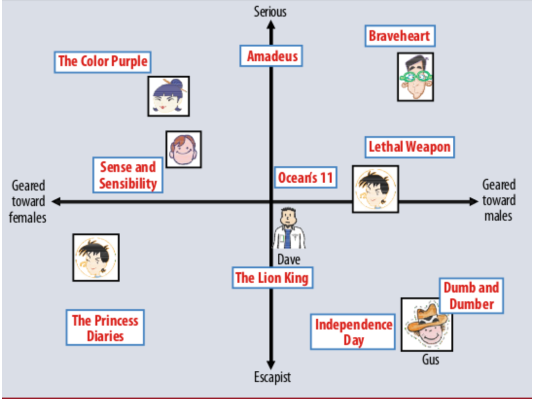
Different Model-based CF Techniques

There are many techniques:

- Cluster users (i.e., customer segmentation) and then recommend items the users in the cluster closest to the active user like.
- Mine association rules (if-then rules) and then use the rules to recommend items.
- Define a null-model (a stochastic process which models usage of independent items) and then find significant deviation from the null-model.
- Learning to rank: Logistic regression, neural networks (deep learning) and many other machine learning methods.
- Learn a latent factor model from the data and then use the discovered factors to find items with high expected ratings.

Latent Factor Approach



Latent factor approach. Koren et al, "Matrix Factorization Techniques for Recommender Systems," IEEE Computer, 2009

Latent semantic indexing (LSI) developed by the IR community (late 80s) addresses sparsity, scalability and can handle synonyms
$\Rightarrow$ Dimensionality reduction.

Matrix Factorization

Given a user-item (rating) matrix $M = (r_{ui})$, map users and items on a joint latent factor space of dimensionality k.

- Each item i is modeled by a vector $q_i \in \mathbb{R}^k$.
- Each user u is modeled by a vector $p_u \in \mathbb{R}^k$.

such that a value close to the actual rating r_{ui} can be computed (e.g., by the dot product also known as the cosine similarity)

$$r_{ui} \approx \hat{r}_{ui} = q_i^T p_u$$

The hard part is to find a suitable latent factor space!

Singular Value Decomposition (Matrix Fact.)

Linear algebra: Singular Value Decomposition (SVD) to factorizes M

$$M = U \Sigma V^T$$

M is the $m \times n$ (users $\times$ items) rating matrix of rank r.Columns of U and V are the left and right singular vectors. Diagonal of Σ contains the r singular values.

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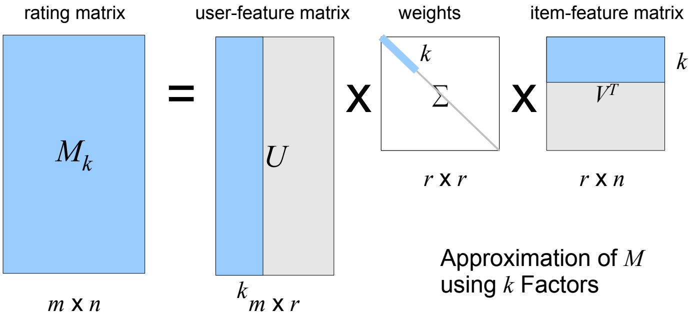
Best rank-k approximation minimizes error $||M - M_k||_F$ (Frobenius norm).



Challenges (Matrix Fact.)

- **Missing values:** Imputation using column means (mean item ratings). For centered columns the mean is zero.

- **SVD is $O(m^3)$:** Use incremental SVD to 'fold in' new users/items without recomputing the whole SVD (Sarwar *et al.*, 2002).

1. Calculate user-feature vector from imputed ratings m_a.

$$u_a = m_a V_k^T \Sigma_k^{-1}$$

2. Predict ratings

$$\hat{m}_a = u_a \Sigma_k V_k^T$$

Works similarly for new items.

Challenges (Matrix Fact.)

Too many missing values are a problem. SVD with missing values by minimizing the square error on only known ratings (regularized to avoid overfitting).

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

where κ are the (u, i) pairs for which r is known.

Good solutions can be found by stochastic gradient descent or alternating least squares (Koren *et al.*, 2009).

1. For new user (item) compute q_i (p_u).
2. After all q_i and p_u are known, prediction is very fast:

$$\hat{r}_{ui} = q_i^T p_u$$

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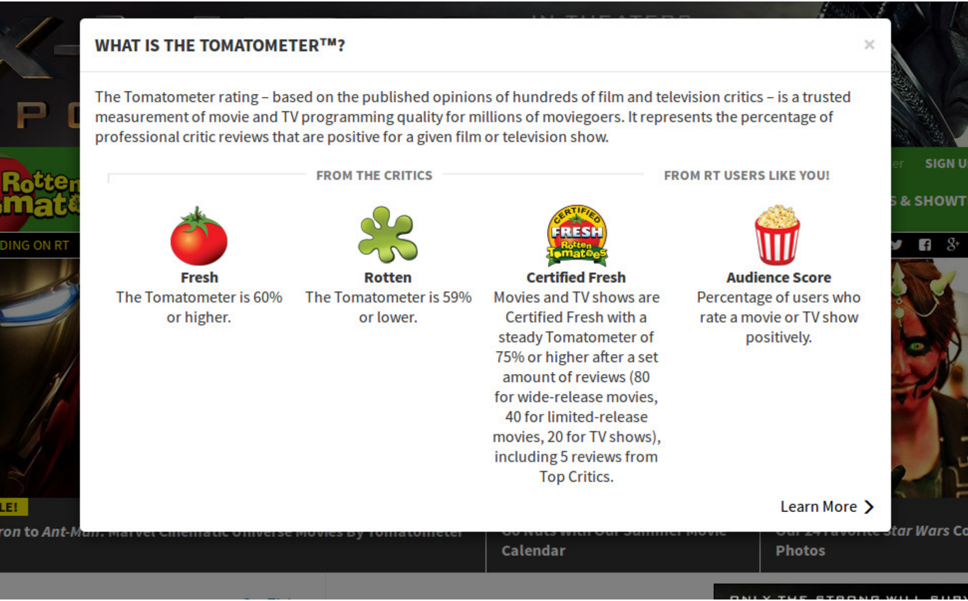
Explaining Recommendations



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Cold Start Problem

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What do we do with new items?

- Content-based filtering techniques.
- Use expert/domain knowledge.
- Pay a focus group to rate new items.

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Security and Recommender Systems

- **Protect recommender neutrality**
  From malicious users who want to push their product and can create fake accounts
  Possible solutions: prevent account creation or detect and remove

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  Possible solutions: Normal de-noising problem

Security and Recommender Systems

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  From malicious users who want to push their product and can create fake accounts
  Possible solutions: prevent account creation or detect and remove
- **Protect recommender accuracy**
  From users who give low-quality, inconsistent ratings.
  Possible solutions: Normal de-noising problem
- **Protect user data (privacy)**
  From other users and from the service provider
  Possible solutions: Use trusted computing infrastructure, pool ratings, add noise

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Revenue Management

Recommender systems have the potential to increase revenue

- cross-selling
- up-selling

How about influencing which items are recommended using revenue considerations?

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- cross-selling
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How about influencing which items are recommended using revenue considerations?

What about **trust + incentive to share information?**

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Open-Source Implementations

- Apache Mahout: ML library including collaborative filtering (Java)
- C/Matlab Toolkit for Collaborative Filtering (C/Matlab)
- Cofi: Collaborative Filtering Library (Java)
- Crab: Components for recommender systems (Python)
- easyrec: Recommender for Web pages (Java)
- LensKit: CF algorithms from GroupLens Research (Java)
- MyMediaLite: Recommender system algorithms. (C#/Mono)
- RACOFI: A rule-applying collaborative filtering system
- Rating-based item-to-item recommender system (PHP/SQL)
- recommenderlab: Infrastructure to test and develop recommender algorithms (R)

See `http://michael.hahsler.net/research/recommender/` for URLs.

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recommenderlab: Reading Data

100k MovieLense ratings data set: The data was collected through movielens.umn.edu from 9/1997 to 4/1998. The data set contains about 100,000 ratings (1-5) from 943 users on 1664 movies.

```
R> library("recommenderlab")
R> data(MovieLense)
R> MovieLense
943 x 1664 rating matrix of class ‘realRatingMatrix’ with
99392 ratings.
R> train <- MovieLense[1:900]
R> u <- MovieLense[901]
R> u
1 x 1664 rating matrix of class ‘realRatingMatrix’ with 124
ratings.
R> as(u, "list")[[1]][1:5]
         Toy Story (1995)                 Babe (1995)
                        5                           3
Usual Suspects, The (1995)    Mighty Aphrodite (1995)
                        5                           1
 Mr. Holland's Opus (1995)
                        5
```

recommenderlab: Creating Recommendations

```
R> r <- Recommender(train, method = "UBCF")
R> r
Recommender of type ‘UBCF’ for ‘realRatingMatrix’
learned using 900 users.
R> recom <- predict(r, u, n = 5)
R> recom
Recommendations as ‘topNList’ with n = 5 for 1 users.
R> as(recom, "list")[[1]]
[1] "Fugitive, The (1993)"
[2] "Shawshank Redemption, The (1994)"
[3] "It's a Wonderful Life (1946)"
[4] "Princess Bride, The (1987)"
[5] "Alien (1979)"
```

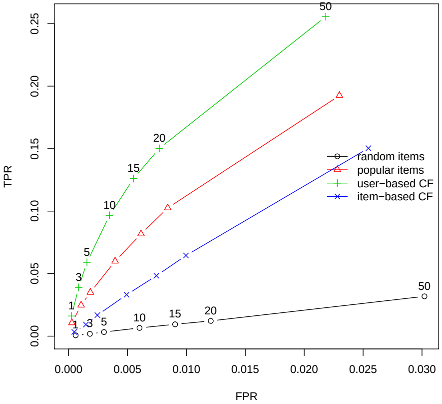
recommenderlab: Compare Algorithms

```
R> scheme <- evaluationScheme(train, method = "cross", k =
4,
+     given = 10, goodRating = 3)
R> algorithms <- list(
+ `random items` = list(name = "RANDOM", param = NULL),
+ `popular items` = list(name = "POPULAR", param = NULL),
+ `user-based CF` = list(name = "UBCF",
+     param = list(method = "Cosine", nn = 50)),
+ `item-based CF` = list(name = "IBCF",
+     param = list(method = "Cosine", k = 50)))
R> results <- evaluate(scheme, algorithms,
+     n = c(1, 3, 5, 10, 15, 20, 50))
```

recommenderlab: Compare Algorithms II

```
R> plot(results, annotate = c(1, 3), legend = "right")
```

‘



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Technology

NETFLIX

http://techblog.netflix.com

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Thank you!

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An introduction can be found at https://cran.r-project.org/web/packages/recommenderlab/vignettes/recommenderlab.pdf