# Recommender Systems

## Harnessing the Power of Personalization

Michael Hahsler

Engineering Management, Information, and Systems (EMIS)
Intelligent Data Analysis Lab (IDA@SMU)
Bobby B. Lyle School of Engineering, Southern Methodist University

Southwest Airlines EDGe Analyst Community Meeting
November 18, 2015

SMU | BOBBY B. LYLE SCHOOL OF ENGINEERING

# IDA@SMU

**Intelligent Data Analysis Lab**

SMU | Bobby B. Lyle School of Engineering

**Mission:** At IDA we create novel techniques inspired by knowledge discovery, data mining, machine learning, artificial intelligence and statistical analysis to work with data from various sources. We currently focus on:

- Order modeling for massive data streams with applications in meteorology (hurricane intensity prediction) and personalized medicine (efficient classification and analysis of metagenomic data)
- Visual analytics using optimized reordering
- Simulation data analytics
- Recommender systems

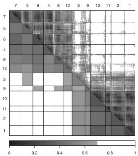
**Team:** 3 faculty, 7 students, 2 collaborators
**Director:** M. Hahsler <mhahsler@lyle.smu.edu>

**Supported by**

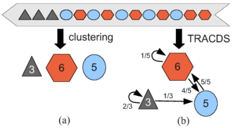
National Human Genome Research Institute, NSF, T-System, UT Southwestern Medical Center, Net-Centric I/UCRC

**http://lyle.smu.edu/IDA/**

***Visual Analytics***

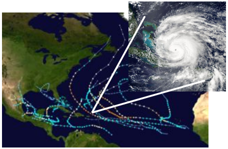


***Order Modeling***
***Data Stream Clustering***




***Simulation Data Analytics***

***Meteorology***



***Personalized Medicine***

# Reproducible Research Using R

R has been consistently voted one of the most important tools for data mining and analytics, and being able to use R is one of the highest paying analytics skills.
Our team has developed and maintains several popular R packages:

### Association Rule Mining

- **arules:** Mining association rules and frequent itemsets.
- **arulesViz:** Visualizing association rules based on package arules.
- **arulesSequences:** Mine frequent sequences.

### Combinatorial Optimization

- **seriation:** Seriation/sequencing techniques to reorder matrices and dendrograms.
- **TSP: I**nfrastructure and algorithms for the traveling salesperson problem.
- **DBSCAN:** Several density-based algorithms for spatial data.
- **QAP:** Heuristics for the Quadratic Assignment Problem (QAP).

### Data Stream Mining

- **stream:** Infrastructure for data stream mining.

### Recommender Systems

- **recommenderlab:** Infrastructure to test and develop recommender algorithms.

**http://michael.hahsler.net/#Software**

# A Message From the Department Chair

The Engineering Management, Information, and Systems Department program includes:

- Management Science
- Operations Research
- Analytics

We are looking for topics for undergraduate senior design projects in any of these areas.

Please contact Sila Centinkaya (`sila@lyle.smu.edu`), Chair EMIS, with inquiries.

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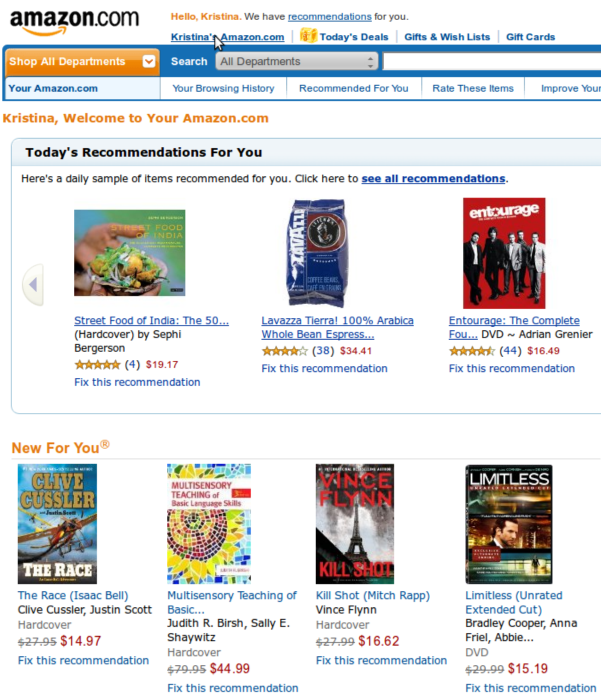
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Kristina's Amazon.com | Today's Deals | Gifts & Wish Lists | Gift Cards
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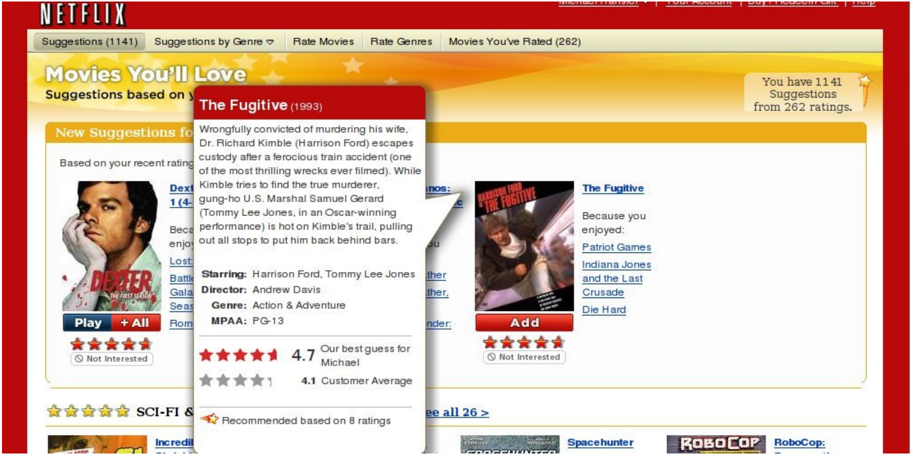
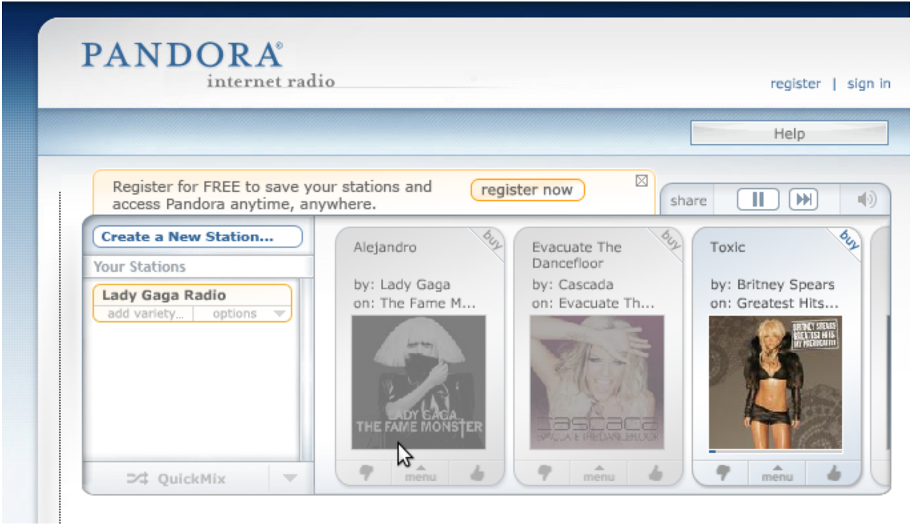
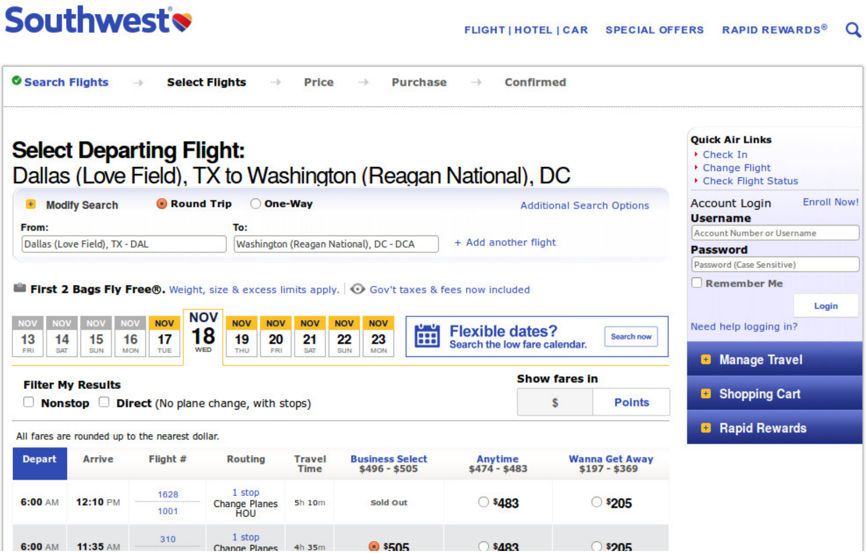

NETFLIX
Suggestions (1141)
Suggestions by Genre
Rate Movies
Rate Genres
Movies You've Rated (262)
Movies You'll Love
Suggestions based on y
You have 1141 Suggestions from 262 ratings.
New Suggestions fo
Based on your recent rating
The Fugitive (1993)
Wrongfully convicted of murdering his wife, Dr. Richard 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...
buy
menu
Evacuate The Dancefloor
by: Cascada
on: Evacuate Th...
buy
menu
Toxic
by: Britney Spears
on: Greatest Hits...
buy
menu


Southwest
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Select Flights
Price
Purchase
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Select Departing Flight:
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Additional Search Options
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Dallas (Love Field), TX - DAL
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NOV 13 FRI
NOV 14 SAT
NOV 15 SUN
NOV 16 MON
NOV 17 TUE
NOV 18 WED
NOV 19 THU
NOV 20 FRI
NOV 21 SAT
NOV 22 SUN
NOV 23 MON
Flexible dates?
Search the low fare calendar.
Search now
Filter My Results
Nonstop
Direct (No plane change, with stops)
Show fares in
$
Points
All fares are rounded up to the nearest dollar.
Depart
Arrive
Flight #
Routing
Travel Time
Business Select $496 - $505
Anytime $474 - $483
Wanna Get Away $197 - $369
6:00 AM
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Change Planes
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Sold Out
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$205
6:00 AM
11:35 AM
310
1 stop
Change Planes
4h 35m
$505
$483
$205
Quick Air Links
Check In
Change Flight
Check Flight Status
Account Login
Enroll Now!
Username
Account Number or Username
Password
Password (Case Sensitive)
Remember Me
Login
Need help logging in?
Manage Travel
Shopping Cart
Rapid Rewards

# Dallas (Love Field), TX to Washington (Reagan National), DC

## Air — Total Price: $1008.96

ITINERARY

| Travel Date | Flight Segments | | | Flight Summary |
|---|---|---|---|---|
| DEPART NOV 18 WED | 06:00 AM | Depart **Dallas (Love Field), TX (DAL)** on Southwest Airlines | **Flight #310** Southwest | |
| | 07:35 AM | Arrive in St. Louis, MO (STL) | WiFi available | **Wednesday, November 18, 2015** |
| | 08:45 AM | Change to Southwes St. Louis, MO (STL) | | |
| | **11:35 AM** | Arrive in **Washington (R National), DC (DCA)** | | |
| RETURN NOV 21 SAT | **06:00 AM** | Depart **Washington (Rea National), DC (DCA)** on Airlines | | |
| | 08:00 AM | Arrive in Atlanta, GA (ATL | | |
| | 09:40 AM | Change to Southwes Atlanta, GA (ATL) | | |
| | **11:00 AM** | Arrive in **Dallas (Love Fi (DAL)** | | |

**What you need to know to travel:**

- **Check-in**: Be sure to arrive at the departure departure time. Otherwise, your reserved spa

**Quick Air Links**

- Check In
- Change Flight
- Check Flight Status

Account Login Enroll Now!

**Username**

Account Number or Username

**Password**

Password (Case Sensitive)

Remember Me

Login

Need help logging in?

## Add a Hotel

We'll keep an eye on your cart for you while you shop. Products not confirmed until purchase.

4 Star Rating

**The George, a Kimpton Hotel**

**$309**/night

View Details

**Search for hotels in Washington (11/18/2015 - 11/21/2015)**

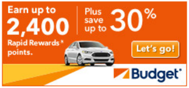
**Close To** (optional) Center of destination **within** 30 miles

**Show Only** (optional) Hotel Chains Shop All Hotel Chains

Find Hotels

## Add a Car

We'll keep an eye on your cart for you while you shop. Products not confirmed until purchase.




Type in any city or airport in the U.S., Canada or Mexico

| Pickup Location | Pickup Date | Dropoff Date |
|---|---|---|
| Washington (Reagan National) | 11/18/2015 | 11/21/2015 |

**Vehicle Type** (optional) Economy

**Which Company?** (optional) Shop All

# A Great Infographic

Can I recommend anything else?

http://www.kdnuggets.com/2015/10/big-data-recommendation-systems-change-lives.html/2

## 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** (Schafer *et al.*, 2001):

- Improve conversion rate: Help customers find a product she/he wants to buy.
- Cross-selling: Suggest additional products.
- Up-selling: Suggest premium products.
- Improve customer loyalty: Create a value-added relationship.

# A Significant Number Of Travelers Can Be Tempted With Up-Sell/Cross-Sell Offers

Percent of US travelers who will consider paying a reasonable premium for the following:

**Receive better service: 48%**

**Save time/reduce hassle: 47%**

**Enjoy more comfort: 45%**

Base US online travelers

Source: Hudson Crossing's US Travel Online Study, Q1 2013

# 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.

# 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.

**Important aspects:**

- Personalization
- Available information
- Incentive structure
- Trust
- Quality of recommendations
- Speed

# Common Approaches

- Content-based filtering: Consumer preferences for product attributes.
- Collaborative filtering: Mimics word-of-mouth based on analysis of rating/usage/sales data from many users.

  (Ansari *et al.*, 2000)

- Hybrid recommender systems: Incorporate content, collaborative and expert information.

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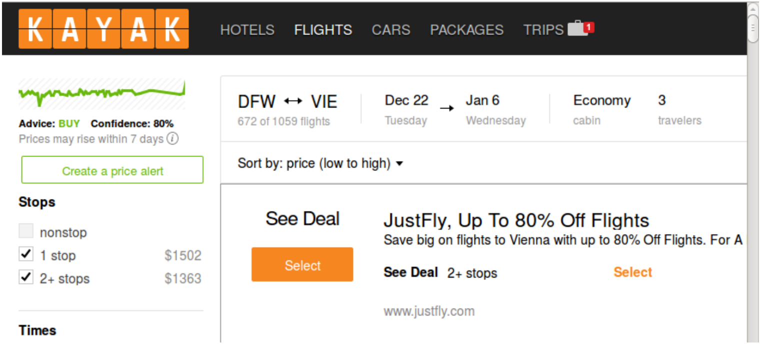
# Content-based Approach


1. Analyze the objects (documents, video, music, etc.) and extract attributes/features (e.g., words, phrases, actors, genre).
2. Recommend objects 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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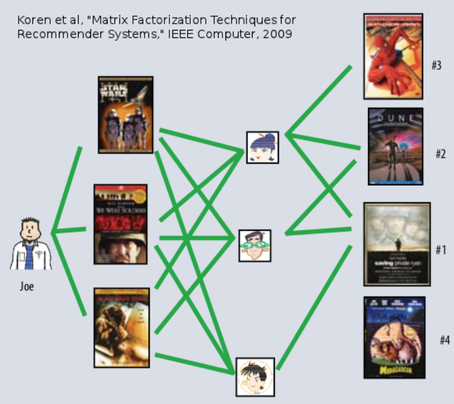
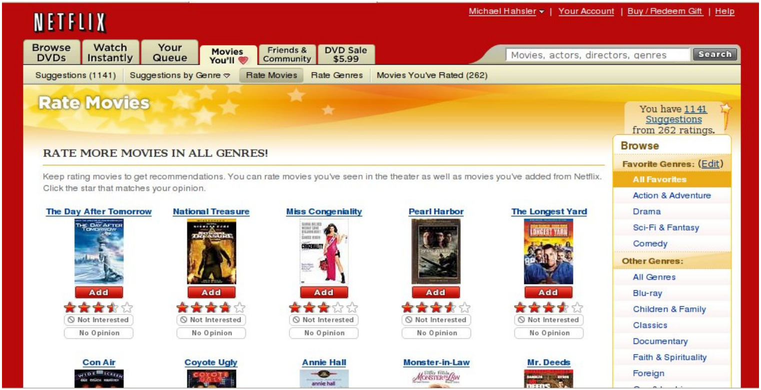
# Collaborative Filtering (CF)




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.

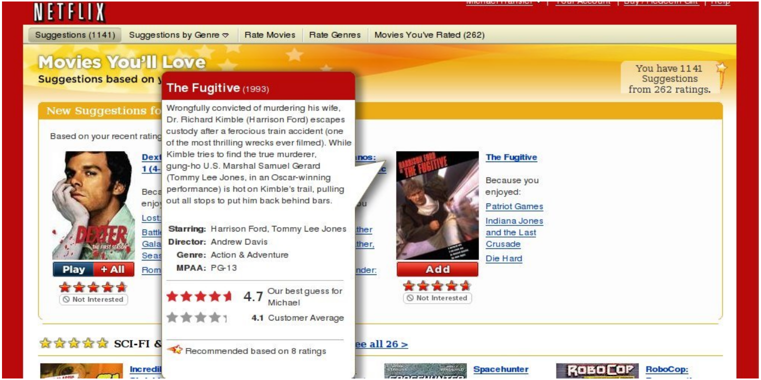
# Data Collection




- Data sources:
  - 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




- Predicted rating of unrated movies (Breese *et al.*, 1998)
- A top-$N$ list of unrated (unknown) movies ordered by predicted rating/score (Deshpande and Karypis, 2004)

# 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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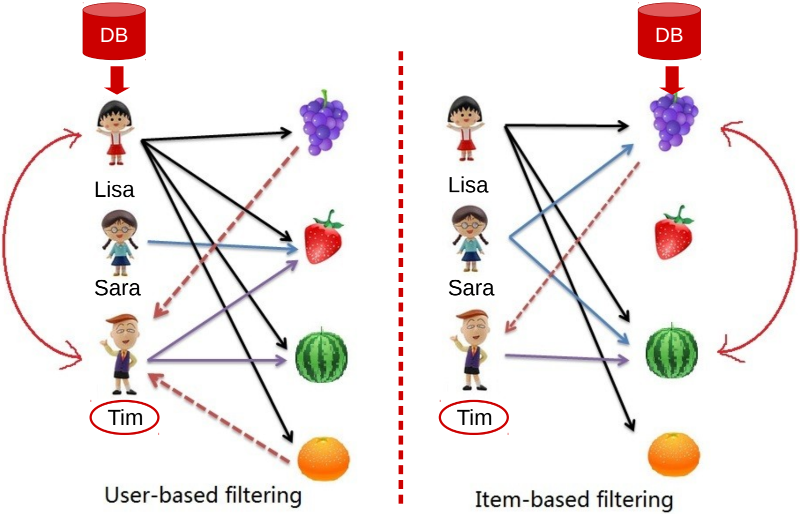
# User-based vs. Item-based CF



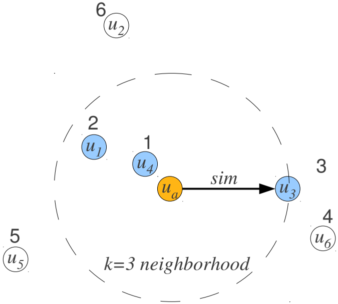

Source: `http://cuihelei.blogspot.com/2012/09/the-difference-among-three.html`

# 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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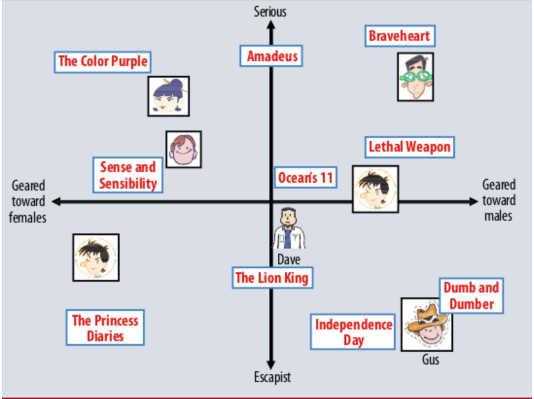
# Different Model-based CF Techniques

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 $\Sigma$ contains the $r$ singular values.

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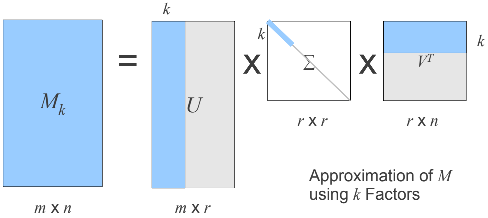
Columns of $U$ and $V$ are the left and right singular vectors.
Diagonal of $\Sigma$ contains the $r$ singular values.

A low-rank approximation of $M$ using only $k$ factors is straight forward.




The approximation minimizes approx. error $||M - M_k||_F$ (Frobenius norm).

# Challenges (Matrix Fact.)

SVD is $O(m^3)$ and missing values are a problem.

1. Use Incremental SVD to add new users/items without recomputing the whole SVD (Sarwar *et al.*, 2002).
2. To avoid overfitting minimize the regularized square error on only known ratings:

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

where $\kappa$ 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).

# Prediction (Matrix Fact.)

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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# Cold Start Problem

What do we recommend to new users for whom we have no ratings yet?

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- Recommend popular items
- Have some start-up questions (e.g., ”What are your 10 favorite movies?”)
- Obtain/purchase personal information

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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# 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

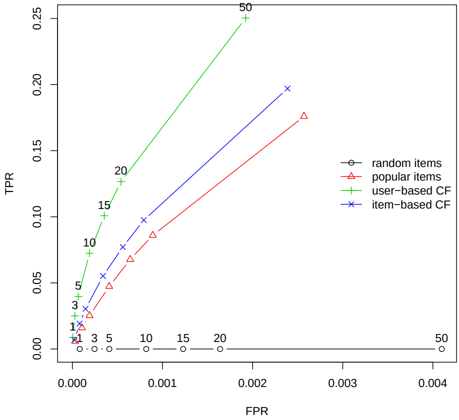
```
R> r <- Recommender(train, method = "UBCF")
R> r
Recommender of type ‘UBCF’ for ‘realRatingMatrix’
learned using 900 users.
R> recom <- predict(r, u, n = 5)
R> recom
Recommendations as ‘topNList’ with n = 5 for 1 users.
R> as(recom, "list")[[1]]
[1] "Fugitive, The (1993)"
[2] "Shawshank Redemption,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

# recommenderlab: Compare Algorithms

```
R> scheme <- evaluationScheme(db, method = "cross", k = 4,
+     given = 10)
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



Java
MEMCACHED
amazon web services™
HTML 5
Cassandra
amazon webservices
HIVE
hadoop
TERADATA
Jenkins

NETFLIX

http://techblog.netflix.com

# References I


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# Thank you!

This presentation can be downloaded from
`http://michael.hahsler.net/` (under publications/talks)

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**recommenderlab** is available in R from CRAN.
An introduction can be found at `https://cran.r-project.org/web/packages/recommenderlab/vignettes/recommenderlab.pdf`