Programming Machine Learning Applications

Lecture Five: Text Categorization & Recommender Systems

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Review of Lecture Four

Classification

Numeric Prediction

Bayes

Decision Trees

Text Classification

Recommender Systems

Lecture Five

Recommender Systems

Predictive User Modeling

The Problem

- Dynamically serve customized content (ads, products, deals, recommendations, etc.) to users based on their profiles, preferences, or expected needs

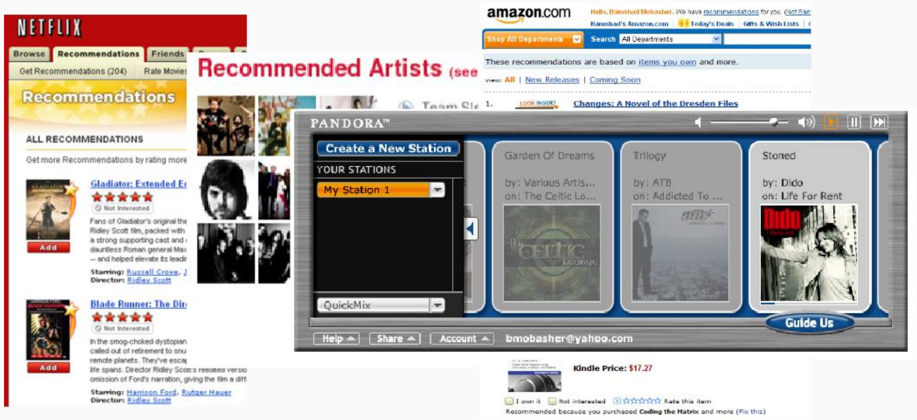
Example: Recommender systems

- Personalized information filtering systems that present items (films, television, video, music, books, news, restaurants, images, web pages, etc.) that are likely to be of interest to a given user

Why we need it?

For businesses: grow customer loyalty / increase sales

- Amazon 35% of sales from recommendation; increasing fast!
- Netflix 40%+ of movie selections from recommendation
- Facebook 90% of user interactions via personalized feeds



Common Approaches

Collaborative Filtering

- Give recommendations to a user based on preferences of “similar” users
- Preferences on items may be explicit or implicit
- Includes recommendation based on social / collaborative content

Content-Based Filtering

- Give recommendations to a user based on items with “similar” content in the user’s profile

Rule-Based (Knowledge-Based) Filtering

- Provide recommendations to users based on predefined (or learned) rules
- age(x, 25-35) and income(x, 70-100K) and children(x, >=3) recommend(x, Minivan)

Hybrid Approaches

The Recommendation Task

Basic formulation as a prediction problem

> Given a profile $\boldsymbol{P_u}$ for a user $\boldsymbol{u}$, and a target item $\boldsymbol{i_t}$, predict the preference score of user $\boldsymbol{u}$ on item $\boldsymbol{i_t}$

Typically, the profile Pu contains preference scores by u on some other items, {i1, …, ik} different from it

- preference scores on i1, …, ik may have been obtained explicitly (e.g., movie ratings) or implicitly (e.g., time spent on a product page or a news article)

Recommendation as Rating Prediction

- Two types of entities: Users and Items
- Utility of item i for user u is represented by some rating r (where $r \in$ Rating)
- Each user typically rates a subset of items
- Recommender system then tries to estimate/predict the unknown ratings, i.e., to extrapolate rating function Rec based on the known ratings:
- Rec: Users × Items → Rating
- i.e., two-dimensional recommendation framework
- The recommendations to each user are made by offering his/her highest-rated items

Collaborative Recommender Systems

- Collaborative filtering recommenders
  - Predictions for unseen (target) items are computed based the other users' with similar interest scores on items in user u's profile
    - i.e. users with similar tastes (aka "nearest neighbors")
    - requires computing correlations between user u and other users according to interest scores or ratings
    - k-nearest-neighbor (knn) strategy

	Star Wars	Jurassic Park	Terminator 2	Indep. Day
Sally	7	6	3	7
Bob	7	4	4	6
Chris	3	7	7	2
Lynn	4	4	6	2
Karen	7	4	3	?

Can we predict Karen's rating on the unseen item Independence Day?

Recommended For You > DVD

Recommendations by Category in DVD

Your Favorites Edit

- DVD
- Specialty Stores

More Categories

- Featured Categories
- Features
- Formats
- Special Features
- Stores

Improve Your Recommendations

Update your Amazon history to improve your recommendations

- Items you own
- Rated items
- Not Interested

Need Help?
Visit our help area to learn more.

These recommendations are based on items you own and more.

view: **All** | New Releases | Coming Soon

1. 

Tales from the Vineyard - First Taste
DVD ~ Tales from the Vineyard
Average Customer Review:
Release Date: November 16, 2004

Our Price: $12.99
Used & new from $11.23

Add to cart
Add to Wish List

I Own It | Not interested | Rate it
Recommended because you purchased Fun To Know: The Secrets Of Wine and more (edit)

2. No image available

Understanding Wine
DVD ~ Travelling Gourmet
Release Date: November 14, 2000

Our Price: $13.99 **Used & new** from $5.65

Add to cart
Add to Wish List

I Own It | Not interested | Rate it
Recommended because you purchased Fun To Know: The Secrets Of Wine and more (edit)

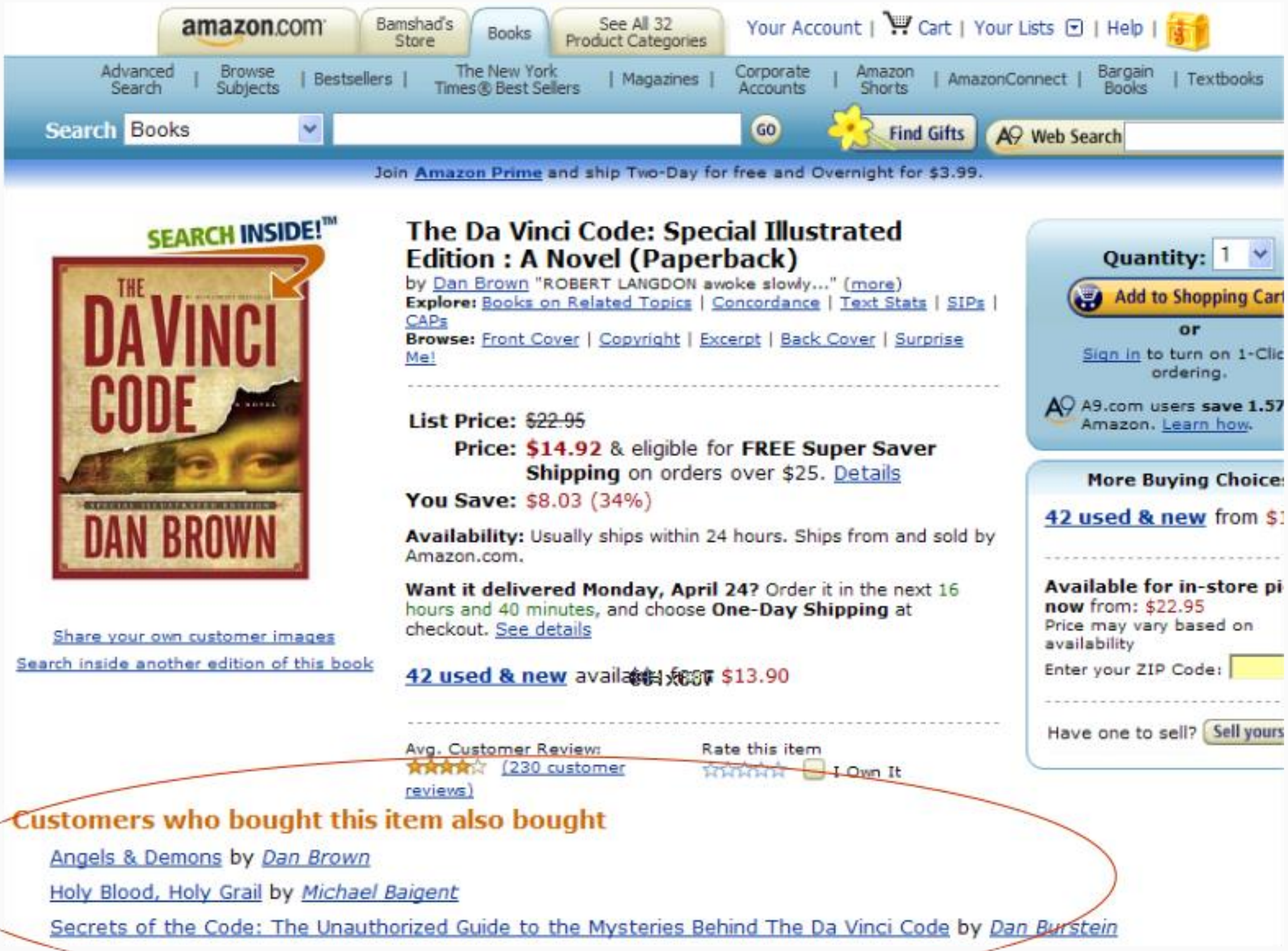
3. 

Jancis Robinson's Wine Course
DVD ~ Jancis Robinson
Average Customer Review:
Release Date: March 16, 2004

Our Price: $35.99
Used & new from $23.29

Add to cart
Add to Wish List

I Own It | Not interested | Rate it
Recommended because you purchased Fun To Know: The Secrets Of Wine and more (edit)


amazon.com
Bamshad's Store
Books
See All 32 Product Categories
Your Account | Cart | Your Lists | Help |
Advanced Search | Browse Subjects | Bestsellers | The New York Times® Best Sellers | Magazines | Corporate Accounts | Amazon Shorts | AmazonConnect | Bargain Books | Textbooks
Search Books GO
Find Gifts
Web Search
Join Amazon Prime and ship Two-Day for free and Overnight for $3.99.
SEARCH INSIDE!™
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The Da Vinci Code: Special Illustrated Edition : A Novel (Paperback)
by Dan Brown "ROBERT LANGDON awoke slowly..." (more)
Explore: Books on Related Topics | Concordance | Text Stats | SIPs | CAPs
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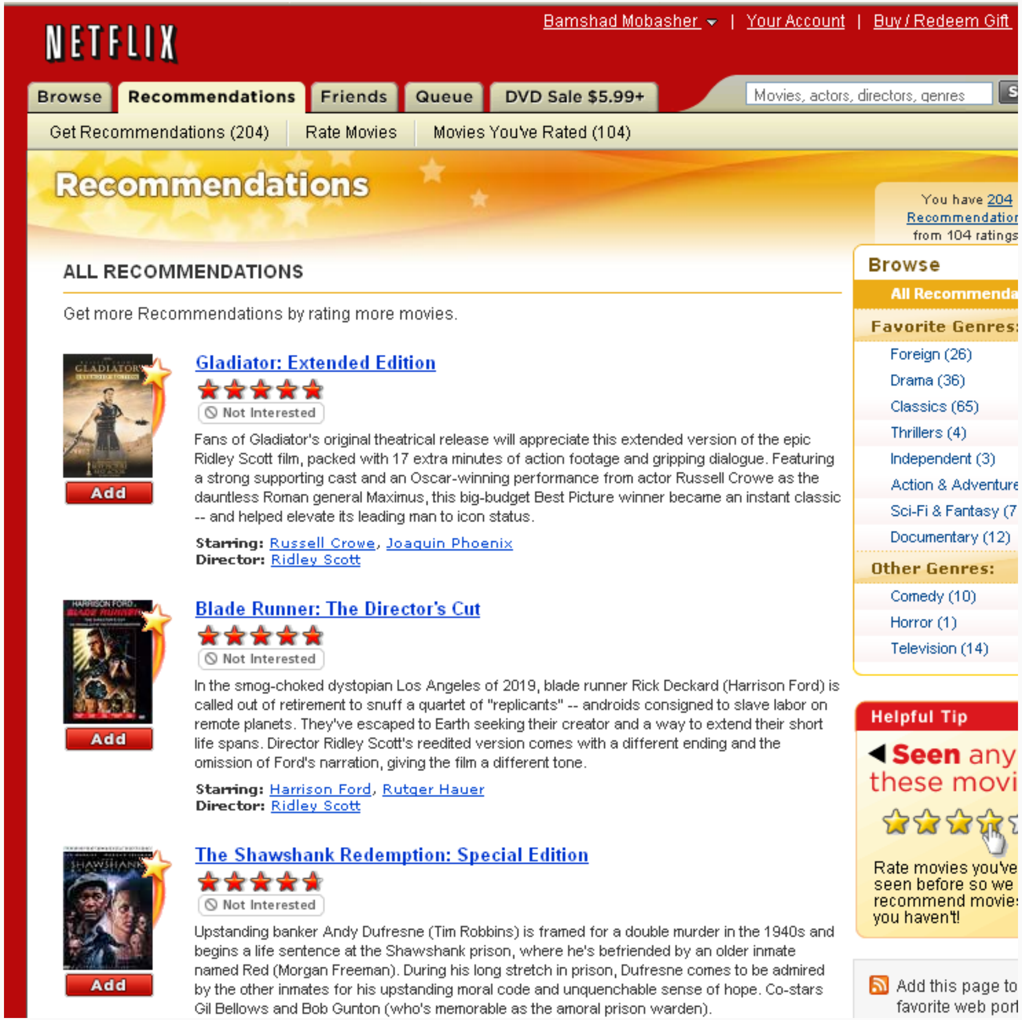
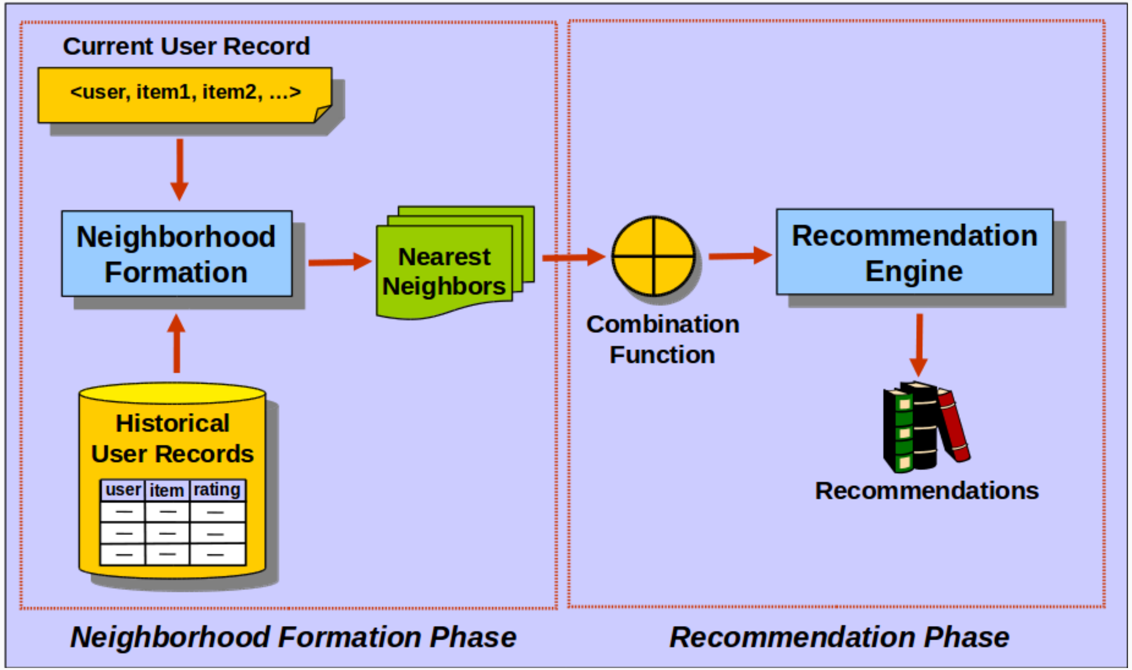
List Price: $22.95
Price: $14.92 & eligible for FREE Super Saver Shipping on orders over $25. Details
You Save: $8.03 (34%)
Availability: Usually ships within 24 hours. Ships from and sold by Amazon.com.
Want it delivered Monday, April 24? Order it in the next 16 hours and 40 minutes, and choose One-Day Shipping at checkout. See details
42 used & new available from $13.90
Avg. Customer Review: (230 customer reviews)
Rate this item
I Own It
Quantity: 1
Add to Shopping Cart
or
Sign in to turn on 1-Click ordering.
A9.com users save 1.57
Amazon. Learn how.
More Buying Choices
42 used & new from $1
Available for in-store pi
now from: $22.95
Price may vary based on availability
Enter your ZIP Code:
Have one to sell? Sell yours
Customers who bought this item also bought
Angels & Demons by Dan Brown
Holy Blood, Holy Grail by Michael Baigent
Secrets of the Code: The Unauthorized Guide to the Mysteries Behind The Da Vinci Code by Dan Burstein


NETFLIX
Bamshad Mobasher | Your Account | Buy / Redeem Gift
Browse
Recommendations
Friends
Queue
DVD Sale $5.99+
Movies, actors, directors, genres
Get Recommendations (204)
Rate Movies
Movies You've Rated (104)
Recommendations
You have 204 Recommendatio
from 104 ratings
ALL RECOMMENDATIONS
Get more Recommendations by rating more movies.
Gladiator: Extended Edition
Not Interested
Fans of Gladiator's original theatrical release will appreciate this extended version of the epic Ridley Scott film, packed with 17 extra minutes of action footage and gripping dialogue. Featuring a strong supporting cast and an Oscar-winning performance from actor Russell Crowe as the dauntless Roman general Maximus, this big-budget Best Picture winner became an instant classic -- and helped elevate its leading man to icon status.
Starring: Russell Crowe, Joaquin Phoenix
Director: Ridley Scott
Add
Blade Runner: The Director's Cut
Not Interested
In the smog-choked dystopian Los Angeles of 2019, blade runner Rick Deckard (Harrison Ford) is called out of retirement to snuff a quartet of "replicants" -- androids consigned to slave labor on remote planets. They've escaped to Earth seeking their creator and a way to extend their short life spans. Director Ridley Scott's reedited version comes with a different ending and the omission of Ford's narration, giving the film a different tone.
Starring: Harrison Ford, Rutger Hauer
Director: Ridley Scott
Add
The Shawshank Redemption: Special Edition
Not Interested
Upstanding banker Andy Dufresne (Tim Robbins) is framed for a double murder in the 1940s and begins a life sentence at the Shawshank prison, where he's befriended by an older inmate named Red (Morgan Freeman). During his long stretch in prison, Dufresne comes to be admired by the other inmates for his upstanding moral code and unquenchable sense of hope. Co-stars Gil Bellows and Bob Gunton (who's memorable as the amoral prison warden).
Add
Browse
All Recommenda
Favorite Genres:
Foreign (26)
Drama (36)
Classics (65)
Thrillers (4)
Independent (3)
Action & Adventure
Sci-Fi & Fantasy (7
Documentary (12)
Other Genres:
Comedy (10)
Horror (1)
Television (14)
Helpful Tip
Seen any these movi
Rate movies you've seen before so we recommend movie you haven't!
Add this page to favorite web port

Basic Collaborative Filtering Process



User Based Collaborative Filtering

- User-User Similarity: Pearson Correlation

$$s(i,j)=\frac{\sum_{u\in U}(R_{u,i}-\bar{R}_u)(R_{u,j}-\bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{u,i}-\bar{R}_u)^2}\sqrt{\sum_{u\in U}(R_{u,j}-\bar{R}_u)^2}}$$

- Making Predictions: K-Nearest-Neighbor

$$p_{a,i}=\bar{R}_a+\frac{\sum_{u=1}^{k}(R_{u,i}-\bar{R}_u)\times sim(a,u)}{\sum_{u=1}^{k} sim(a,u)}$$

$\bar{R}_u$ = mean rating for user *u*
$R_{u,i}$ = rating of user *u* on item *i*
sim(i,j) = Pearson correlation between *users i and j*

$P_{a,i}$ = *predicted rating of user a on item I*
R_a = mean rating for target user *a*
Sim(a,u) similarity (Pearson) between user *a* and neighbor *u*

Example

	Item1	Item 2	Item 3	Item 4	Item 5	Item 6	Correlation with Alice
Alice	5	2	3	3		?	
User 1	2		4		4	1	-1.00
User 2	2	1	3		1	2	0.33
User 3	4	2	3	2		1	.90
User 4	3	3	2		3	1	0.19
User 5		3		2	2	2	-1.00
User 6	5	3		1	3	2	0.65
User 7		5		1	5	1	-1.00

Using k-nearest neighbor with k = 1

Item Based Collaborative Filtering

- Find similarities among the items based on ratings across users
  - Often measured based on a variation of Cosine measure
- Prediction of item I for user *a* is based on the past ratings of user *a* on items similar to *i*.

	Star Wars	Jurassic Park	Terminator 2	Indep. Day
Sally	7	6	3	7
Bob	7	4	4	6
Chris	3	7	7	2
Lynn	4	4	6	2
Karen	7	4	3	?

- Suppose: **sim(Star Wars, Indep. Day) > sim(Jur. Park, Indep. Day) > sim(Termin., Indep. Day)**
- Predicted rating for Karen on Indep. Day will be 7, because she rated Star Wars 7
  - That is if we only use the most similar item
  - Otherwise, we can use the k-most similar items and again use a weighted average

Item Based Collaborative Filtering

- item similarity measures
  - cosine

$$sim(i,j) = cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{\|i\| * \|j\|} = \frac{\sum_{u\in U} R_{u,i}R_{u,j}}{\sqrt{\sum_{u\in U} R_{u,i}^2}\sqrt{\sum_{u\in U} R_{u,j}^2}}$$

(Items & Ratings as vectors)

  - adjusted cosine

$$sim(i,j) = \frac{\sum_{u\in U}(R_{u,i}-\bar{R}_u)(R_{u,j}-\bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{u,i}-\bar{R}_u)^2}\sqrt{\sum_{u\in U}(R_{u,j}-\bar{R}_u)^2}}$$

(Adjusted for different user rating schemes)

  - pearson correlation

$$sim(i,j) = \frac{Cov(i,j)}{\sigma_i\sigma_j} = \frac{\sum_{u\in U}(R_{u,i}-\bar{R}_i)(R_{u,j}-\bar{R}_j)}{\sqrt{\sum_{u\in U}(R_{u,i}-\bar{R}_i)^2}\sqrt{\sum_{u\in U}(R_{u,j}-\bar{R}_j)^2}}$$

(How much ratings deviate from average)

Example

	Item1	Item 2	Item 3	Item 4	Item 5	Item 6
Alice	5	2	3	3		?
User 1	2		4		4	1
User 2	2	1	3		1	2
User 3	4	2	3	2		1
User 4	3	3	2		3	1
User 5		3		2	2	2
User 6	5	3		1	3	2
User 7		5		1	5	1
Item similarity	0.76	0.79	0.60	0.71	0.75	

Evaluation

Split users into train/test sets

For each user a in the test set:

- split a's votes into observed (I) and to-predict (P)
- measure average absolute deviation between predicted and actual votes in P
- MAE = mean absolute error
- Or RMSE = root mean squared error

Average over all test users

Data Sparsity Problems

Cold start problem

- How to recommend new items? What to recommend to new users?

Straightforward approaches

- Ask/force users to rate a set of items
- Use another method (e.g., content-based, demographic or simply non-personalized) in the initial phase

Alternatives

- Use better algorithms (beyond nearest-neighbor approaches)
- In nearest-neighbor approaches, the set of sufficiently similar neighbors might be too small to make good predictions
- Use model-based approaches (clustering; dimensionality reduction, etc.)

Example Algorithms for Sparsity

Recursive CF

- Assume there is a very close neighbor n of u who has not yet rated the target item i .
- Apply CF-method recursively and predict a rating for item i for the neighbor
- Use this predicted rating instead of the rating of a more distant direct neighbor

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	?
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

sim = 0.85

Predict rating for User1

Model Based Approaches

Matrix factorization techniques, statistics

- singular value decomposition, principal component analysis

Approaches based on clustering

Association rule mining

- compare: shopping basket analysis

Probabilistic models

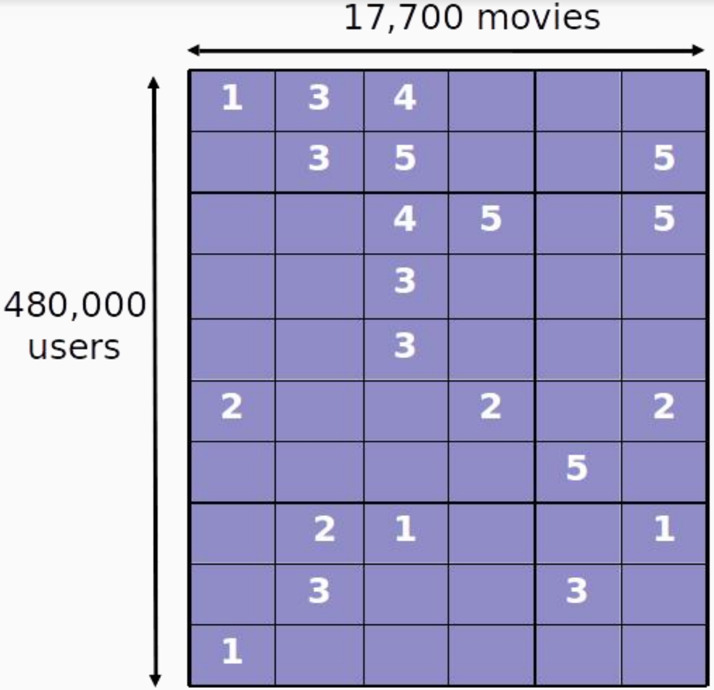
- clustering models, Bayesian networks, probabilistic Latent Semantic Analysis

Various other machine learning approaches

Dimensional Reduction

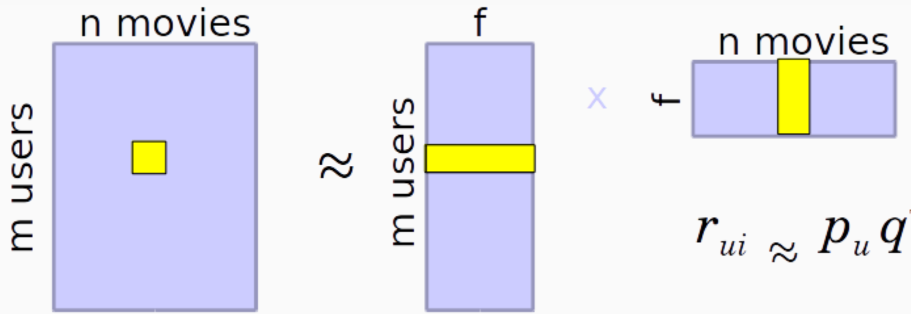
- Basic idea: Trade more complex offline model building for faster online prediction generation
- Singular Value Decomposition for dimensionality reduction of rating matrices
  - Captures important factors/aspects and their weights in the data
  - factors can be genre, actors but also non-understandable ones
  - Assumption that k dimensions capture the signals and filter out noise (K = 20 to 100)
- Constant time to make recommendations
- Approach also popular in information retrieval (Latent Semantic Indexing), data compression, …

Netflix Prize



The $1 Million Question

Matrix Factorization of Ratings Data



$$r_{ui} \approx p_u q^T_i$$

- Based on the idea of Latent Factor Analysis
  - Identify latent (unobserved) factors that “explain” observations in the data
  - In this case, observations are user ratings of movies
  - The factors may represent combinations of features or characteristics of movies and users that result in the ratings

Matrix Factorization

P_k	Dim 1	Dim 2
Alice	0.47	-0.30
Bob	-0.44	0.23
Mary	0.70	-0.06
Sue	0.31	0.93

Q_k^T					
Dim 1	-0.44	-0.57	0.06	0.38	0.57
Dim 2	0.58	-0.66	0.26	0.18	-0.36

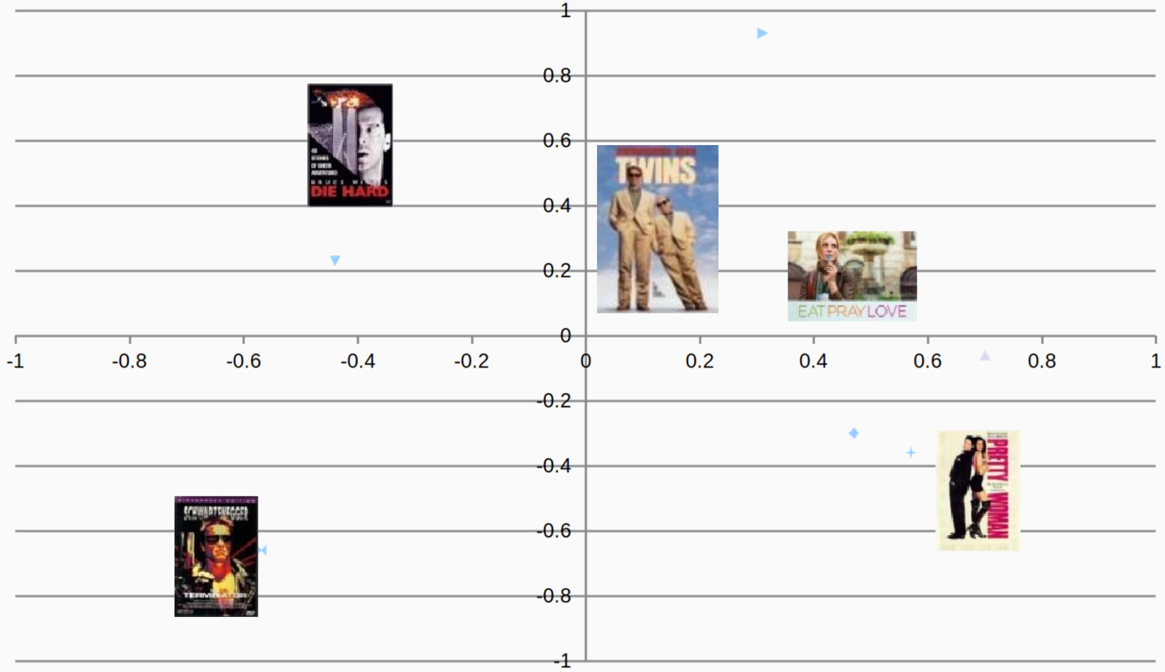
Prediction:

$$\hat{r}_{ui} = p_k(Alice) \times q_k^T(EPL)$$

Note: Can also do factorization via Singular Value Decomposition (SVD)

- **SVD:** $M_k = U_k \times \Sigma_k \times V_k^T$

Lower Dimensional Feature Space

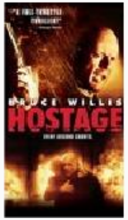


Content Based Recommendations

- Collaborative filtering does NOT require any information about the items,
  - However, it might be reasonable to exploit such information
  - E.g. recommend fantasy novels to people who liked fantasy novels in the past
- What do we need:
  - Some information about the available items such as the genre ("content")
  - Some sort of *user profile* describing what the user likes (the preferences)
- The task:
  - Learn user preferences
  - Locate/recommend items that are "similar" to the user preferences

Content Based Recommendations

- Predictions for unseen (target) items are computed based on their similarity (in terms of content) to items in the user profile.
- E.g., user profile P_u contains

recommend highly: 

and recommend “mildly”: 

Content Representation

Title	Genre	Author	Type	Price	Keywords
The Night of the Gun	Memoir	David Carr	Paperback	29.90	Press and journalism, drug addiction, personal memoirs, New York
The Lace Reader	Fiction, Mystery	Brunonia Barry	Hardcover	49.90	American contemporary fiction, detective, historical
Into the Fire	Romance, Suspense	Suzanne Brockmann	Hardcover	45.90	American fiction, Murder, Neo-nazism
...					

- Represent items as vectors over features
  - Features may be items attributes, keywords, tags, etc.
  - Often items are represented a keyword vectors based on textual descriptions with TFxIDF or other weighting approaches
    - applicable to any type of item (images, products, news stories) as long as a textual description is available or can be constructed
  - Items (and users) can then be compared using standard vector space similarity measures (e.g., Cosine similarity)

Content Based Recommendation

- Basic approach
  - Represent items as vectors over features
  - User profiles are also represented as aggregate feature vectors
    - Based on items in the user profile (e.g., items liked, purchased, viewed, clicked on, etc.)
  - Compute the similarity of an unseen item with the user profile based on the keyword overlap (e.g. using the Dice coefficient)
  - $sim(b_i, b_j) =$
  - Other similarity measures such as Cosine can also be used
  - Recommend items most similar to the user profile

Personalized Search

- **How can the search engine determine the "user's intent"?**

Query: "Madonna and Child"

?

?

PeopleNews

Madonna Ready for Another Baby?

Wednesday Nov 24, 2004 1:55pm EST

By Todd Gold

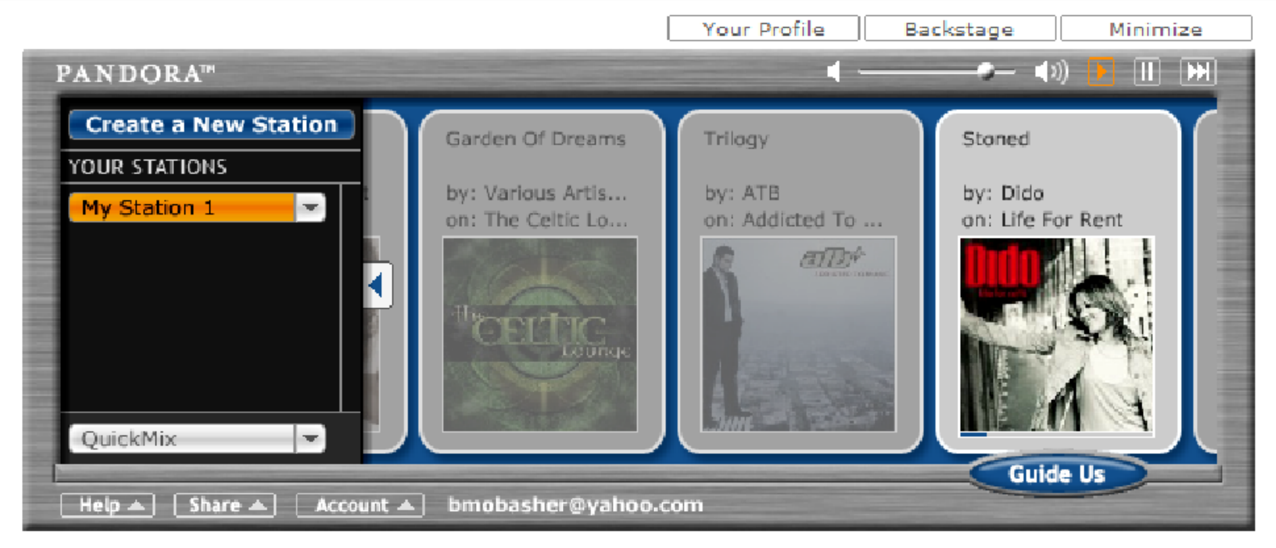
CREDIT: JO HALE / GETTY

Three months after finishing her Re-Invention Tour, Madonna is currently enjoying quiet time with her family in London, she's just published her fourth book for young readers, *The Adventures of Abdi* – and, at 46, she tells PEOPLE she wouldn't mind getting pregnant again.

She's not making any definite plans, but the pop icon says: "I'm going to have fun with my husband and see what happens."

- Need to "learn" the user profile:
  - User is an art historian?
  - User is a pop music fan?

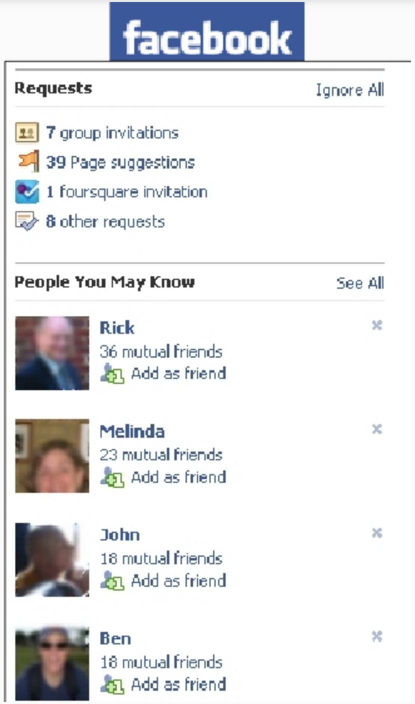
Example



Example: [Pandora]

Social Recommendation

- A form of collaborative filtering using social network data
  - Users profiles represented as sets of links to other nodes (users or items) in the network
  - Prediction problem: infer a currently non-existent link in the network



Social / Collaborative Tags

Example Tags Describe the Resource

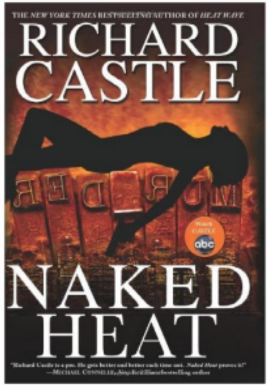

Tags Customers Associate with This Product (What's this?)
Click on a tag to find related items, discussions, and people.

Check the boxes next to the tags you consider relevant or enter your own tags in the field below.

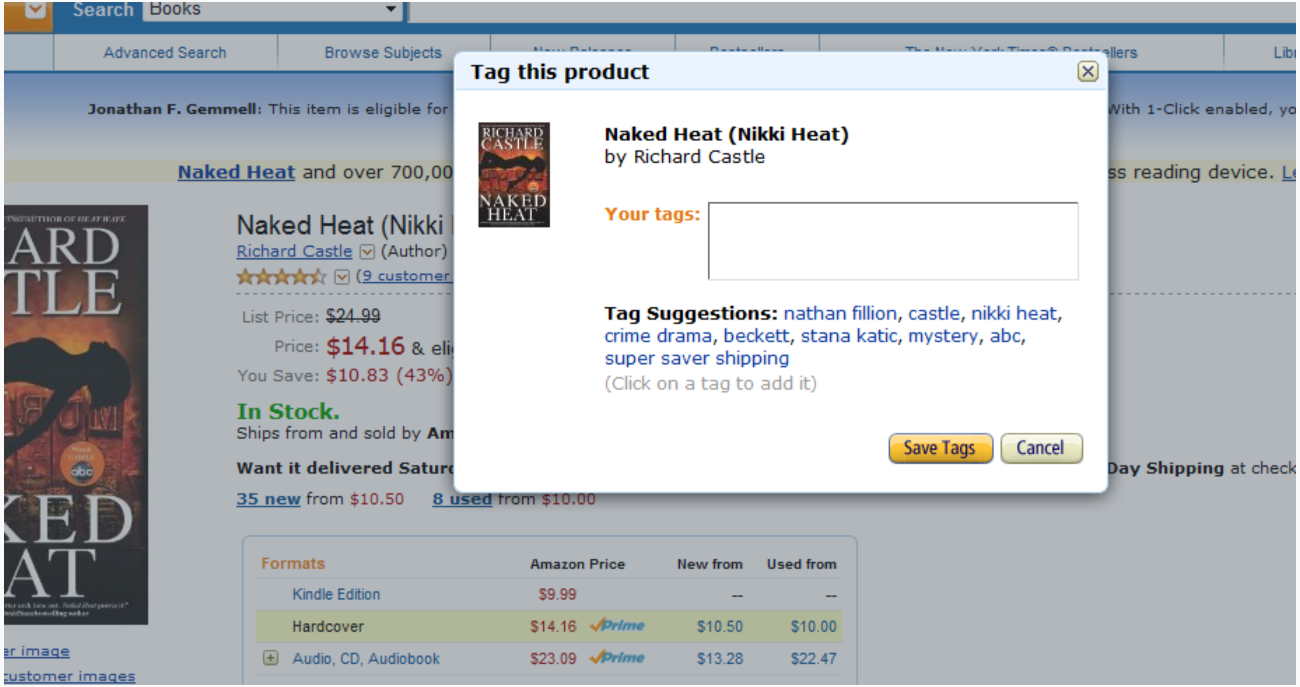
- nathan fillion (24)
- castle (22)
- nikki heat (21)
- crime drama (16)
- beckett (14)
- stana katic (14)
- mystery (10)
- abc (6)
- super saver shipping (2)
- boycott over 9 99 (1)
- cascett (1)
- ficticious fiction (1)

Agree with these tags?

Tags can describe
The resource (genre, actors, etc)
Organizational (toRead)
Subjective (awesome)
Ownership (abc)
etc



Tag Recommendation



Tags Describe the User

- These systems are “collaborative.”
  - Recommendation / Analytics based on the “wisdom of crowds.”

Rai Aren’s profile
co-author
“Secret of the Sands”

Location: Canada

Web Page: www.secretofthesands.com

In My Own Words:
RAI AREN

Rai loves the stories of Lord of the Rings, Star Wars, Star Trek, Indiana Jones (her first kitty cat is named Indiana, Indy for short), and The Matrix (take the red pill!), to name a few. She loves getting lost in these enchanting worlds and studying their underlying philosophies. Ancient Egypt has held a particular fascination for her since childhood.

Rai feels that novels have the abi...
Read more

Interests
Reading, writing novels (there are lots of fascinating & very cool ones to come, so stay tuned!), travel, movies, being good to mama earth & all of her inhabitants :)

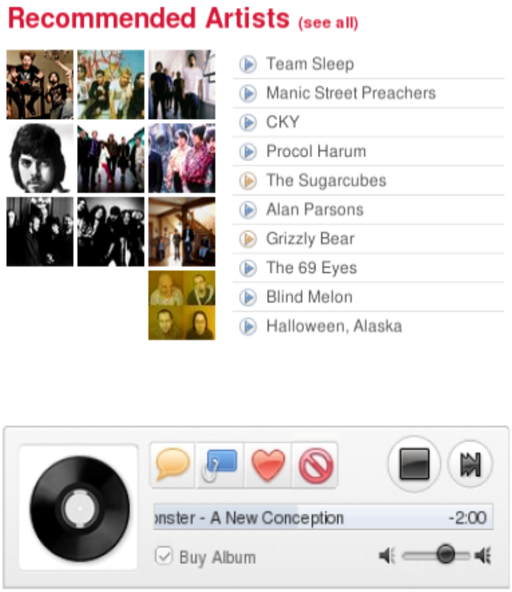
Frequently Used Tags
action action adventure action thriller adventure archaeology childrens books egypt fantasy fiction historical fiction horror humor indiana jones inspirational kindle kindle authors kindle book love love story magic memoir mystery novel paranormal paranormal romance romance science fiction suspense thriller young adult

› **See all 1,832 tagged items**

Using Tags for Recommendation

Last.fm recommendations

- Recommendations:
  - Primarily Collaborative Filtering
  - Item-Item (artist recommendations
  - User-User (Neighbors)
  - Could use:
    tags, audio, metadata
- Evaluating (rel. feedback)
  - Tracking Love/Ban behavior



Combining Content and Collaborative Recommendation

- Example: Semantically Enhanced CF
  - Extend item-based collaborative filtering to incorporate both similarity based on ratings (or usage) as well as semantic similarity based on content / semantic information
- Semantic knowledge about items
  - Can be extracted automatically from the Web based on domain-specific reference ontologies
  - Used in conjunction with user-item mappings to create a combined similarity measure for item comparisons
  - Singular value decomposition used to reduce noise in the content data
- Semantic combination threshold
  - Used to determine the proportion of semantic and rating (or usage) similarities in the combined measure

Semantically Enhanced Hybrid Recommendation

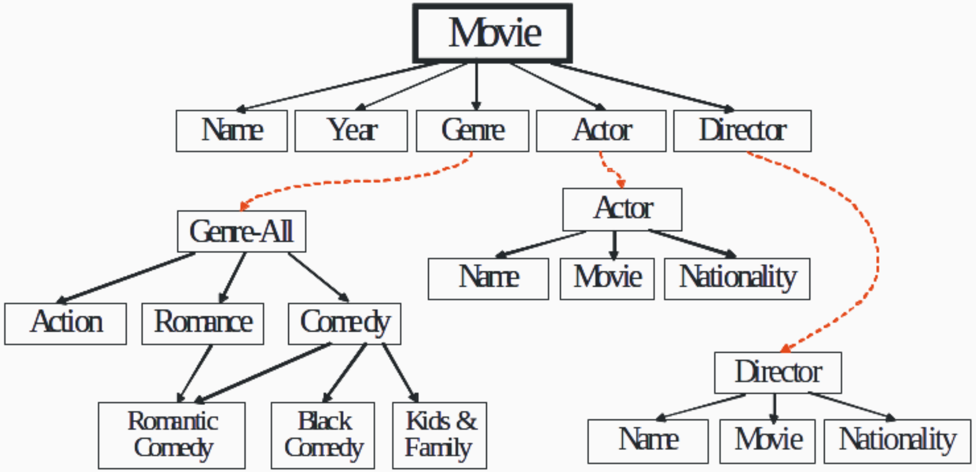
- An extension of the item-based algorithm
  - Use a combined similarity measure to compute item similarities:

$$\boxed{CombinedSim(i_p, i_q) = (1-\alpha) \cdot SemSim(i_p, i_q) + \alpha \cdot RateSim(i_p, i_q)}$$

  - where,
    - *SemSim* is the similarity of items i_p and i_q based on semantic features (e.g., keywords, attributes, etc.); and
    - *RateSim* is the similarity of items i_p and i_q based on user ratings (as in the standard item-based CF)
  - α is the semantic combination parameter:
    - α = 1 ▯ only user ratings; no semantic similarity
    - α = 0 ▯ only semantic features; no collaborative similarity

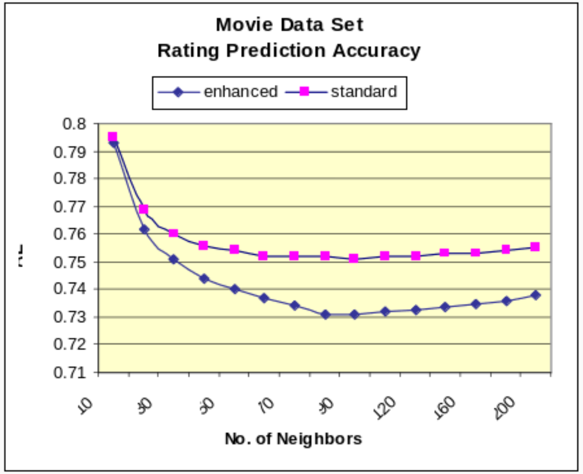
Semantically Enhanced CF

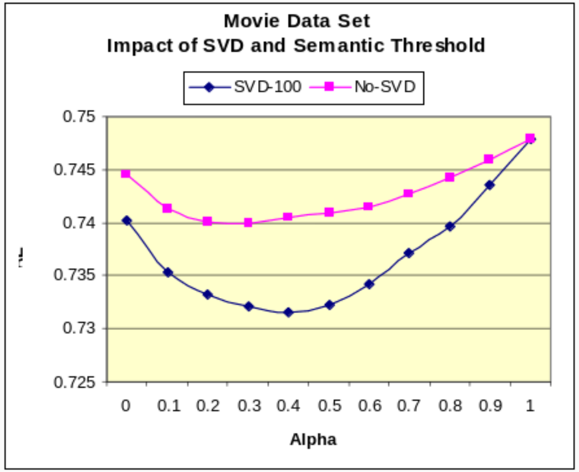
- Movie data set
  - Movie ratings from the movielens data set
  - Semantic info. extracted from IMDB based on the following ontology



Semantically Enhanced CF

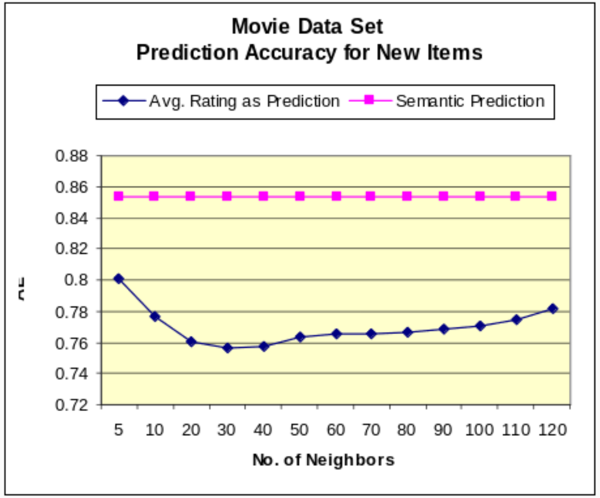
- Used 10-fold x-validation on randomly selected test and training data sets
- Each user in training set has at least 20 ratings (scale 1-5)

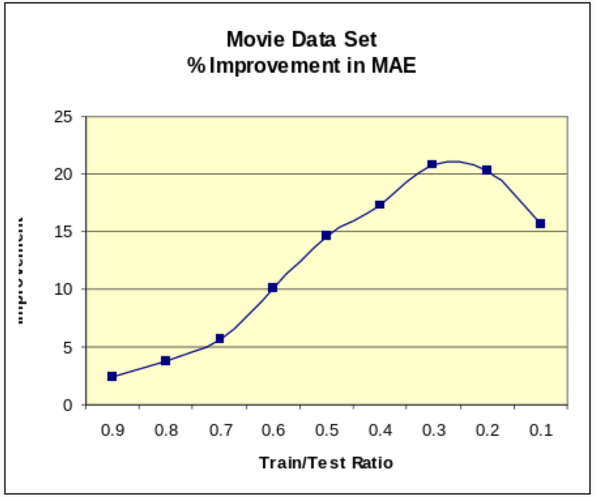




Semantically Enhanced CF

- Dealing with new items and sparse data sets
  - For new items, select all movies with only one rating as the test data
  - Degrees of sparsity simulated using different ratios for training data





Representation of User Profile Data

Items

User Profiles

	A	B	C	D	E	F
user0	15	5	0	0	0	185
user1	0	0	32	4	0	0
user2	12	0	0	56	236	0
user3	9	47	0	0	0	134
user4	0	0	23	15	0	0
user5	17	0	0	157	69	0
user6	24	89	0	0	0	354
user7	0	0	78	27	0	0
user8	7	0	45	20	127	0
user9	0	38	57	0	0	15

Using Clusters for Web Personalization

User navigation sessions

	A.html	B.html	C.html	D.html	E.html	F.html
user0	1	1	0	0	0	1
user1	0	0	1	1	0	0
user2	1	0	0	1	1	0
user3	1	1	0	0	0	1
user4	0	0	1	1	0	0
user5	1	0	0	1	1	0
user6	1	1	0	0	0	1
user7	0	0	1	1	0	0
user8	1	0	1	1	1	0
user9	0	1	1	0	0	1

Result of Clustering

		A.html	B.html	C.html	D.html	E.html	F.html
Cluster 0	user 1	0	0	1	1	0	0
	user 4	0	0	1	1	0	0
	user 7	0	0	1	1	0	0
Cluster 1	user 0	1	1	0	0	0	1
	user 3	1	1	0	0	0	1
	user 6	1	1	0	0	0	1
	user 9	0	1	1	0	0	1
Cluster 2	user 2	1	0	0	1	1	0
	user 5	1	0	0	1	1	0
	user 8	1	0	1	1	1	0

PROFILE 0 (Cluster Size = 3)

1.00 C.html
1.00 D.html

PROFILE 1 (Cluster Size = 4)

1.00 B.html
1.00 F.html
0.75 A.html
0.25 C.html

PROFILE 2 (Cluster Size = 3)

1.00 A.html
1.00 D.html
1.00 E.html
0.33 C.html

Given an active session A □ B, the best matching profile is Profile 1. This may result in a recommendation for page F.html, since it appears with high weight in that profile.

Clustering and Collaborative Filtering

Tag Clustering

Wrapping-up the Lecture

Questions

What is the difference tf idf?

What is the intuition of tf x idf?

How do you evaluate the performance of recommender systems?