CSCI567 Machine Learning (Spring 2018)

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Lecture 24: April 18, 2018

Outline

Outline

Administrative

- Quiz 3 coming up
- Remember your ID, pencil(s)

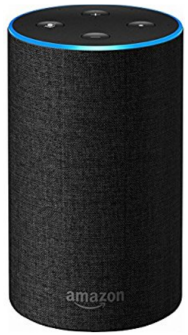
Outline

Example: Amazon.com

Deals recommended for you See all deals

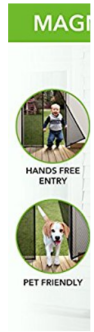
$105.99 - $1,289.99
Ends in 03:52:40

$48.95
~~$69.99~~
Ends in 03:42:41



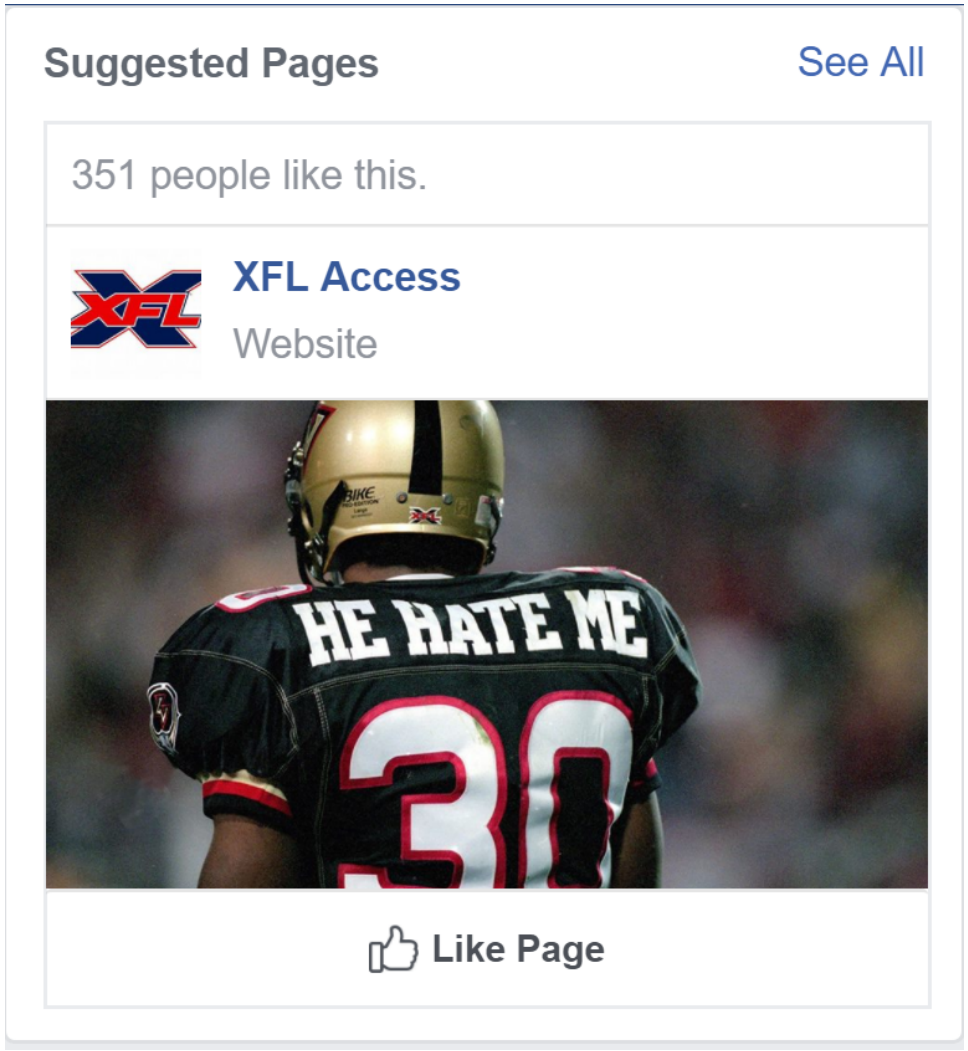
$84.99 - $104.99

$12.28
~~$20.35~~
Ends in 52:41

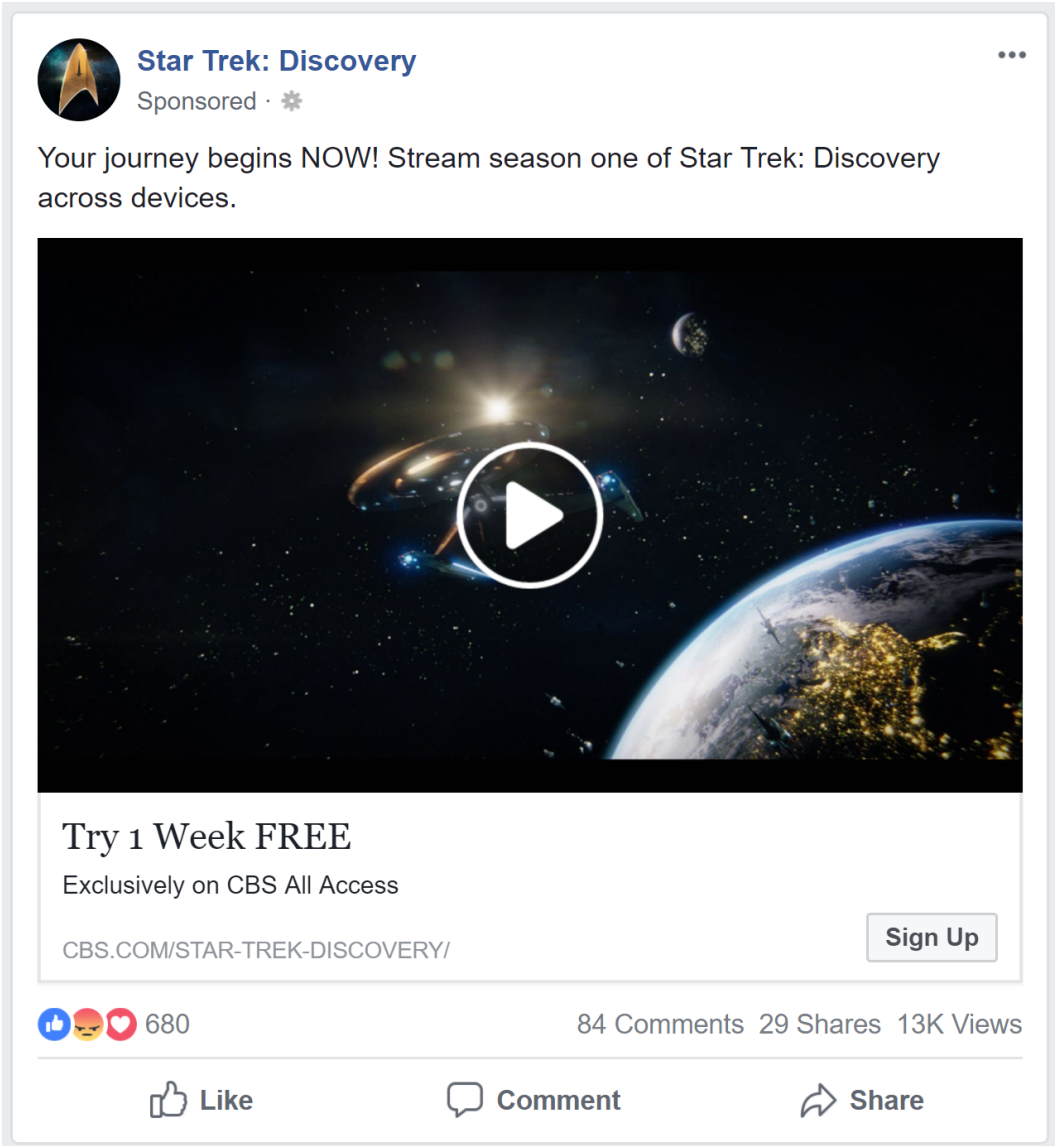


$12.70
Ends in (

Example: The Facebook



Example: The Facebook



Example: Netflix

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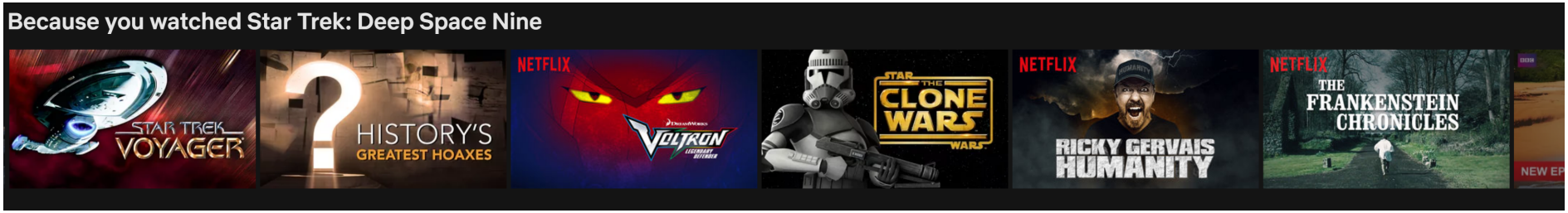


Example: Movie recommendation

Training data

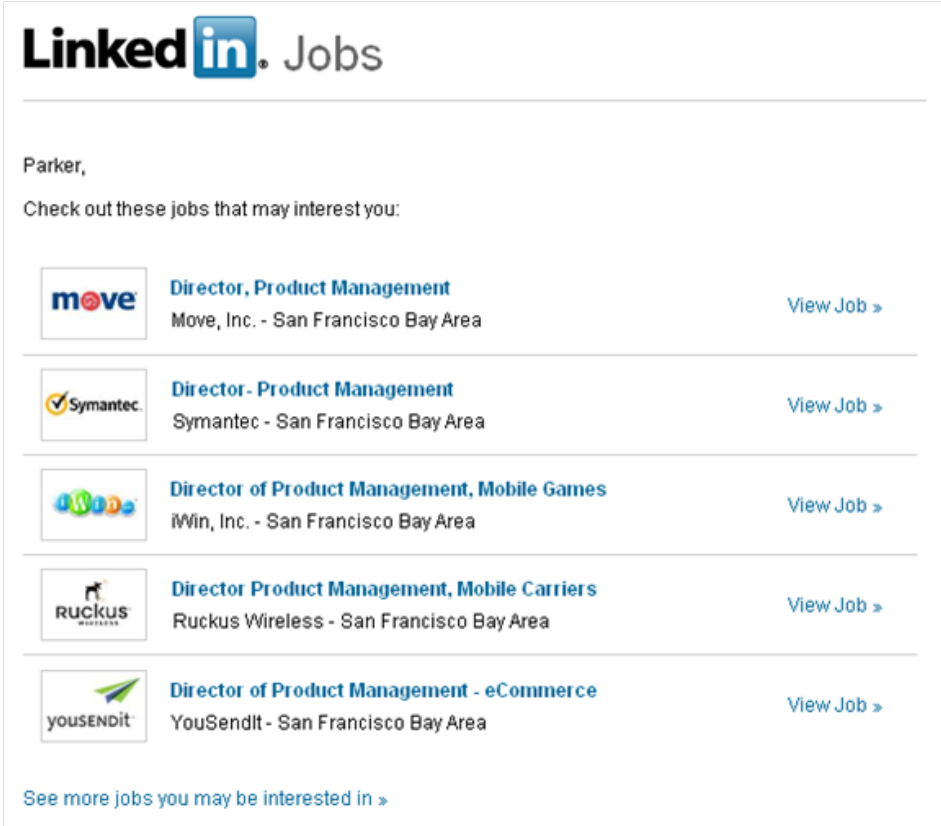
user	movie	score
1	21	1
1	213	5
2	345	4
2	123	4
2	768	3
3	76	5
4	45	4
5	568	1
5	342	2
5	234	2
6	76	5
6	56	4

Test data

user	movie	score
1	62	?
1	96	?
2	7	?
2	3	?
3	47	?
3	15	?
4	41	?
4	28	?
5	93	?
5	74	?
6	69	?
6	83	?

Recommender Systems: Other Examples

- Recommendation of groups, jobs or people on LinkedIn
- Friend recommendation and ad personalization on Facebook
- News recommendation at Forbes.com
- etc.



Why using Recommender Systems?

- Value for the customer
  - Find things that are interesting
  - Narrow down the set of choices
  - Help me explore the space of options
  - Discover new things
  - Entertainment, ...
- Value for the provider
  - Additional and probably unique personalized service for the customer
  - Increase sales, click trough rates, conversion etc.
  - Opportunities for promotion, persuasion
  - Obtain more knowledge about customers

Value of Recommender Systems

- Netflix: 2/3 of the movies watched are recommended
- Google News: recommendations generate 38% more clickthrough
- Amazon: 35% sales from recommendations
- Choicestream: 28% of the people would buy more music if they found what they liked.

Recommender Systems: Problem

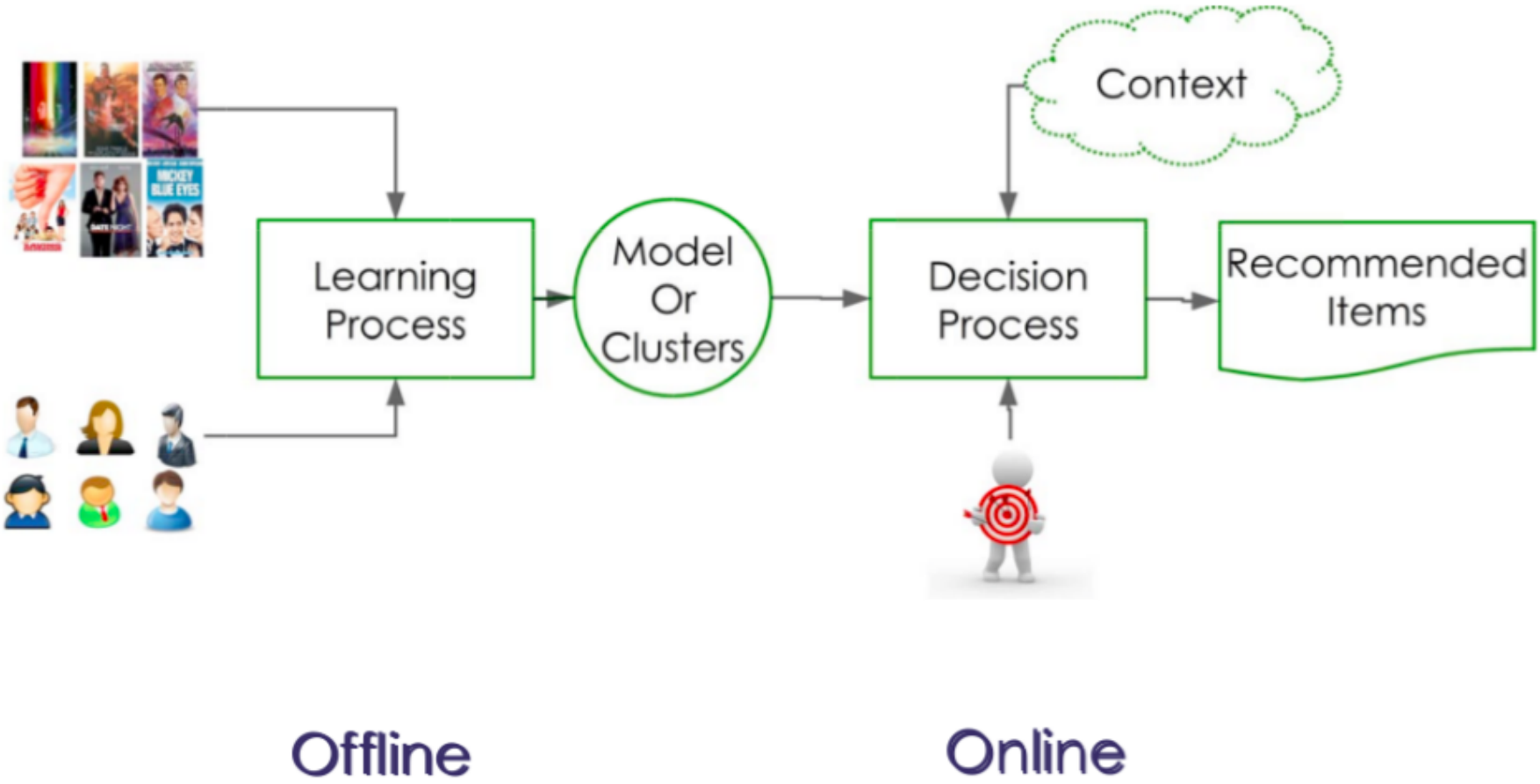
Estimate a utility function that automatically predicts how a user will like an item.
Based on:

- Past behavior
- Relations to other users
- Item similarity
- Context
- ...

Recommender Systems: Problem

- Let U be set of all users and let I be set of all possible recommendable items
- Let F be a utility function measuring the usefulness of item i to user u, i.e., $F : I \times U \rightarrow R$, where R is a totally ordered set.
- For each user $u \in U$, we want to choose items $i \in I$ that maximize F.

Recommender Systems: Two-step Process



Recommender Systems: Approaches

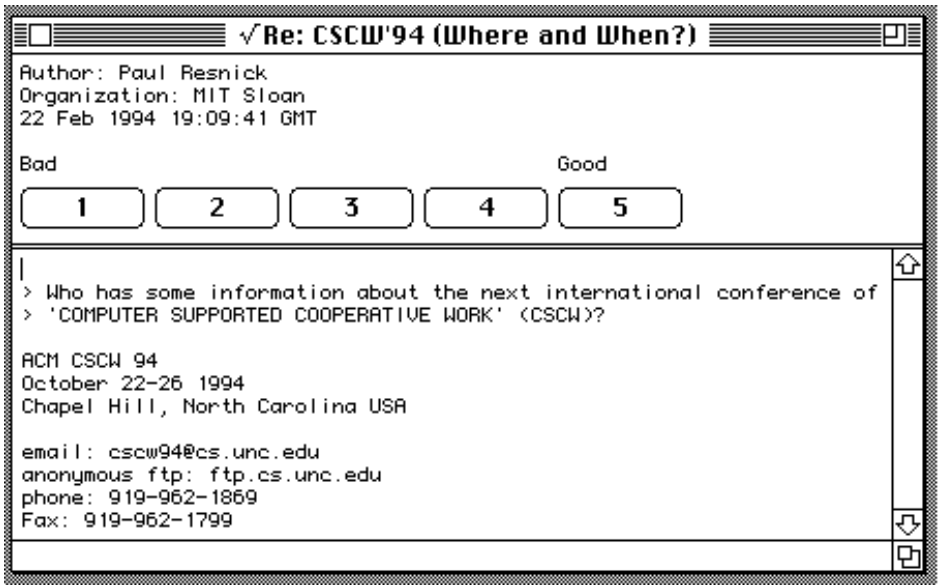
Popular approaches:

- Content-based recommendations:
  - The user will be recommended items based on profile information or similar to the ones the user preferred in the past
- Collaborative filtering (or collaborative recommendations):
  - The user will be recommended items that people with similar tastes and preferences liked in the past
- Hybrids:
  - Combine collaborative and content-based methods

Why so many online sources?

The first collaborative filtering

- Tapestry, 1994: http://ccs.mit.edu/papers/CCSWP165.html



The Netflix Challenge

- https://www.netflixprize.com
- October 2006: Netflix Prize for improving recommendation algorithm.
- $1 Million to whoever gets 10% improvement.
- Netflix published a dataset:
  - $\approx 17,000$ movies
  - 500,000 users.
  - 100 million ratings (training set was 99 million)
- Judged on root mean-square error

The Netflix Challenge

- Lasted about three years
- Eventually won: "Bellkor's Pragmatic Chaos" at 10.6%
- 40,000 teams entered, 186 countries

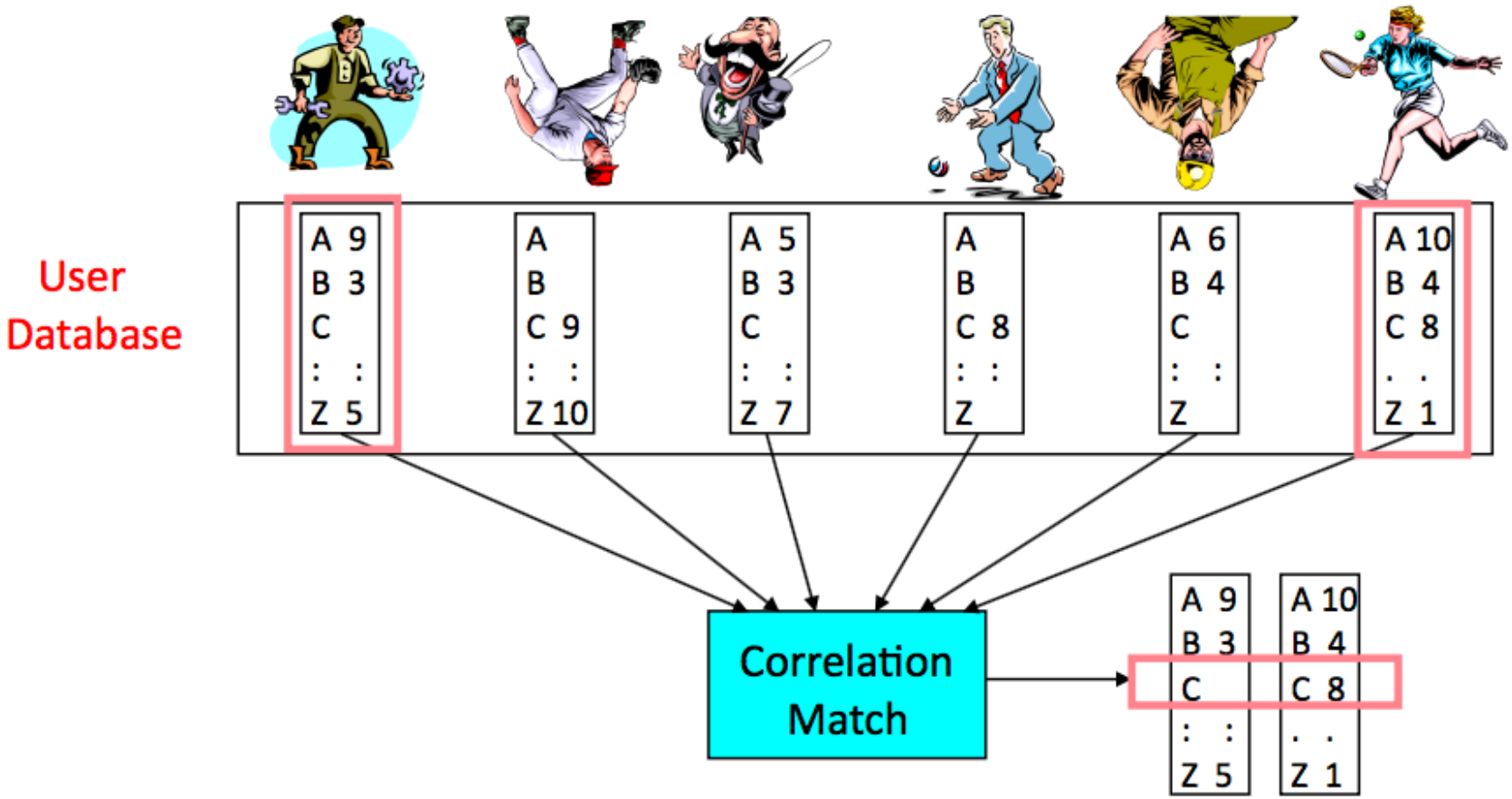
Outline

Content-based recommendations

- Recommend items that matches the User Profile.
- The Profile is based on items user has liked in the past or explicit interests that he defines.
- A content-based recommender system matches the profile of the item to the user profile to decide on its relevancy to the user.

Outline

Collaborative Filtering



Collaborative Filtering

- Collaborative filtering (CF):
  - k-nearest neighbor (kNN)
  - matrix factorization
- The most prominent approach to generate recommendations: Used by large, commercial e-commerce sites
- Well-understood, various algorithms and variations exist
- Applicable in many domains (book, movies, DVDs, ..)
- Approach: use the wisdom of the crowd to recommend items
- Basic assumption and idea
  - Users give ratings to catalog items (implicitly or explicitly)
  - Customers who had similar tastes in the past, will have similar tastes in the future

Collaborative Filtering: User-based Model

GroupLens: an open architecture for collaborative filtering of netnews, P. Resnick et al., ACM CSCW, 1994.

- Goal: given an active user (Alice) and an item i not yet seen by Alice, the goal is to estimate Alices rating for this item.
- Basic idea: People who agreed in their subjective evaluations in the past are likely to agree again in the future
- Algorithm: find a set of users (peers) who liked the same items as Alice in the past and who have rated item p, e.g. the average of their ratings to predict, if Alice will like item p; do this for all items (Alice has not seen and recommend the best-rated)

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

Collaborative Filtering: Important Questions

- How do we measure similarity?
- How many neighbors should we consider?
- How do we generate a prediction from the neighbors ratings?

Collaborative Filtering: Important Questions

- How do we measure similarity?
  Answer: Pearson correlation

$$sim(a,b) = \frac{\sum_p (r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_p (r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_p (r_{b,p} - \bar{r}_b)^2}}$$

- How many neighbors should we consider?
  Answer: Use similarity threshold or fixed number of neighbors.

Collaborative Filtering: Important Questions

- How do we generate a prediction from the neighbors ratings? Answer:

$$pred(a,p) = \bar{r}_a + \frac{\sum_{b \in N(a)} sim(a,b) * (r_{b,p} - \bar{r}_b)}{\sum_{b \in N(a)} sim(a,b)}$$

a. Calculate whether the neighbors ratings for the unseen item i are higher or lower than their average

b. Combine the rating differences using the similarity as a weight

c. Add/subtract the neighbors bias from the active users average and use this as a prediction

User-based CF: Example

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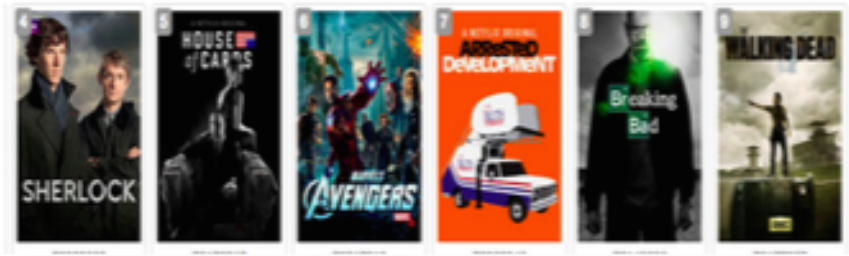


						sim(u,v)
	2			4	5		NA
	5		4			1	0.87
			5		2		1
		1		5		4	-1
	3.51*	3.81*	4	2.42*	2.48*	2	
	4	5		1			NA

User-based CF: Challenges

- Sparsity evaluation of large item sets, users purchases are under 1%.
- Difficult to make predictions based on nearest neighbor algorithms $\rightarrow$ Accuracy of recommendation may be poor.
- Scalability - Nearest neighbor require computation that grows with both the number of users and the number of items.
- Poor relationship among like minded but sparse-rating users.
- Solution : usage of latent models to capture similarity between users and items in a reduced dimensional space

Collaborative Filtering: Item-based Model

Item-based collaborative filtering recommendation algorithms, B. Sarwar et al., WWW 2001.

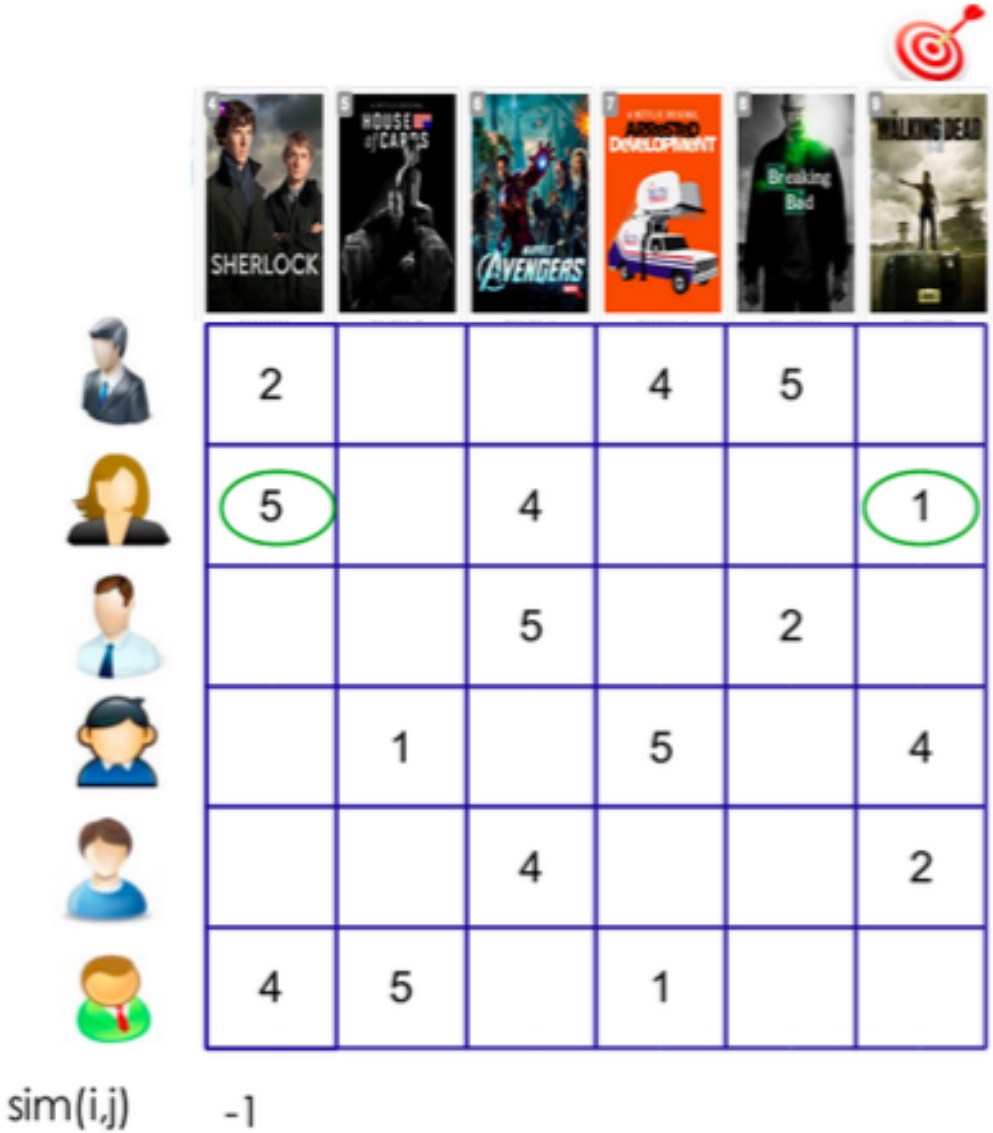
- Scalability issues arise with user-based model if there are many more users than items ($m >> n, m = \#$ of users, $n = \#$ of items). e.g. amazon.com.
  - Space complexity is $O(m^2)$ when pre-computed;
  - Time complexity for computing Pearson is $O(m^2 n)$.
- High sparsity leads to few common ratings between two users
- Basic idea: Item-based CF exploits relationships between items first, instead of relationships between users.

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

Collaborative Filtering: Item-based Model

- Item-based filtering does not solve the scalability problem itself
- Pre-processing approach by Amazon.com (in 2003)
  (1) Calculate all pair-wise item similarities in advance
  (2) The neighborhood to be used at run-time is typically rather small, because only items are taken into account which the user has rated
  (3) Item similarities are supposed to be more stable than user similarities
- Memory requirements: Up to N^2 pair-wise similarities to be memorized (N = number of items) in theory; In practice, this is significantly lower (items with no co-ratings)
- Minimum threshold for co-ratings (items, which are rated at least by n users)
- Limit the size of the neighborhood (might affect recommendation accuracy)

Item-based CF: Example



Item-based CF: Example

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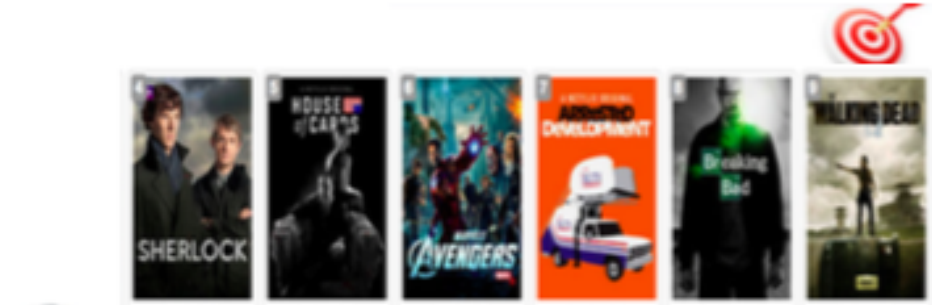


	2			4	5	2.94*
	5		4			1
			5		2	2.48*
		1		5		4
			4			2
	4	5		1		1.12*
sim(i,j)	-1	-1	0.86	1	NA	

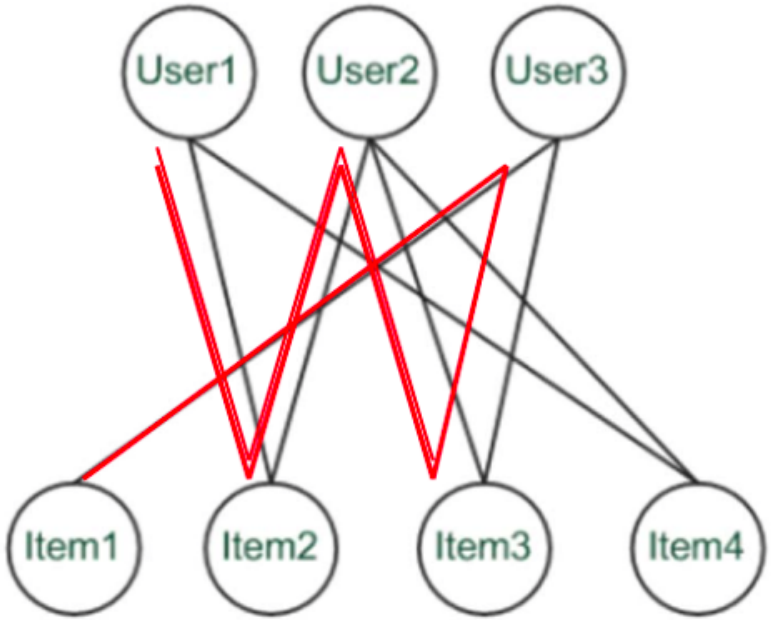
Performance Implications

- Bottleneck - Similarity computation.
- Time complexity, highly time consuming with millions of users and items in the database.
  - Isolate the neighborhood generation and predication steps.
  - off-line component / model similarity computation, done earlier and stored in memory.
  - on-line component prediction generation process.

Collaborative Filtering: Graph-based Model

Spreading activation (sketch)

- Use paths of lengths $>= 3$ to recommend items
- Length 3: Recommend Item 3 to User 1
- Length 5: Item 1 also recommendable



Collaborative Filtering: Dimension Reduction

Application of Dimensionality Reduction in Recommender System, B. Sarwar et al., WebKDD Workshop, 2000.

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, or some semantics
- Assumption that k dimensions capture the signals and filter out noise

Collaborative Filtering: Dimension Reduction

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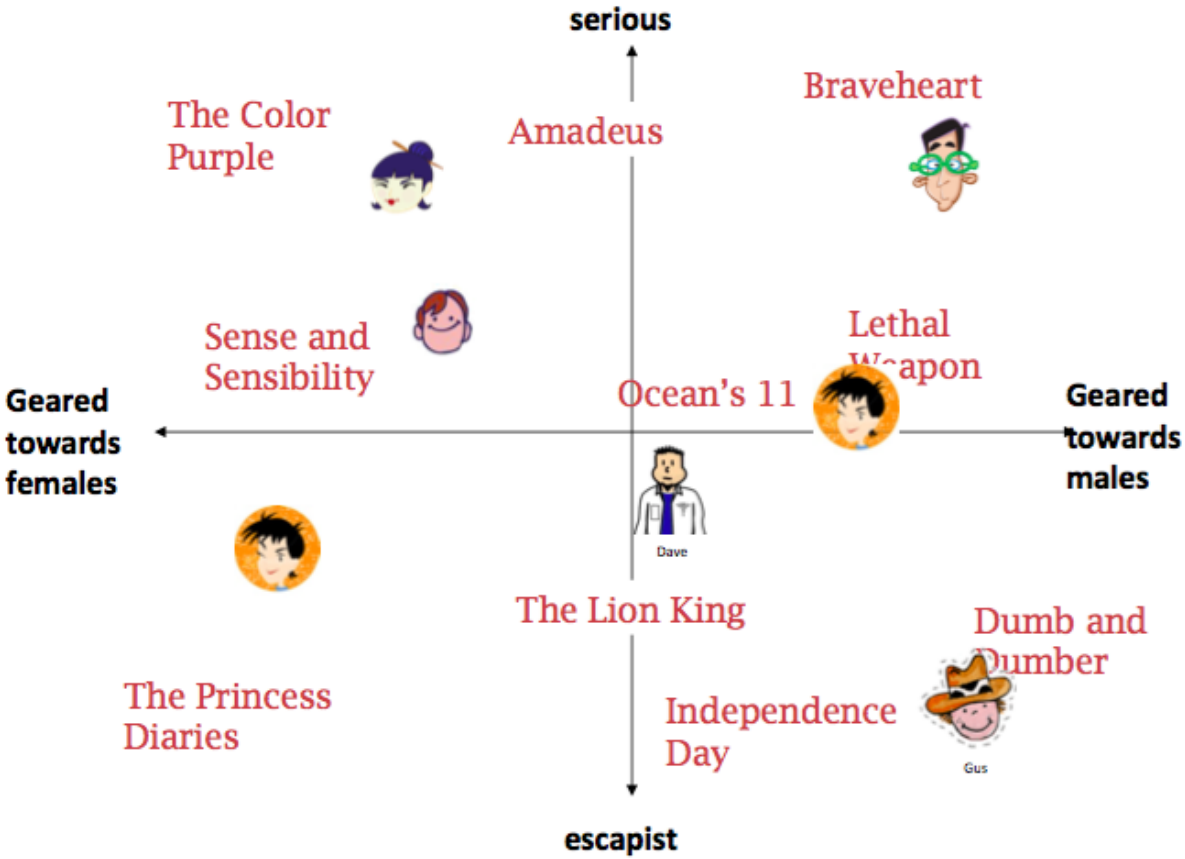


Collaborative Filtering: Dimension Reduction

Application of Dimensionality Reduction in Recommender System, B. Sarwar et al., WebKDD Workshop, 2000.

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

U_k	Dim1	Dim2
Alice	0.47	-0.30
Bob	-0.44	0.23
Mary	0.70	-0.06
Sue	0.31	0.93

V_k^T					
Dim1	-0.44	-0.57	0.06	0.38	0.57
Dim2	0.58	-0.66	0.26	0.18	-0.36

- **Prediction:** $\hat{r}_{ui} = \bar{r}_u + U_k(Alice) \times \Sigma_k \times V_k^T(EPL)$

  = 3 + 0.84 = 3.84

Σ_k	Dim1	Dim2
Dim1	5.63	0
Dim2	0	3.23

Collaborative Filtering: Latent Class Models

Latent Class Models for Collaborative Filtering, Hofmann and Puzieha, IJCAI 1999.

- Input: user u and item i with rating v
- One example of the latent class model: the vote on an item is independent of the users identity given the true value of the latent variable z, i.e.,

$$P(v|u,i) = \sum_z P(v|u,i,z)P(z|u) = \sum_z P(v|i,z)P(z|u).$$

Collaborative Filtering: Hybrid Approach

Factorization meets the neighborhood: a multifaceted collaborative filtering model, Y. Koren, ACM SIGKDD, 2008.

Basic idea: Combination of different approaches in one prediction single function

- Baseline estimates: $v_{u,i} = \mu + b_u + b_i$. The resulting optimization problem is:

$$\min_{b^*} \sum_{(u,i)\in\mathcal{K}} (v_{u,i} - \mu - b_u - b_i)^2 + \lambda_1 (\sum_{u'} b_{u'}^2 + \sum_{v'} b_{v'}^2)$$

- Baseline + Latent model: $v_{u,i} = \mu + b_u + b_i + p_u^T q_i$. The resulting optimization problem is:

$$\min_{b^*,p^*,q^*} \sum_{(u,i)\in\mathcal{K}} (v_{u,i} - \mu - b_u - b_i - p_u^T q_i)^2 + \lambda_1 (\sum_{u'} b_{u'}^2 + \sum_{v'} b_{v'}^2) + \lambda_2 (||p||_2 + ||q||_2)$$

Evaluation Metrics

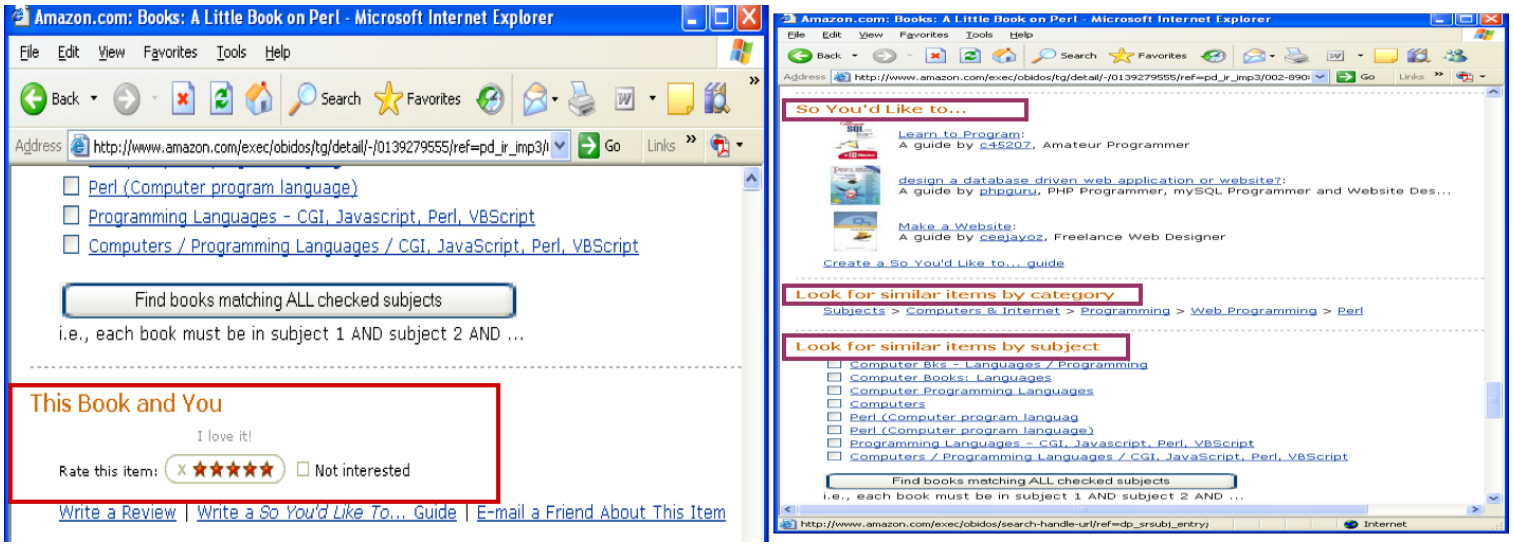
- Novelty: The ability of a recommender system to recommend items that the user was not already aware of.
- Serendipity: Users are given recommendations for items that they would not have seen given their existing channels of discovery. A measure of how surprising the recommendations are
- Coverage: The percentage of the items known to the recommender system for which it can generate predictions.
- Learning Rate: How quickly the CF system becomes an effective predictor of taste as data begins to arrive
- Confidence: Ability to evaluate the likely quality of its predictions
- User Satisfaction: By surveying the users or measuring retention and use statistics

Evaluation Metrics

- Accuracy
  - Predict accuracy: The ability of a recommender system to predict a users rating for an item
    - Mean absolute error (MAE)
  - Rank accuracy
    - Precision: percentage of items in a recommendation list that the user would rate as useful
    - Half-life utility: the utility of a recommendation list to a user
      Assumption: the likelihood that a user examines a recommended object decays exponentially with the objects ranking

Practical Issues: Ratings

- Explicit ratings:
  - Users rate themselves for an item
  - Most accurate descriptions of a users preference
  - Challenging in collecting data
- Implicit ratings
  - Observations of user behavior
  - Can be collected with little or no cost to user
  - Ratings inference may be imprecise.



Practical Issues: Cold start

Not enough data in order to make accurate recommendations

- New user
  - Rate some initial items
  - Non-personalized recommendations - Describe tastes
  - Demographic info.
- New Item
  - Non-CF : content analysis, metadata

Practical Issues: Others

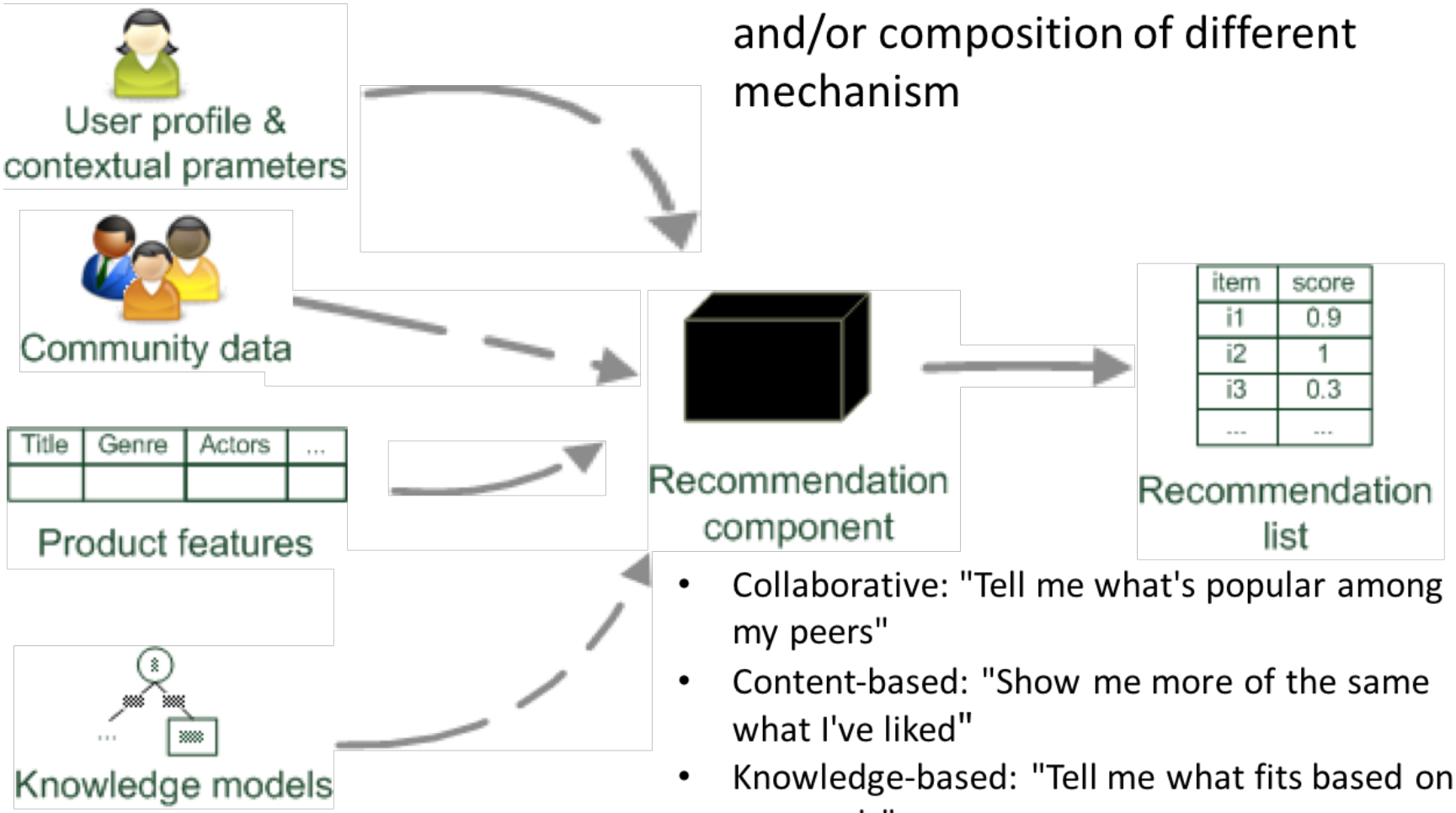
- Scalability:
  - Usually, there are millions of users and products
  - Large amount of computation power is necessary
- Sparsity:
  - The number of items is extremely large
  - The most active users will only have rated a small subset of the overall database
  - Even the most popular items have a very few ratings
- Privacy and Trust:
  - Users profiles, Personalized information
  - Recommender system may break trust when malicious users give ratings that are not representative of their true preferences.

Collaborative Filtering: Summary

- Pros: well-understood, works well in some domains, no knowledge engineering required
- Cons: requires user community, sparsity problems, no integration of other knowledge sources, no explanation of results
- What is the best CF method? Differences between methods could be very small with limited data
- How to evaluate the prediction quality? MAE / RMSE
  - What does an MAE of 0.7 actually mean?

Outline

Hybrid recommendation



Hybrid: combinations of various inputs and/or composition of different mechanism

- Collaborative: "Tell me what's popular among my peers"
- Content-based: "Show me more of the same what I've liked"
- Knowledge-based: "Tell me what fits based on my needs"

Credits

Parts of this lecture note is based on the slides of:

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- Alex Smola@CMU
- Yahuda Koren@Yahoo labs
- Bing Liu@UIC
- Xaviar Amatriain@ Netflix
- Parisa Mansourifard