Data Valorization: Recommender System

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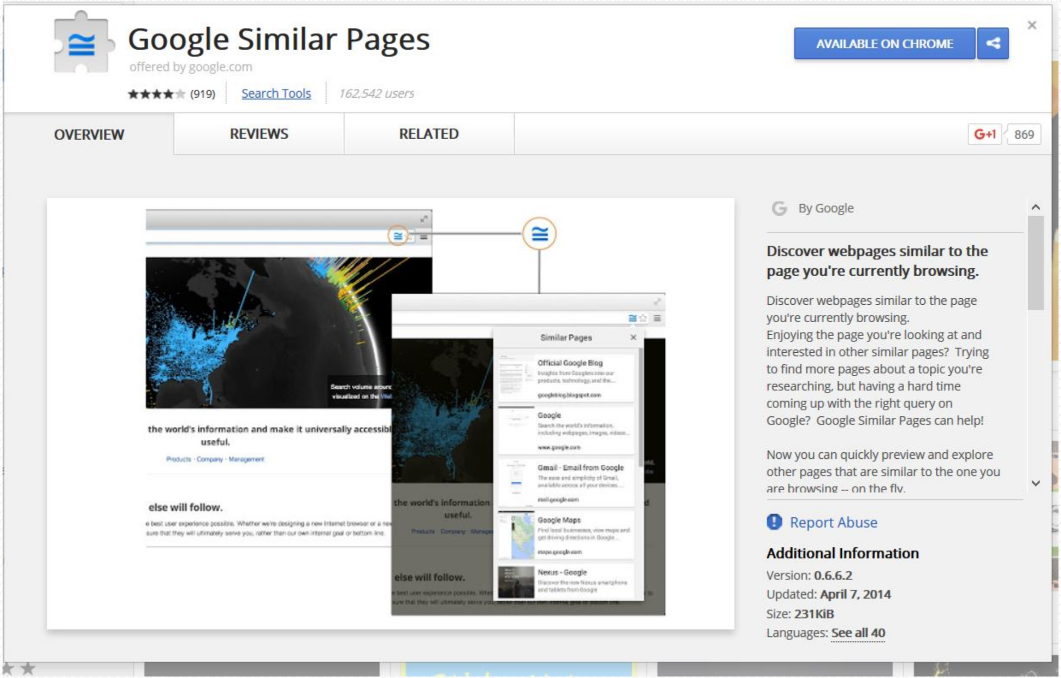
Outline

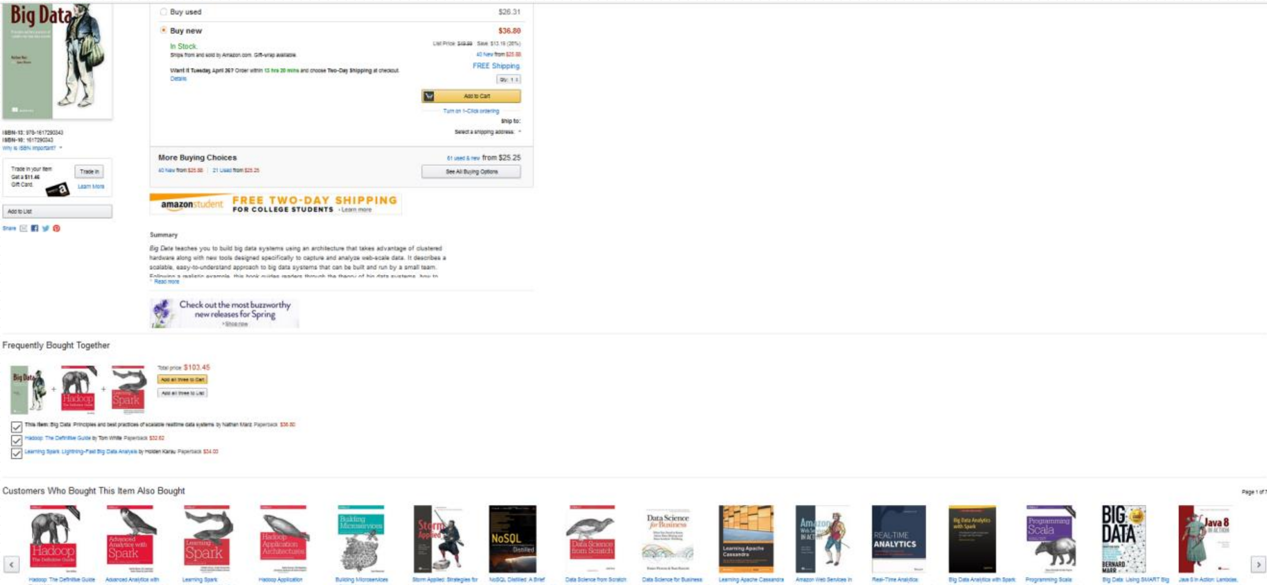
- Introduction
- Collaborative Filtering
- Memory-Based: Baseline Algorithm
- Matrix Factorization
- Practical Issues
- Conclusion

1 Introduction

Example: Similar Pages



Example: on-line shopping



User Ratings

- Many systems ask users to *rate* items – e.g. on a scale of 1 to 10. These ratings then enable the system to give more precise/accurate recommendations, and use a variety of sophisticated learning/prediction algorithms.

- Example: Here are user ratings for some items ("?" means unrated).

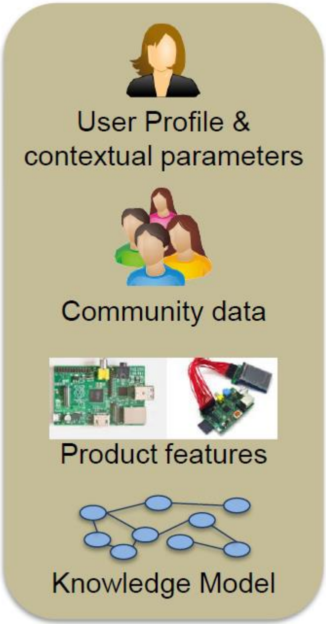
	A	B	C	D	E	F	G	H
You:	7	2	1	8	9	9	?	?
User1	1	8	8	2	?	2	8	7
User2	6	3	3	7	6	5	3	1
User3	7	2	1	7	7	?	3	1

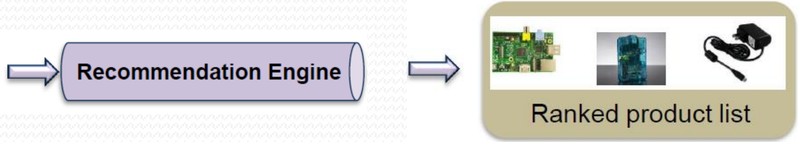
- How might a system predict your rating for items G and H?

Example: Netflix Prize

- Task
  - Given customer ratings on some movies
  - Predict customer ratings on other movies
- If John rates
  - “Mission Impossible” a 5
  - “Over the Hedge” a 3, and
  - “Back to the Future” a 4,
  - How would he rate “Harry Porter”, … ?
- Performance
  - Error rate (accuracy)
- Grand Prize (2009)
  - $1M
  - 10% improvement

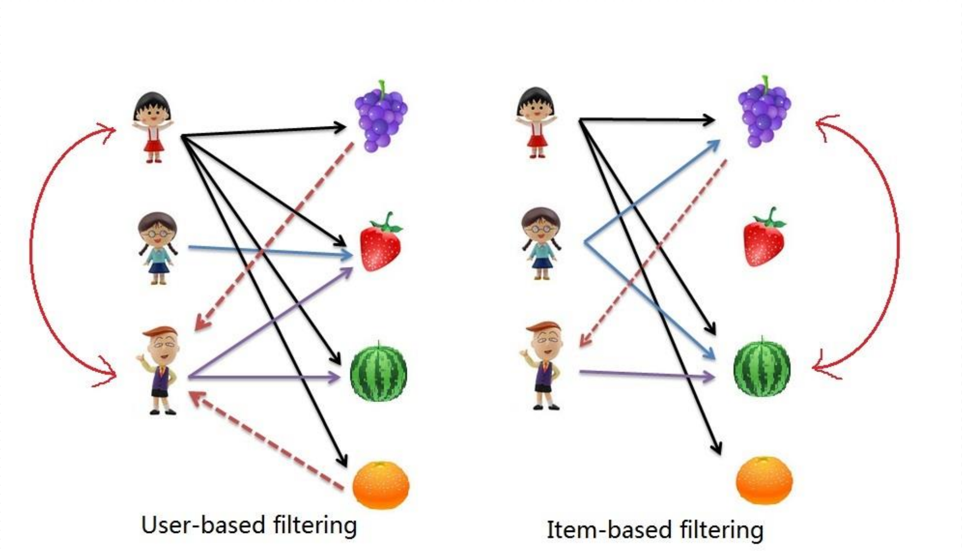
Types of Recommender Systems





1. Personalized recommendations
2. Collaborative: « Tell me what's popular among my peers »
3. Content-based: « Show me more of the same what I've liked »
4. Knowledge-based: « Tell me what fits based on my needs »
5. Hybrid: combinations of various inputs and/or composition of different mechanisms

User-based versus Item-based



User Profiles

- For user-based recommendation, sites need to have some kind of user profile.
- Similarity with other users is based on distance measurements based on the profile.
- What do you think could be in a user profile?

Potential contents of user profiles

- Demographic data: age, gender, salary, profession, country of residence, country of origin, religion …

- Site behaviour: purchase history at the site; viewing history, perhaps including time spent on certain pages/items; clickstream sequence

Specifities

- Complexity grows linearly with the number of customers and items

- The sparsity of recommendations on the data set
  - Even active customers may have purchased well under 1% of the products

2 Collaborative Filtering

Basic Strategies

- Predict and Recommend

- **Predict** the opinion: how likely that the user will have on this item

- **Recommend** the “best” items based on
  - the user’s previous likings, and
  - the opinions of like-minded users whose ratings are similar

- **Assumption:** users with similar taste in past will have similar taste in future

Why “collaborative”?

- Basically, someone else (in fact many someones) have gone to the effort of viewing/filtering things, and chosen the best few. You get a recommendation of the best few, without having to spend the effort.

- Main CF Techniques
  - Clustering based
  - Memory based
    - Nearest neighbors (user, item)
  - Model based
    - Matrix factorization/Latent factors

Clustering Techniques

- Work by identifying **groups** of consumers who appear to have **similar** preferences

- Performance can be good with smaller size of group

- May **hurt accuracy** while dividing the population into clusters

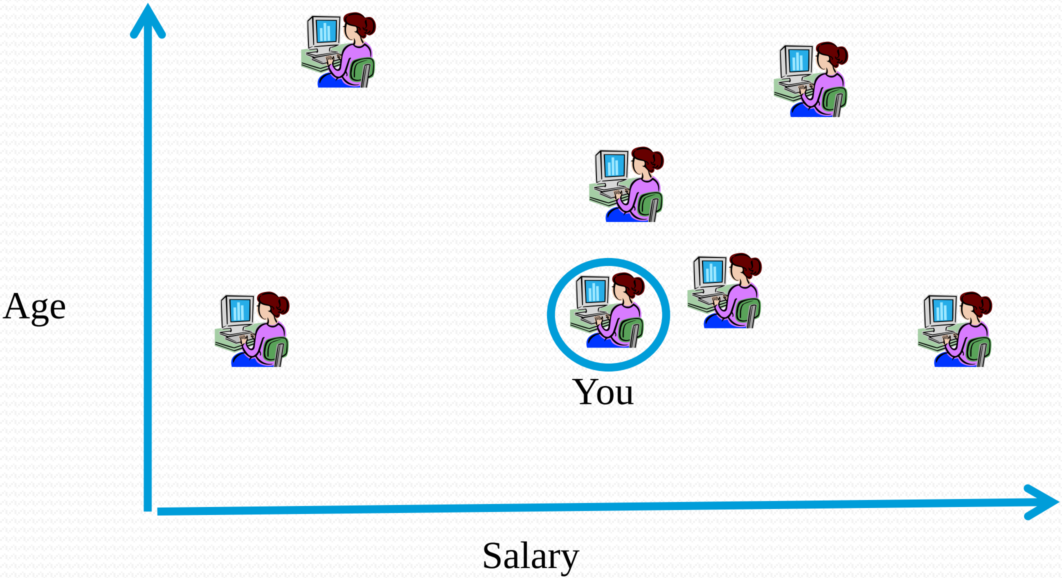
Example: clustering

	Book1	Book2	Book3	Book4	Book5	Book6
Customer A	X			X		
Customer B		X	X		X	
Customer C		X	X			
Customer D		X				X
Customer E	X				X	

- B, C & D form the first cluster vs. A & E form another cluster.
- « Typical » preferences for first cluster are:
  - Book 2, very high
  - Book 3, high
  - Books 5 & 6, may be recommended
  - Books 1 & 4, not recommended

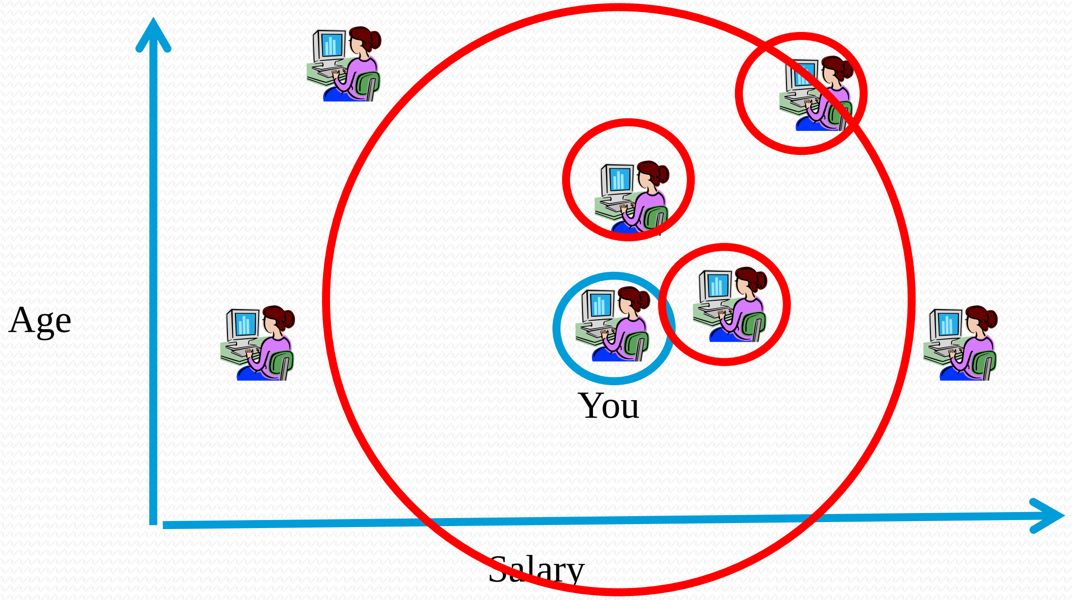
3 Memory-Based: Baseline Algorithm

K-Nearest Neighbour based Recommendation



(Think in terms of many dimensions, not just these two)

K-Nearest Neighbour based Recommendation



Your neighbours: recommend things that they have viewed/purchased

Item-to-Item Collaborative Filtering

- No more matching the user to similar customers
- Build a **similar-items table** by finding that customers tend to purchase together
- Amazon.com used this method
- Scales independently of the catalog size or the total number of customers
- Acceptable performance by creating the expensive similar-item table offline

Memory-Based Algorithms

	$v_{b,j}$	item j							
		A	B	C	D	E	F	G	H
	User1	7	2	1	8	9	9	?	?
User b	User2	1	8	8	2	?	2	8	7
	User3	6	3	3	7	6	5	3	1
	User4	7	2	1	7	7	?	3	1

- $v_{b,j}$= vote of user b on item j
- I_b = set of items for which user b has voted
- Mean vote for user b is $\bar{v}_b = \frac{1}{|I_b|}\sum_{j \in I_b} v_{b,j}$
- Predicted vote for "active user" a is weighted sum

$$p_{a,j} = \bar{v}_a + \gamma \sum_{b=1}^{n} w(a,b)\left(v_{b,j} - \bar{v}_b\right)$$

normalizer

weights of n similar users who have voted for item j

$$\gamma = 1/\sum_{b=1}^{n} |w(a,b)|$$

Memory-Based Algorithms

- K-nearest neighbor:

$$w(a,b) = \begin{cases} 1 & \text{if} \quad b \in \text{neighbors}(a) \\ 0 & \text{else} \end{cases}$$

- Pearson correlation coefficient:

$$w(a,b) = \frac{\sum_{j \in I_a \cap I_b} (v_{a,j} - \bar{v}_a)(v_{b,j} - \bar{v}_b)}{\sqrt{\sum_{j \in I_a \cap I_b} (v_{a,j} - \bar{v}_a)^2 \sum_{j \in I_a \cap I_b} (v_{b,j} - \bar{v}_b)^2}}$$

- Cosine distance (unobserved item receive a zero vote):

$$w(a,b) = \sum_{j \in I_a \cup I_b} \frac{v_{a,j}}{\sqrt{\sum_{k \in I_a} v_{a,k}^2}} \frac{v_{b,j}}{\sqrt{\sum_{k \in I_b} v_{b,k}^2}}$$

4 Matrix Factorization

Matrix of Ratings

d products

n customers

$$\begin{pmatrix} \\ A \\ \\ \end{pmatrix}$$

A_{ij} = rating of j-th product by the i-th customer

Find subsets of products that capture the behavior or the customers

Singular Value Decomposition

$$A = U \ \Sigma \ V^T = [u_1, u_2, \cdots, u_r] \begin{bmatrix} \sigma_1 & & & 0 \\ & \sigma_2 & & \\ & & \ddots & \\ 0 & & & \sigma_r \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_r^T \end{bmatrix}$$

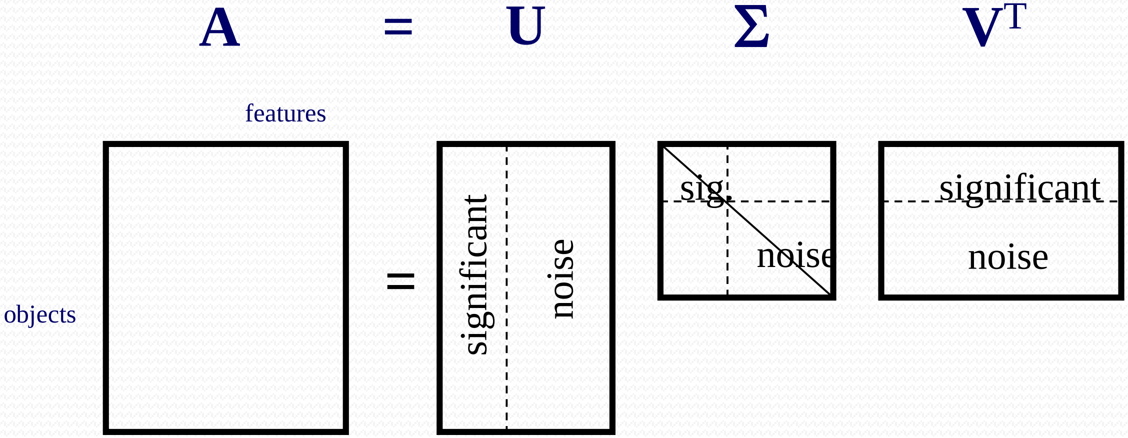
$$[n \times m] = [n \times r][r \times r][r \times m]$$

r: rank of matrix A

- $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r$: singular values of matrix A (also, the square roots of eigenvalues of AA^T and $A^T A$)
- $u_1, u_2, \dots, u_r$: left singular vectors of A (also eigenvectors of AA^T)
- $v_1, v_2, \dots, v_r$: right singular vectors of A (also, eigenvectors of $A^T A$)

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \cdots + \sigma_r u_r v_r^T$$

SVD and Rank-k approximation



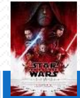
Application: Recommender systems

- Data: Users rating movies
  - Sparse and often noisy
- Assumption: there are r basic user profiles, and each user is a linear combination of these profiles
  - E.g., action, comedy, drama, romance
  - Each user is a weighted combination of these profiles
  - The “true” matrix has rank r
- What we observe is a noisy, and incomplete version $\tilde{A}$ of this matrix A
  - The rank-k approximation $\tilde{A}_k$ is provably close to A
- Algorithm: compute $\tilde{A}_k$ and predict for user u and movie m, the value $\tilde{A}_k[m, u]$.

Example: Matrix of Ratings (2 factors)

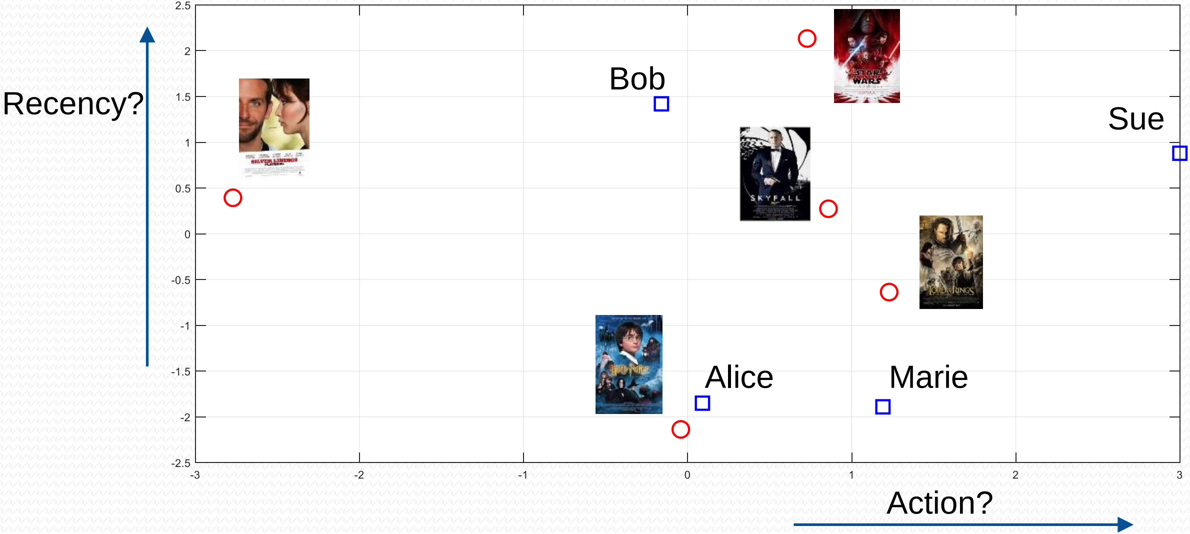
A_{ij}	M1	M2	M3	M4	M5
Alice	-4	-1	0	1	4
Bob	3	1	0	-1	-3
Mary	-3	-4	0	3	4
Sue	4	-8	3	3	-2

	Dim1	Dim2
Alice	0.09	-1,85
Bob	-0.16	1.42
Mary	1.19	-1.89
Sue	3.00	0.88

					
Dim1	0.73	-2.77	0.86	1.23	-0.04
Dim2	2.13	0.39	0.27	-0.64	-2.14

Prediction: $\hat{r}_{ij} = 0{,}09 \times 1{,}23 + (-1{,}85) \times (-0{,}64) = 1{,}2947 \approx 1$

Lower Dimensional Feature Space



5 Practical Issues

Practical Issues : Ratings

- Rating Scales
  - Scalar ratings
    - Numerical scales
    - $1-5, 1-7$, etc.
  - Binary ratings
    - Agree/Disagree, Good/Bad, etc.
  - Unary ratings
    - Good, Purchase, etc.
    - Absence of rating indicates no information

Practical Issues : Cold Start

- New user
  - Rate some initial items
  - Non-personalized recommendations
  - Describe tastes
  - Demographic info

- New item
  - Non-CF : content analysis, metadata
  - Randomly selecting items “close” to the new item

Evaluation Metrics

- Accuracy
  - Predict accuracy
    - The ability of a CF system to predict a user's rating for an item
    - Mean absolute error (MAE)

$$\text{MAE} = \frac{\sum_{(a,j)\in W} \left| v_{a,j}^{p} - v_{a,j} \right|}{|W|}$$

      - $v_{a,j}^{p}$ is the predicted value of $v_{a,j}$
      - W is the set of all predicted couples (user,item)
    - The MAE used the same scale as the data being measured.

  - Rank accuracy
    - Percentage of items in a recommendation list that the user would rate as useful

Evaluation Metrics

- Novelty
  - The ability of a CF system to recommend items that the user was not already aware of.
- Coverage
  - The percentage of the items known to the CF system for which the CF system can generate predictions.
- Serendipity
  - Users are given recommendations for items that they would not have seen given their existing channels of discovery.

Serendipity

- Unsought finding
- Unexpected, but useful result
- Do not recommend items the user already knows or would find anyway, try something more interesting

- Example
  - I like movies by Steven Spielberg, Peter Jackson, and James Cameron
  - Recommending another movie by Steven Spielberg not very useful
  - Recommending Quentin Tarantino = serendipity

Evaluation Metrics

- 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

Additional Issues : Privacy & Trust

- User profiles
  - Personalized information

- Distributed architecture
  - Security of distributed systems

- Recommender system may break trust when malicious users give ratings that are not representative of their true preferences.

6 Conclusion

Conclusion

- Recommender systems have had broadly visible impact:
  - Google, TIVO, Amazon, personal radio stations, ...
- Critical tool for finding “consensus information” present in a large community (or large corpus of web pages, or large database of purchase records, ...)
- Relatively-well established, especially in certain narrow directions, on a few datasets
- Set of applications still being expanded