Recommendation Systems

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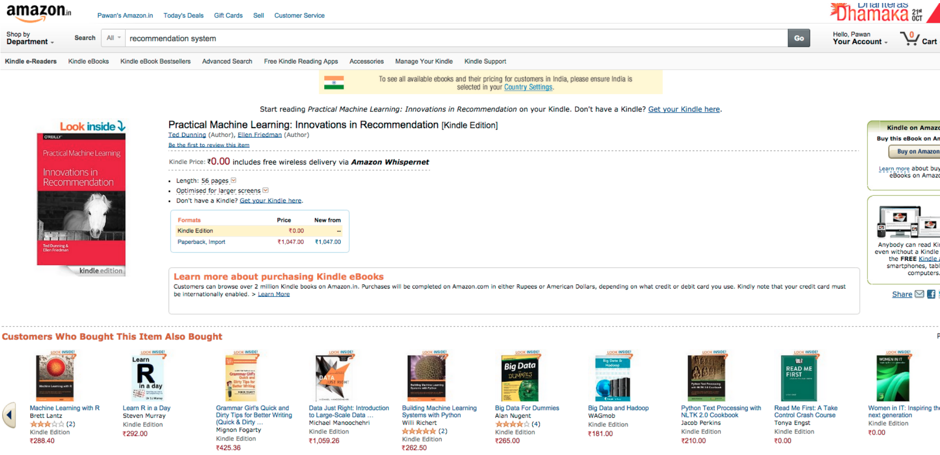
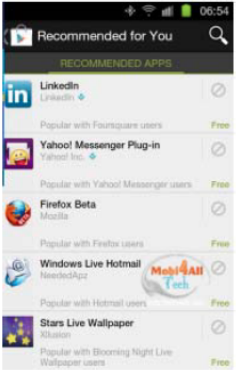
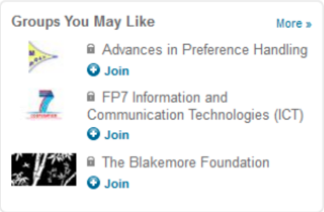
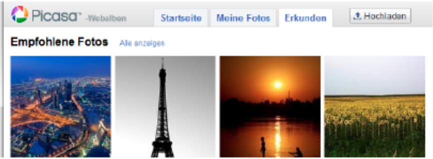
Recommendation System?



Recommendation in Social Web







Why using Recommender Systems?

Value for the customers

- Find things that are interesting
- Narrow down the set of choices
- Discover new things
- Entertainment ...

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Value for the provider

- Additional and unique personalized service for the customer
- Increase trust and customer loyalty
- Increase sales, click through rates, conversion etc
- Opportunity for promotion, persuasion
- Obtain more knowledge about customers

Real-world check

Myths from industry

- Amazon.com generates X percent of their sales through the recommendation lists ($X > 35\%$)
- Netflix generates X percent of their sales through the recommendation lists ($X > 30\%$)

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There must be some value in it

- See recommendation of groups, jobs or people on LinkedIn
- Friend recommendation and ad personalization on Facebook
- Song recommendation at last.fm
- News recommendation at Forbes.com ($+37\%$ CTR)

Recommender Systems as a function

What is given?

- User model: ratings, preferences, demographics, situational context
- Items: with or without description of item characteristics

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Final Goal

Recommend items that are assumed to be relevant

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Relevance score: used for ranking

Final Goal

Recommend items that are assumed to be relevant

But

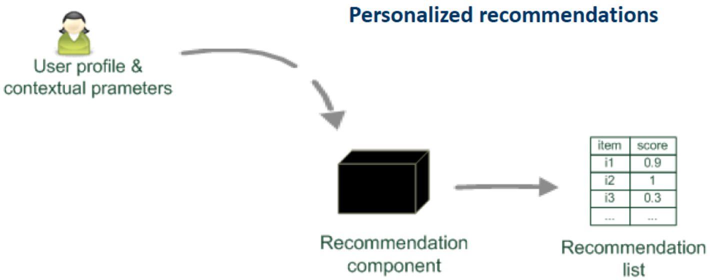
- Remember that relevance might be context-dependent
- Characteristics of the list might be important (diversity)

Recommender systems reduce information overload by estimating relevance

item	score
i1	0.9
i2	1
i3	0.3
...	...

Recommendation list

Paradigms of Recommender Systems



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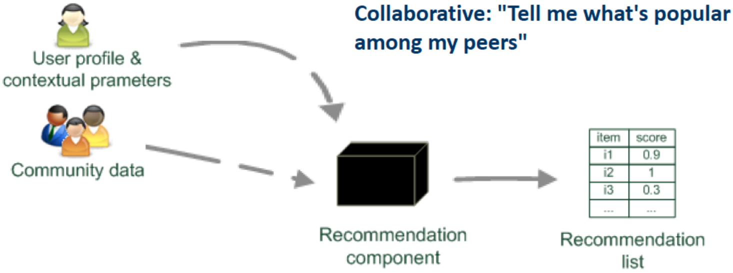
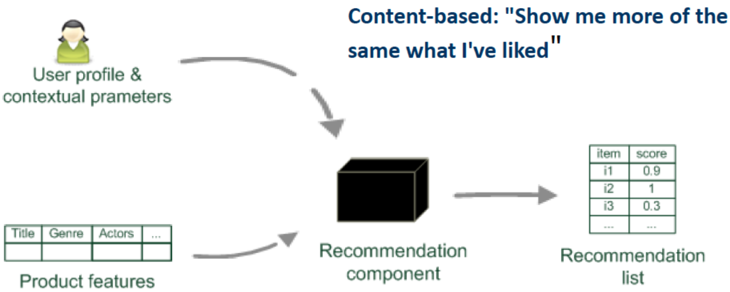
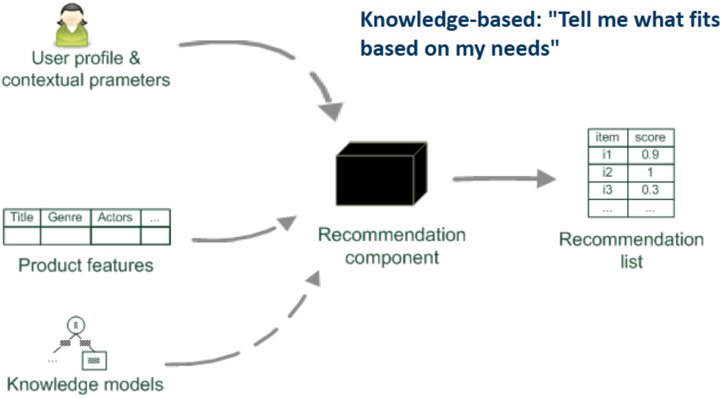


Paradigms of Recommender Systems

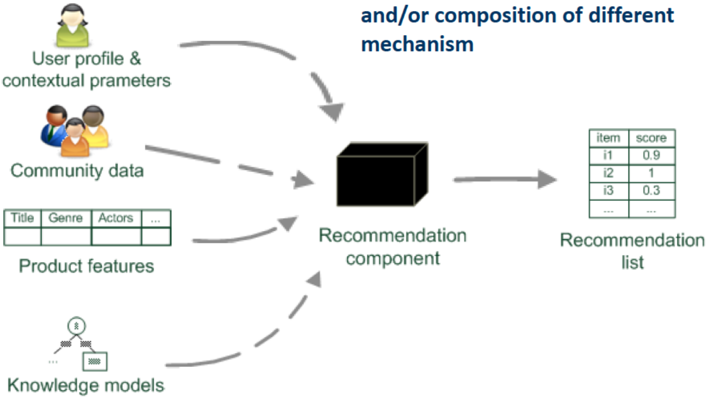


Paradigms of Recommender Systems



Paradigms of Recommender Systems

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



Comparison across the paradigms

	Pros	Cons
Collaborative	No knowledge-engineering effort, serendipity of results, learns market segments	Requires some form of rating feedback, cold start for new users and new items
Content-based	No community required, comparison between items possible	Content descriptions necessary, cold start for new users, no surprises
Knowledge-based	Deterministic recommendations, assured quality, no cold-start, can resemble sales dialogue	Knowledge engineering effort to bootstrap, basically static, does not react to short-term trends

Collaborative Filtering (CF)

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, ...)

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Approach

Use the “wisdom of the crowd” to recommend items

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Approach

Use the "wisdom of the crowd" to recommend items

Basic assumption and idea

- Users give ratings to catalog items (implicitly/explicitly)
- Customers with certain tastes in the past, might have similar tastes in the future

User-based Collaborative Filtering

- Given an active user *Alice* and an item i not yet seen by Alice
- The goal is to estimate Alice's rating for this item, e.g., by

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- The goal is to estimate Alice's rating for this item, e.g., by
  - Find a set of users who liked the same items as Alice in the past and who have rated item i
  - use, e.g. the average of their ratings to predict, if Alice will like item i
  - Do this for all items Alice has not seen and recommend the best-rated ones

	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

User-based Collaborative Filtering

Some first questions

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

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Popular similarity model

Pearson Correlation

$$sim(a,b) = \frac{\sum_{p \in P}(r_{a,p} - \overline{r_a})(r_{b,p} - \overline{r_b})}{\sqrt{\sum_{p \in P}(r_{a,p} - \overline{r_a})^2}\sqrt{\sum_{p \in P}(r_{b,p} - \overline{r_b})^2}}$$

- a, b: users
- $r_{a,p}$: rating of user a for item p
- P: set of items, rated both by a and b
- $\overline{r_a}$, $\overline{r_b}$: user's average ratings
- Possible similarity values are between -1 to 1

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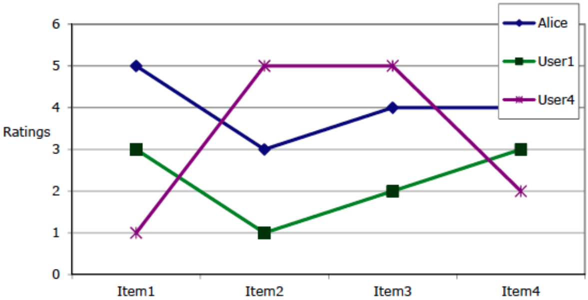
For the example considered

- sim(Alice, User1) = 0.85
- sim(Alice, User4) = -0.79

Pearson Correlation

Takes Difference in rating behavior into account



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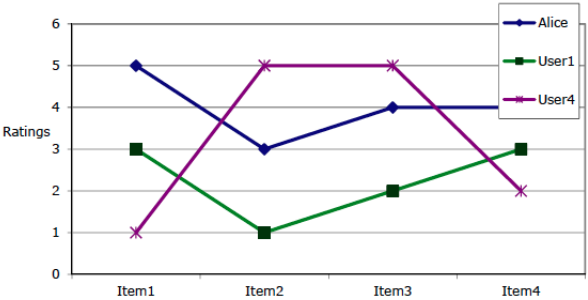

Works well in usual domains

Making Predictions

- A common prediction function:

$$pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(a,b)}$$

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- Calculate, whether the neighbor's ratings for the unseen item i are higher or lower than their average
- Combine the rating differences - use similarity as a weight
- Add/subtract neighbor's bias from the active user's average and use this as a prediction

Item-based Collaborative Filtering

Basic Idea

Use the similarity between items to make predictions

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Use the similarity between items to make predictions

For Instance

- Look for items that are similar to Item5
- Take Alice's ratings for these items to predict the rating for Item5

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Similarity Measure

- Ratings are seen as vector in $n-$dimensional space
- Similarity is calculated based on the angle between the vectors

$$sim(\vec{a},\vec{b}) = \frac{\vec{a}\cdot\vec{b}}{|\vec{a}| * |\vec{b}|}$$

- Adjusted cosine similarity: take average user ratings into account

$$sim(a,b) = \frac{\sum_{u\in U}(r_{u,a}-\overline{r_u})(r_{u,b}-\overline{r_u})}{\sqrt{\sum_{u\in U}(r_{u,a}-\overline{r_u})^2}\sqrt{\sum_{u\in U}(r_{u,b}-\overline{r_u})^2}}$$

Pre-processing for Item-based filtering

- Calculate all pair-wise item similarities in advance
- The neighborhood to be used at run-time is typically rather small, because only those items are taken into account which the user has rated
- Item similarities are supposed to be more stable than user similarities

More on ratings

Pure CF-based systems only rely on the rating matrix

Explicit ratings

- Most commonly used (1 to 5, 1 to 10 response scales)
- **Research topics:** what about multi-dimensional ratings?
- **Challenge:** Sparse rating matrices, how to stimulate users to rate more items?

More on ratings

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Explicit ratings

- Most commonly used (1 to 5, 1 to 10 response scales)
- **Research topics:** what about multi-dimensional ratings?
- **Challenge:** Sparse rating matrices, how to stimulate users to rate more items?

Implicit ratings

- clicks, page views, time spent on some page, demo downloads ..
- Can be used in addition to explicit ones; question of correctness of interpretation

Data sparsity problems

Cold start problems

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

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Straight-forward approach

Use another method (e.g., content-based, demographic or simply non-personalized) in the initial phase

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Alternatives

- Use better algorithms (beyond nearest-neighbor approaches)
- Example: Assume "transitivity" of neighborhoods

Example algorithms for sparse datasets

Recursive CF

- Assume there is a very close neighbor n of u who however has not rated the target item i yet.

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Example algorithms for sparse datasets

Recursive CF

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

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sim = 0.85

Predict rating for User1

Example algorithms for sparse datasets

Graph-based methods: Spreading activation

- Idea: Use paths of lengths 3 and 5 to recommend items
- Length 3: Recommend Item3 to User1
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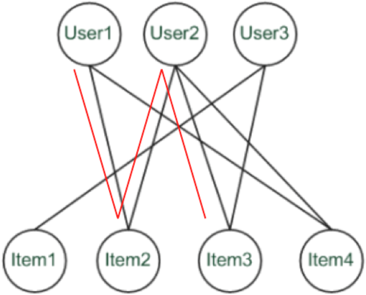

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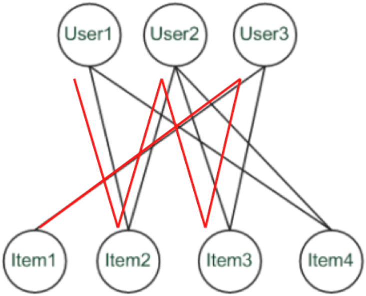

Matrix Factorization Methods

- Are shown to be superior to the classic nearest-neighbor techniques for product recommendations
- Allow the incorporation of additional information such as implicit feedback, temporal effects, and confidence levels

User-oriented neighborhood method

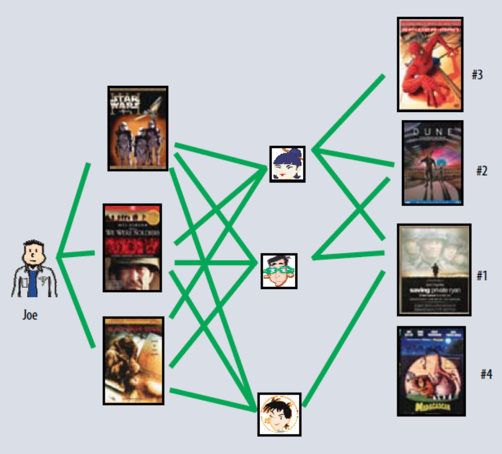

Figure 1. The user-oriented neighborhood method. Joe likes the three movies on the left. To make a prediction for him, the system finds similar users who also liked those movies, and then determines which other movies they liked. In this case, all three liked *Saving Private Ryan*, so that is the first recommendation. Two of them liked *Dune*, so that is next, and so on.

Latent Factor Approach

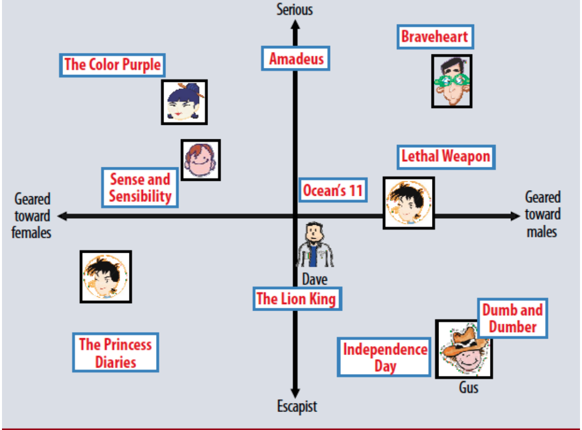

Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

Matrix Factorization Methods

Basic Idea

- Both users and items are characterized by vectors of factors, inferred from item rating patterns
- High correspondence between item and user factors leads to a recommendation.

Using Singular Value Decomposition

- Let M be the matrix of user - item interactions
- Use SVD to get a $k-$rank approximation

$$M_k = U_k \times \Sigma_k \times {V_k}^T$$

- Prediction: $\hat{r_{ui}} = \overline{r_u} + U_k(u) \times \Sigma_k \times {V_k}^T(i)$

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- Prediction: $\hat{r_{ui}} = \overline{r_u} + U_k(u) \times \Sigma_k \times {V_k}^T(i)$
- The problem, however, is the high portion of missing values
- Using only relatively few entries may lead to overfitting

A Basic Matrix Factorization Model

- Both users and items are mapped to a joint latent factor space of dimensionality f,
- user-item interactions are modeled as inner products in that space
- Each item i associated with a vector $q_i \in R^f$, and each user u associated with a vector $p_u \in R^f$
- q_i measures the extent to which the item possesses the factors, positive or negative
- p_u measures the extent of interest the user has in items that are high on the corresponding factors, positive or negative
- ${q_i}^T p_u$ captures the interaction between user u and item i
- This approximates user u's rating of item i, denoted by r_{ui}

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

A Basic Matrix Factorization Model

Major Challenge

Computing the mapping of each item and user to factor vectors $q_i, p_u \in R^f$

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The Learning Problem

To learn the factor vectors p_u and q_i, the system minimizes the regularized squared error on the set of known ratings:

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

where k is the set of (u,i) pairs for which r_{ui} is known.

Stochastic Gradient Descent

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

Let $e_{ui} = r_{ui} - {q_i}^T p_u$
Gradient descent can be written as

- $q_i \leftarrow q_i + \gamma(e_{ui}p_u - \lambda q_i)$
- $p_u \leftarrow p_u + \gamma(e_{ui}q_i - \lambda p_u)$

Modifying the basic approach: Adding Biases

Matrix factorization is quite flexible in dealing with various data aspects and other application-specific requirements.

Adding Biases

- Some users might always give higher ratings than others, some items are widely perceived as better than others.
- Full rating value may not be explained solely by ${q_i}^T p_u$
- Identify the portion that individual user or item biases can explain

$$b_{ui} = \mu + b_i + b_u$$

- μ is the overall average rating, b_u and b_i indicate the observed deviations of user u and item i respectively, from the average

Adding Biases

An Example

- You want a first-order estimate for user Joe's rating of the movie *Titanic*.
- Let the average rating over all movies, μ, is 3.7 stars
- Titanic tends to be rated 0.5 stars above the average
- Joe is a critical user, who tends to rate 0.3 stars lower than the average
- Thus, the estimate for Titanic's rating by Joe would be (3.7+0.5-0.3) = 3.9 stars

Modifying the original approach

Biases modify the interaction equation as

$$\hat{r_{ui}} = \mu + b_i + b_u + {q_i}^T p_u$$

Four components: global average, item bias, user bias, user-item interaction
The squared error function:

$$min_{p^*,q^*,b^*} \sum_{(u,i) \in K} (r_{ui} - \mu - b_i - b_u - {q_i}^T p_u)^2 + \lambda(||q_i||^2 + ||p_u||^2 + {b_u}^2 + {b_i}^2)$$

Additional Input Sources

- Many users may supply very few ratings
- Difficult to reach general conclusions on their taste

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- Many users may supply very few ratings
- Difficult to reach general conclusions on their taste
- Incorporate additional sources of information about the users
- E.g., gather implicit feedback, use purchases or browsing history to learn the tendencies

Modeling Implicit Feedback

Boolean Implicit Feedback

- $N(u)$: set of items for which user u expressed an implicit preference
- Let item i be associated with $x_i \in R^f$
- The user can be characterized by the vector $\sum_{i \in N(u)} x_i$
- Normalizing the sum: $\frac{\sum_{i \in N(u)} x_i}{\sqrt{|N(u)|}}$

Modeling Demographics

- Consider boolean attributes where user u corresponds to a set of attributes $A(u)$
- These attributes can describe gender, age group, Zip code, income level etc.
- Let a feature vector $y_a \in R^f$ correspond to each attribute to describe a user through this set as: $\sum_{a \in A(u)} y_a$

Integrating enhanced user representation in the matrix factorization model:

$$\hat{r_{ui}} = \mu + b_i + b_u + {q_i}^T [p_u + |N(u)|^{-0.5} \sum_{i \in N(u)} x_i + \sum_{a \in A(u)} y_a]$$

Adding Temporal Dynamics

- In reality, product perception and popularity constantly change as new selections emerge
- Customers' inclinations evolve, leading them to redefine their taste
- The system should account for the temporal effects reflecting the dynamic, time-drifting nature of user-item interactions

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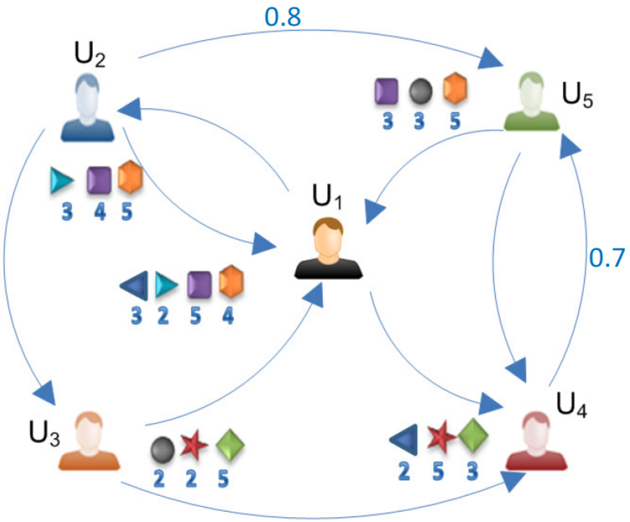
- In reality, product perception and popularity constantly change as new selections emerge
- Customers' inclinations evolve, leading them to redefine their taste
- The system should account for the temporal effects reflecting the dynamic, time-drifting nature of user-item interactions
- Items that can vary over time: item biases, $b_i(t)$; user biases, $b_u(t)$; user preferences, $p_u(t)$
- It can be integrated in the matrix factorization model as:

$$\hat{r_{ui}}(t) = \mu + b_i(t) + b_u(t) + {q_i}^T p_u(t)$$

Recommendation in Social Networks



Effects in Social Networks

Social Influence

Ratings are influenced by ratings of friends, i.e. friends are more likely to have similar ratings than strangers

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Benefits

- Can deal with cold-start users, as long as they are connected to the social network
- Exploit social influence, correlational influence, transitivity
- Are more robust to fraud, in particular to profile attacks

Memory Based Approaches

- Explore the network to find raters in the neighborhood of the target user
- Aggregate the ratings of these raters to predict the rating of the target user
- Different methods to calculate the "trusted neighborhood" of users

TidalTrust; Goldbeck (2005)

- Modified breadth-first search in the network
- Consider all raters v at the shortest distance from the target user u
- Trust between u and v:

$$t_{u,v} = \frac{\sum_{w \in N_u} t_{u,w} t_{w,v}}{\sum_{w \in N_u} t_{u,w}}$$

  where N_u denotes the set of (direct) neighbors (friends) of u
- Trust depends on all connecting paths

TidalTrust

Predicted Rating

$$\hat{r_{u,i}} = \frac{\sum\limits_{v \in raters} t_{u,v} r_{v,i}}{\sum\limits_{v \in raters} t_{u,v}}$$

$r_{v,i}$ denotes rating of user v for item i

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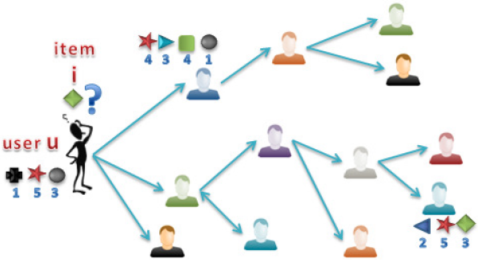
Shortest distance?

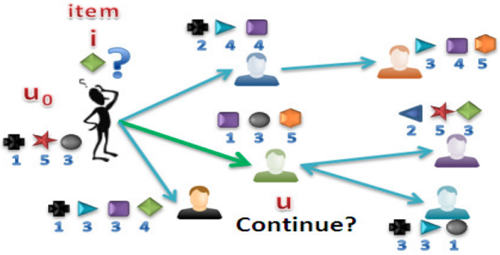
- Efficient
- Taking a short distance gives high precision and low recall
- One can consider raters up to a maximum-depth d, a trade-off between precision (and efficiency) and recall

TrustWalker

- How far to explore the network?: trade-off between precision and coverage
- Instead of far neighbors who have rated the target item, use near neighbors who have rated similar items



Random Walk Starting from a Target User u_0



At step k, at node u

- If u has rated i, return $r_{u,i}$
- With probability $\phi_{u,i,k}$, stop random walk, randomly select item j rated by u and return $r_{u,j}$
- With probability $1-\phi_{u,i,k}$, continue the random walk to a direct neighbor of u

Selecting $\phi_{u,i,k}$

- $\phi_{u,i,k}$ gives the probability of staying at u to select one of its items at step k, while we are looking for a prediction on target item i
- This probability should be related to the similarities of the items rated by u and the target item i, consider the maximum similarity
- The deeper we go into the network, the probability of continuing random walk should decrease, so $\phi_{u,i,k}$ should increase with k

$$\phi_{u,i,k} = max_{j \in RI_u} sim(i,j) \times \frac{1}{1 + e^{-\frac{k}{2}}}$$

where RI_u denotes the set of items rated by user u

Selecting $\phi_{u,i,k}$

Selecting $sim(i,j)$

Let $UC_{i,j}$ be the set of common users, who have rated both items i and j, we can define the correlation between items i and j as:

$$corr(i,j) = \frac{\sum_{u \in UC_{i,j}} (r_{u,i} - \overline{r_u})(r_{u,j} - \overline{r_u})}{\sqrt{\sum_{u \in UC_{i,j}} (r_{u,i} - \overline{r_u})^2} \sqrt{\sum_{u \in UC_{i,j}} (r_{u,j} - \overline{r_u})^2}}$$

Selecting $\phi_{u,i,k}$

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Taking the effect of common users

The size of the common users is also important. For the same value of $corr(i,j)$, if number of common users, $|UC_{i,j}|$, is higher, the similarity should be higher

$$sim(i,j) = \frac{1}{1 + e^{-\frac{|UC_{i,j}|}{2}}} \times corr(i,j)$$

When does a random walk terminate?

Three alternatives

- Reaching a node which has expressed a rating on the target item i
- At some user node u, decide to stay at the node and select one of the items rated by u and return the rating for that item as result of the random walk
- The random walk might continue forever, so terminate when it is very far ($k > max - depth$). What value of k ?

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- "six-degrees of separation"

How to recommend a rating?

Perform several random walks, as described before and the aggregation of all ratings returned by different random walks are considered as the predicted rating $\hat{r_{u_0,i}}$