ADVANCED RECOMMENDATION TECHNIQUES

Outline

- Intro
- Goals
- Organization, Grading
- Overview of Recommendation Techniques

Intro

- What are recommendation techniques?
- Where are they being used?
- What are they good for?

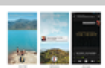
Goals

Neue Feedly-Beta für Android erschienen

5. April 2013 Kategorie: Android, geschrieben von: caschy

Bei Feedly bittet man um Mithilfe. In den nächsten acht Wochen will man möglichst viele Bugs eliminieren, das Leseerlebnis vereinfachen und natürlich an der Geschwindigkeitsschraube drehen. Aus diesem Grunde hat man eine Betaversion des RSS-Readers für Android veröffentlicht, die jeder von euch nutzen kann, sofern er einfach ausprobieren oder mithelfen will. Die Beta nebst den Installationsanweisungen bekommt ihr im Feedly-Blog und wenn ihr noch einen RSS-Feed zum Test benötigt, dann nehmt diesen 😉

Außerdem zum Thema:



Facebook Home: das Video, die Erklärung und die Umfrage, ob...

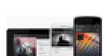
Facebook Home ist da und ich habe schon fast alles dazu geschrieben. Jetzt noch einmal ein paar offizielle News und die Frage, ob ihr installiert -... ...mehr

YouTube-App zeigt Abonnements direkt an

Endlich! Ich gehöre zu den Leuten, die ein paar Kanäle auf YouTube abonniert haben. Man will ja bezüglich einiger Hersteller und Menschen auf dem... ...mehr

Facebook Home: Facebook auf dem Android-Smartphone

Heute war es also soweit - Facebook lüftete den Mantel des Schweigens und zeigte, was es Neues auf der Plattorm Android zu sehen gab. Natürlich habe... ...mehr



Deezer für Android bekommt neues Design

Beim Musikdienst Deezer habe ich immer ein wenig das Gefühl, dass er hierzulande deutlich

Goals

- Cross-Site article recommendations
- Dataset: Articles from 22 different news websites
  - + tweets/retweets from their Twitter accounts
- Implement different recommendation techniques, test on dataset
- Compare results

Organization

- Teams of two students each
- First weeks regular seminar
  - Learn about different recommendation techniques
  - Form Team, pick technique to implement
- Individual feedback and progress sessions
  - Frequency depends on progress, problems, etc.
- Intermediate Presentation
- Final Presenation
- (Short) project report

Grading

- Presentations: ~ 25%
- Implementation: ~ 40%
- Project Report: ~ 20%
- Participation: ~ 15%

- Goal: Cross-platform recommendation for posts on the Web
  - Given a post on a website, find relevant (i.e., similar) posts from other websites
  - Analyze features of post, author, website, …
  - Compare different state-of-the-art recommendation techniques

Sim	I_1	…	I_j	…	I_n
I_1					
I_2					
…					
I_i			?		
…					
I_n					

Calculate $Sim(I_i, I_j)$ (i.e., the similarity between Items I_i and I_j)

Recommend top-k items

Student Questions

Questions???

Collaborative filtering

- Goals
  - Predict the user's opinion on a given item based on the user's previous likings and the opinions of other like-minded users
  - Recommend to a given user the items he/she might like most

R	I_1	…	I_j	…	I_n
u_1					
u_2					
…					
u_i			?		
…					
u_m					

Predict $R_{u_i}(I_j)$ (i.e., the rating of active user u_i for item I_j)

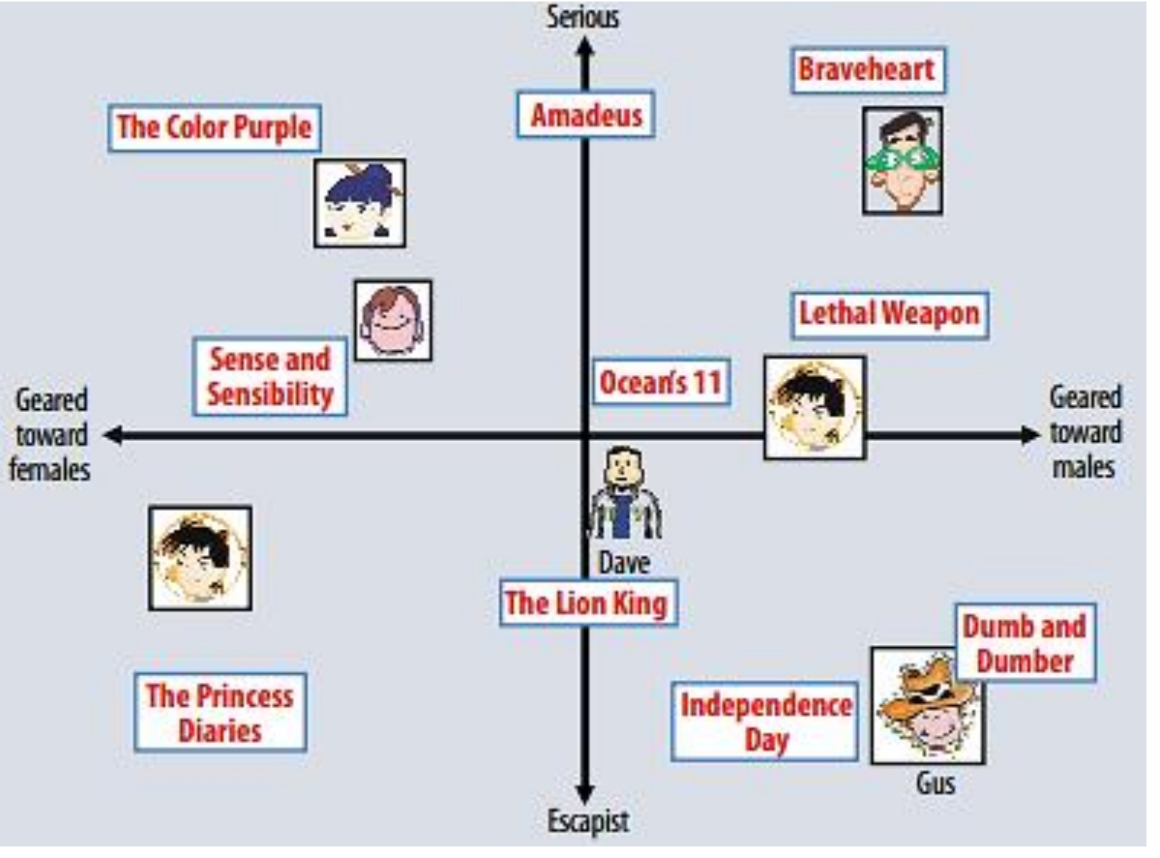
Recommend top-k items, the user might be most interested in

Collaborative filtering techniques (overview)

- Neighborhood-based models
  - Derive user profile from user's neighborhood (i.e., most similar users)
    → user-user models
  - Derive item profile from item's neighborhood (i.e., most similar items)
    → item-item models
  - Similar models used in: Pandora.com, Music Genome Project, …

Collaborative filtering techniques (overview)

- Latent factor models
  - Derive **factors** that characterize both users and items at the same time



Source: [Koren et al., IEEE 2009]

Neighborhood-based user-user models

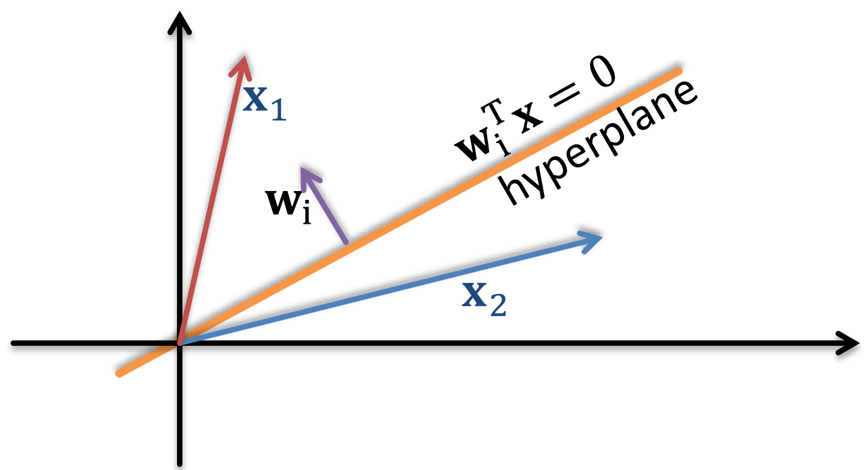
$$R_u(item) = \frac{\sum_{u' \in N(u)} sim(u,u') \cdot R_{u'}(item)}{\sum_{u' \in N(u)} sim(u,u')}$$

- Possible similarity measures
  - Cosine similarity: $sim(\mathbf{u},\mathbf{u}') = \frac{\mathbf{u}^T\mathbf{u}'}{\|\mathbf{u}\|\|\mathbf{u}'\|}$
  - Pearson correlation (for ratings) : $sim(\mathbf{u},\mathbf{u}') = \frac{\sum_i (u_i - \bar{u})\left(u'_i - \overline{u'}\right)}{\sqrt{\sum_i (u_i - \bar{u})^2}\sqrt{\sum_i \left(u'_i - \overline{u'}\right)^2}}$
  - Scalar agreement: $sim(\mathbf{u},\mathbf{u}') = \exp\left(-d(\mathbf{u},\mathbf{u}')\right)$,

    where $d(\mathbf{u},\mathbf{u}') = \frac{1}{dim(u)} \sum_i \frac{(u_i - u'_i)}{|domain\ u_i|}$ is the disagreement between $\mathbf{u}, \mathbf{u}'$
  - Jaccard similarity: $sim(\mathbf{u},\mathbf{u}') = \frac{|\mathbf{u} \cap \mathbf{u}'|}{|\mathbf{u} \cup \mathbf{u}'|}$
  - Problem: vectors can be large and comparisons can be costly

Locality Sensitive Hashing for nearest neighbor search (1)

- LSH with Random-projections for cosine similarity estimation
  - Given a collection of d-dimensional vectors, chose a random hyperplane defined by unit normal vector $\mathbf{w_i}$ and define hash function as $h_i(\mathbf{x}) = \mathbf{w_i} \cdot \mathbf{x}\ \ (\in \{+1, -1\})$



  - Resemblance between two vectors $\mathbf{x}_1, \mathbf{x}_2$ can be estimated as

$$P\big(h_i(\mathbf{x}_1) = h_i(\mathbf{x}_2)\big) = 1 - \frac{\theta(\mathbf{x}_1, \mathbf{x}_2)}{\pi}$$

Inner angle between $\mathbf{x}_1$ and $\mathbf{x}_2$ in π

  - Note that $\cos\big(\theta(\mathbf{x}_1, \mathbf{x}_2)\big) = \cos\Big(\Big(1 - P\big(h_i(\mathbf{x}_1) = h_i(\mathbf{x}_2)\big)\Big) \cdot \pi\Big)$

Locality Sensitive Hashing for nearest neighbor search (2)

- LSH with Random-projections for cosine similarity estimation

  Sources: A. Gionis et al., VLDB 1999 and D. Ravichandran et al., ACL 2005

  General algorithm for preprocessing:

  1. Given a family for LSH functions, construct l different hash tables $g_1(h_{11}, \dots, h_{1k}), \dots, g_l(h_{l1}, \dots, h_{lk})$, where each h_{ij} is randomly chosen
  2. Run all n input vectors through each of the hash tables

Running time: $O(kln)$

Neighborhood-based Item-item models

- Rating of an item is estimated using known ratings made by the same user on similar items
- Item-item similarity estimation is crucial
- General model

$$\hat{R}_u(i) = B_u(i) + \frac{\sum_{j \in N(i)} sim(i,j) \cdot (R_u(j) - B_u(j))}{\sum_{j \in N(i)} sim(i,j)}$$

Items most similar to i

Baseline estimation of user's rating on j

- Possible similarity measure (based on Pearson correlation)

$$sim(i,j) = \frac{\sum_{u \in U(i,j)} (R_u(i) - B_u(i))(R_u(j) - B_u(j))}{\sqrt{\sum_{u \in U(i,j)} (R_u(i) - B_u(i))^2 \sum_{u \in U(i,j)} (R_u(j) - B_u(j))^2}} \cdot \frac{|U(i,j)|}{|U(i,j)| + \lambda}$$

The larger the number of users who rated i and j, the better the estimation

User-user- & item-item-based models(summary)

- Advantages
  - Relatively easy to understand and implement
  - Results can be explained based on the data,
  - New users can be easily added (similarities have to be recomputed after some time)

- Disadvantages
  - Introducing new items leads to updated vector representations and similarity parameters
  - High dependency on the quantity and quality of ratings

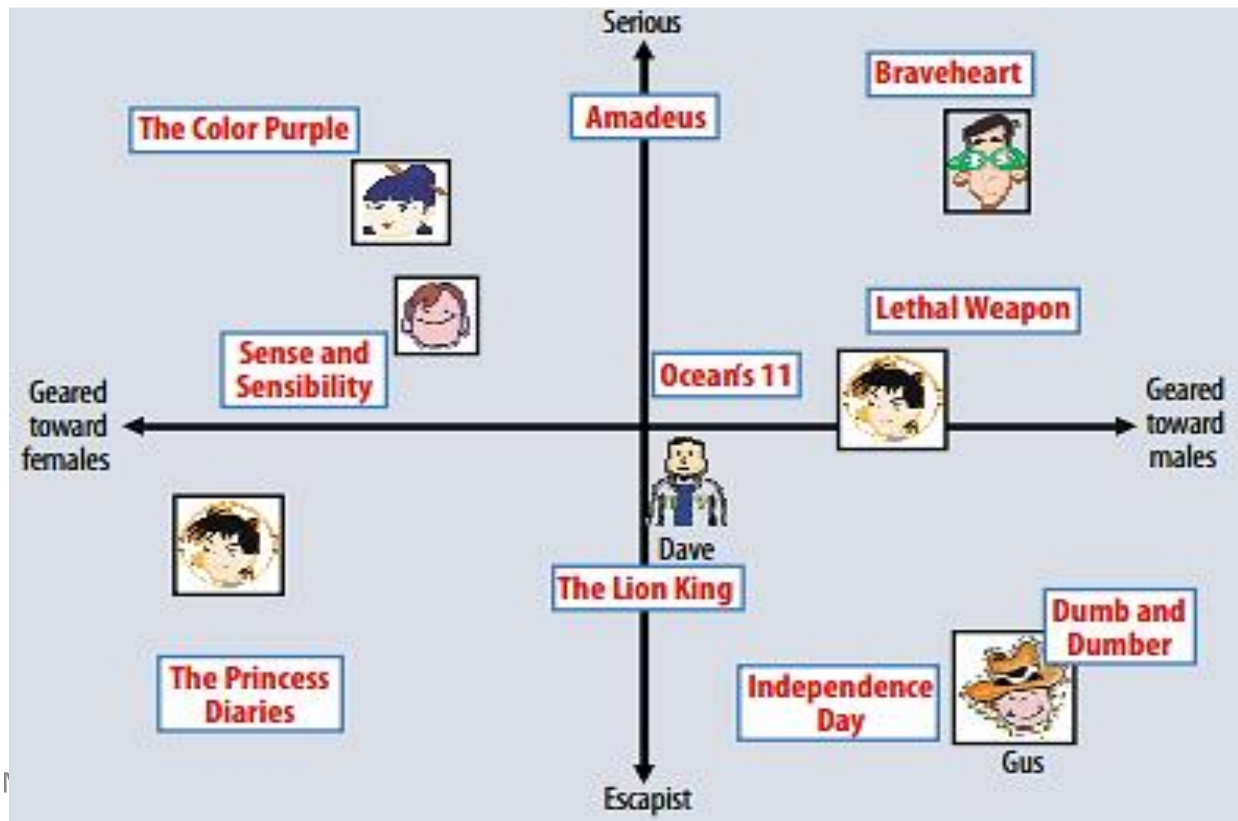
    (performance degrades considerably on large and sparse datasets)
  - Dependent on efficient and effective similarity estimation

For more details see: Y. Koren, TKDD 2010

Matrix factorization techniques for recommendation (1)

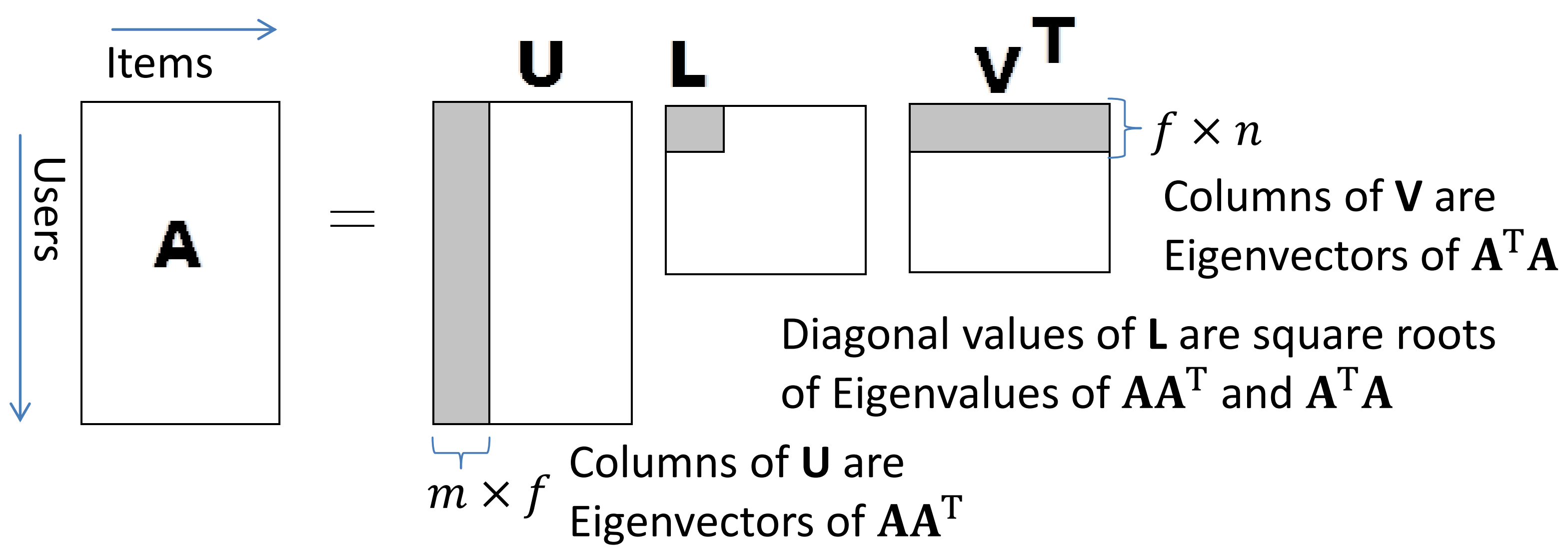
- General model
  - Map user $\mathbf{u} \in \mathbb{R}^n$ to $\hat{\mathbf{u}} \in \mathbb{R}^f$
  - Map item $\mathbf{i} \in \mathbb{R}^m$ to $\hat{\mathbf{i}} \in \mathbb{R}^f$
  - $f \ll n, m$
  - Estimate: $\hat{R}_u(i) = \mu + b_u + b_i + \hat{\mathbf{u}}^T\, \hat{\mathbf{i}}$ (inner product between $\hat{\mathbf{u}}$ and $\hat{\mathbf{i}}$)

avg. rating
user bias
item bias



Matrix factorization techniques for recommendation (2)

- General model
  - Map user $\mathbf{u} \in \mathbb{R}^n$ to $\hat{\mathbf{u}} \in \mathbb{R}^f$
  - Map item $\mathbf{i} \in \mathbb{R}^m$ to $\hat{\mathbf{i}} \in \mathbb{R}^f$
  - $f \ll n, m$
  - Estimate: $\hat{R}_u(i) = \mu + b_u + b_i + \overbrace{\hat{\mathbf{u}}^T \hat{\mathbf{i}}}^{\text{Plain model}}$ (combination of average rating, user bias, item bias, and inner product between $\hat{\mathbf{u}}$ and $\hat{\mathbf{i}}$)
  - Main challenge: generate appropriate mappings of $\mathbf{u}$ and $\mathbf{i}$ into $\mathbb{R}^f$
  - Typical approach: Singular Value Decomposition



Matrix factorization techniques for recommendation (3)

- Problem with SVD for collaborative filtering
  - User-item matrix is too sparse (i.e., there are many values missing)
  - Filling in missing values correctly is difficult
  - Other possibility: estimate $\hat{\mathbf{u}}$ and $\hat{\mathbf{i}}$ as

$$\min_{\hat{\mathbf{u}},\hat{\mathbf{i}},\mathbf{b}} \sum_{\mathbf{A}\ni(u,i)\neq\mathbf{0}} \left(R_u(i) - \mu - b_u - b_i - \hat{\mathbf{u}}^T\hat{\mathbf{i}}\right)^2 + \underbrace{\lambda\left(\|\hat{\mathbf{u}}\|^2 + \|\hat{\mathbf{i}}\|^2 + b_u^2 + b_i^2\right)}$$

Regularization term
avoids overfitting to observed data
λ can be learned through cross validation

  - Other information such as **temporal dynamics, implicit feedback,** and **user features** (e.g., age, gender, group, etc.) can be added
  - Two approaches for minimizing above equation:

(1) **Stochastic gradient descent**

(2) **Alternating least squares**

Netflix competition (1)

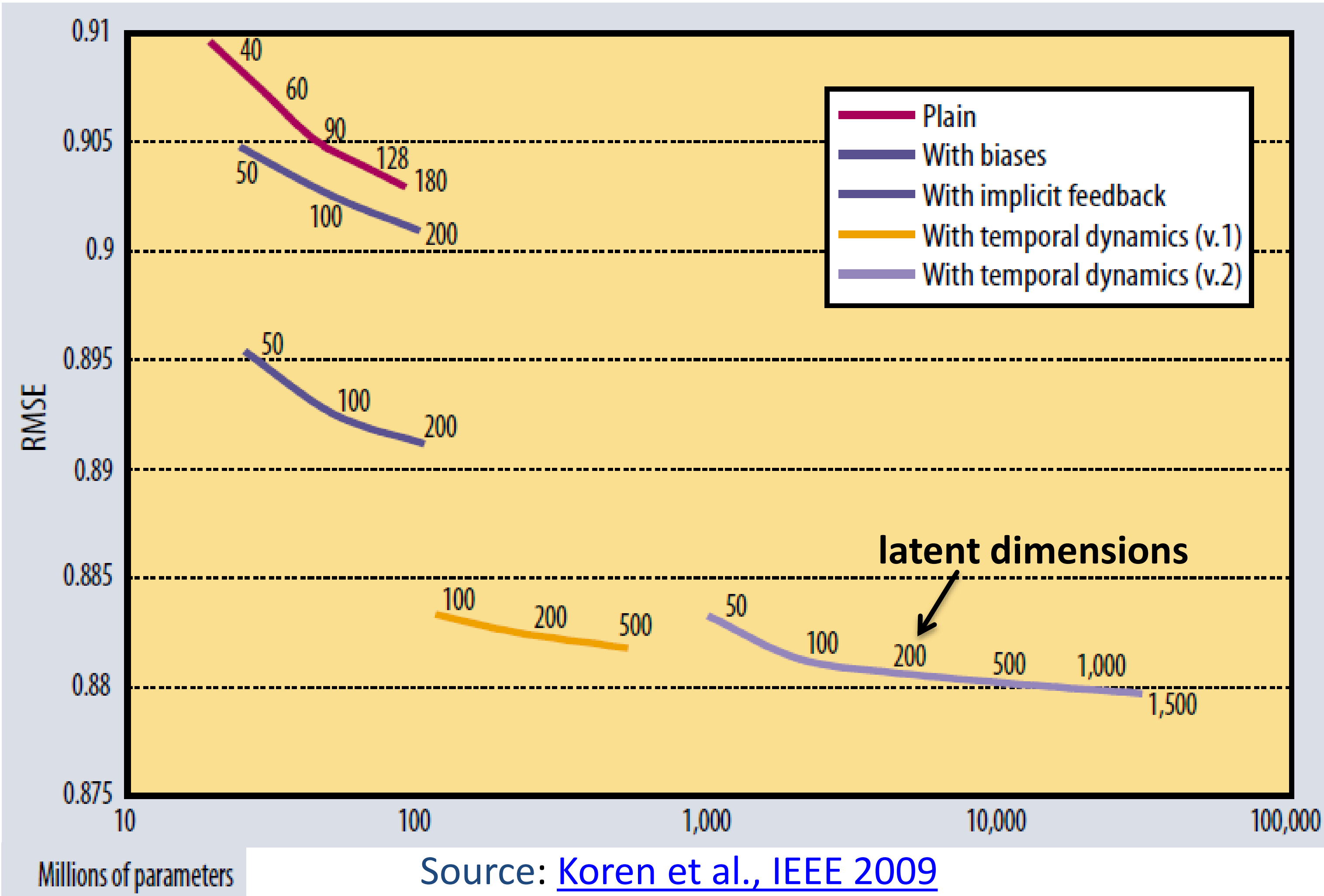
- In 2006, Netflix (an online DVD rental company) announced a contest to improve the state of its recommender system
- 100 million ratings on more than 17,000 movies, spanning about 500,000 anonymous customers and their ratings
- Movies rated on a scale of 1 to 5 stars
- Test set with approximately 3 million ratings
- The first team that can improve on the root mean square error ($RMSE$) of the Netflix system by 10 % or more could win \$1 million

$$RMSE = \sqrt{\frac{\sum_{(u,i)\in TestSet}\left(R_u(i) - \hat{R}_u(i)\right)^2}{|TestSet|}}$$

- $RMSE$ of the Netflix system: 0.95

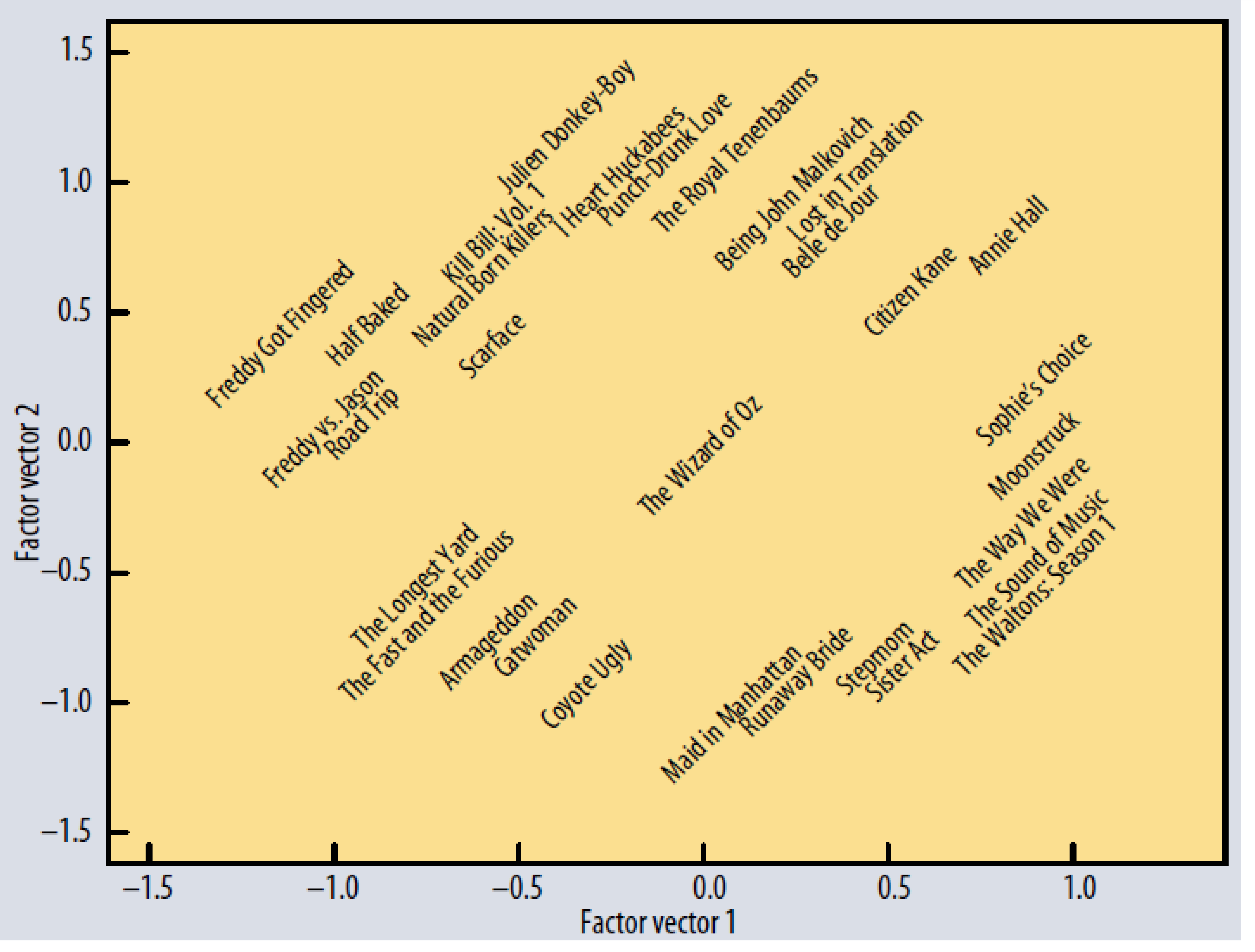
Netflix competition (2)

- Winning team shorlty before submitting on July 26th, 2009



Source: [Koren et al., IEEE 2009]()

Example factors



Source: [Koren et al., IEEE 2009]

Lessons learned from the Netflix challenge

- Matrix factorization techniques are superior to neighborhood-based ones
- But they need to combine many different aspects (e.g., temporal aspect, implicit feedback, user features, user and item bias)
- Filling in missing values correctly is difficult
- Winning system had many different algorithms stitched together
- Many concerns about $RMSE$ as a measure (as it does not capture well user satisfaction)

Research problems in collaborative filtering

- Data sparsity and noise
  - Fill in missing values correctly or remove noise
- Cold start problem
  - Recommending items to new users (i.e., learn preference for new users)
  - Predicting rating for new items
- Scalability
  - Factorization of large sparse matrices is difficult
- Recognizing adversarial users or dealing with users who, from time to time, largely disagree with common opinion
- How to promote diversity in recommendations?

Summary

- Neighborhood-based models for collaborative filtering
  - User-user models
  - Item-item models
  - Explainable results, easy to understand and implement but difficult to scale and update (at least for new items added)

- Latent factor (i.e., matrix factorization) models for collaborative filtering
  - Map user and item vectors to lower-dimensional space and measure similarity in that space
  - SVD can be used but results suffer from sparse data
  - Learn mappings directly from observed data through optimization problem
  - Take other aspects into account (e.g.: time, implicit feedback, user bias, item bias, features, etc.)
  - Scalable models that are superior to the neighborhood based ones