

Recommender Systems

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Content of This Course

- Overview of personalized recommendation
- Collaborative filtering
- Rating prediction
- Top-N ranking

A Data Mining Application: Recommendation

Overview

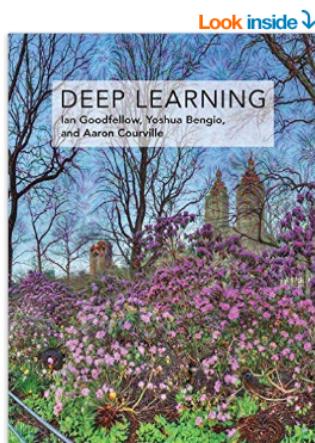
Collaborative Filtering

Rating prediction

Top-N ranking

Sincerely thank Prof. Jun Wang

Book Recommendation



Look inside ↓



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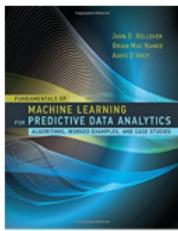
"Written by three experts in the field, *Deep Learning* is the only comprehensive book on the subject." --

Elon Musk, cochair of OpenAI; cofounder and CEO of Tesla and SpaceX

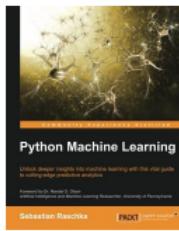
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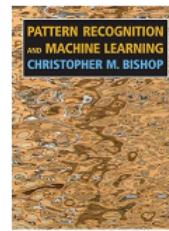
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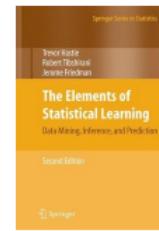
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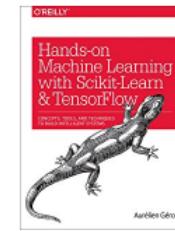
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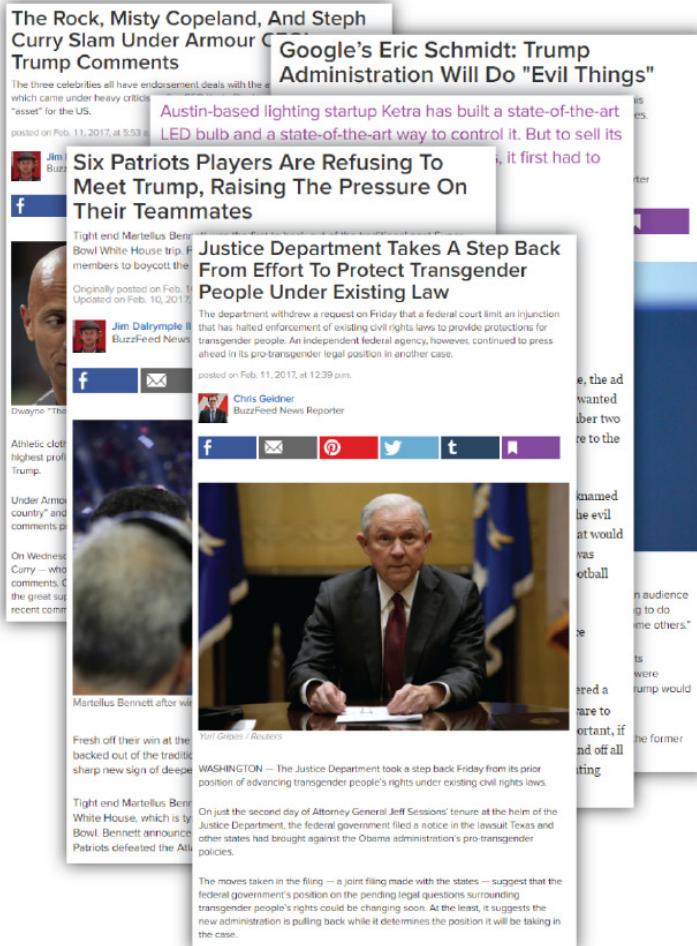


The Elements of
Statistical Learning
Data Mining, Inference, and Prediction
Second Edition
Springer Series in Statistics
Trevor Hastie, Robert Tibshirani, Jerome Friedman
The Elements of Statistical Learning: Data Mining, Inference, and Prediction
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Springer
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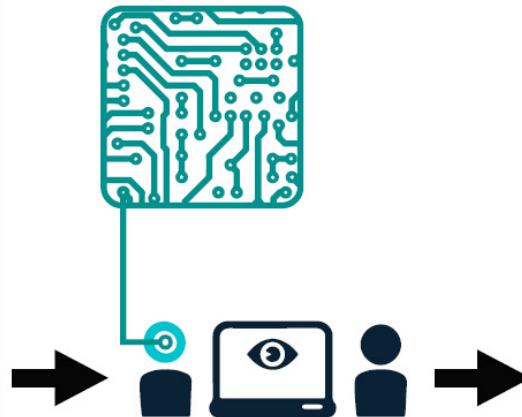
Hands-On Machine
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› Aurélien Géron
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News Feed Recommendation

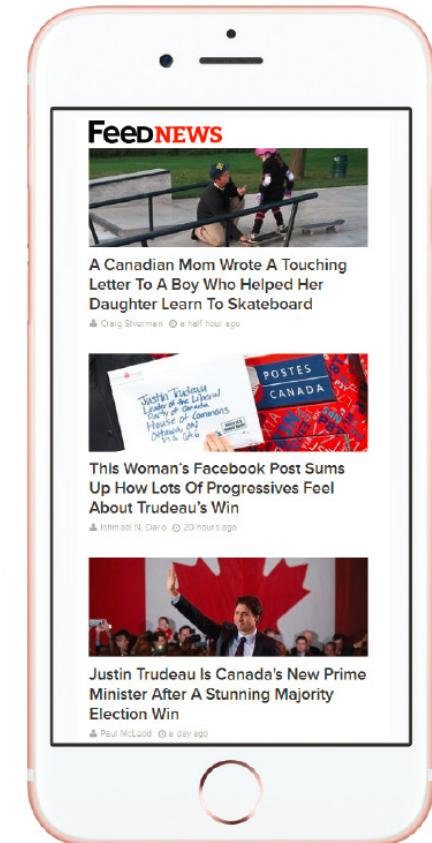


Huge numbers of candidate articles daily

Recommender System



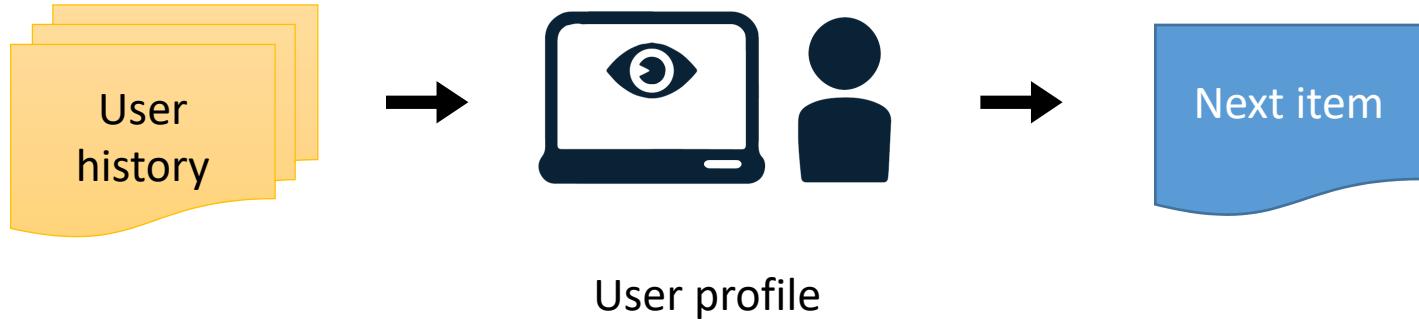
Editors manually select quality articles



Quality articles selected for news feed to end users

Personalized Recommendation

- Personalization framework



Build user profile from her history

- Ratings [amazon.com]
 - Explicit, but time-consuming
- Visits [newsfeed]
 - Implicit

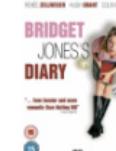
Personalization Methodologies

- Given the user's previous liked movies, how to recommend more movies she would like?
 - Method 1: recommend the movies that share the actors/actresses/director/genre with those the user likes
 - Method 2: recommend the movies that the users with similar interest to her like

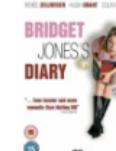
Information Filtering

- Information filtering deals with the delivery of information that the user is likely to find interesting or useful
 - Recommender system: information filtering in the form of suggestions
 - Two approaches for information filtering
 - Content-based filtering
 - recommend the movies that share the actors/actresses/director/genre with those the user likes
 - Collaborative filtering (the focus of this lecture)
 - recommend the movies that the users with similar interest to her like

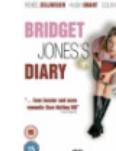
A (small) Rating Matrix

								
	Die Hard	Mission: Impossible	GoldenEye	Casino Royale	Titanic	Notting Hill	Bridget Jones's Diary	Love Actually
Boris	★★★★★	★★★★★	★★★★★			★★★★★		
Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

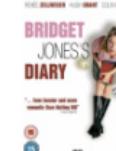
The Users

	 Die Hard	 Mission: Impossible	 GoldenEye	 Casino Royale	 Titanic	 Notting Hill	 Bridget Jones's Diary	 Love Actually
Boris	★★★★★	★★★★★	★★★★★			★★★★★		
Dave		★★★★★	★★★★★	★★★★★			★★★★★	
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

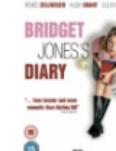
The Items

	 Die Hard	 Mission: Impossible	 GoldenEye	 Casino Royale	 Titanic	 Notting Hill	 Bridget Jones's Diary	 Love Actually
Boris	★★★★★	★★★★★	★★★★★			★★★★★		
Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

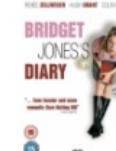
A User-Item Rating

	 Die Hard	 Mission: Impossible	 GoldenEye	 Casino Royale	 Titanic	 Notting Hill	 Bridget Jones's Diary	 Love Actually
Boris	★★★★★	★★★★★	★★★★★				★★★★★	
Dave		★★★★★	★★★★★	★★★★★	★★★★★			★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

A User Profile

								
	Die Hard	Mission: Impossible	GoldenEye	Casino Royale	Titanic	Notting Hill	Bridget Jones's Diary	Love Actually
Boris	★★★★★	★★★★★	★★★★★			★★★★★		
Dave	←		★★★★★	★★★★★	★★★★★			★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

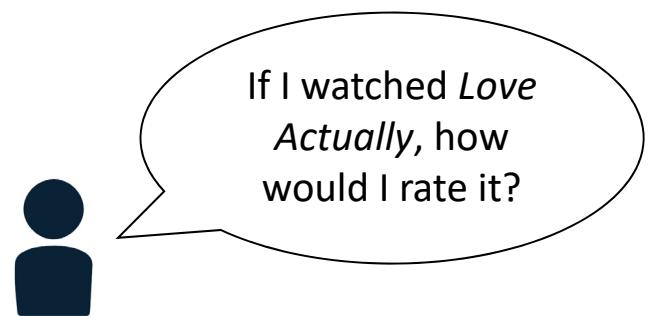
An Item Profile

								
	Die Hard	Mission: Impossible	GoldenEye	Casino Royale	Titanic	Notting Hill	Bridget Jones's Diary	Love Actually
Boris	★★★★★	★★★★★	★★★★★			★★★★★		
Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

A Null Rating Entry

Die Hard		Mission: Impossible		GoldenEye		Casino Royale		Titanic		Notting Hill		Bridget Jones's Diary		Love Actually	
Boris	★★★★★	★★★★★	★★★★★					★★★★★							
Dave		★★★★★	★★★★★	★★★★★									★★★★★		
Will		★★★★★				★★★★★	★★★★★	★★★★★					★★★★★		
George	★★★★★	★★★★★	★★★★★	★★★★★									★★★★★		

- Recommendation on explicit data
 - Predict the null ratings



K Nearest Neighbor Algorithm (KNN)

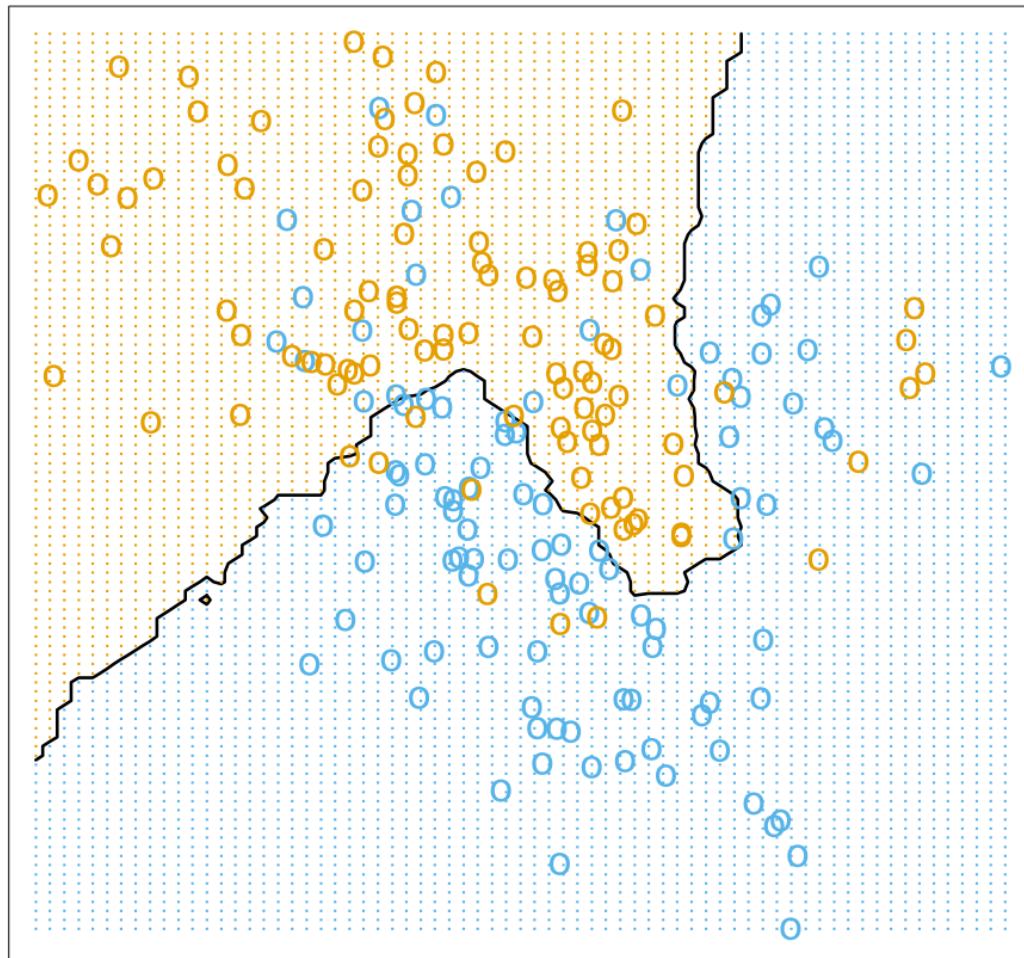
- A **non-parametric** method used for classification and regression
 - for each input instance x , find k closest training instances $N_k(x)$ in the feature space
 - the prediction of x is based on the average of labels of the k instances

$$\hat{y}(x) = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i$$

- For classification problem, it is the majority voting among neighbors

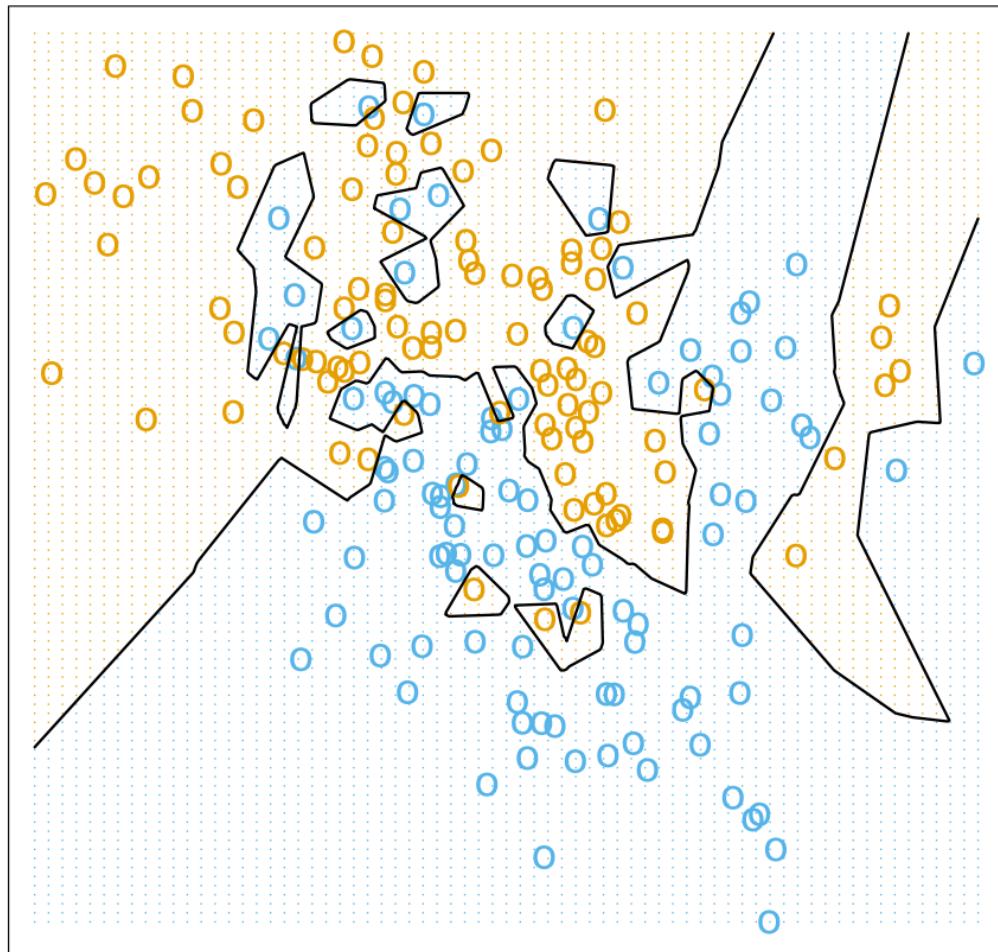
kNN Example

15-nearest neighbor



kNN Example

1-nearest neighbor



K Nearest Neighbor Algorithm (KNN)

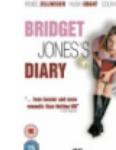
- Generalized version
 - Define similarity function $s(x, x_i)$ between the input instance x and its neighbor x_i
 - Then the prediction is based on the weighted average of the neighbor labels based on the similarities

$$\hat{y}(x) = \frac{\sum_{x_i \in N_k(x)} s(x, x_i) y_i}{\sum_{x_i \in N_k(x)} s(x, x_i)}$$

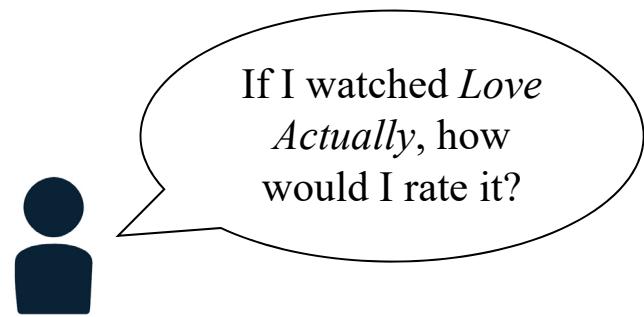
Non-Parametric kNN

- No parameter to learn
 - In fact, there are N parameters: each instance is a parameter
 - There are N/k effective parameters
 - Intuition: if the neighborhoods are non-overlapping, there would be N/k neighborhoods, each of which fits one parameter
- Hyperparameter k
 - We cannot use sum-of-squared error on the training set as a criterion for picking k , since $k=1$ is always the best
 - Tune k on validation set

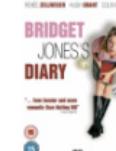
A Null Rating Entry

								
	Die Hard	Mission: Impossible	GoldenEye	Casino Royale	Titanic	Notting Hill	Bridget Jones's Diary	Love Actually
Boris	★★★★★	★★★★★	★★★★★		★★★★★	★★★★★		
Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

- Recommendation on explicit data
 - Predict the null ratings

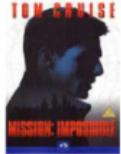
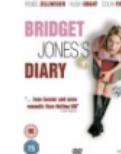


Collaborative Filtering Example

								
	Die Hard	Mission: Impossible	GoldenEye	Casino Royale	Titanic	Notting Hill	Bridget Jones's Diary	Love Actually
Boris	★★★★★	★★★★★	★★★★★			★★★★★		?
Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

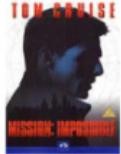
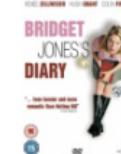
- What do you think the rating would be?

User-based kNN Solution

								
	Die Hard	Mission: Impossible	GoldenEye	Casino Royale	Titanic	Notting Hill	Bridget Jones's Diary	Love Actually
► Boris	★★★★★	★★★★★	★★★★★			★★★★★		?
► Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
► George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

- Find similar users (neighbors) for Boris
 - Dave and George

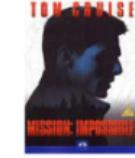
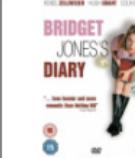
Rating Prediction

								
► Boris	★★★★★	★★★★★	★★★★★			★★★★★		★★★★★
► Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
► George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

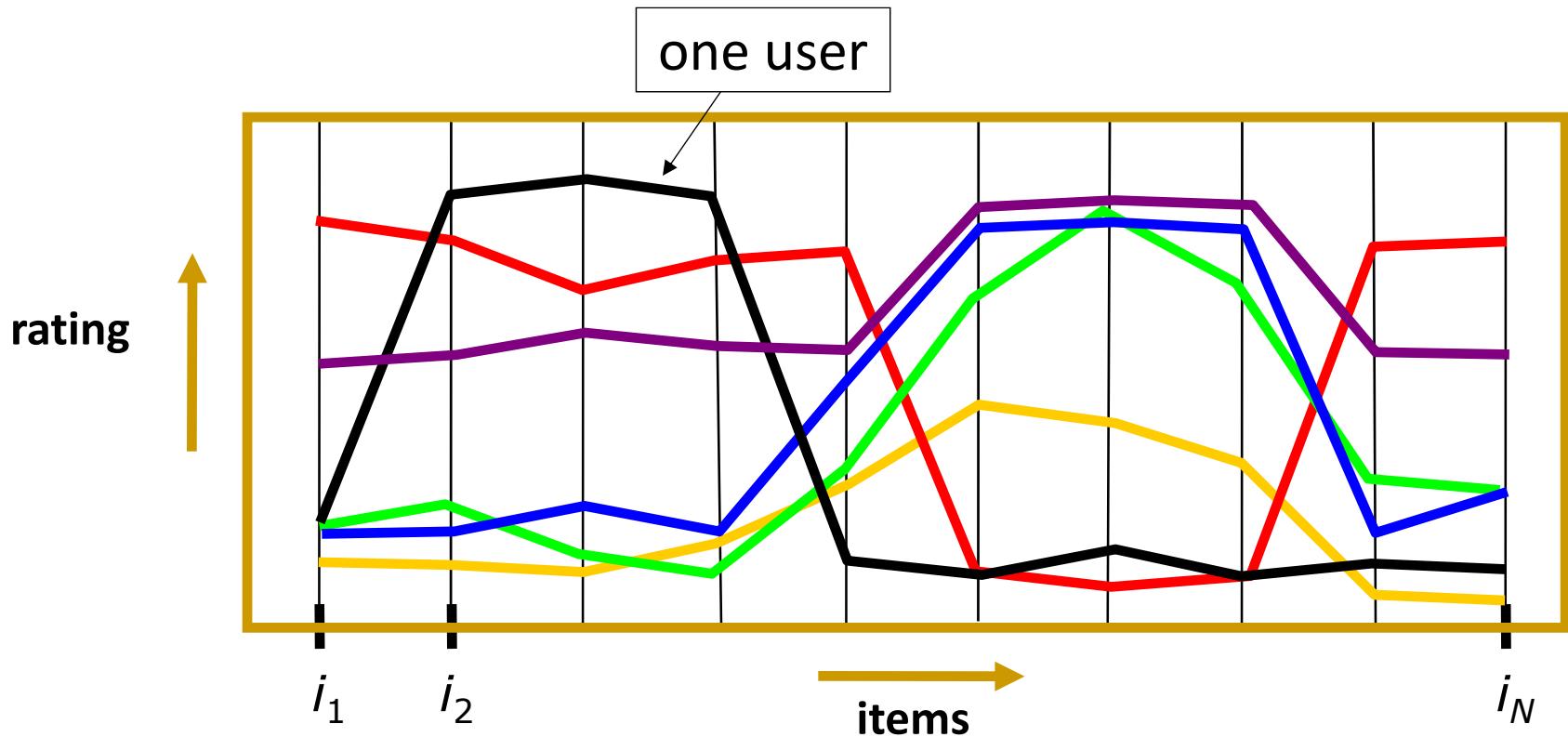
- Average Dave's and George's rating on Love Actually
 - Prediction = $(1+2)/2 = 1.5$

Collaborative Filtering for Recommendation

- Basic user-based kNN algorithm
 - For each target user for recommendation
 1. Find similar users
 2. Based on similar users, recommend new items

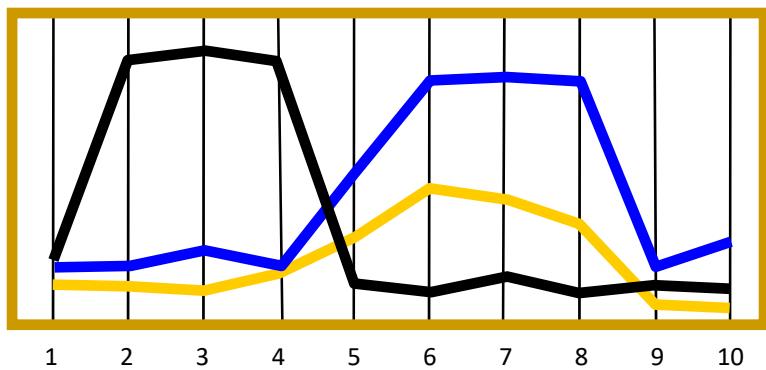
	 Die Hard	 Mission: Impossible	 GoldenEye	 Casino Royale	 Titanic	 Notting Hill	 Bridget Jones's Diary	 Love Actually
► Boris	★★★★★	★★★★★	★★★★★			★★★★★		★★★★★
► Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
► George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★

Similarity between Users



- Each user's profile can be directly built as a vector based on her item ratings

Similarity between Users



user
yellow

correlated

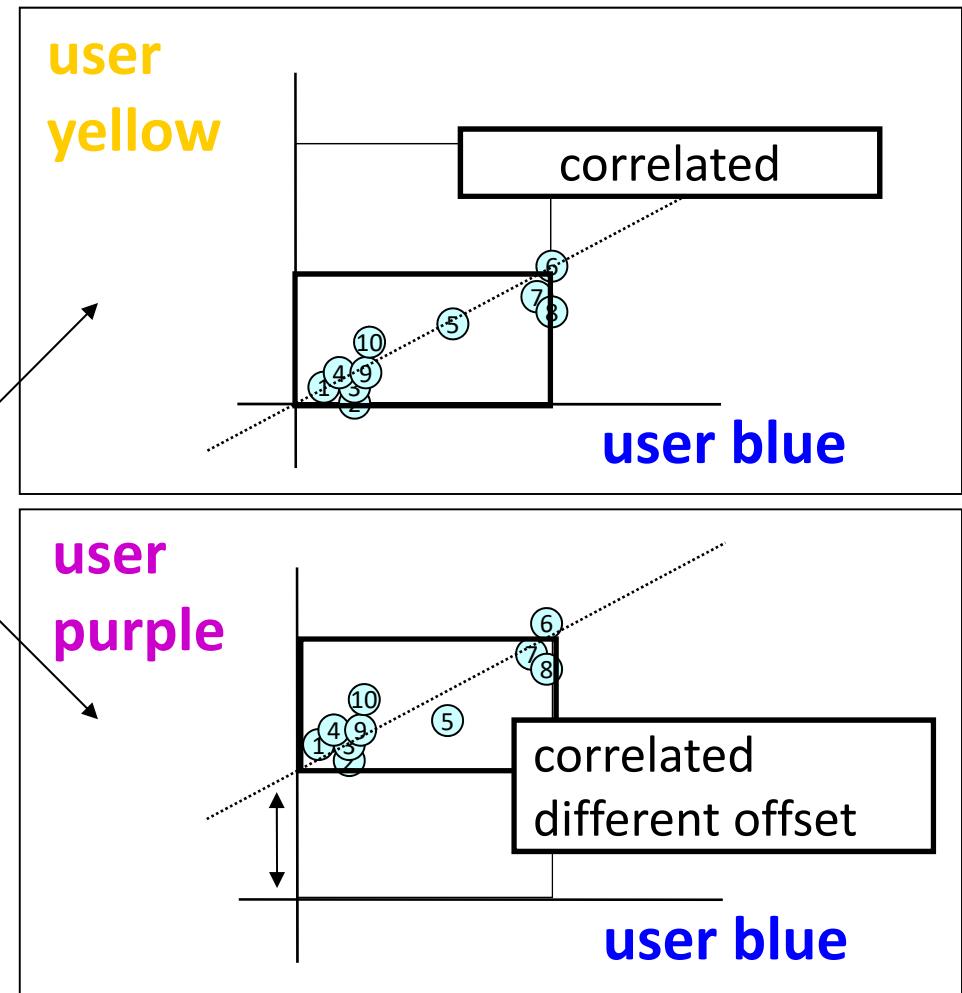
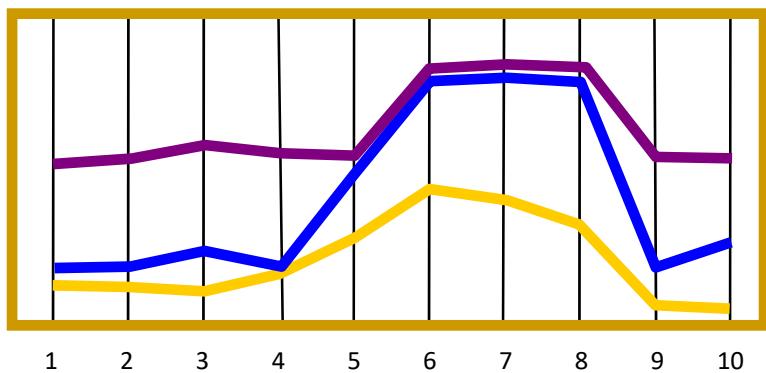
user blue

user
black

not correlated

user blue

Similarity between Users



Similarity Measures (Users)

- Similarity measures between two users a and b
 - Cosine (angle)

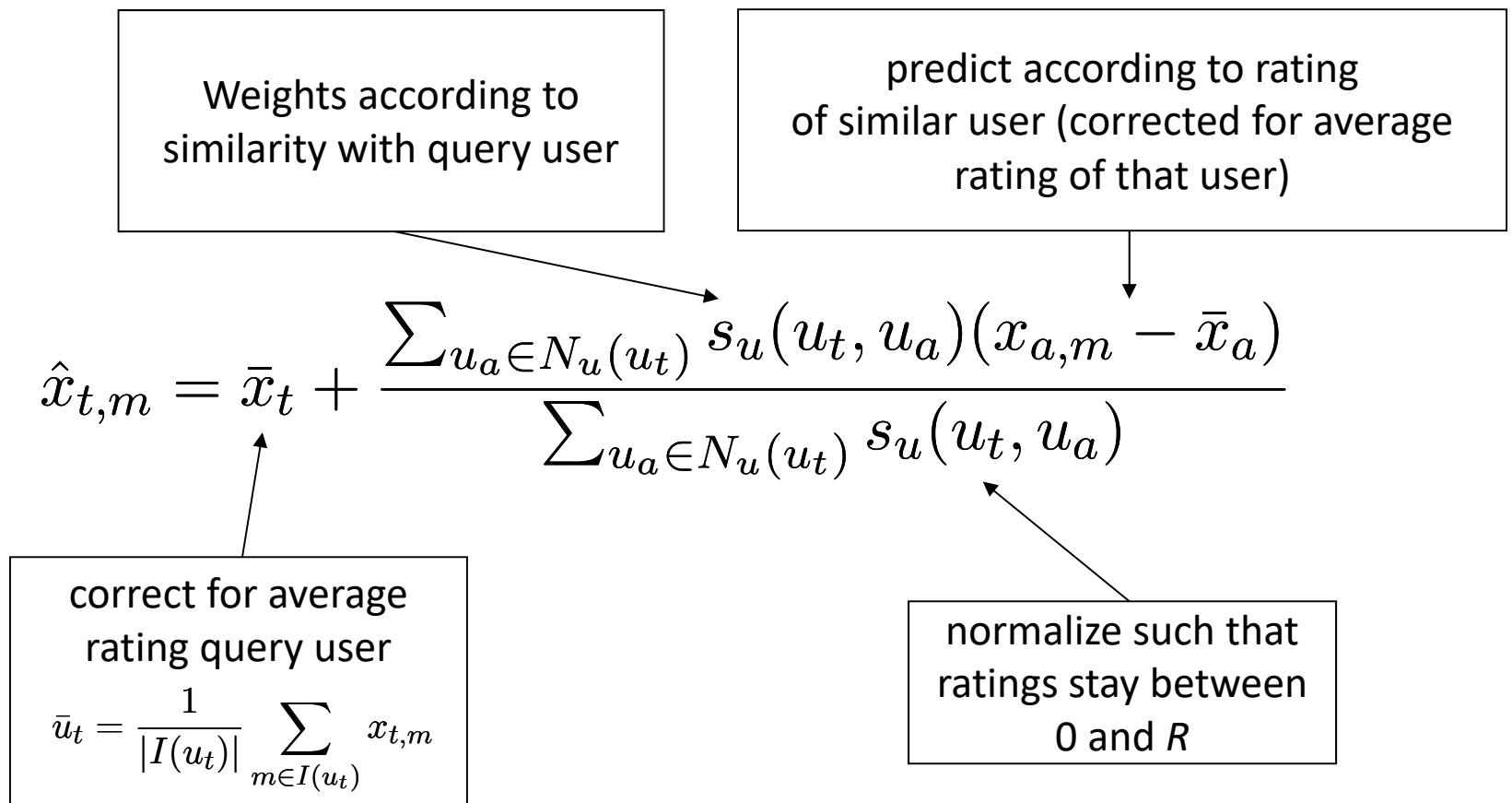
$$s_u^{\cos}(u_a, u_b) = \frac{u_a^\top u_b}{\|u_a\| \|u_b\|} = \frac{\sum_m x_{a,m} x_{b,m}}{\sqrt{\sum_m x_{a,m}^2 \sum_m x_{b,m}^2}}$$

- Pearson Correlation

$$s_u^{\text{corr}}(u_a, u_b) = \frac{\sum_m (x_{a,m} - \bar{x}_a)(x_{b,m} - \bar{x}_b)}{\sqrt{\sum_m (x_{a,m} - \bar{x}_a)^2 \sum_m (x_{b,m} - \bar{x}_b)^2}}$$

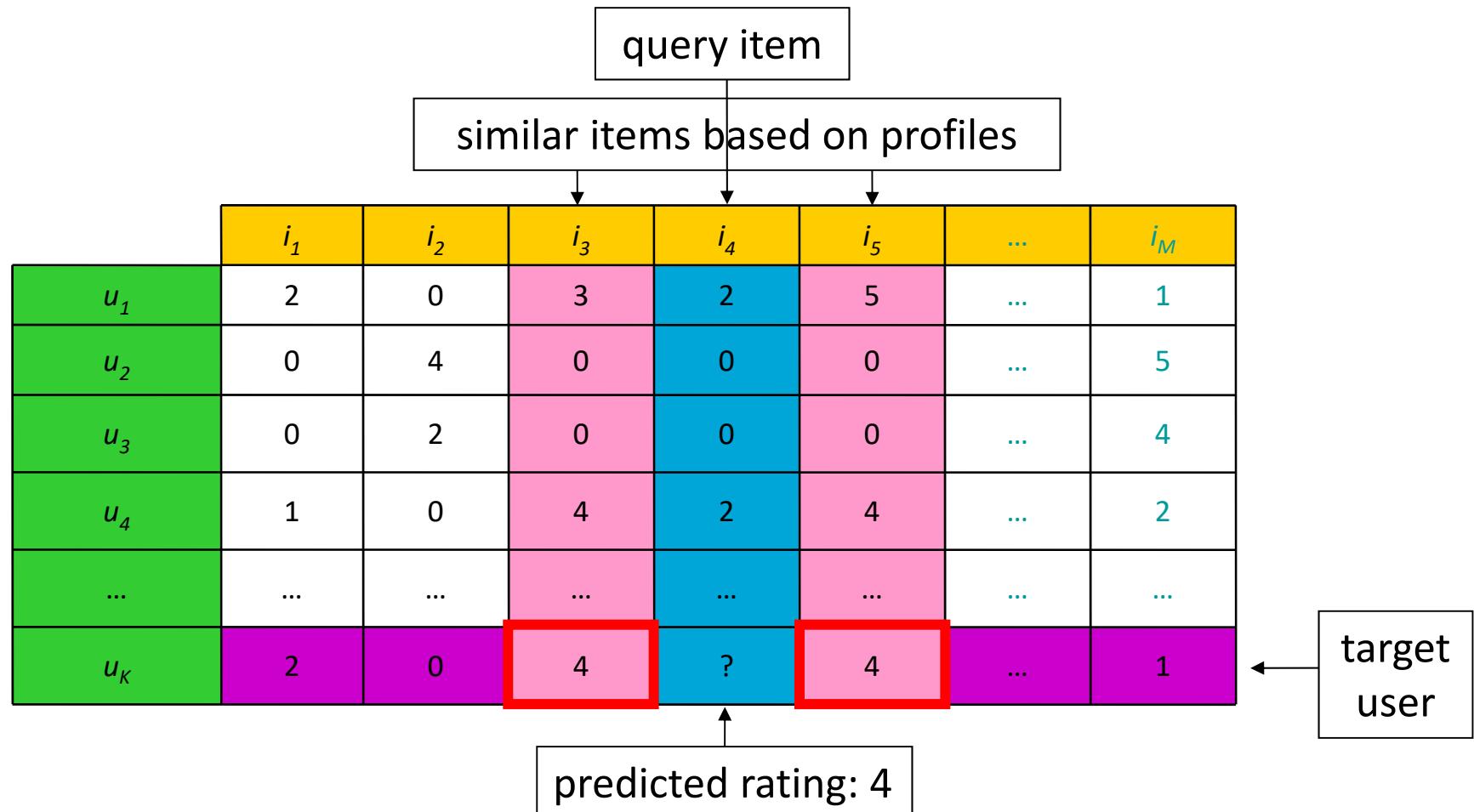
User-based kNN Rating Prediction

- Predicting the rating from target user t to item m



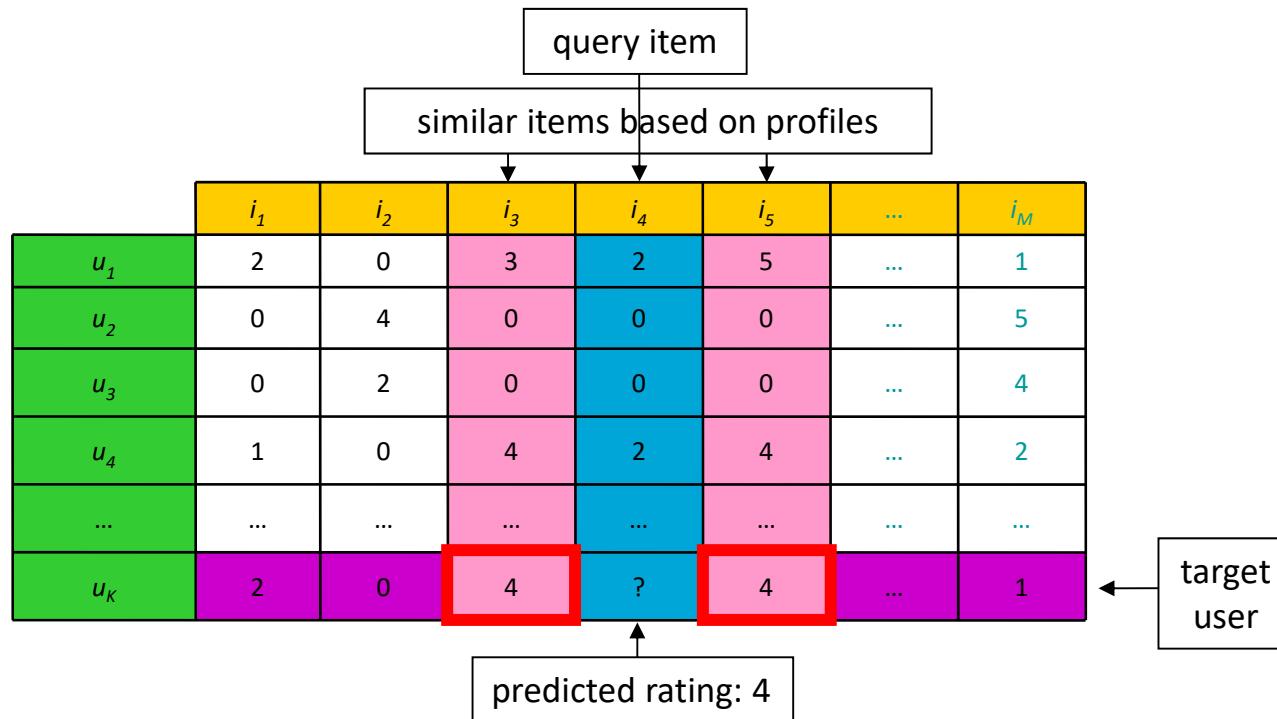
Item-based kNN Solution

- Recommendation based on item similarity



Item-based kNN Solution

- For each unrated items m of the target user t
 - Find similar items $\{a\}$
 - Based on the set of similar items $\{a\}$
 - Predict the rating of the item m



Similarity Measures (Items)

- Similarity measures between two items a and b
 - Cosine (angle)

$$s_i^{\text{cos}}(i_a, i_b) = \frac{i_a^\top i_b}{\|i_a\| \|i_b\|} = \frac{\sum_u x_{u,a} x_{u,b}}{\sqrt{\sum_u x_{u,a}^2 \sum_u x_{u,b}^2}}$$

- Adjusted Cosine

$$s_i^{\text{adcos}}(i_a, i_b) = \frac{\sum_u (x_{u,a} - \bar{x}_u)(x_{u,b} - \bar{x}_u)}{\sqrt{\sum_u (x_{u,a} - \bar{x}_u)^2 \sum_u (x_{u,b} - \bar{x}_u)^2}}$$

- Pearson Correlation

$$s_i^{\text{corr}}(i_a, i_b) = \frac{\sum_u (x_{u,a} - \bar{x}_a)(x_{u,b} - \bar{x}_b)}{\sqrt{\sum_u (x_{u,a} - \bar{x}_a)^2 \sum_u (x_{u,b} - \bar{x}_b)^2}}$$

Item-based kNN Rating Prediction

- Get top- k neighbor items that the target user t rated

$$N_i(u_t, i_a) = \{i_b | r_i(i_a, i_b) < K^*, x_{t,b} \neq 0\}$$

Rank position

Choose K^* such that $|N_i(u_t, i_a)| = k$

- Predict ratings for item a that the target user t did not rate

$$\hat{x}_{t,a} = \frac{\sum_{i_b \in N_i(u_t, i_a)} s_i(i_a, i_b) x_{t,b}}{\sum_{i_b \in N_i(u_t, i_a)} s_i(i_a, i_b)}$$

Don't need to correct for users average rating since query user itself is used to do predictions

Empirical Study

- Movielens dataset from 
- <http://www.grouplens.org/node/73>
- Users visit Movielens
 - rate and receive recommendations for movies
- Dataset (ML-100k)
 - 100k ratings from 1 to 5
 - 943 users, 1682 movies (rated by at least one user)
 - Sparsity level
$$1 - \frac{\text{\#non-zero entries}}{\text{total entries}} = 1 - \frac{10^5}{943 \times 1682} = 93.69\%$$

Experiment Setup

- Split data in training ($x\%$) and test set ($(100-x)\%$)
 - Can be repeated T times and results averaged

- Evaluation metrics

- Mean-Absolute Error (MAE)

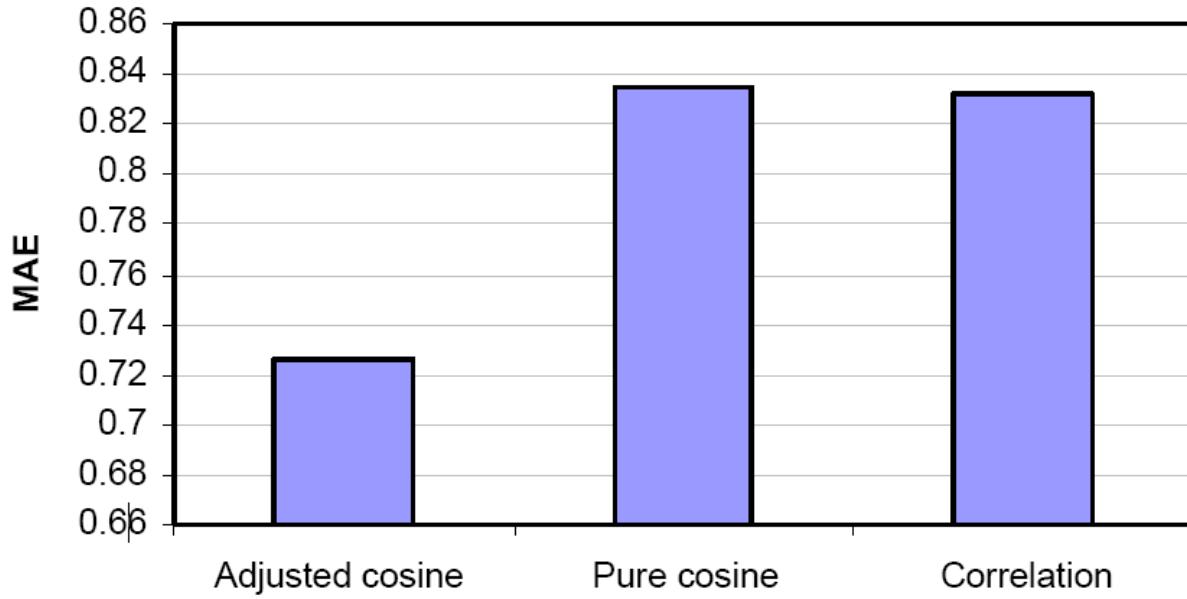
$$\text{MAE} = \frac{1}{|D_{\text{test}}|} \sum_{(u,i,r) \in D_{\text{test}}} |r - \hat{r}_{u,i}|$$

- Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{|D_{\text{test}}|} \sum_{(u,i,r) \in D_{\text{test}}} (r - \hat{r}_{u,i})^2}$$

Impact of Similarity Measures

Relative performance of different similarity measures



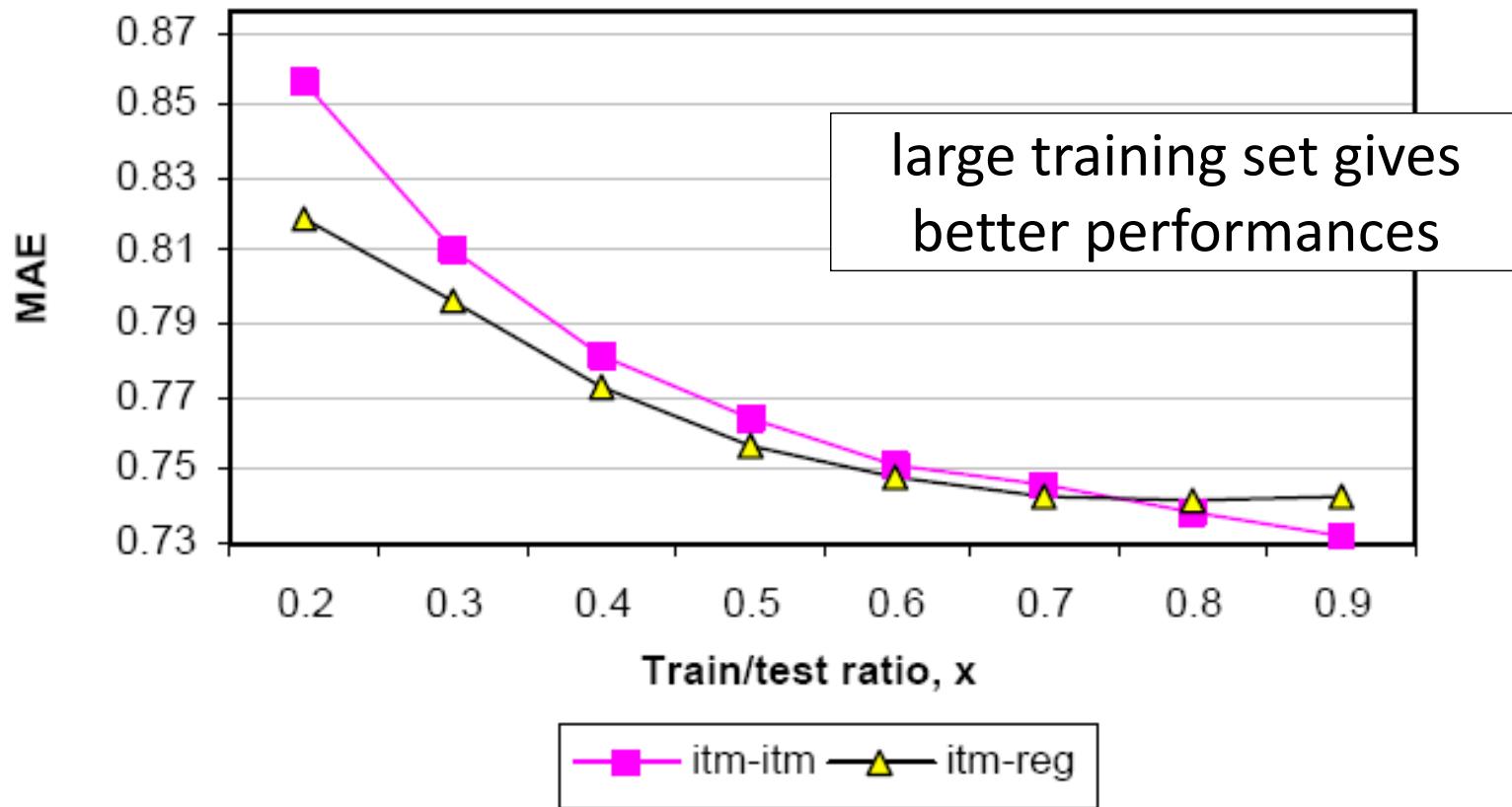
$$s_i^{\text{adcos}}(i_a, i_b) = \frac{\sum_u (x_{u,a} - \bar{x}_u)(x_{u,b} - \bar{x}_u)}{\sqrt{\sum_u (x_{u,a} - \bar{x}_u)^2 \sum_u (x_{u,b} - \bar{x}_u)^2}}$$

$$s_i^{\text{cos}}(i_a, i_b) = \frac{i_a^\top i_b}{\|i_a\| \|i_b\|} = \frac{\sum_u x_{u,a} x_{u,b}}{\sqrt{\sum_u x_{u,a}^2 \sum_u x_{u,b}^2}}$$

$$s_i^{\text{corr}}(i_a, i_b) = \frac{\sum_u (x_{u,a} - \bar{x}_a)(x_{u,b} - \bar{x}_b)}{\sqrt{\sum_u (x_{u,a} - \bar{x}_a)^2 \sum_u (x_{u,b} - \bar{x}_b)^2}}$$

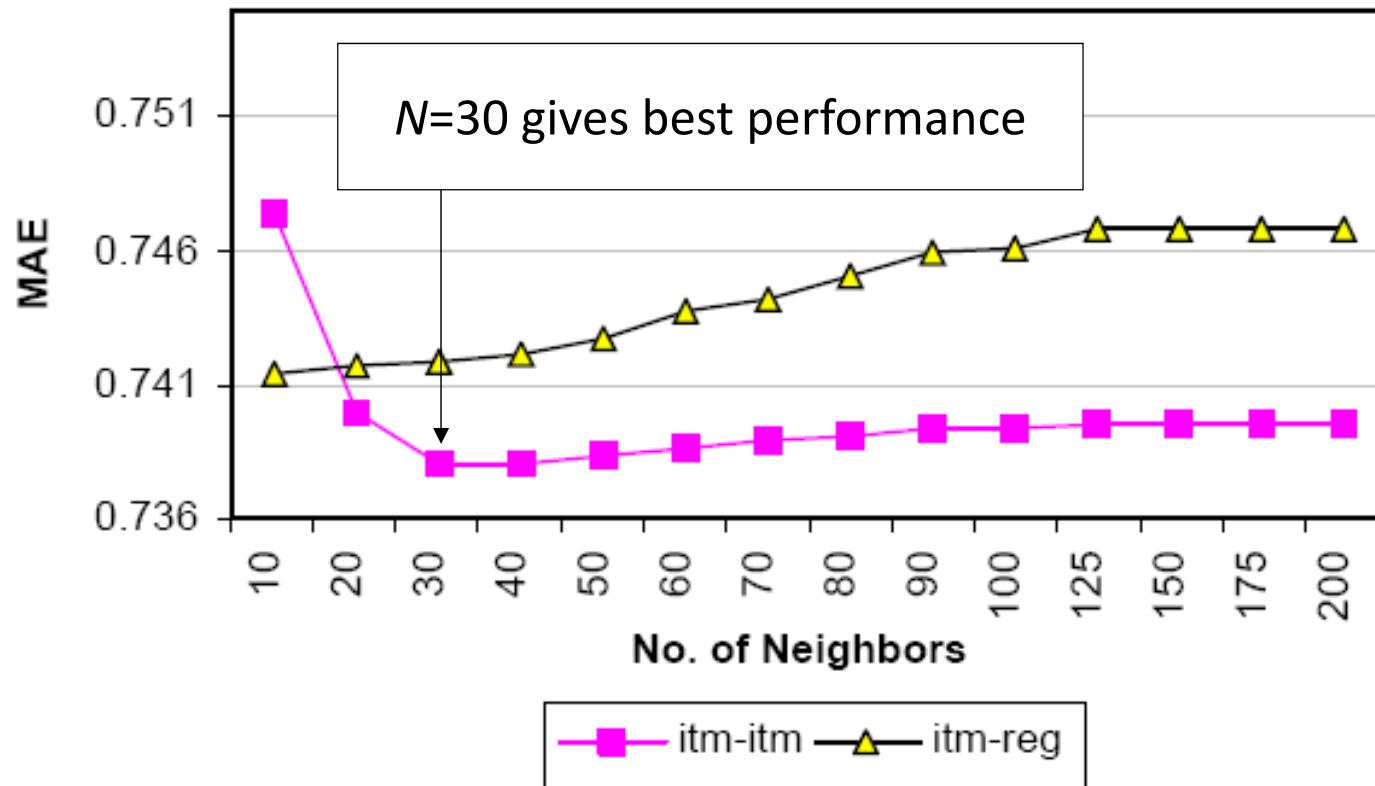
Sensitivity of Train/Test Ratio

Sensitivity of the parameter x

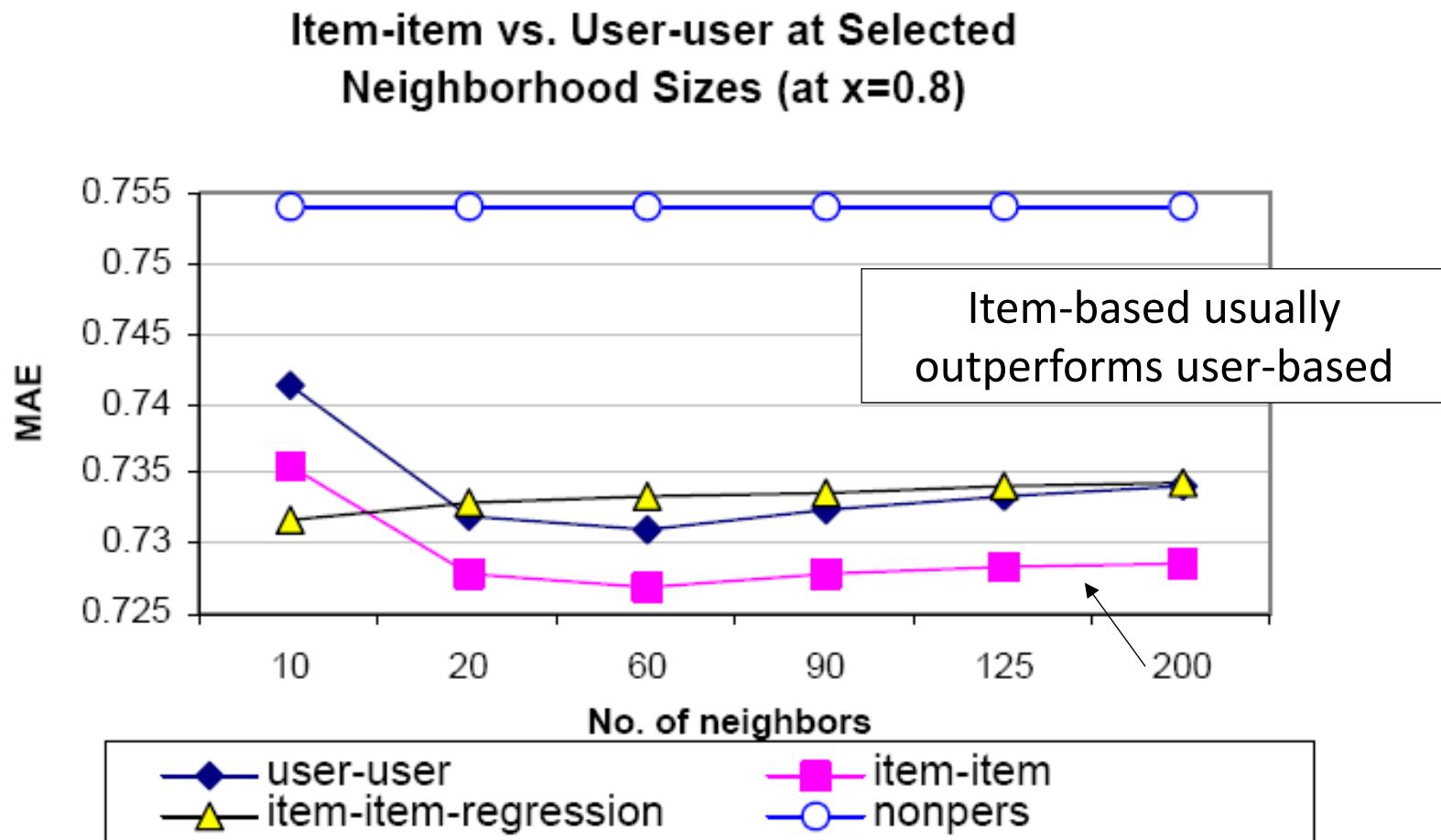


Sensitivity Neighborhood Size k

Sensitivity of the Neighborhood Size



Item-based vs. User-based



- Item-item similarity is usually more stable and objective

kNN based Methods Summary

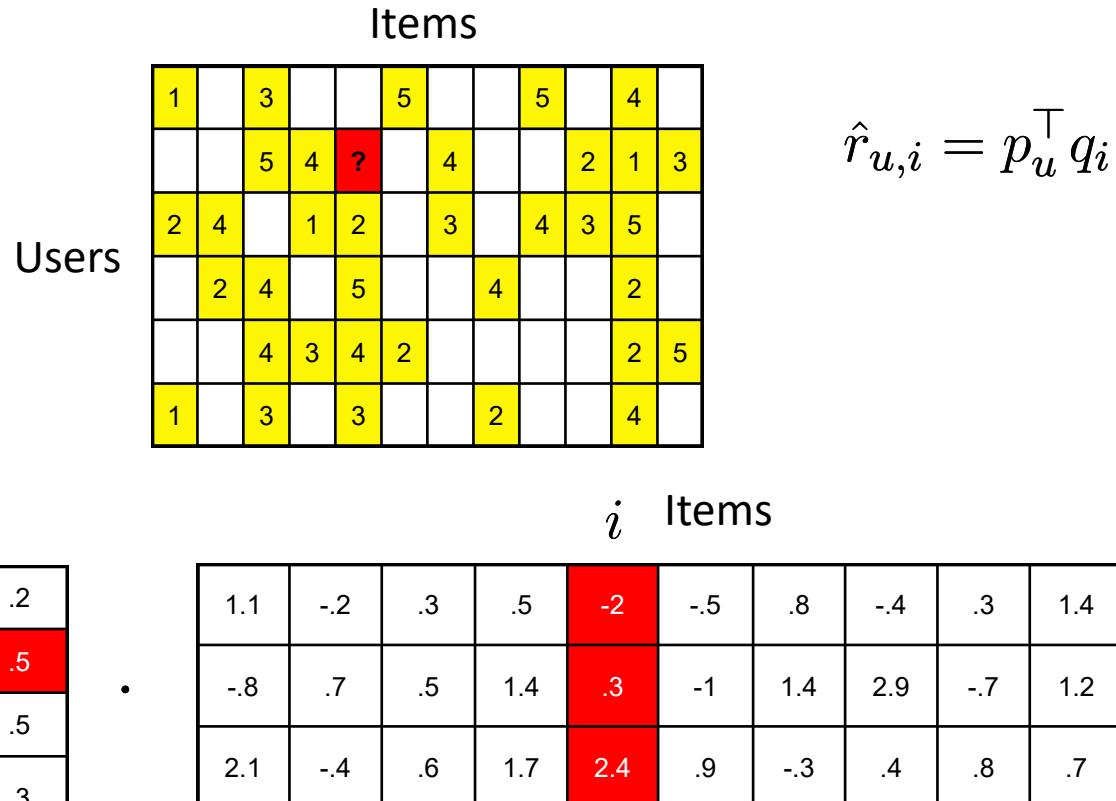
- Straightforward and highly explainable
- No parameter learning
 - Only one hyperparameter k to tune
 - Cannot get improved by learning
- Efficiency could be a serious problem
 - When the user/item numbers are large
 - When there are a huge number of user-item ratings
- We may need a parametric and learnable model

Matrix Factorization Techniques

	Die Hard	Mission: Impossible	GoldenEye	Casino Royale	Titanic	Notting Hill	Bridget Jones's Diary	Love Actually
Boris	★★★★★	★★★★★	★★★★★			★★★★★		★★★★★
Dave		★★★★★	★★★★★	★★★★★				★★★★★
Will		★★★★★			★★★★★	★★★★★	★★★★★	★★★★★
George	★★★★★	★★★★★	★★★★★	★★★★★				★★★★★



Matrix Factorization Techniques



\approx

u
Users

.1	-.4	.2
-.5	.6	.5
-.2	.3	.5
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

•

1.1	-.2	.3	.5	-2							
-.8	.7	.5	1.4	.3							
2.1	-.4	.6	1.7	2.4							

Basic MF Model

- Prediction of user u 's rating on item i

$$\hat{r}_{u,i} = p_u^\top q_i \quad \text{Bilinear model}$$

- Loss function

$$\mathcal{L}(u, i, r_{u,i}) = \frac{1}{2}(r_{u,i} - p_u^\top q_i)^2$$

- Training objective

$$\min_{P, Q} \sum_{r_{u,i} \in D} \frac{1}{2}(r_{u,i} - p_u^\top q_i)^2 + \frac{\lambda}{2}(\|p_u\|^2 + \|q_i\|^2)$$

- Gradients

$$\frac{\partial \mathcal{L}(u, i, r_{u,i})}{\partial p_u} = (p_u^\top q_i - r_{u,i})q_i + \lambda p_u$$

$$\frac{\partial \mathcal{L}(u, i, r_{u,i})}{\partial q_i} = (p_u^\top q_i - r_{u,i})p_u + \lambda q_i$$

MF with Biases

- Prediction of user u 's rating on item i

$$\hat{r}_{u,i} = \mu + b_u + b_i + p_u^\top q_i$$

↑ ↑ ↑ ↑
Global User Item User-item
bias bias bias Interaction

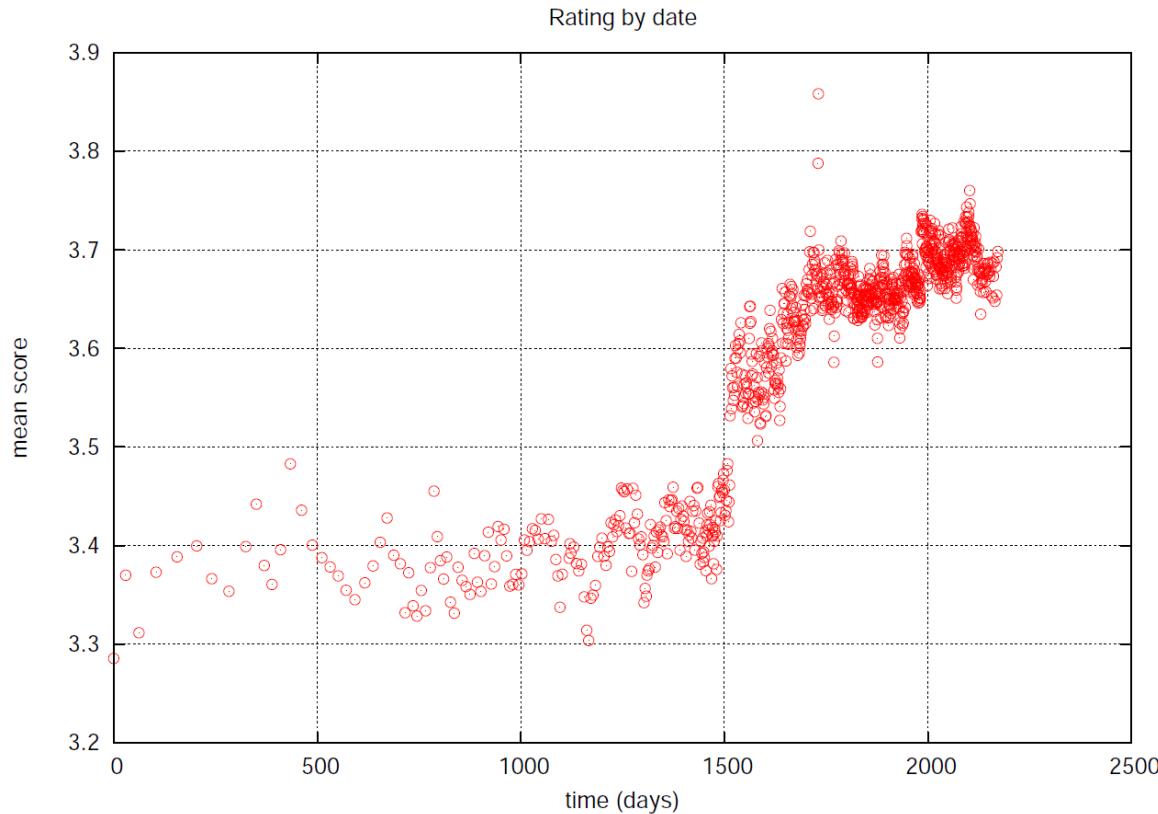
- Training objective

$$\min_{P,Q} \sum_{r_{u,i} \in D} \frac{1}{2} \left(r_{u,i} - (\mu + b_u + b_i + p_u^\top q_i) \right)^2 + \frac{\lambda}{2} (\|p_u\|^2 + \|q_i\|^2 + b_u^2 + b_i^2)$$

- Gradient update

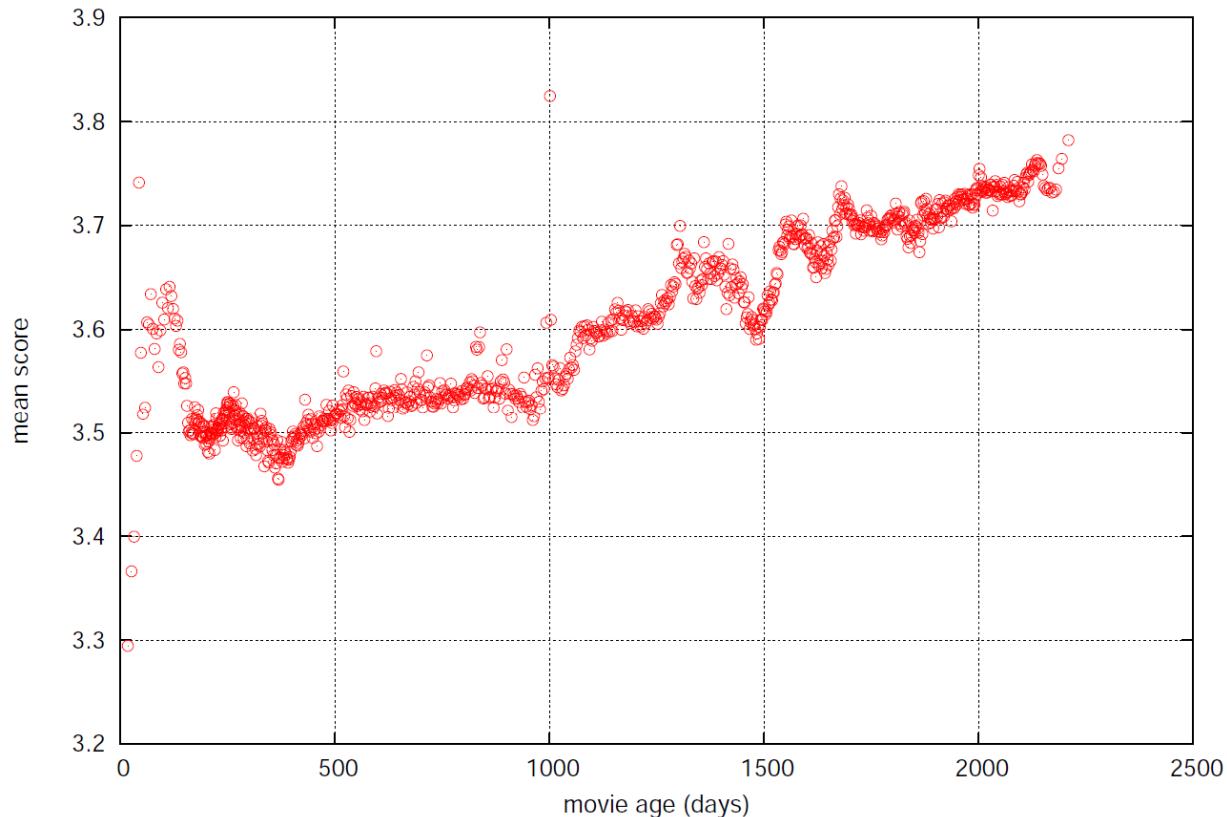
$$\begin{aligned}\delta &= r_{u,i} - (\mu + b_u + b_i + p_u^\top q_i) \\ \mu &\leftarrow \mu + \eta \delta \\ b_u &\leftarrow (1 - \eta \lambda) b_u + \eta \delta \\ b_i &\leftarrow (1 - \eta \lambda) b_i + \eta \delta \\ p_u &\leftarrow (1 - \eta \lambda) p_u + \eta \delta q_i \\ q_i &\leftarrow (1 - \eta \lambda) q_i + \eta \delta p_u\end{aligned}$$

Temporal Dynamics



- A sudden rise in the average movie rating beginning around 1500 days (early 2004) into the dataset

Temporal Dynamics



- People tend to give higher ratings as movies become older

Multiple sources of temporal dynamics

- Item-side effects
 - Product perception and popularity are constantly changing
 - Seasonal patterns influence items' popularity
- User-side effects
 - Customers ever redefine their taste
 - Transient, short-term bias
 - Drifting rating scale
 - Change of rater within household

Addressing temporal dynamics

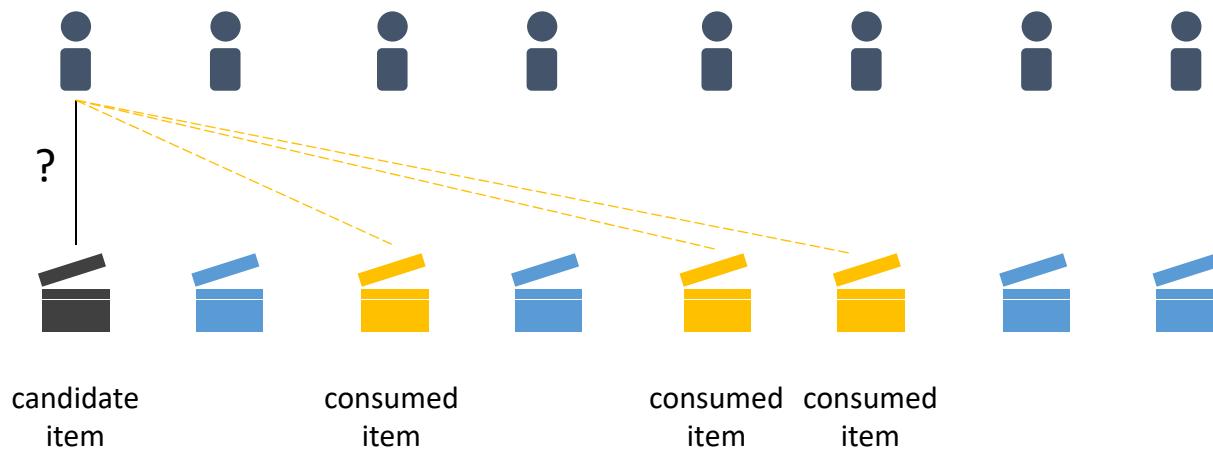
- Factor model conveniently allows separately treating different aspects
- We observe changes in:
 - Rating scale of individual users $b_u(t)$
 - Popularity of individual items $b_i(t)$
 - User preferences $p_u(t)$

$$r_{u,i}(t) = \mu + b_u(t) + b_i(t) + p_u(t)^\top q_i$$

- Design guidelines
 - Items show slower temporal changes
 - Users exhibit frequent and sudden changes
 - Factors $p_u(t)$ are expensive to model
 - Gain flexibility by heavily parameterizing the functions

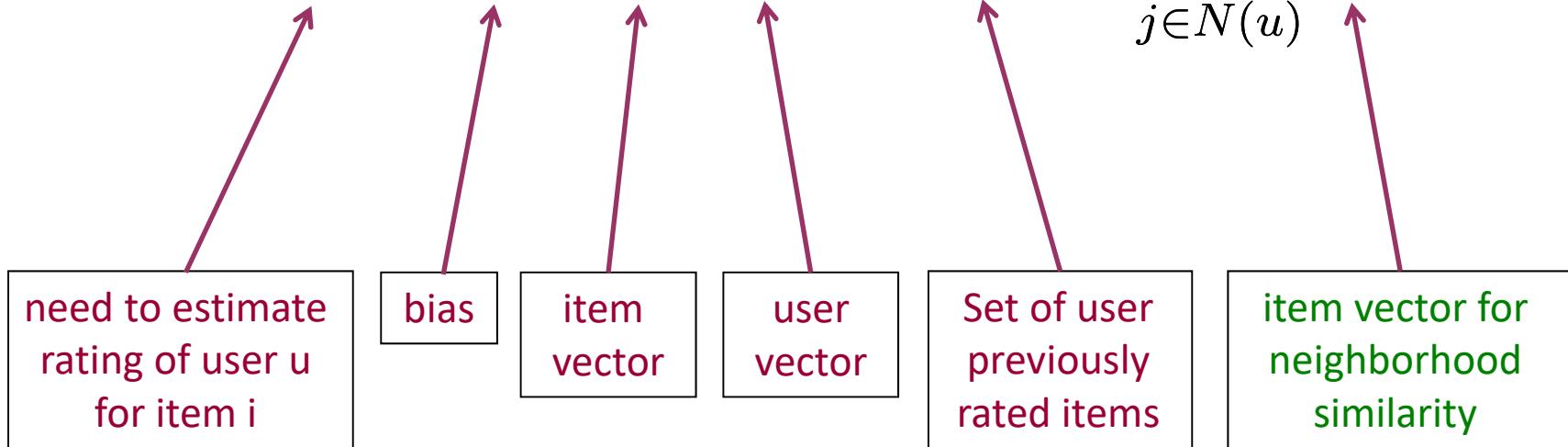
Neighborhood (Similarity)-based MF

- Assumption: user's previous consumed items reflect her taste
- Derive unknown ratings from those of “similar” items (item-item variant)



Neighborhood based MF modeling: SVD++

$$\hat{r}_{u,i} = b_{u,i} + q_i^\top \left(p_u + |N(u)|^{-\frac{1}{2}} \sum_{j \in N(u)} y_j \right)$$

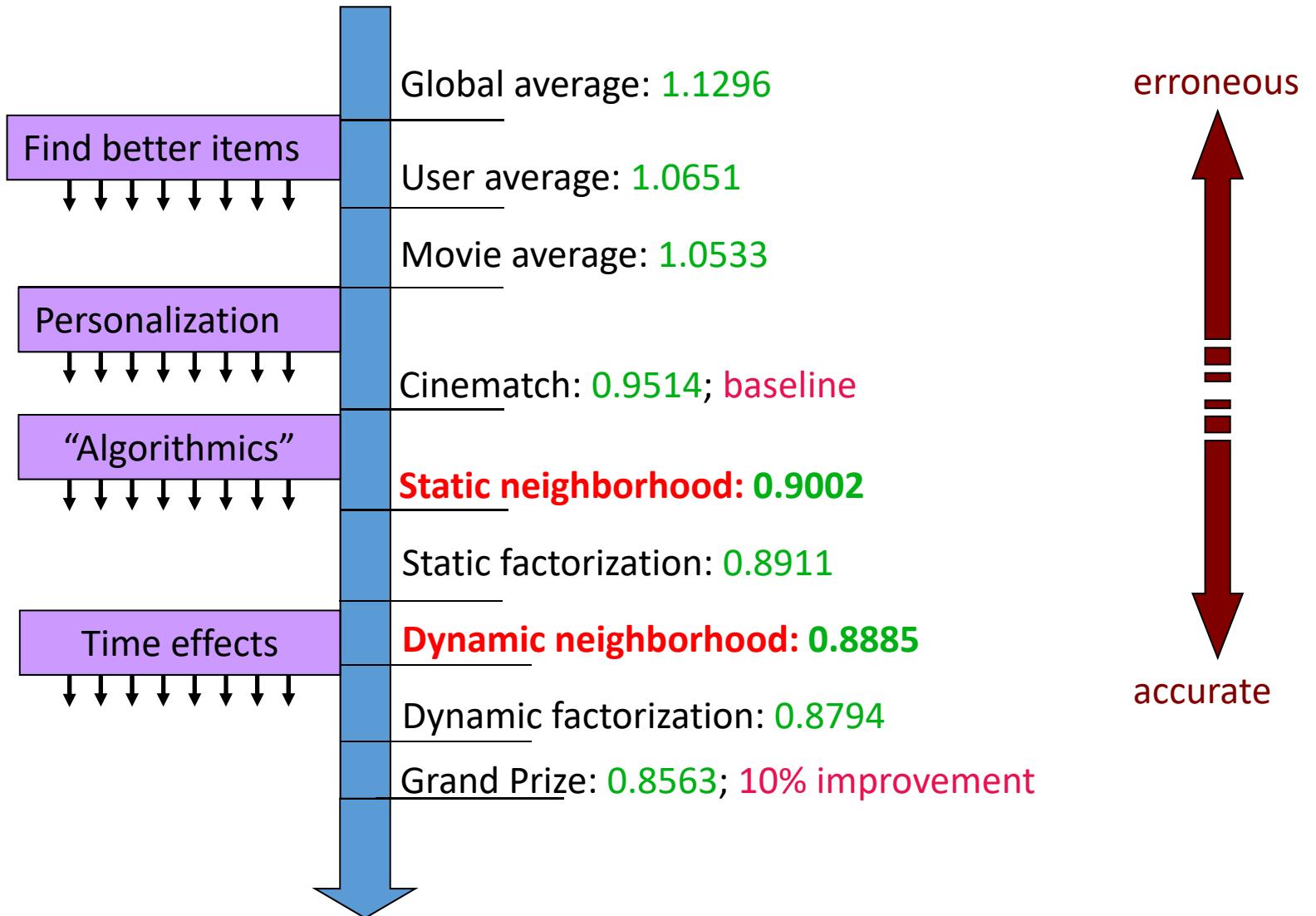


- Each item has two latent vectors
 - The standard item vector q_i
 - The vector y_i when it is used for estimation the similarity between the candidate item and the target user

Netflix Prize

- An open competition for the best collaborative filtering algorithm for movies
 - Began on October 2, 2006.
 - A million-dollar challenge to improve the accuracy (RMSE) of the Netflix recommendation algorithm by 10%
- Netflix provided
 - Training data: 100,480,507 ratings:
 - 480,189 users x 17,770 movies.
 - Format: <user, movie, date, rating>
- Two popular approaches:
 - Matrix factorization
 - Neighborhood





Temporal neighborhood model delivers same relative RMSE improvement (0.0117) as temporal factor model (!)



PAY TO THE
ORDER OF: BellKor's Pragmatic Chaos

\$1,000,000
00/100

AMOUNT: ONE MILLION

FOR: The Netflix Prize

Reed Hastings

2009

DATE: 09.21.09

Feature-based Matrix Factorization

$$\hat{y} = \mu + \left(\sum_j b_j^{(g)} \gamma_j + \sum_j b_j^{(u)} \alpha_j + \sum_j b_j^{(i)} \beta_j \right) + \left(\sum_j p_j \alpha_j \right)^\top \left(\sum_j q_j \beta_j \right)$$

- Regard all information as features
 - User id and item id
 - Time, item category, user demographics etc.
- User and item features are with latent factors

T. Chen et al. Feature-based matrix factorization. arXiv:1109.2271

<http://svdfeature.apexlab.org/wiki/images/7/76/APEX-TR-2011-07-11.pdf>

Open source: http://svdfeature.apexlab.org/wiki/Main_Page

Factorization Machine

$$\hat{y}(\mathbf{x}) = w_0 + \sum_{i=1}^n w_i x_i + \sum_{i=1}^n \sum_{j=i+1}^n \langle v_i, v_j \rangle x_i x_j$$

- One-hot encoding for each discrete (categorical) field
- One real-value feature for each continuous field
- All features are with latent factors
- A more general regression model

Steffen Rendle. Factorization Machines. ICDM 2010

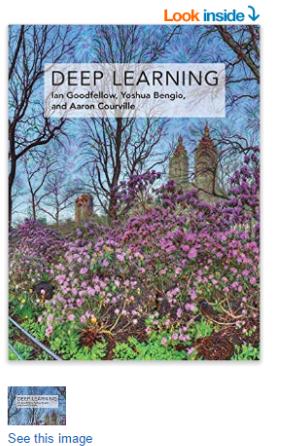
<http://www.ismll.uni-hildesheim.de/pub/pdfs/Rendle2010FM.pdf>

Open source: <http://www.libfm.org/>

Beyond Rating Prediction

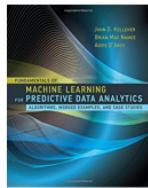
LambdaRank CF

Recommendation is always rendered by ranking



See this image

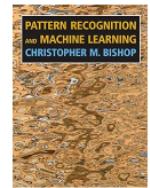
Customers Who Bought This Item Also Bought



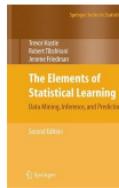
Fundamentals of Machine Learning for Predictive Data Analytics:...
› John D. Kelleher
★★★★★ 22
Hardcover
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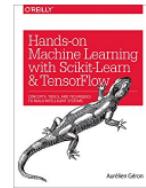
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› Sebastian Raschka
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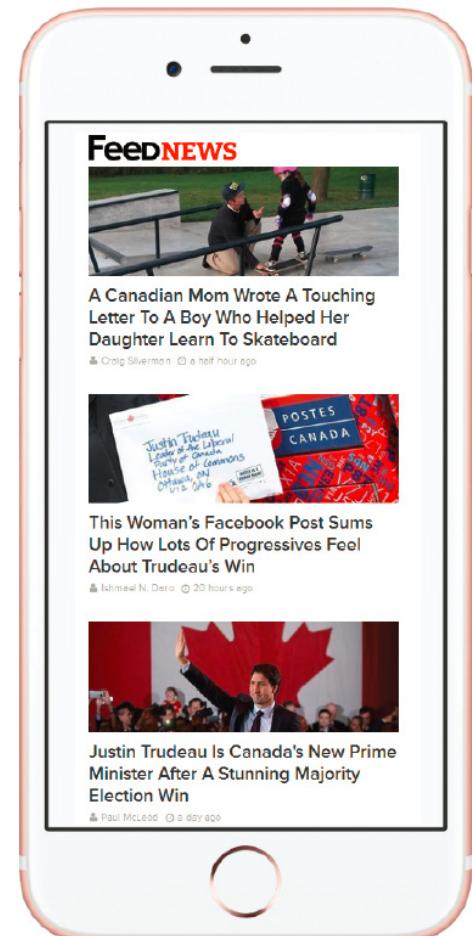
Pattern Recognition and Machine Learning (Information Science and...
› Christopher M. Bishop
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Hardcover
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The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition
› Trevor Hastie
★★★★★ 92
#1 Best Seller in Bioinformatics
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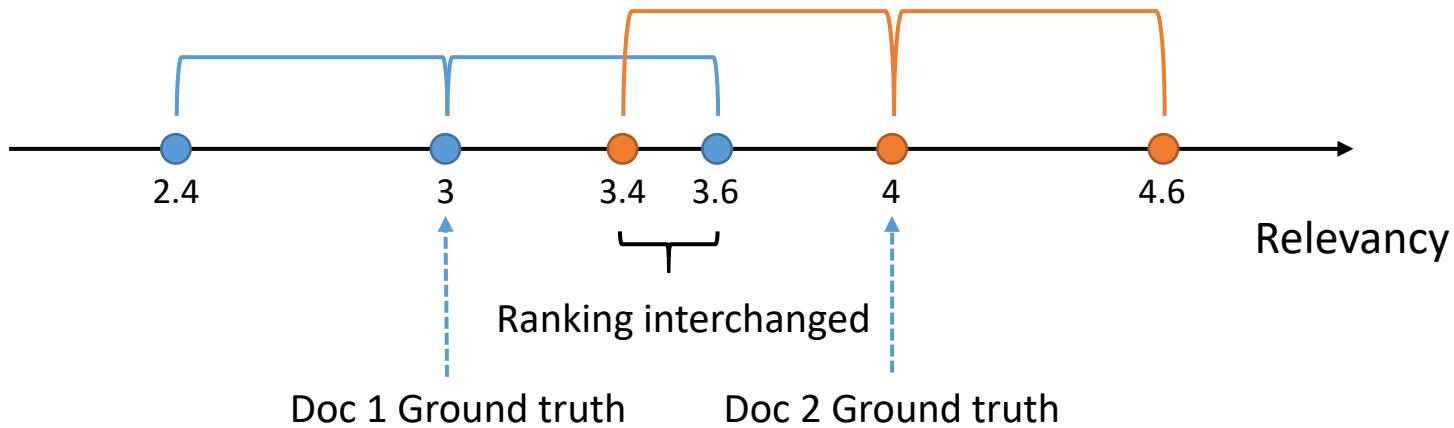


Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques...
› Aurélien Géron
Paperback
\$28.56



Rating Prediction vs. Ranking

- Rating prediction may not be a good objective for top-N recommendation (i.e. item ranking)



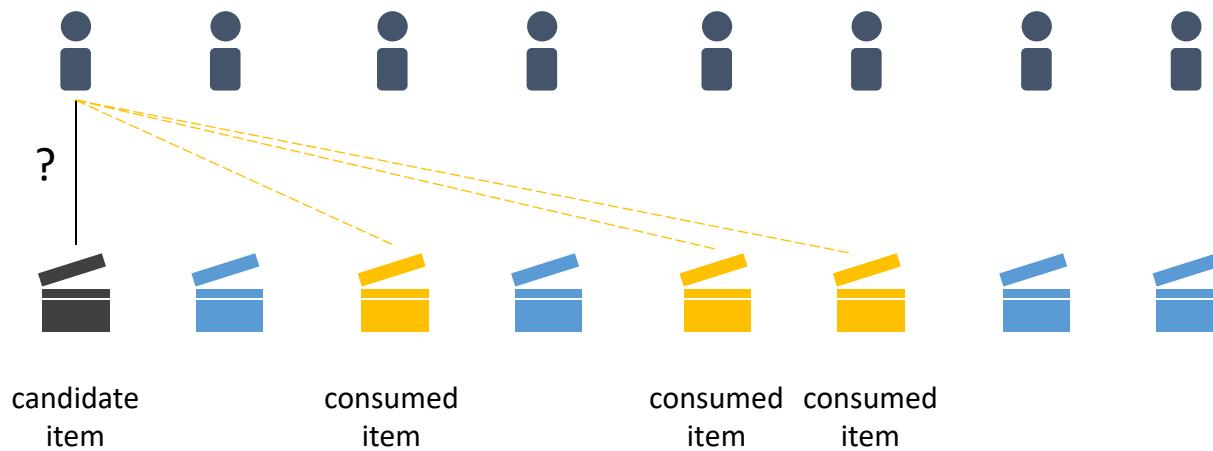
- Same RMSE/MAE might lead to different rankings

Learning to Rank in Collaborative Filtering

- Previous work on rating prediction can be regarded as pointwise approaches in CF
 - MF, FM, kNN, MF with temporal dynamics and neighborhood information etc.
- Pairwise approaches in CF
 - Bayesian personalized ranking (BPR)
- Listwise approaches in CF
 - LambdaRank CF, LambdaFM

Implicit Feedback Data

- No explicit preference, e.g. rating, shown in the user-item interaction
 - Only clicks, share, comments etc.



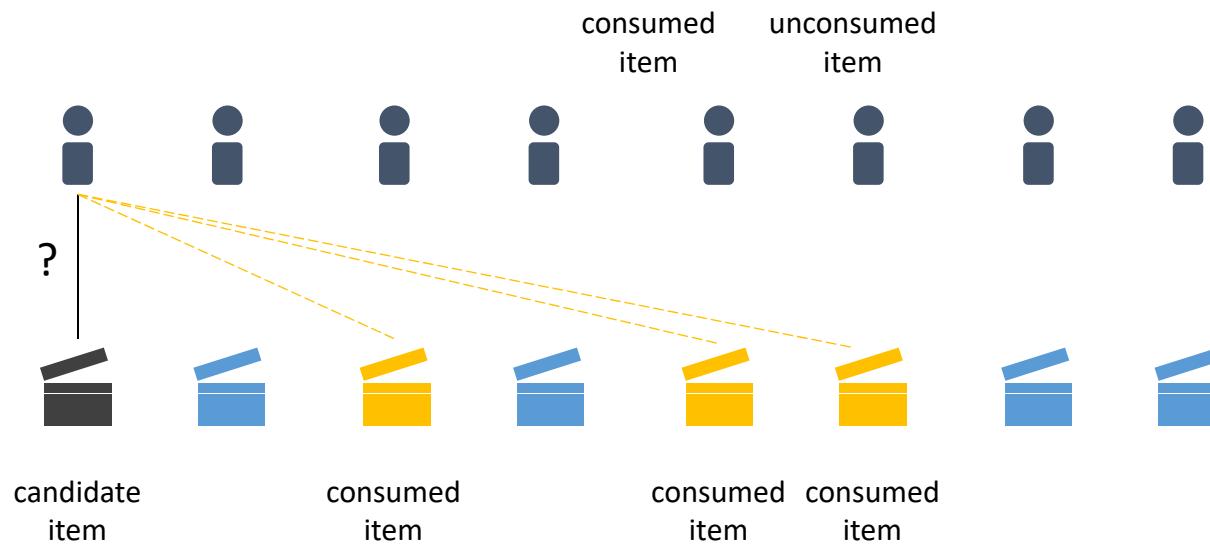
Bayesian Personalized Ranking (BPR)

- Basic latent factor model (MF) for scoring

$$\hat{r}_{u,i} = \mu + b_u + b_i + p_u^\top q_i$$

- The (implicit feedback) training data for each user u

$$D_u = \{\langle i, j \rangle_u | i \in I_u \wedge j \in I \setminus I_u\}$$



Bayesian Personalized Ranking (BPR)

- Loss function on the ranking prediction of $\langle i, j \rangle_u$

$$\mathcal{L}(\langle i, j \rangle_u) = z_u \cdot \frac{1}{1 + \exp(\hat{r}_{u,i} - \hat{r}_{u,j})}$$

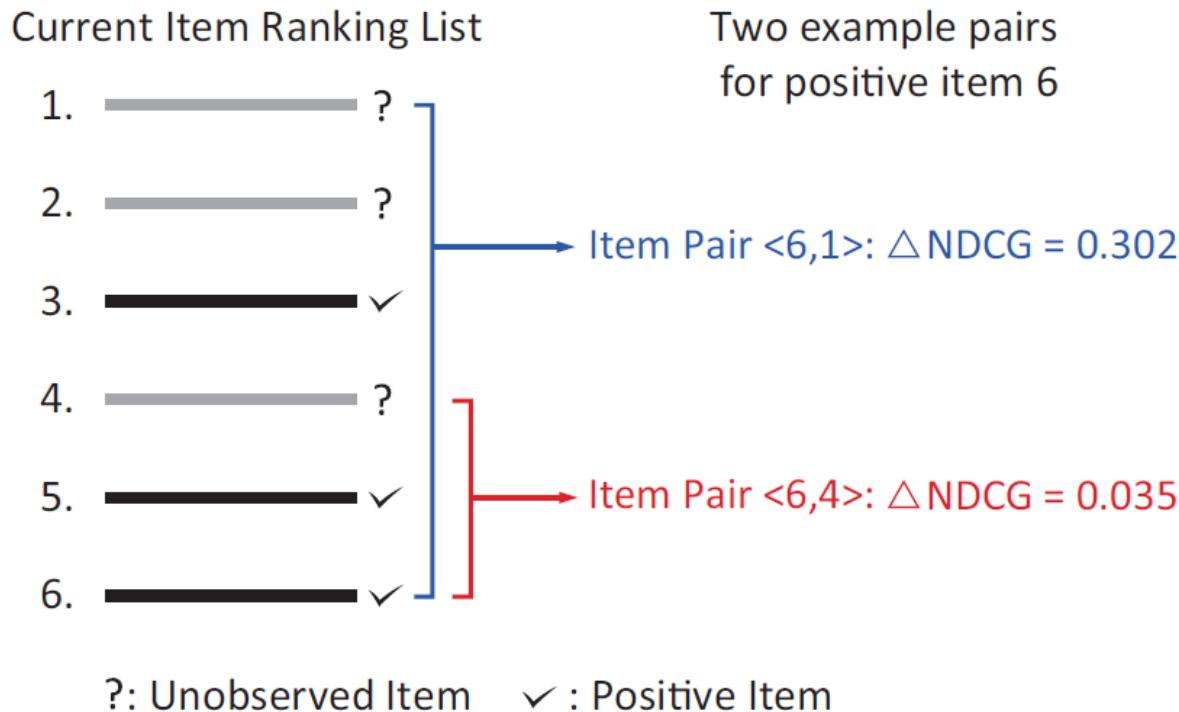
↑ ↑
Normalizer Inverse logistic loss

- Gradient

$$\begin{aligned}\frac{\partial \mathcal{L}(\langle i, j \rangle_u)}{\partial \theta} &= \frac{\partial \mathcal{L}(\langle i, j \rangle_u)}{\partial (\hat{r}_{u,i} - \hat{r}_{u,j})} \frac{\partial (\hat{r}_{u,i} - \hat{r}_{u,j})}{\partial \theta} \\ &\equiv \lambda_{i,j} \left(\frac{\partial \hat{r}_{u,i}}{\partial \theta} - \frac{\partial \hat{r}_{u,j}}{\partial \theta} \right)\end{aligned}$$

LambdaRank CF

- Use the idea of LambdaRank to optimize ranking performance in recommendation tasks



Recommendation vs. Web Search

- Difference between them
 - Recommender system should rank all the items
 - Usually more than 10k
 - Search engine only ranks a small subset of retrieved documents
 - Usually fewer than 1k
- For each training iteration, LambdaRank needs the model to rank all the items to get $\Delta\text{NDCG}_{i,j}$, super large complexity

LambdaRank CF Solution

- Idea: to generate the item pairs with the probability proportional to their lambda

$$\frac{\partial \mathcal{L}(\langle i, j \rangle_u)}{\partial \theta} = f(\lambda_{i,j}, \zeta_u) \left(\frac{\partial \hat{r}_{u,i}}{\partial \theta} - \frac{\partial \hat{r}_{u,j}}{\partial \theta} \right)$$

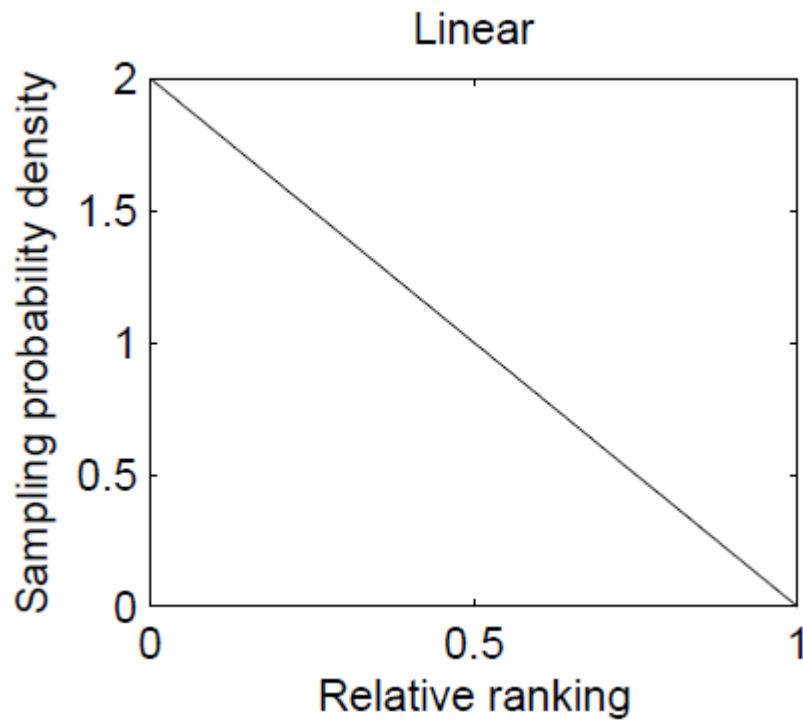
$$f(\lambda_{i,j}, \zeta_u) \equiv \lambda_{i,j} \Delta NDCG_{i,j}$$

$$p_j \propto f(\lambda_{i,j}, \zeta_u) / \lambda_{i,j}$$

- $x_i \in [0, 1]$ is the relative ranking position
 - 0 means ranking at top, 1 means ranking at tail

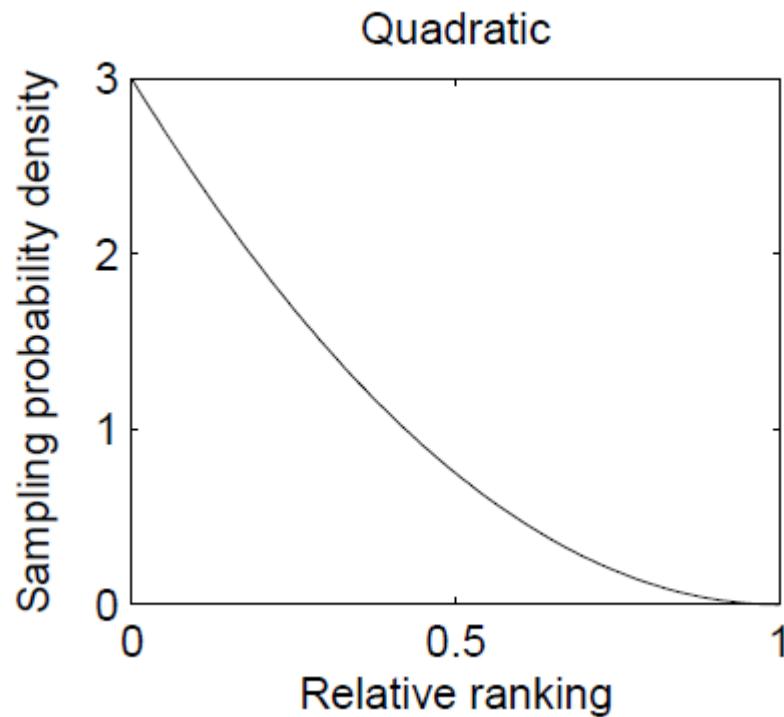
Different Sampling Methods

- For each positive item, find 2 candidate items, then choose the one with higher prediction score as the negative item.



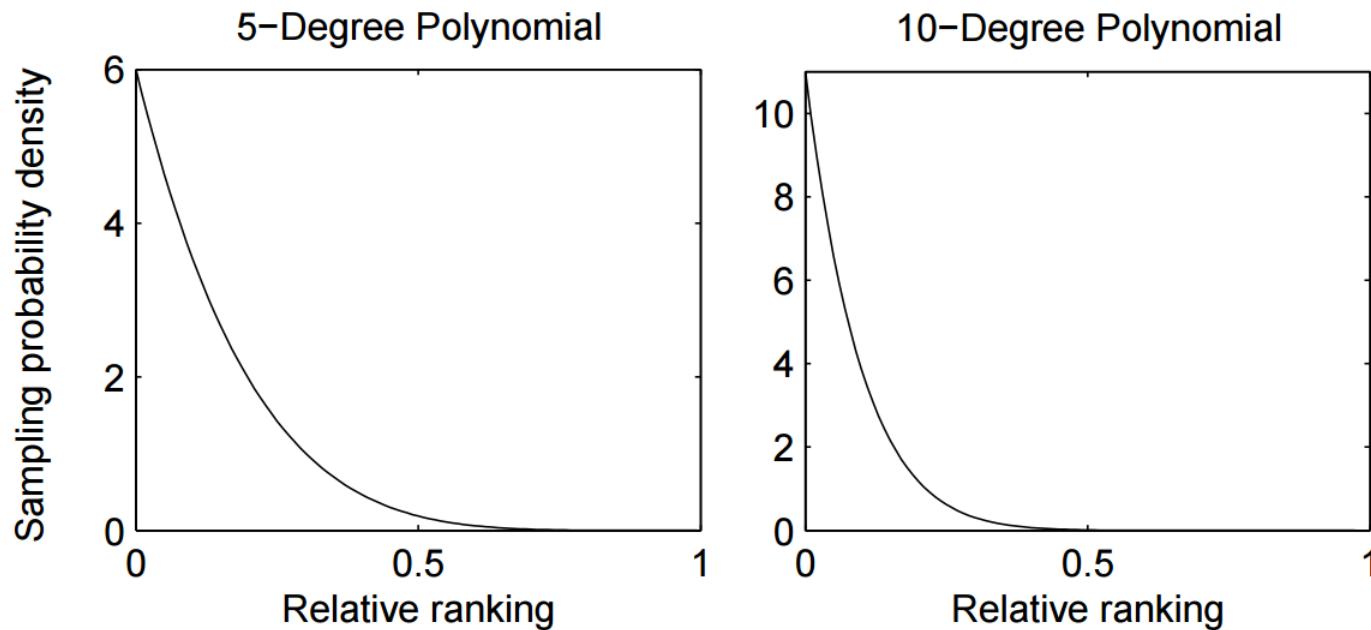
Different Sampling Methods

- For each positive item, find **3** candidate items, then choose the one with the **highest** prediction score as the negative item.



Different Sampling Methods

- For each positive item, find k candidate items, then choose the one with the **highest** prediction score as the negative item.



Experiments on Top-N Recommendation

- Top-N recommendation on 3 datasets

Dataset	Netflix	Yahoo! Music	Last.fm
Users	480,189	1,000,990	992
Items	17,770	624,961	961,417
Ratings	100,480,507	262,810,175	19,150,868

- Performance (DNS is our LambdaCF algorithm)

Netflix

	P@5	P@10	NDCG@5	NDCG@10	MAP
BPR	0.3826	0.3272	0.2052	0.2017	0.1403
DNS	0.4708	0.4012	0.2906	0.2887	0.2036
Impv.	23.1%*	22.6%*	41.6%*	43.1%*	45.1%*

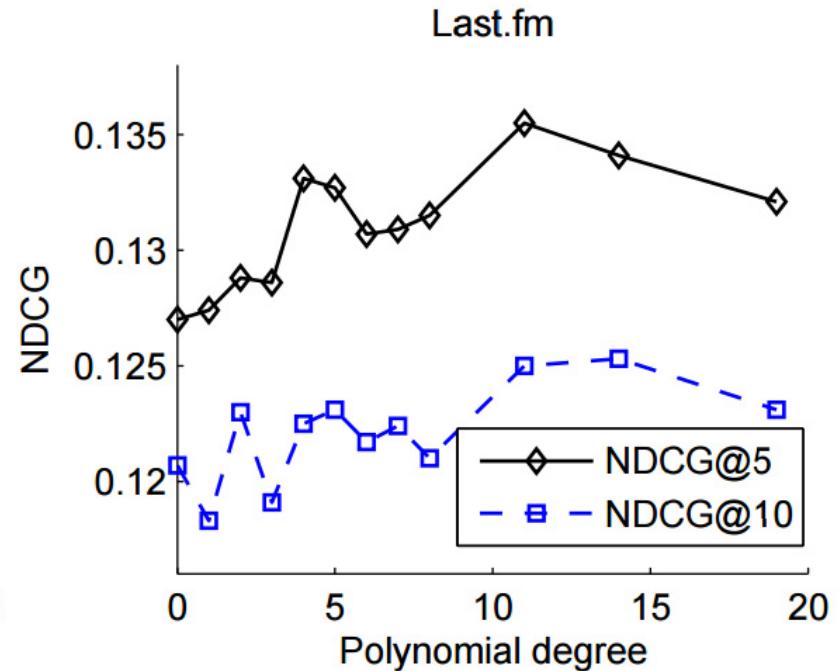
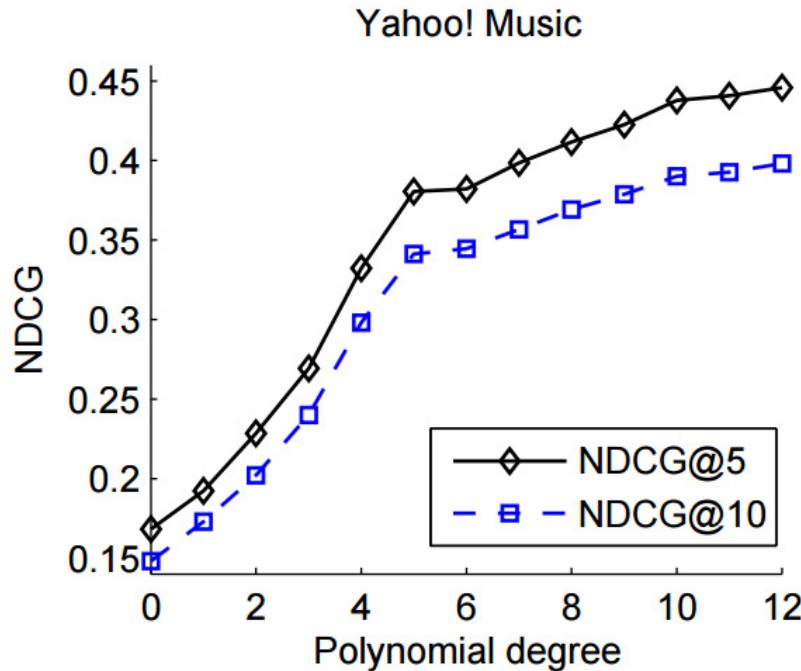
Yahoo! Music

	P@5	P@10	NDCG@5	NDCG@10	MAP
BPR	0.1588	0.1359	0.1683	0.1481	0.0615
DNS	0.4243	0.3671	0.4458	0.3981	0.1644
Impv.	167.2%*	170.1%*	164.9%*	168.8%*	167.3%*

Last.fm

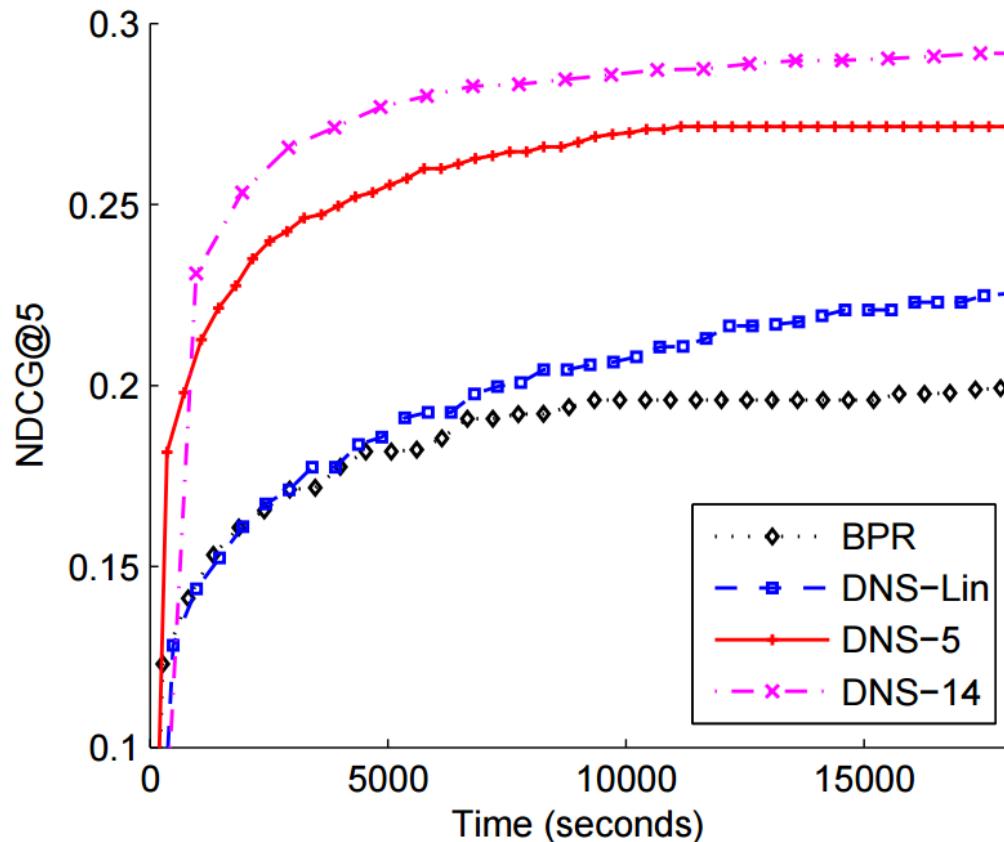
	P@5	P@10	NDCG@5	NDCG@10	MAP
BPR	0.1231	0.1168	0.1270	0.1207	0.0221
DNS	0.1323	0.1202	0.1355	0.1250	0.0223
Impv.	7.5%*	2.9%	6.7%*	3.6%	0.9%

More Empirical Results



- NDCG performance against polynomial degrees on Yahoo! Music and Last.fm datasets

More Empirical Results



Performance convergence against training time on Netflix.

Course Work 2: Collaborative Filtering based Rating Prediction

Problem

Instructions