CS249: ADVANCED DATA MINING

Recommender Systems

Instructor: Yizhou Sun

yzsun@cs.ucla.edu

May 17, 2017

Methods Learnt: Last Lecture

	Vector Data	Text Data	Recommender System	Graph & Network
Classification	**Decision Tree**; **Naïve Bayes**; **Logistic Regression** **SVM; NN**			Label Propagation
Clustering	**K-means; hierarchical clustering; DBSCAN; Mixture Models; kernel k-means**	**PLSA;** **LDA**	Matrix Factorization	SCAN; Spectral Clustering
Prediction	**Linear Regression** **GLM**		Collaborative Filtering	
Ranking				PageRank
Feature Representation		**Word embedding**		Network embedding

Methods to Learn

	Vector Data	Text Data	Recommender System	Graph & Network
Classification	Decision Tree; Naïve Bayes; Logistic Regression SVM; NN			Label Propagation
Clustering	K-means; hierarchical clustering; DBSCAN; Mixture Models; kernel k-means	PLSA; LDA	Matrix Factorization	SCAN; Spectral Clustering
Prediction	Linear Regression GLM		Collaborative Filtering	
Ranking				PageRank
Feature Representation		Word embedding		Network embedding

Recommender Systems

- What is Recommender System?
- Collaborative Filtering
- Content-based Recommendation
- Hybrid methods
- Evaluation Metrics
- Summary

Recommender Systems

- Application areas

You may also like

Jack & Jones
JAMIE - Polo shirt - orange
£21.00
Free delivery & returns

ALTERNATIVE PRODUCTS

Beko Washing Machine
Code: WMB81431LW
£269.99

Zanussi Washing Machine
Code: ZWH6130P
£269.99

Blomberg Washing Machine
Code: WNF6221
£299.99

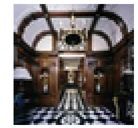
You may also like

(109)

(53)

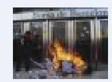
(33)

Related hotels...



Hotel 41
1,170 Reviews
London, England
Show Prices

Read | Commented | Recommended



Germany Just Rejected The Idea That The European Bailout Fund Would Buy Spanish Debt

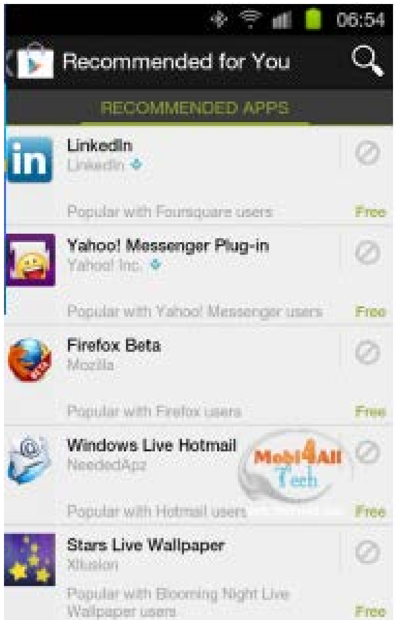
There Is Almost No Gold In The Olympic Gold Medal

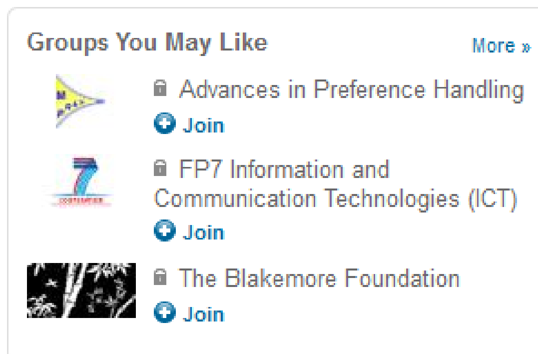
MOST POPULAR | RECOMMENDED

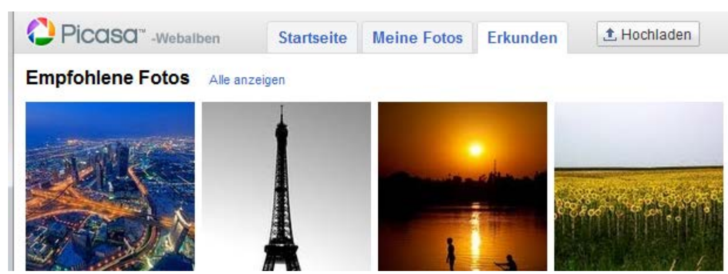
How to Break NRA's Grip on Politics: Michael R. Bloomberg

Growth in U.S. Slows as Consumers Restrain Spending

In the Social Web







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 trust and customer loyalty
  - Increase sales, click trough rates, conversion etc.
  - Opportunities for promotion, persuasion
  - Obtain more knowledge about customers
  - …

Matrix Representation

- Sparse Matrix
  - Explicit Feedback

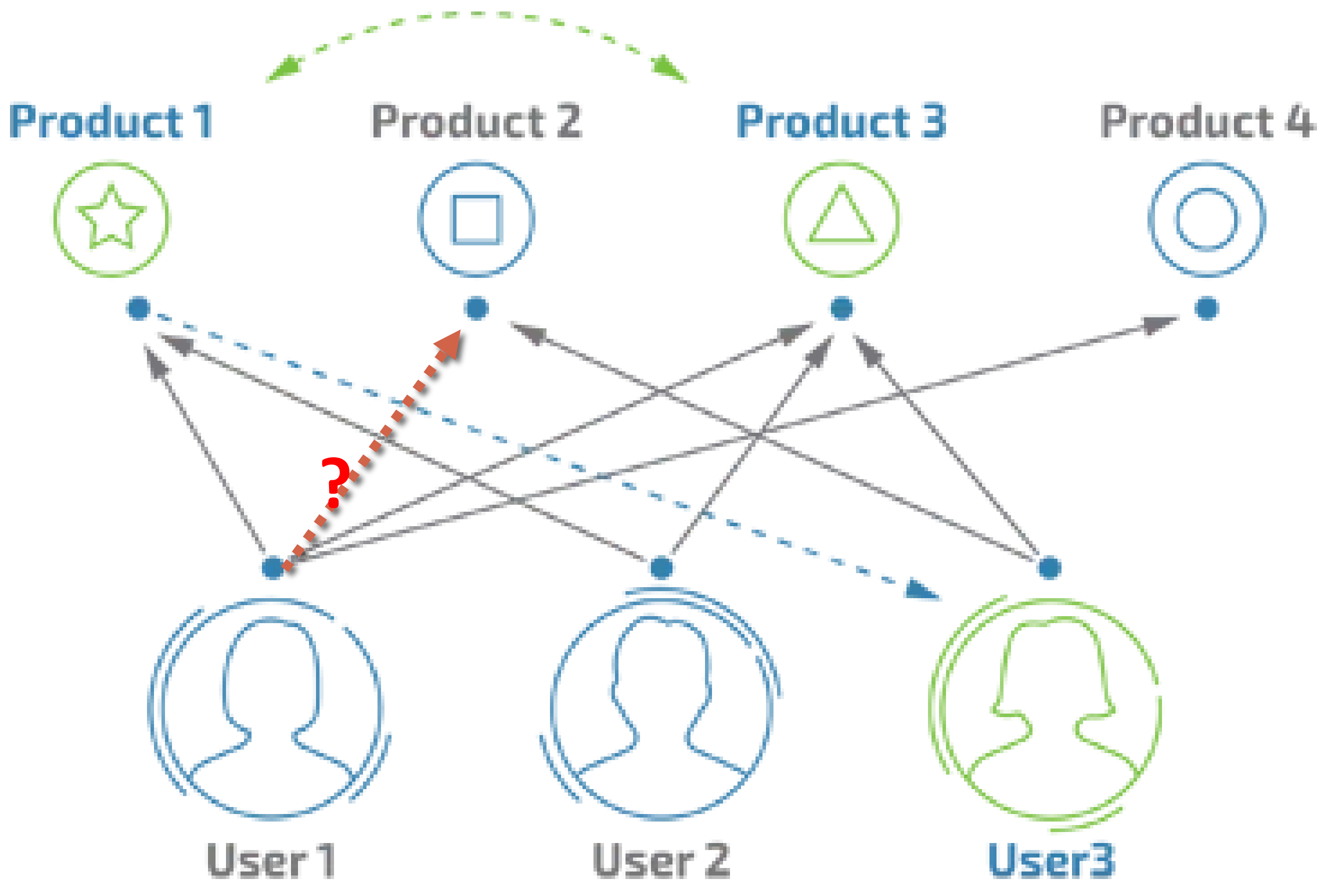
Users	Movie1	Movie2	Movie3	Movie4	Movie5	Movie6	...
User1	?	?	4	?	1	?	...
User2	2	5	2	?	?	2	...
User3	?	?	5	3	2	4	...
User4	1	?	?	4	?	?	...
User5	2	3	?	?	?	?	...
...	...	...	...	...	...	...	...

- Implicit Feedback: only know whether user and item has interacted

	Items					
						...
Users	Alice	1	1	0	0	
	Bob	0	0	1	1	
	Corey	1	0	1	0	
	...					

A Network Point of View

- Link prediction problem



Methods

- Collaborative filtering
- Content-based recommendation
- Hybrid methods

Recommender Systems

- What is Recommender System?
- Collaborative Filtering
- Content-based Recommendation
- Hybrid methods
- Evaluation Metrics
- Summary

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, 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

Major Methods for CF

- Memory-based Collaborative Filtering
  - User-based CF
    - Compute similarity between users and active users, and use similar users' ratings as prediction
  - Item-based CF
    - Compute similarity between items, and predict similar rating to similar items that the active user has rated before
- Model-based Collaborative Filtering

User-based Collaborative Filtering

1. Define similarity between users according to the history matrix
2. Decide how many "peers" to consider
3. Use peers' ratings to predict the rating between an active user and an item

	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

(1) Define Similarities between Users

- Pearson correlation between user a and b

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

  - $r_{a,p}$: *rating of user a to item p*
  - P: *a set of items that are rated by both a and b*
  - $\overline{r_a}, \overline{r_b}$: *average rating of user a and b*
- Or, $sim(a,b) = \frac{cov(r_a, r_b)}{\sigma(r_a)\sigma(r_b)}$
  - $cov(r_a, r_b)$: covariance between a and b
  - $\sigma(r_a), \sigma(r_b)$: standard deviation of a and b

Example

- $sim(Alice, User1)$
  - $\overline{r_{Alice}} = \frac{5+3+4+4}{4} = 4; \sigma(Alice) = 0.707$
  - $\overline{r_{User1}} = \frac{3+1+2+3}{4} = 2.25; \sigma(User1) = 0.9574$
  - $cov(Alice, User1) = 0.6667;$
  - $\Rightarrow \boldsymbol{sim(Alice, User1) = \frac{0.6667}{0.707 * 0.9574} = 0.8528}$

	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

sim = 0.85
sim = 0.70
sim = -0.79

(2) Decide how many peers to use

- Usually only use top K most similar users for prediction
  - i.e., based on top-K most similar users' rating for an item

(3) Predict the rating

- A common prediction function:

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

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

Example

- Use top-2 neighbor for prediction
  - Alice's top-2 neighbor are User1 and User2
  - $pred(Alice, Item5) = \overline{r_{Alice}} + \frac{sim(Alice,User1)(r_{User1,Item5} - \overline{r_{User1}}) + sim(Alice,User2)(r_{User2,Item5} - \overline{r_{User2}})}{sim(Alice,User1) + sim(Alice,User2)}$

$$= 4 + \frac{0.85*(3-2.25)+0.70*(5-3.5)}{0.85+0.70} = 5.0887$$

	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

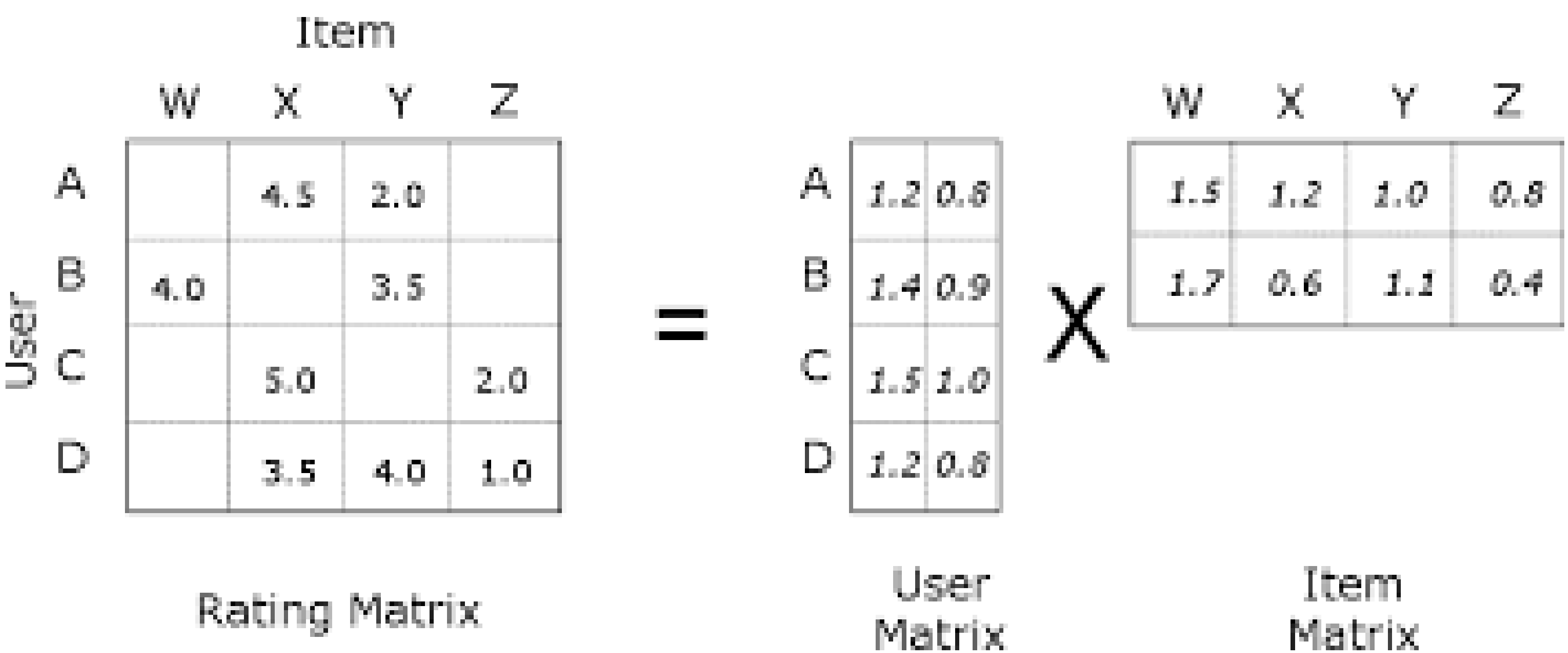
sim = 0.85
sim = 0.70

Model-based Collaborative Filtering

- User-based CF is said to be "memory-based"
  - the rating matrix is directly used to find neighbors / make predictions
  - does not scale for most real-world scenarios
  - large e-commerce sites have tens of millions of customers and millions of items
- Model-based approaches
  - based on an offline pre-processing or "model-learning" phase
  - at run-time, only the learned model is used to make predictions
  - models are updated / re-trained periodically
  - large variety of techniques used
  - model-building and updating can be computationally expensive

Matrix Factorization for Recommendation

- Map users and items into the same latent space



Reference: Koren et al., "Matrix Factorization Techniques for Recommender System", Computer (Volume: 42, Issue: 8), 2009

Now users and items are comparable

- Recommendation: find items that are close to users in the new space

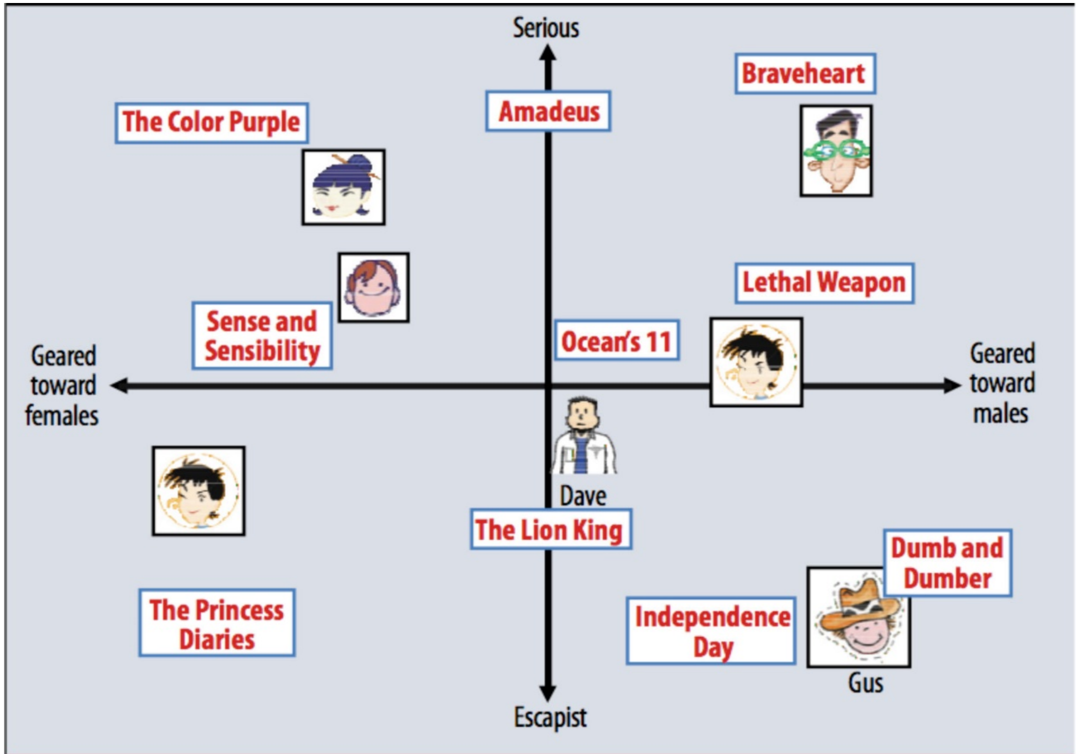


Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

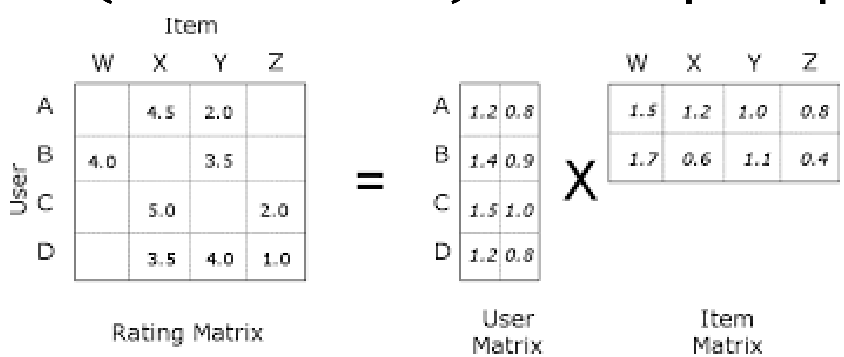
Procedure

- Training stage
  - Use existing matrix to learn the latent feature vector for both users and items by matrix factorization
- Recommendation stage
  - Predict the score for unknown (user, item) pairs

Training Stage

- r_{ui}: the rating from u to i
- p_u: the latent feature vector for user u
- q_i: the latent feature vector for item I
- $\hat{r}_{ui}$: score function for (u,i), $\hat{r}_{ui} = q_i^T p_u$
- Objective function:

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



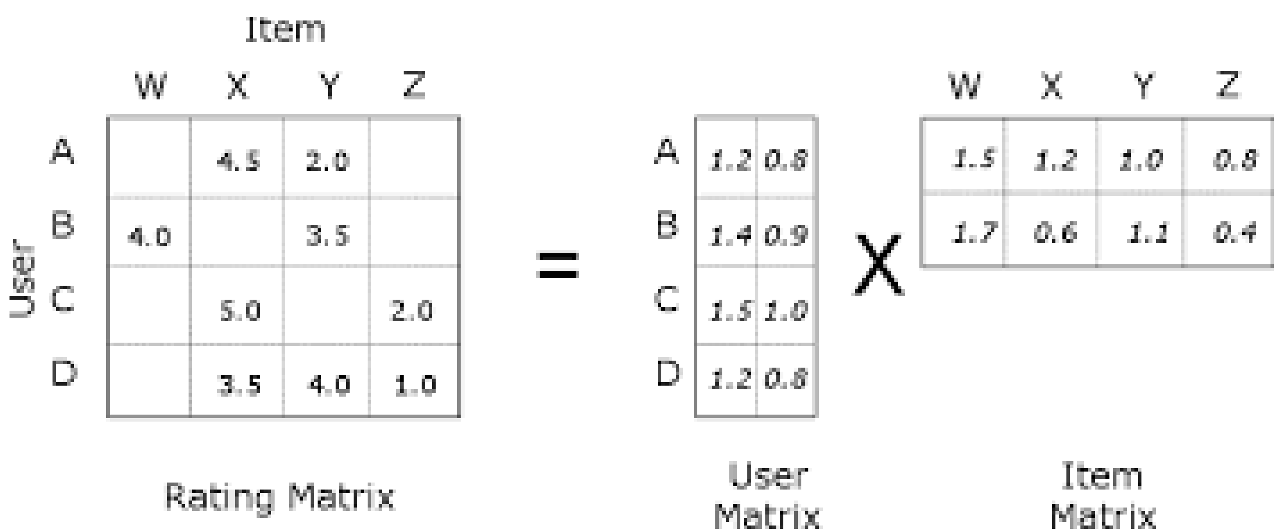
Learning Algorithm

- Stochastic gradient descent
- For each rating (u, i):
  - $update\ p_u : p_u \leftarrow p_u + \eta \cdot ((r_{ui} - \hat{r}_{ui})q_i - \lambda p_u)$
  - $update\ q_i : q_i \leftarrow q_i + \eta \cdot \big((r_{ui} - \hat{r}_{ui})p_u - \lambda q_i\big)$

  - Where η is the learning rate

Prediction Stage

- For an unseen pair (u, i)
  - $\hat{r}_{ui} = q_i^T p_u = p_u^T q_i$
- Example:
  - $r_{AW} = p_A^T q_W = 1.2 * 1.5 + 0.8 * 1.7 = 3.16$



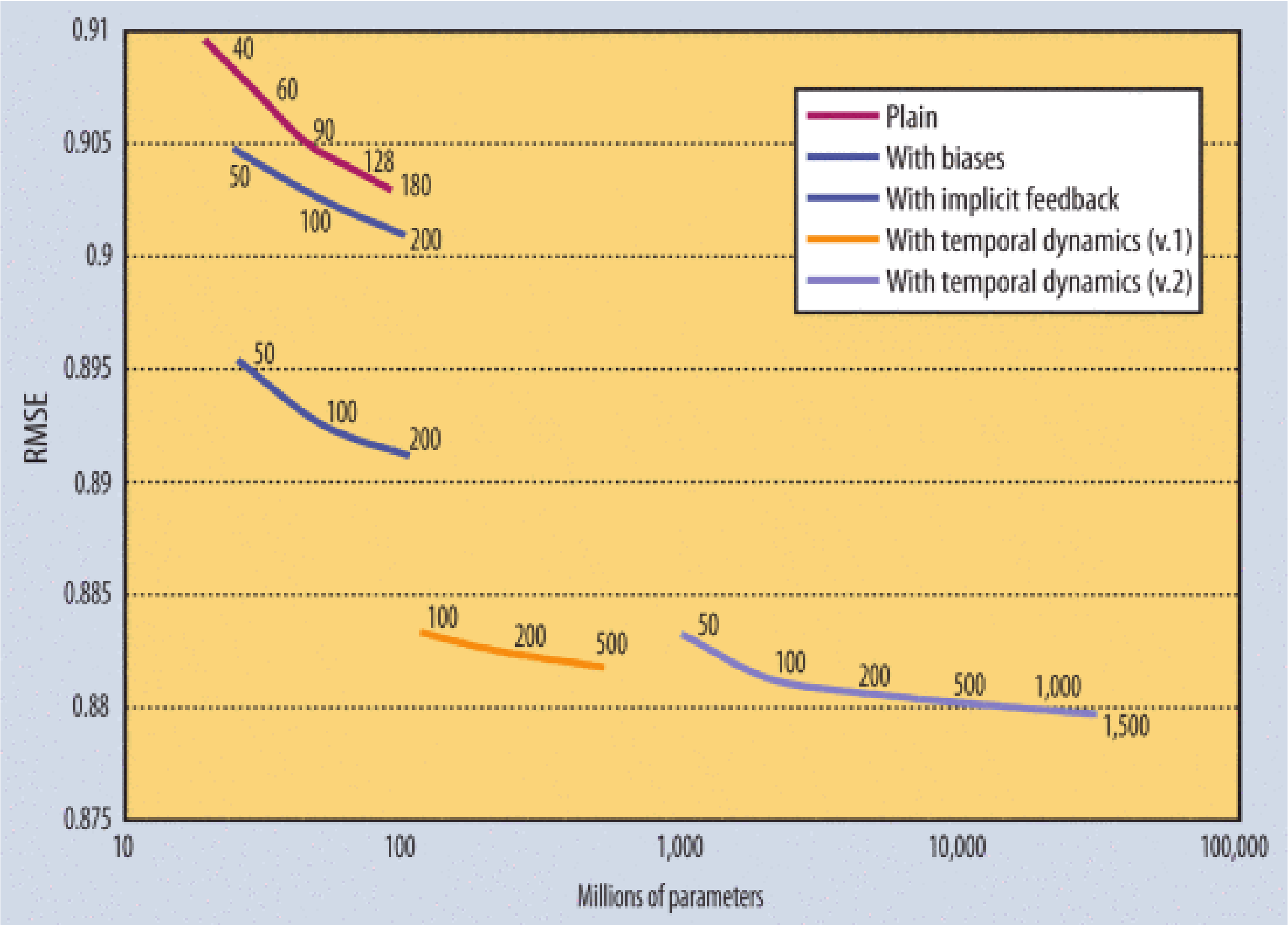
Variations

- Adding biases
  - $b_{ui} = \mu + b_i + b_u$
  - $\hat{r}_{ui} = \mu + b_i + b_u + q_i^T p_u$
  - Objective function:

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

- Adding temporal dynamics
  - $\hat{r}_{ui}^{(t)} = \mu + b_i(t) + b_u(t) + q_i^T p_u(t)$

Results



0.91
0.905
0.9
0.895
0.89
0.885
0.88
0.875
RMSE
10
100
1,000
10,000
100,000
Millions of parameters
Plain
With biases
With implicit feedback
With temporal dynamics (v.1)
With temporal dynamics (v.2)
40
60
90
128
180
50
100
200
50
100
200
100
200
500
50
100
200
500
1,000
1,500

Implicit Feedback Models

- Only implicit signals are received
  - E.g., click though, music streaming play

- Methods:
  - Turn it into binary classification problem: Logistic Matrix Factorization
    - Johnson, Logistic Matrix Factorization for Implicit Feedback Data, NIPS workshop 2014
  - Turn it into ranking problem: BPR: Bayesian Personalized Ranking
    - Rendel et al., BPR: Bayesian Personalized Ranking from Implicit Feedback, UAI'09

Logistic MF

- Model:

$$p(l_{ui} \mid x_u, y_i, \beta_i, \beta_j) = \frac{\exp(x_i y_i^T + \beta_u + \beta_i)}{1 + \exp(x_u y_i^T + \beta_u + \beta_i)}$$

- Loss function
  - For each user-item pair:

$$J_{ui} = -\mathbf{1}_{(\mathrm{l_{ui}}=1)}\mathrm{logp}(\mathrm{l_{ui}} = 1) - \mathbf{1}_{(\mathrm{l_{ui}}=0)}\mathrm{logp}(\mathrm{l_{ui}} = 0)$$

Bayesian Ranking

- Data re-arrangement:
  - $D_s = \{(u,i,j) | i \in I_u^+ \ and \ j \in I \backslash \mathrm{I}_u^+\}$
    - For user u, s/he ranks item i higher than j,
- Model:

$$p(i >_u j | \Theta) = \sigma(\hat{x}_{uij}(\Theta))$$

where $\hat{x}_{uij} = \hat{x}_{ui} - \hat{x}_{uj}$ and $\hat{x}_{ui} = <\boldsymbol{w}_u, \boldsymbol{h}_\mathrm{i}>$

- Loss Function

$$\prod_{u \in U} p(>_u | \Theta) = \prod_{(u,i,j) \in U \times I \times I} p(i >_u j | \Theta)^{\delta((u,i,j) \in D_S)} \cdot (1 - p(i >_u j | \Theta))^{\delta((u,j,i) \notin D_S)}$$

Issues of CF

- **Cold Start**: There needs to be enough other users already in the system to find a match.
- **Sparsity**: If there are many items to be recommended, even if there are many users, the user/ratings matrix is sparse, and it is hard to find users that have rated the same items.
- **First Rater**: Cannot recommend an item that has not been previously rated.
  - New items
  - Esoteric items
- **Popularity Bias**: Cannot recommend items to someone with unique tastes.
  - Tends to recommend popular items.

Recommender Systems

- What is Recommender System?
- Collaborative Filtering
- Content-based Recommendation
- Hybrid methods
- Evaluation Metrics
- Summary

Content-based recommendation

- Collaborative filtering does NOT require any information about content,
  - However, it might be reasonable to exploit such information
  - E.g. recommend fantasy novels to people who liked fantasy novels in the past
- What do we need:
  - Some information about the available items such as the genre ("content")
  - Some sort of *user profile* describing what the user likes (the preferences)
- The task:
  - Learn user preferences
  - Locate/recommend items that are "similar" to the user preferences

Content representation and item similarities

User profile

Title	Genre	Author	Type	Price	Keywords
The Night of the Gun	Memoir	David Carr	Paperback	29.90	Press and journalism, drug addiction, personal memoirs, New York
The Lace Reader	Fiction, Mystery	Brunonia Barry	Hardcover	49.90	American contemporary fiction, detective, historical
Into the Fire	Romance, Suspense	Suzanne Brockmann	Hardcover	45.90	American fiction, Murder, Neo-nazism
...					

Item

Title	Genre	Author	Type	Price	Keywords
...	Fiction, Suspense	Brunonia Barry, Ken Follet, ..	Paperback	25.65	detective, murder, New York

- Simple approach
  - Compute the similarity of an unseen item with the user profile based on the keyword overlap (e.g. using the Dice coefficient)
  - $\mathrm{sim}(b_i, b_j) = \dfrac{2 * |keywords(b_i) \cap keywords(b_j)|}{|keywords(b_i)| + |keywords(b_j)|}$
- Other advanced similarity measure

Recommender Systems

- What is Recommender System?
- Collaborative Filtering
- Content-based Recommendation
- Hybrid methods
- Evaluation Metrics
- Summary

Hybrid Methods

- Combining both user-item interaction and other external sources of information

- One example:
  - Factorization Machines
  - Steffen Rendle, "Factorization Machines," in ICDM'10, Sydney, Australia.

Factorization Machines

- Treat each user-item transaction as one data point
  - U = {Alice (A), Bob (B), Charlie (C), ...}
  - I = {Titanic (TI), Notting Hill (NH), Star Wars (SW), Star Trek (ST), . .}
  - S = {(A, TI, 2010-1, 5), (A,NH, 2010-2, 3), (A, SW, 2010-4, 1), (B, SW, 2009-5, 4), (B, ST, 2009-8, 5), (C, TI, 2009-9, 1), (C, SW, 2009-12, 5)}

FM: Feature Preparation

- Each data point has a feature vector ***x***, and a target value (e.g., rating score)

Feature vector **x** | Target y

	User				Movie					Other Movies rated					Time	Last Movie rated					Target y	
	A	B	C	...	TI	NH	SW	ST	...	TI	NH	SW	ST	...	Time	TI	NH	SW	ST	...		
$\mathbf{x}^{(1)}$	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	13	0	0	0	0	...	5	$y^{(1)}$
$\mathbf{x}^{(2)}$	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	14	1	0	0	0	...	3	$y^{(2)}$
$\mathbf{x}^{(3)}$	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	16	0	1	0	0	...	1	$y^{(2)}$
$\mathbf{x}^{(4)}$	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	5	0	0	0	0	...	4	$y^{(3)}$
$\mathbf{x}^{(5)}$	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	8	0	0	1	0	...	5	$y^{(4)}$
$\mathbf{x}^{(6)}$	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	9	0	0	0	0	...	1	$y^{(5)}$
$\mathbf{x}^{(7)}$	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	12	1	0	0	0	...	5	$y^{(6)}$

The Model

- Model second-order interaction to overcome the sparsity

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

- w_0: $global\ bias$
- w_i: $strength\ of\ ith\ variable$
- $\widehat{w}_{ij} =< \boldsymbol{v}_i, \boldsymbol{v}_j >$
  : $strength\ of\ the\ interaction\ of\ ith\ and\ jth\ variable$
  - E.g., interaction between Alice and Titanic, or Alice and Bob

Time Complexity of Second-Order Interaction

- O(kn)
  - k: dimension of ***v***, n: dimension of ***x***

$$
\begin{aligned}
&\sum_{i=1}^{n}\sum_{j=i+1}^{n}\langle\mathbf{v}_i,\mathbf{v}_j\rangle\,x_i\,x_j \\
=&\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\langle\mathbf{v}_i,\mathbf{v}_j\rangle\,x_i\,x_j-\frac{1}{2}\sum_{i=1}^{n}\langle\mathbf{v}_i,\mathbf{v}_i\rangle\,x_i\,x_i \\
=&\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{f=1}^{k}v_{i,f}\,v_{j,f}\,x_i\,x_j-\sum_{i=1}^{n}\sum_{f=1}^{k}v_{i,f}\,v_{i,f}\,x_i\,x_i\right) \\
=&\frac{1}{2}\sum_{f=1}^{k}\left(\left(\sum_{i=1}^{n}v_{i,f}\,x_i\right)\left(\sum_{j=1}^{n}v_{j,f}\,x_j\right)-\sum_{i=1}^{n}v_{i,f}^2\,x_i^2\right) \\
=&\frac{1}{2}\sum_{f=1}^{k}\left(\left(\sum_{i=1}^{n}v_{i,f}\,x_i\right)^2-\sum_{i=1}^{n}v_{i,f}^2\,x_i^2\right)
\end{aligned}
$$

Apply to Recommendation

- Explicit Feedback:
  - Treat it as a prediction task, with mean square error loss
- Implicit Feedback:
  - Treat it as a binary classification or ranking task, with logistic loss or pairwise logistic loss
- Learning:
  - Stochastic gradient descent

Recommender Systems

- What is Recommender System?
- Collaborative Filtering
- Content-based Recommendation
- Hybrid methods
- Evaluation Metrics
- Summary

Accuracy measures: Explicit Feedback

- Datasets with items rated by users
  - MovieLens datasets 100K-10M ratings
  - Netflix 100M ratings
- Historic user ratings constitute ground truth
- Metrics measure error rate
  - Mean Absolute Error (*MAE*) computes the deviation between predicted ratings and actual ratings

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|p_i - r_i|$$

  - Root Mean Square Error (*RMSE*) is similar to *MAE*, but places more emphasis on larger deviation

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - r_i)^2}$$

Implicit Feedback: Precision and Recall

- **Precision:** a measure of exactness, determines the fraction of relevant items retrieved out of all items retrieved
  - E.g. the proportion of recommended movies that are actually good

$$Precision = \frac{tp}{tp + fp} = \frac{|good\ movies\ recommended|}{|\text{all recommendations}|}$$

- **Recall:** a measure of completeness, determines the fraction of relevant items retrieved out of all relevant items
  - E.g. the proportion of all good movies recommended

$$Recall = \frac{tp}{tp + fn} = \frac{|good\ movies\ recommended|}{|all\ good\ movies|}$$

More Implicit Feedback Measures

- Precision@k; recall@k
- AUC:
  - Area under ROC curve
- Area under Precision-Recall Curve
- MRR:
  - Mean reciprocal rank over a set of queries Q
  - $MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{rank_i}$, $rank_i$ is the rank position of the first relevant item for the ith query

Recommender Systems

- What is Recommender System?
- Collaborative Filtering
- Content-based Recommendation
- Hybrid methods
- Evaluation Metrics
- Summary

Summary

- Recommendation
  - User-based CF, matrix factorization-based CF
  - Explicit feedback, implicit feedback
  - Content-based recommendation
  - Hybrid methos
  - Evaluation

References

- http://ijcai13.org/files/tutorial_slides/td3.pdf
- http://research.microsoft.com/pubs/115396/EvaluationMetrics.TR.pdf
- https://datajobs.com/data-science-repo/Recommender-Systems-[Netflix].pdf
- http://www.librec.net/tutorial.html