CS 5683: Big Data Analytics

Recommender Systems: Content-based Systems & Collaborative Filtering

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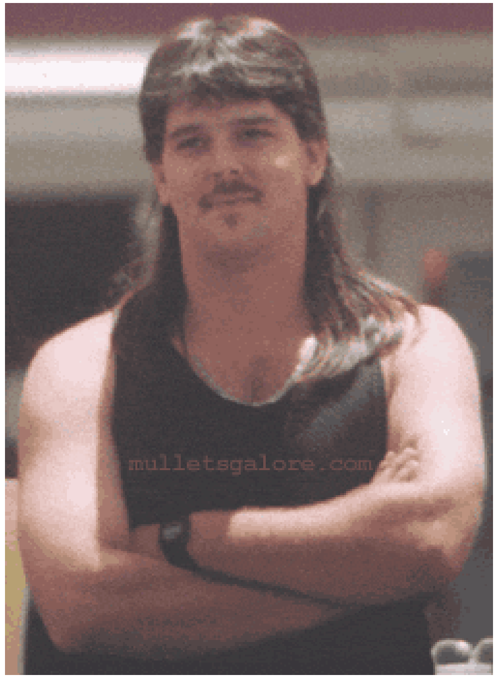
Topics Overview

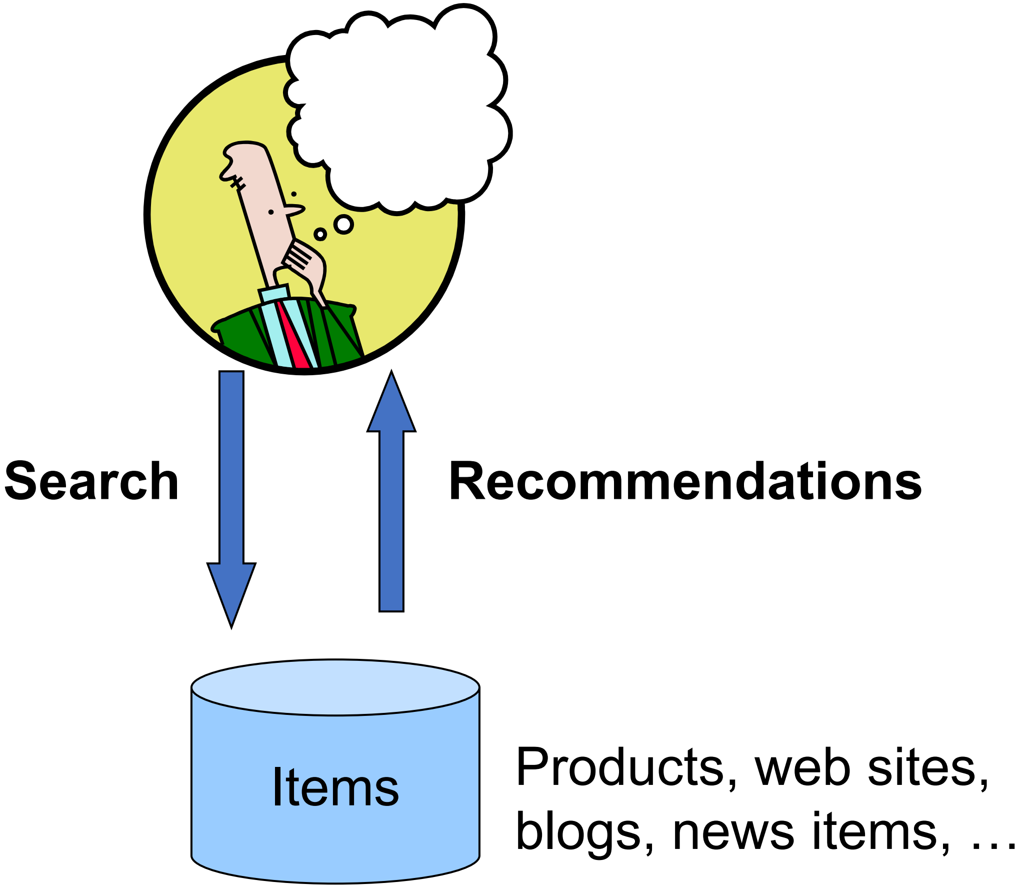
High. Dim. Data	Text Data	Graph Data	Others
Data Features	Clustering	PageRank	Data Streams Mining
Dimensionality Reduction	Non-linear Dim. Reduction	ML for Graphs	Intro. to Apache Spark
Application Rec. Systems	*Application* IR	Community Detection	

Example Recommender Systems



- **Customer X**
  - Buys the book “Origin”
  - Buys the audio book “Inferno”
- **Customer Y**
  - Does search on “Origin”
  - Recommender system suggests Inferno from data collected about customer **X**

Recommendations



Examples:

amazon.com
PANDORA
StumbleUpon
del.icio.us
NETFLIX
movielens
helping you find the *right* movies
last.fm
the social music revolution
Google News
YouTube
XBOX LIVE

Types of Recommendations

- **Editorial and hand curated**
  - List of favorites
  - Lists of “essential” items
- **Simple aggregates**
  - Top 10, Most Popular, Recent Uploads
- **Tailored to individual users**
  - Amazon, Netflix, …
  - Focus in this course

Formal Recommender Model

- ***X*** = set of **Customers**
- ***S*** = set of **Items**

- **Utility function** ***u***: ***X*** × ***S*** → ***R***
  - ***R*** = set of ratings
  - ***R*** is a totally ordered set
  - e.g., **0-5** stars, real number in **[0,1]**

Utility Matrix

	Avatar	LOTR	Matrix	Pirates
Alice	1		0.2	
Bob		0.5		0.3
Carol	0.2		1	
David				0.4

Key Problems

(1) Gathering "known" ratings for matrix

- How to collect the data in the utility matrix?

(2) Extrapolate unknown ratings from the known ones

- Mainly interested in unknown ratings
  - We are not interested in knowing what you don't like but what you like

(3) Evaluating extrapolation methods

- How to measure success/performance of recommendation methods?

(1) Gathering Ratings

- **Explicit**
  - Ask people to rate items
  - Doesn’t work well in practice – people can’t be bothered

- **Implicit**
  - Learn ratings from user actions
    - E.g., purchase implies high rating
  - What about low ratings?

(2) Extrapolating Utilities

- **Key problem:** Utility matrix ***U*** is **sparse**
  - Most people have not rated most items
  - **Cold start:**
    - New items have no ratings
    - New users have no history
- **Three approaches to recommender systems:**
  - **1)** Content-based
  - **2)** Collaborative
  - **3)** Latent factors

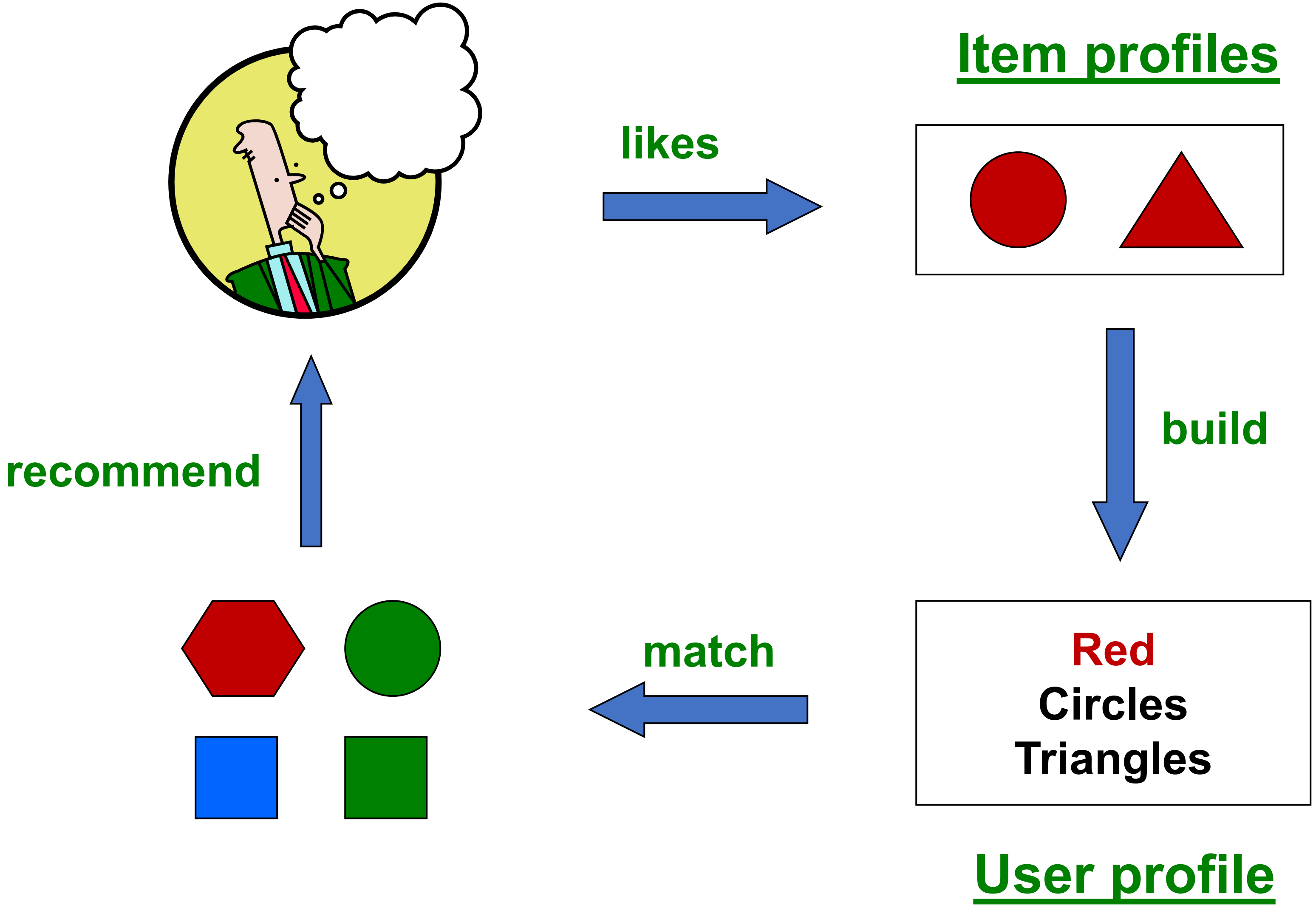
(1) Content-based Recommender Systems

- **Main idea:** Recommend items to customer ***x*** which are similar to previous items rated highly by ***x***

Example:

- **Movie recommendations**
  - Recommend movies with same actor(s), director, genre, …
- **Websites, blogs, news**
  - Recommend other sites with "similar" content

Plan of Action



Item Profiles

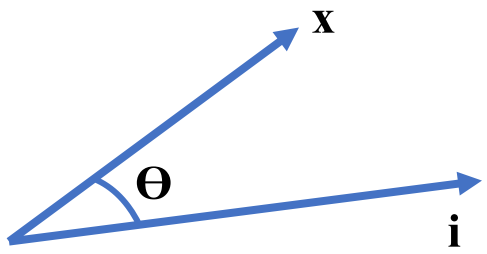
- For each item, create an **item profile**
- **Profile is a set (vector) of features** – one entry per feature and each entry could be Boolean or real valued
  - **Movies:** author, title, actor, director,…
  - **Text:** Set of “important” words in document
  - **People:** Set of friends
- **How to pick important features?**
  - Usual heuristic from text mining is **TF-IDF** (Term frequency * Inverse Doc Frequency)
    - **Term … Feature**
    - **Document … Item**

User Profiles and Prediction

- **User profile possibilities:**
  - (Weighted) average of rated item profiles $\boldsymbol{i_1,\ldots,i_n}$
  - **Variation:** weight by difference from average rating for item
  - …

- **Prediction heuristic:**
  - Given user profile ***x*** and item profile ***i***, estimate

$$u(\boldsymbol{x},\boldsymbol{i}) = \cos(\theta) = \frac{\boldsymbol{x}\cdot\boldsymbol{i}}{||\boldsymbol{x}||\cdot||\boldsymbol{i}||}$$



Pros: Content-based Approach

- **+: No need for data on other users**
  - No sparsity problems
- **+: Able to recommend to users with unique tastes**
- **+: Able to recommend new & unpopular items**
  - No first-rater problem
- **+: Able to provide explanations**
  - Can provide explanations of recommended items by listing content-features that caused an item to be recommended

Cons: Content-based Approach

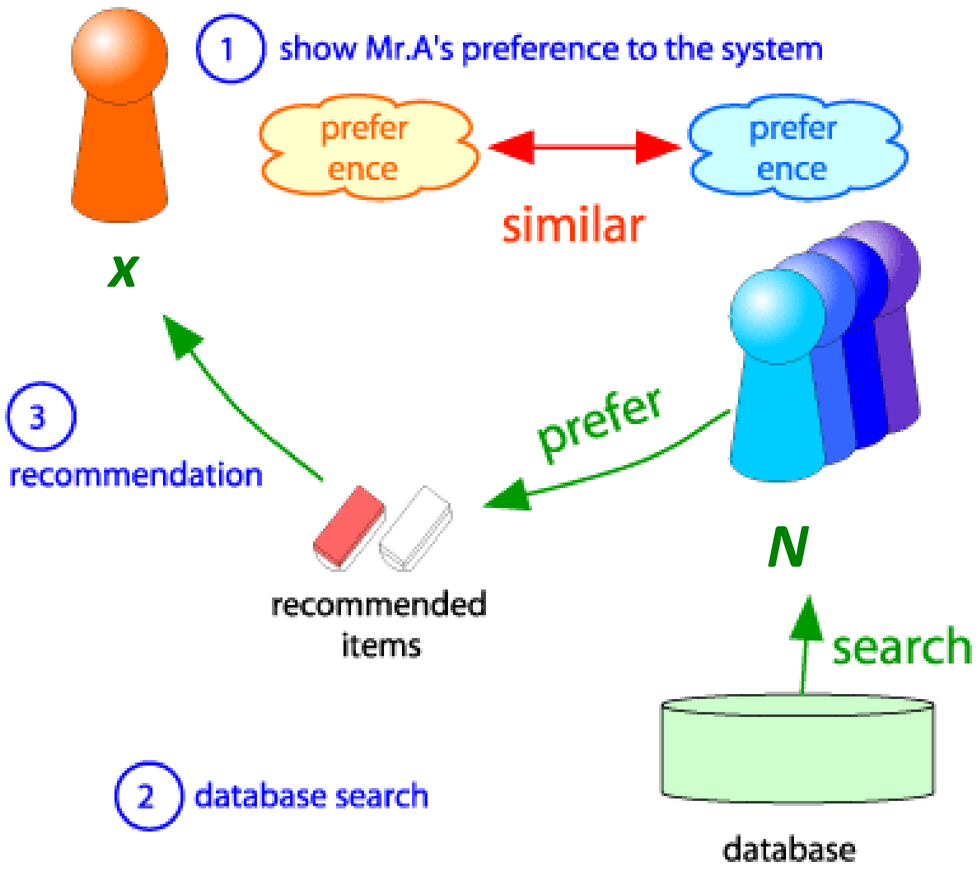
- **–: Finding the appropriate features is hard**
  - E.g., images, movies, music
- **–: Recommendations for new users**
  - **How to build a user profile?**
- **–: Overspecialization**
  - Never recommends items outside user's content profile
  - People might have multiple interests
  - **Unable to exploit quality judgments of other users**

(2) Collaborative Filtering

- Harness quality judgement of other users

- Consider user ***X***
- Find a set ***N*** of other users whose ratings are "**similar**" to ***X***'s ratings

- Estimate X's ratings based on ratings of users in ***N***



Finding "Similar" Users

r_x = [*, _, _, *, ***]
r_y = [*, _, **, **, _]

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

- Let r_x be the vector of user x's ratings
- **Jaccard similarity measure**
  - $sim(x, y) = \frac{|r_x \cap r_y|}{|r_x \cup r_y|}$
  - **Problem:** Ignores the value of the rating
- **Cosine similarity measure**
  - sim(x, y) = cos(r_x, r_y) = $\frac{r_x \cdot r_y}{||r_x|| \cdot ||r_y||}$
  - **Problem:** Treats missing ratings as "negative"
- **Pearson correlation coefficient**
  - Scale the rating r_{xs} of user x by the user's average rating
  - Low ratings to negative values and empty ratings to zeros

$$r`_{xs} = r_{xs} - \overline{r_x}$$

r_x, r_y as sets:
r_x = {1, 4, 5}
r_y = {1, 3, 4, 2}

r_x, r_y as points:
r_x = {1, 0, 0, 1, 3}
r_y = {1, 0, 2, 2, 0}

$\overline{r_x}$ = avg. rating of **x**

Similarity Metric

$$sim(x,y) = \frac{\sum_i r_{xi} \cdot r_{yi}}{\sqrt{\sum_i r_{xi}^2} \cdot \sqrt{\sum_i r_{yi}^2}}$$

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

- **Intuitively we want: sim(*A*, *B*) > sim(*A*, *C*)**
- **Jaccard similarity:** 1/5 < 2/4
- **Cosine similarity:** 0.386 > 0.322
  - Considers missing ratings as "negative" – **Problem!**
  - **Solution: normalize by subtracting the (row) mean –** centered cosine similarity / pearson correlation

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	$2/3$			$5/3$	$-7/3$		
B	$1/3$	$1/3$	$-2/3$				
C				$-5/3$	$1/3$	$4/3$	
D		0					0

sim A,B vs. A,C:
0.092 > -0.559

Notice cosine sim. is correlation when data is centered at 0

User-User Collaborative Filtering

From similarity metric to recommendations:

- Let $\boldsymbol{r_x}$ be the vector of user ***x***'s ratings
- Let ***N*** be the set of ***k*** users most similar to ***x*** who have rated item ***i***
- **Prediction for item *i* of *user x*:**

  1. $r_{xi} = \frac{1}{k} \sum_{y \in N} r_{yi}$
  2. $r_{xi} = \frac{\sum_{y \in N} s_{xy} \cdot r_{yi}}{\sum_{y \in N} s_{xy}}$

Shorthand:
$\boldsymbol{s_{xy} = sim(x, y)}$

Item-Item Collaborative Filtering

- **So far: User-user collaborative filtering**

- **Another view: Item-item**
  - For item ***i***, find other similar items
  - Estimate rating for item ***i*** based on ratings for similar items
  - Can use same similarity metrics and prediction functions as in user-user model

$$\boxed{r_{xi} = \frac{\sum_{j \in N(i;x)} s_{ij} \cdot r_{xj}}{\sum_{j \in N(i;x)} s_{ij}}}$$

s_{ij}… similarity of items i and j
r_{xj}…rating of user x on item j
$N(i;x)$… set items rated by x similar to i

Item-Item Collaborative Filtering (|N|=2)

movies	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3			5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

- unknown rating

- rating between 1 to 5

Item-Item Collaborative Filtering (|N|=2)

movies

	1	2	3	4	5	6	7	8	9	10	11	12
1	1		3		?	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

- Estimate rating of movie 1 by user 5

Item-Item Collaborative Filtering (|N|=2)

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12	sim(1,m)
1	1		3		?	5			5		4		1.00
2			5	4			4			2	1	3	-0.18
3	2	4		1	2		3		4	3	5		**0.41**
4		2	4		5			4			2		-0.10
5			4	3	4	2					2	5	-0.31
6	1		3		3			2			4		**0.59**

Neighbor selection:
Identify movies similar to movie **1**, **rated by user 5**

Here we use Pearson correlation as similarity:

1) Subtract mean rating m_i from each movie i

$m_1 = (1+3+5+5+4)/5 = 3.6$

row 1: *[-2.6, 0, -0.6, 0, 0, 1.4, 0, 0, 1.4, 0, 0.4, 0]*

2) Compute cosine similarities between rows

Item-Item Collaborative Filtering (|N|=2)

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12	sim(1,m)
1	1		3		?	5			5		4		1.00
2			5	4			4			2	1	3	-0.18
3	2	4		1	2		3		4	3	5		**0.41**
4		2	4		5			4			2		-0.10
5			4	3	4	2					2	5	-0.31
6	1		3		3			2			4		**0.59**

Compute similarity weights:

$s_{1,3}=0.41$, $s_{1,6}=0.59$

Item-Item Collaborative Filtering (|N|=2)

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12	**sim(1,m)**
1	1		3		2.6	5			5		4		**1.00**
2			5	4			4			2	1	3	**-0.18**
3	2	4		1	2		3		4	3	5		**0.41**
4		2	4		5			4			2		**-0.10**
5			4	3	4	2					2	5	**-0.31**
6	1		3		3			2			4		**0.59**

Predict by taking weighted average:

$r_{1.5}$ = **(0.41*2 + 0.59*3) / (0.41+0.59) = 2.6**

$$r_{ix} = \frac{\sum_{j \in N(i;x)} s_{ij} \cdot r_{jx}}{\sum s_{ij}}$$

Item-Item Vs. user-User

	Avatar	LOTR	Matrix	Pirates
Alice	1		0.8	
Bob		0.5		0.3
Carol	0.9		1	0.8
David			1	0.4

- **Theory:** User-user and item-item should perform equally
- **In practice, it has been observed that item-item often works better than user-user**
- **Why?** Items are simpler, users have multiple tastes

Collaborative Filtering: Complexity

- Expensive step is finding ***k*** most similar customers (or items): **O(|U|)**
  - **|U| = size of the utility matrix**
- **Too expensive to do at runtime**
  - Could pre-compute
- Naïve pre-computation takes time **O(n ·|U|)**
    - n … set of customers (items)
- **We already know how to do this!**
  - Clustering
  - Dimensionality reduction

Collaborative Filtering: Complexity

- **Leverage all the data**
  - Don’t try to reduce data size in an effort to make fancy algorithms work
  - Simple methods on large data do best

- **Add more data**
  - e.g., add IMDB data on genres

- **More data beats better algorithms**

http://anand.typepad.com/datawocky/2008/03/more-data-usual.html

Pros/Cons of Collaborative Filtering

- **+: Works for any kind of items**
  - No feature selection is required
- **–: Cold start**
  - Cannot recommend an item that has not been previously rated
  - New items
- **–: Sparsity**
  - User/ratings matrix is sparse
  - Hard to find users that have rated same items
- **–: Popularity bias**
  - Cannot recommend an item to someone with unique taste
  - Tends to recommend popular items

Hybrid Methods

- **Implement two or more different recommenders and combine predictions**
  - Perhaps using a linear model

- **Add content-based methods to collaborative filtering**
  - Item profiles for new item problem
  - Demographics to deal with new user problem

Modelling Local and Global Effects

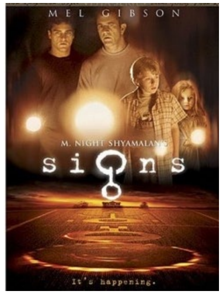
- **Global:**
  - Mean movie rating: **3.7 stars**
  - *The Sixth Sense* is **0.5** stars above avg.
  - Joe rates **0.2** stars below avg.

    ⇒ **Baseline estimation:**

    Joe **will rate** ***The Sixth Sense*** **4 stars**

- **Local neighborhood (CF/NN):**
  - *Joe* didn't like related movie *Signs*
  - ⇒ **Final estimate:**

    Joe **will rate** ***The Sixth Sense*** **3.8 stars**



Collaborative Filtering: Common Practice

Before:

$$r_{xi} = \frac{\sum_{j \in N(i;x)} s_{ij} r_{xj}}{\sum_{j \in N(i;x)} s_{ij}}$$

- Define **similarity** s_{ij} of items i and j
- Select k nearest neighbors $N(i; x)$
  - Items most similar to i, that were rated by x
- Estimate rating r_{xi} as the weighted average:

$$r_{xi} = b_{xi} + \frac{\sum_{j \in N(i;x)} s_{ij} \cdot (r_{xj} - b_{xj})}{\sum_{j \in N(i;x)} s_{ij}}$$

Global baseline estimate for r_{xi}

$$\boldsymbol{b_{xi} = \mu + b_x + b_i}$$

- μ = overall mean movie rating
- b_x = rating deviation of user x
  = *(avg. rating of user* x*)* – μ
- b_i = rating deviation of movie i

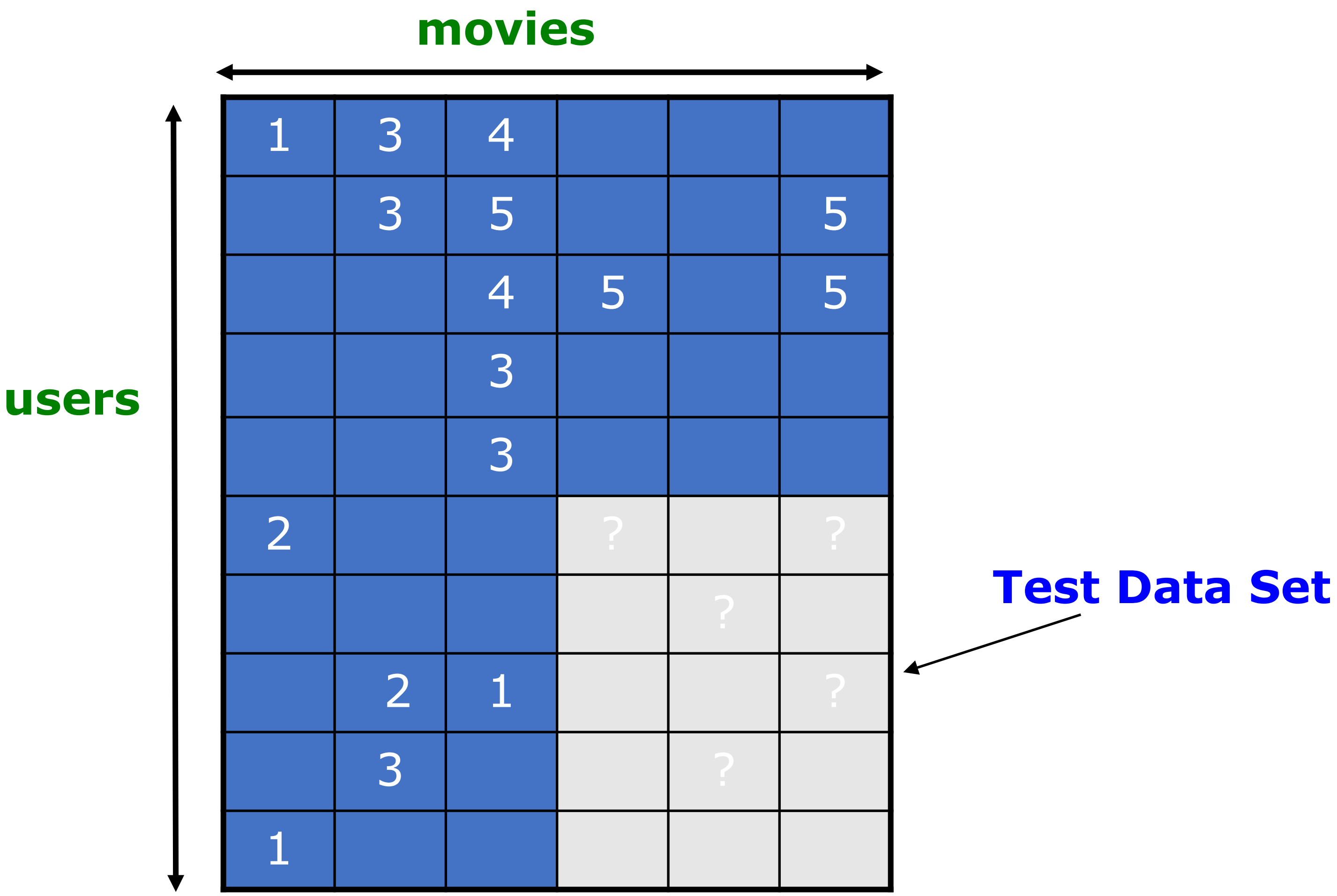
(3) Evaluation – Practical Tips

movies

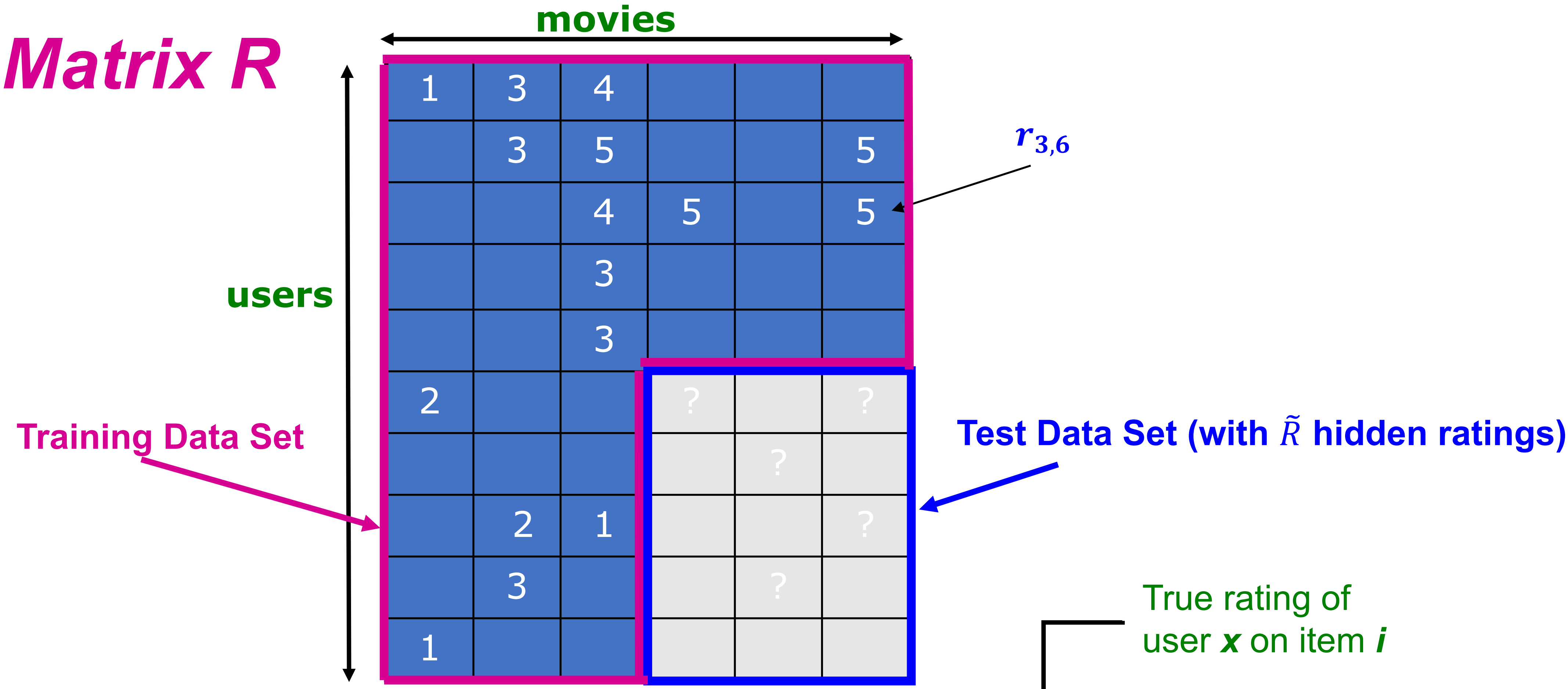
users

1	3	4			
	3	5			5
		4	5		5
		3			
		3			
2			2		2
				5	
	2	1			1
	3			3	
1					

Evaluation – Practical Tips



Common Practice



True rating of user ***x*** on item ***i***

$$\textbf{RMSE} = \sqrt{\frac{1}{\tilde{R}} \sum_{(i,x)\in\tilde{R}} (\hat{r}_{xi} - r_{xi})^2}$$

Predicted rating

Evaluating Predictions

- **Compare predictions with known ratings**
  - **Root-mean-square error** (RMSE)
    - $\sqrt{\frac{1}{R^*}\sum_{xi}\left(r_{xi} - r_{xi}^*\right)^2}$ where $\boldsymbol{r_{xi}}$ is predicted, $\boldsymbol{r_{xi}^*}$ is the true rating of $\boldsymbol{x}$ on $\boldsymbol{i}$
  - **Precision/Recall at top *n***:
    - % of those in top 10
  - **Rank Correlation**:
    - Spearman's *correlation* between system's and user's complete rankings

- **Another approach: 0/1 model**
  - **Coverage:**
    - Number of items/users for which system can make predictions
  - **Precision:**
    - Accuracy of predictions
  - **Receiver operating characteristic** (ROC)
    - Tradeoff curve between false positives and false negatives

Problem with Error Measures

- **Narrow focus on accuracy sometimes misses the point**
  - Prediction Diversity
  - Prediction Context
  - Order of predictions
- **In practice, we care only to predict high ratings:**
  - RMSE might penalize a method that does well for high ratings and badly for others

Questions???

Acknowledgements

Most of this lecture slides are obtained from the Mining Massive Datasets course: http://www.mmds.org/