

# Recommender Systems: Latent Factor Models

Mining of Massive Datasets  
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# The Netflix Prize

- **Movie recommender system**
- **Training data:**
  - 100 million ratings, 480,000 users, 17,770 movies
  - 6 years of data: 2000-2005
- **Test data**
  - Last few ratings of each user (2.8 million)

# The Netflix Utility Matrix $R$

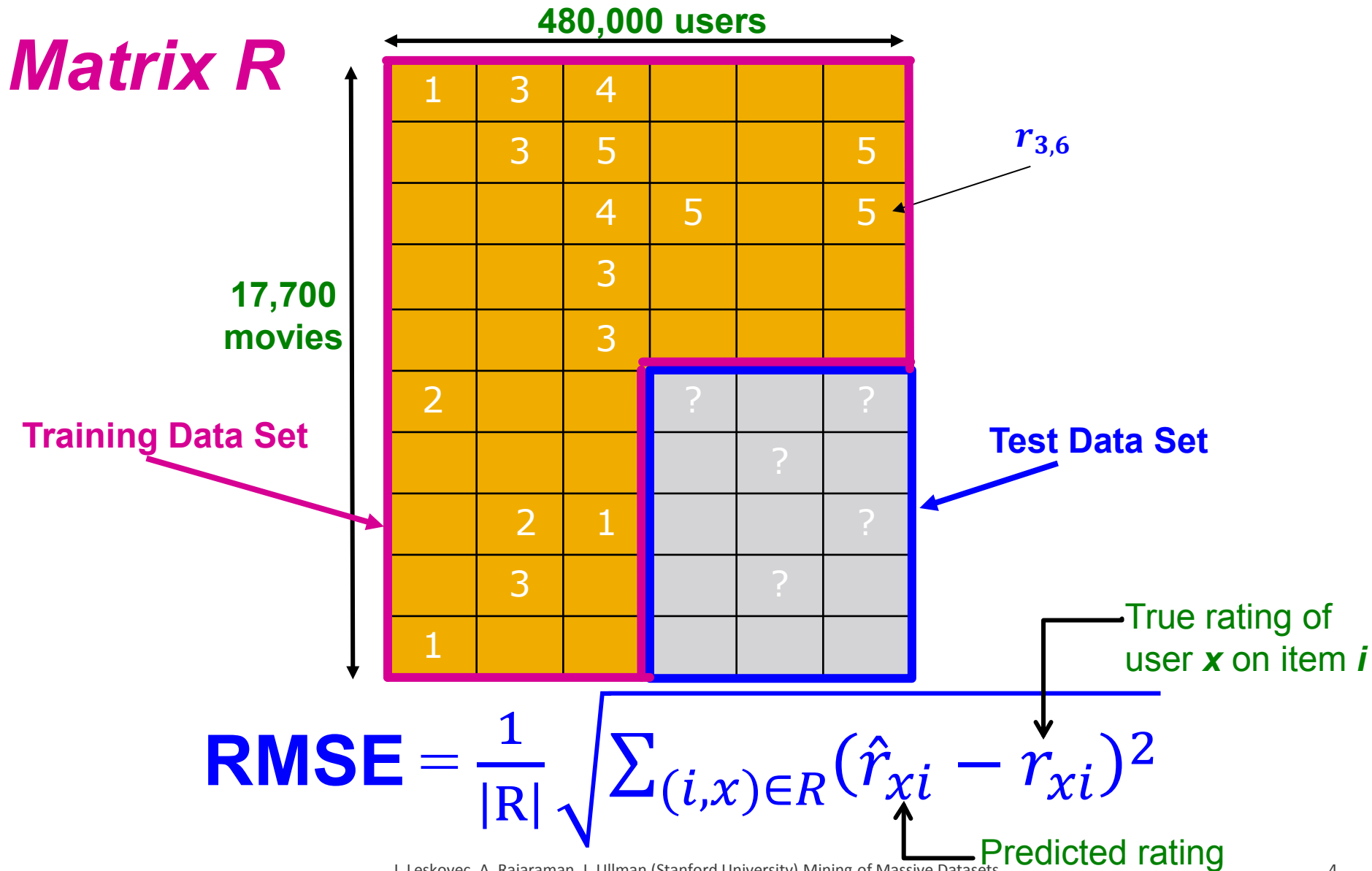
*Matrix  $R$*

480,000 users

17,700 movies

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

# Utility Matrix $R$ : Evaluation



# The Netflix Prize

- **Given the training data**

- 100 million ratings

- **Predict last few ratings of each user**

- **Evaluation criterion: Root Mean Square Error (RMSE)**

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

- **Netflix's system RMSE: 0.9514**

- **Competition**

- 2,700+ teams
- **\$1 million** prize for 10% improvement on Netflix

# A Modern Recommender System

- **Multi-scale modeling of the data:**

Combine top level, “regional” modeling of the data, with a refined, local view:

- **Global:**

- Overall deviations of users/movies

- **Factorization:**

- Addressing “regional” effects

- **Collaborative filtering:**

- Extract local patterns

# Modeling Local & 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:**

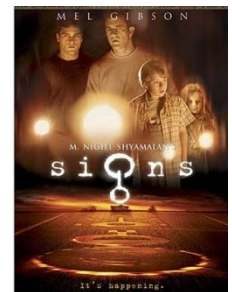
*Joe will rate The Sixth Sense 4 stars*

## ■ Local neighborhood (CF/NN):

- Joe didn't like related movie *Signs*

⇒ **Final estimate:**

*Joe will rate The Sixth Sense 3.8 stars*



# Recap: Collaborative Filtering (CF)

- Earliest and most popular **collaborative filtering method**
- Derive unknown ratings from those of “similar” movies (item-item variant)
- Define **similarity measure**  $s_{ij}$  of items  $i$  and  $j$
- Select  $k$ -nearest neighbors, compute the rating
  - $N(i; x)$ : items most similar to  $i$  that were rated by  $x$

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

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



# Modeling Local & Global Effects

- In practice we get better estimates if we model deviations:

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

baseline estimate for  $r_{xi}$

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

- $\mu$  = overall mean rating
- $b_x$  = rating deviation of user  $x$   
= (avg. rating of user  $x$ ) -  $\mu$
- $b_i$  = (avg. rating of movie  $i$ ) -  $\mu$

## Problems/Issues:

- 1) Similarity measures are “arbitrary”
- 2) Pairwise similarities neglect interdependencies among users
- 3) Taking a weighted average can be restricting

# RMSE of Various Methods

