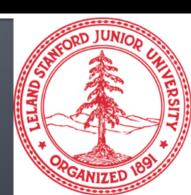
Extending Latent Factor Model to Include Biases

Mining of Massive Datasets Leskovec, Rajaraman, and Ullman Stanford University



Modeling Biases and Interactions

user bias



movie bias



user-movie interaction



Baseline predictor

- Separates users and movies
- Benefits from insights into user's behavior
- Among the main practical contributions of the competition
 - $\mu = \mu$ = overall mean rating
 - $\mathbf{b}_{\mathbf{x}}$ = bias of user \mathbf{x}
 - $\mathbf{b}_{i}^{\hat{}}$ = bias of movie \mathbf{i}

User-Movie interaction

- Characterizes the matching between users and movies
- Attracts most research in the field
- Benefits from algorithmic and mathematical innovations

Baseline Predictor

We have expectations on the rating by user x of movie i, even without estimating x's attitude towards movies like i







- Rating scale of user x
- Values of other ratings user gave recently (day-specific mood, anchoring, multi-user accounts)

- (Recent) popularity of movie i
- Selection bias; related to number of ratings user gave on the same day ("frequency")

Putting It All Together

$$r_{xi} = \mu + b_x + b_i + q_i \cdot p_x^T$$

Overall Bias for Bias for Movie interaction

Mean rating user x movie i

Overall Bias for Movie interaction

Example:

- Mean rating: $\mu = 3.7$
- You are a critical reviewer: your ratings are 1 star lower than the mean: $b_x = -1$
- Star Wars gets a mean rating of 0.5 higher than average movie: $b_i = +0.5$
- Predicted rating for you on Star Wars:

$$= 3.7 - 1 + 0.5 = 3.2$$

Fitting the New Model

Solve:

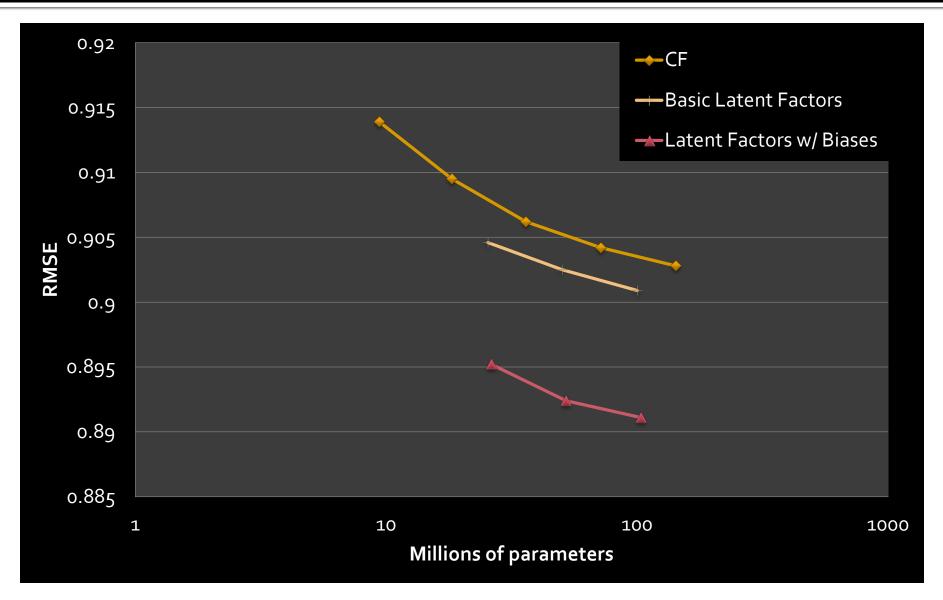
$$\min_{Q,P} \sum_{(x,i)\in R} (r_{xi} - (\mu + b_x + b_i + q_i p_x^T))^2$$
goodness of fit

$$+ \lambda \left(\sum_{i} \|q_{i}\|^{2} + \sum_{x} \|p_{x}\|^{2} + \sum_{x} \|b_{x}\|^{2} + \sum_{i} \|b_{i}\|^{2} \right)$$
regularization regularization

 λ is selected via grid-search on a validation set

- Stochastic gradient decent to find parameters
 - Note: Both biases b_u , b_i as well as interactions q_i , p_u are treated as parameters (we estimate them)

Performance of Various Methods



Performance of Various Methods

Global average: 1.1296

User average: 1.0651

Movie average: 1.0533

Netflix: 0.9514

Basic Collaborative filtering: 0.94

Latent factors: 0.90

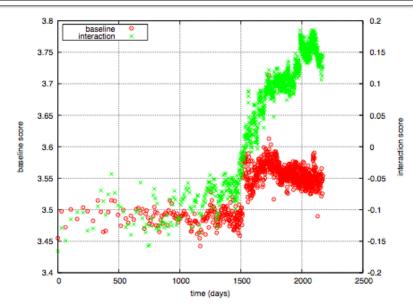
Latent factors+Biases: 0.89

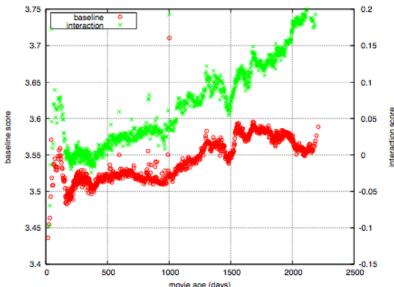
Grand Prize: 0.8563

Temporal Biases Of Users

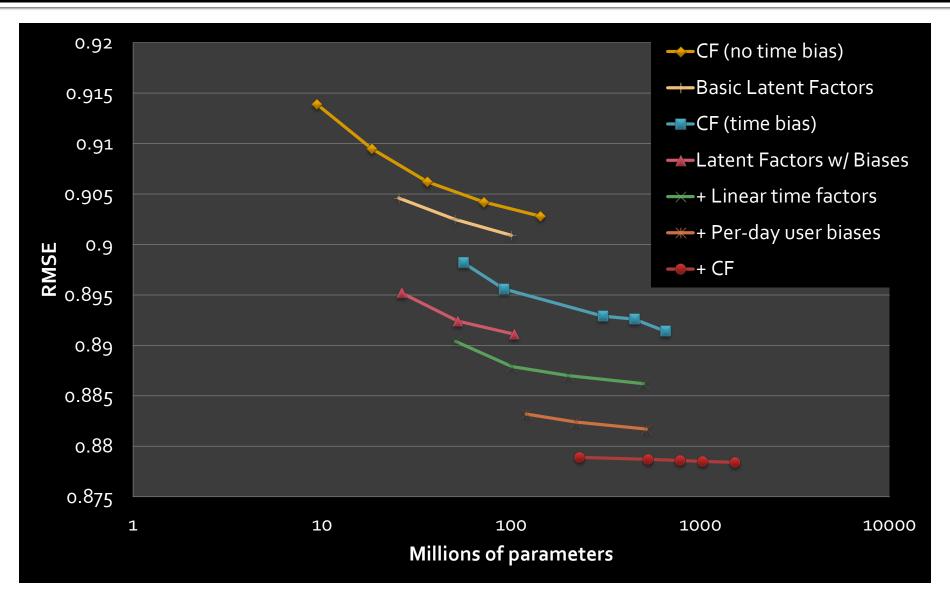
- Sudden rise in the average movie rating (early 2004)
 - Improvements in Netflix
 - GUI improvements
 - Meaning of rating changed
- Movie age
 - Users prefer new movies without any reasons
 - Older movies are just inherently better than newer ones

Y. Koren, Collaborative filtering with temporal dynamics, KDD '09





Adding Temporal Effects



Performance of Various Methods

Global average: 1.1296

User average: 1.0651

Movie average: 1.0533

Netflix: 0.9514

Basic Collaborative filtering: 0.94

Collaborative filtering++: 0.91

Latent factors: 0.90

Latent factors+Biases: 0.89

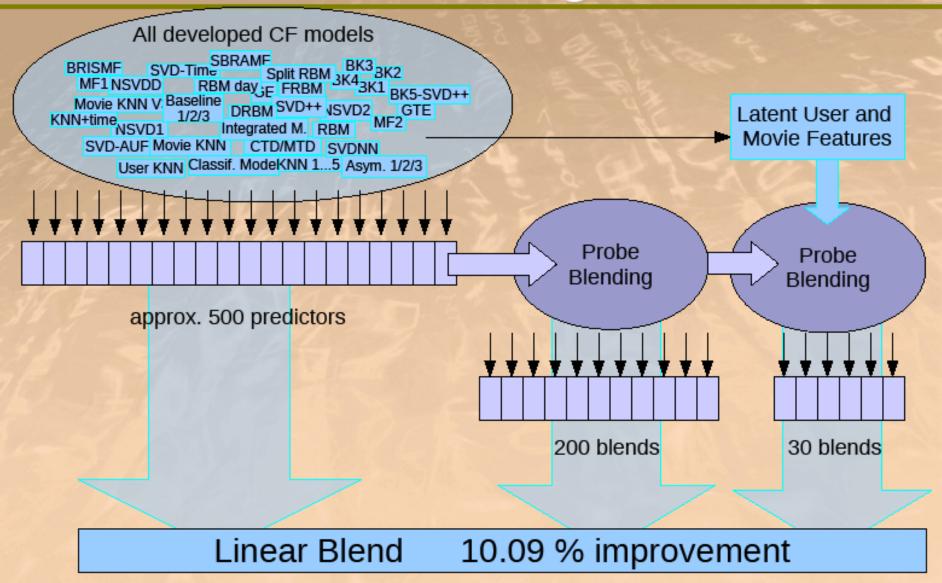
Latent factors+Biases+Time: 0.876

Still no prize! (2)
Getting desperate.
Try a "kitchen sink" approach!

Grand Prize: 0.8563

The big picture

Solution of BellKor's Pragmatic Chaos



Standing on June 26th 2009



June 26th submission triggers 30-day "last call"

Million \$ Awarded Sept 21st 2009

