



# Optimal Recommendations under Attraction, Aversion and Social Influence

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# Users Engaging with Recommender Systems



Attraction 😊



Aversion ☹️



Influence...

# Challenges

- Making recommendations & modeling user interest are intertwined
  - Since recommendations play a role in changing user interest
- Recommendations should be made in a global manner
  - Since social influence effect may trigger interest cascade

# Main Contributions

- An ***interest evolution model*** with attraction, aversion, and social influence
- Use ***Semi-Definite Programming (SDP)*** to provide near-optimal recommendations
  - Outperform matrix factorization recommendations significantly
- Show from real data that attraction and aversion phenomena do exist

# Interest Evolution Model



Inherent interests

Personal  
 $1 - \beta$

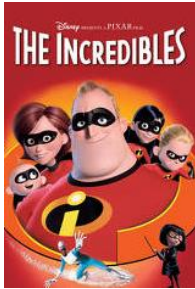
Social  
 $\beta$



Social Influence



Attracted to recommendations



$\gamma_i$



Aversive to recommendations



$\delta_i$

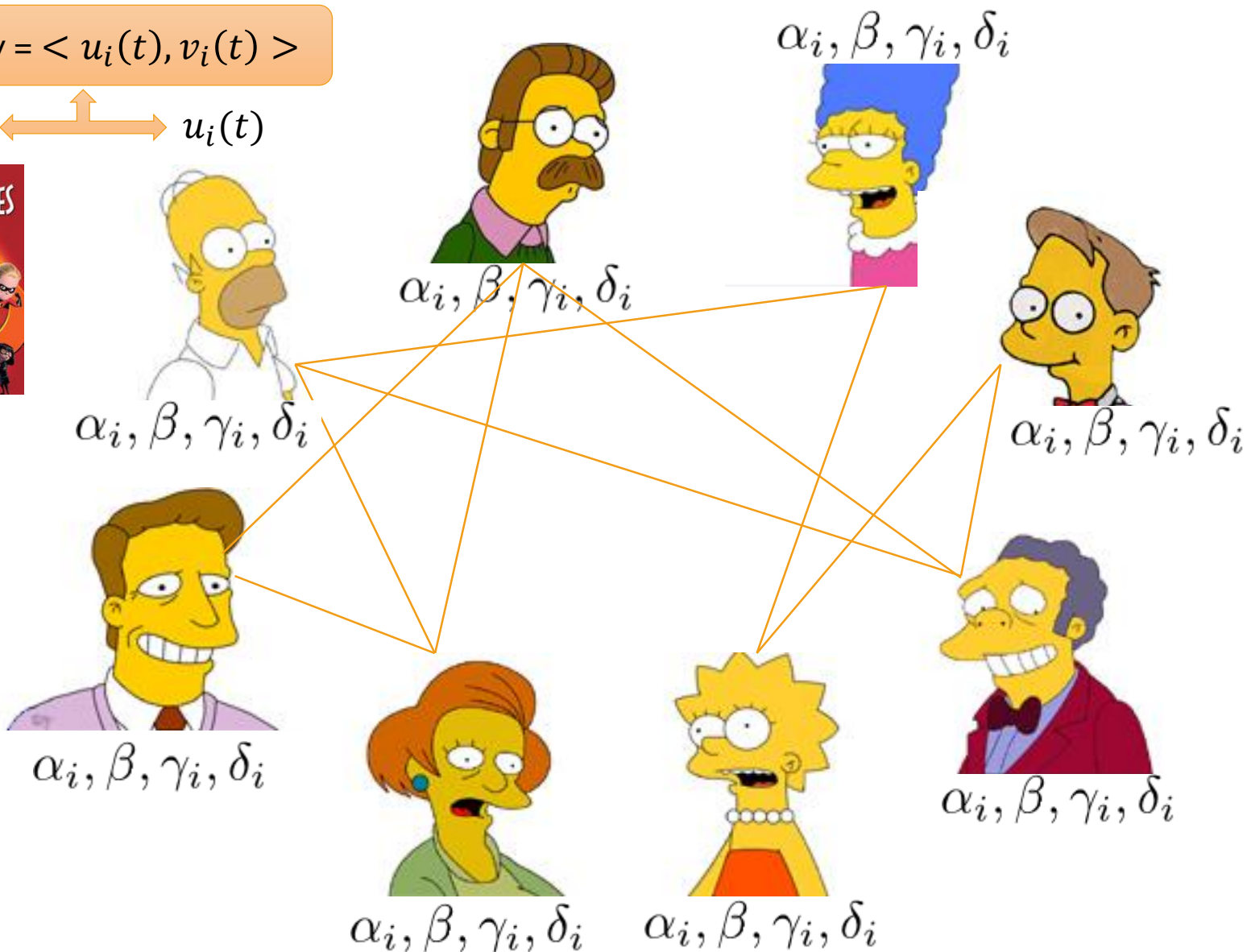
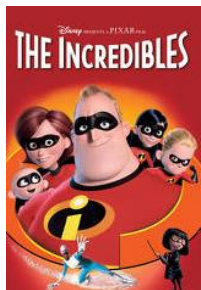
$$\alpha_i + \gamma_i + \delta_i = 1$$

At any time  $t$ , user selects social behavior with probability  $\beta$  and personal behavior with probability  $1 - \beta$

# Dynamic system of interest evolution

Utility =  $\langle u_i(t), v_i(t) \rangle$

$v_i(t)$   $\longleftrightarrow$   $u_i(t)$

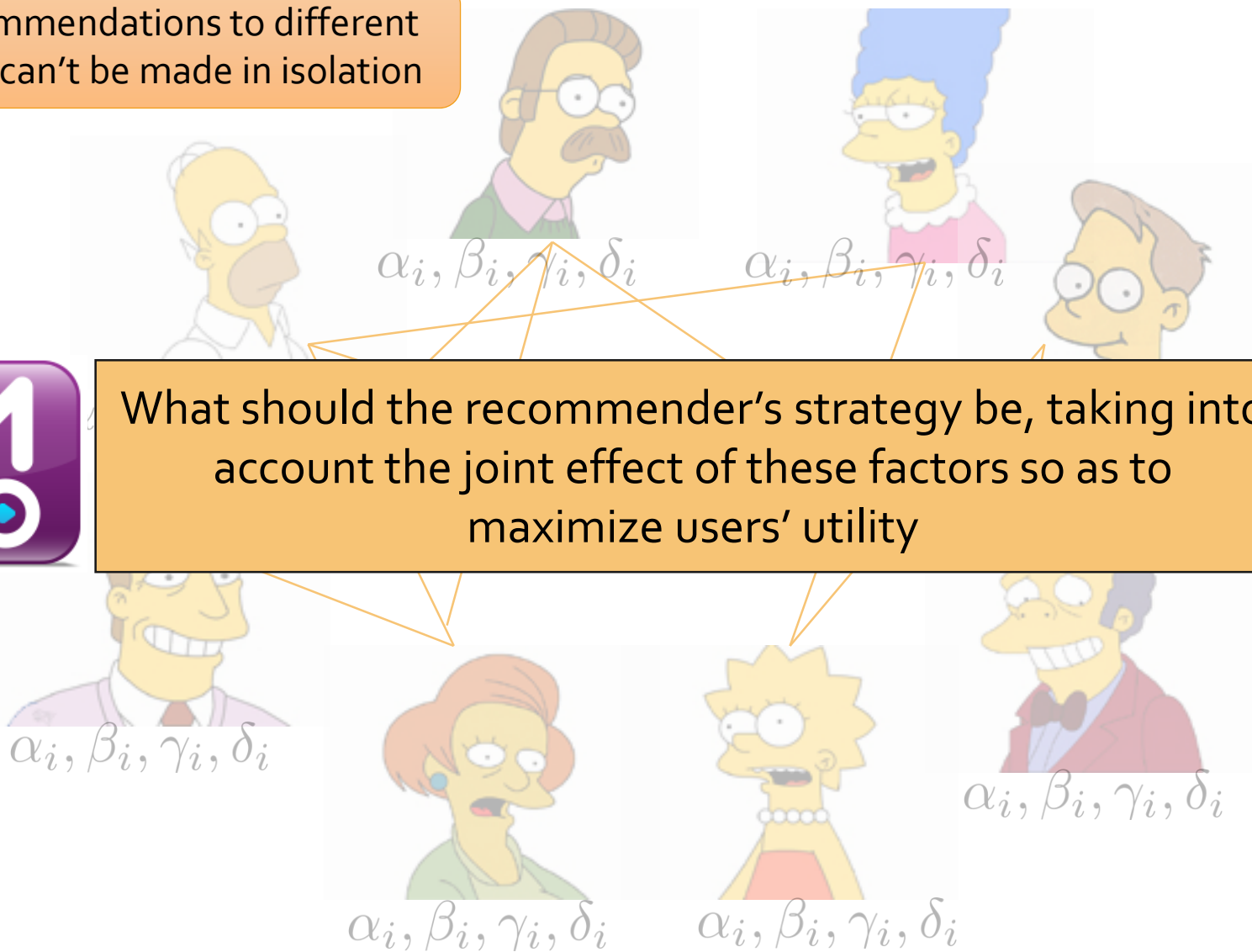


# Recommendation Problem

Recommendations to different users can't be made in isolation



What should the recommender's strategy be, taking into account the joint effect of these factors so as to maximize users' utility



# Interest Evolution: Steady State

The evolution process is a *Markov Chain*

It converges to a *steady state*

$$\bar{U} = A\bar{U}^0 + \beta P\bar{U} + (\Gamma - \Delta)\bar{V}$$

Expected user  
profile matrix  
(1 row per user)

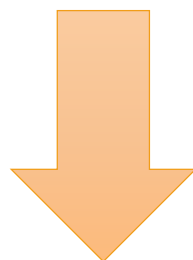
prob. of  
inherent  
interest

expected  
inherent  
profile  
matrix

social  
influence  
matrix

prob. of  
attraction,  
aversion  
matrices

expected  
item profile  
matrix



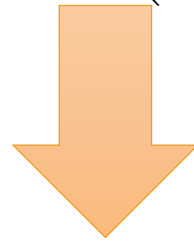
$$\bar{U} = (I - \beta P)^{-1} (A\bar{U}^0 + (\Gamma - \Delta)\bar{V})$$





# Recommendation Objective

$$\bar{U} = (I - \beta P)^{-1} (A\bar{U}^0 + (\Gamma - \Delta)\bar{V})$$



Multiply with  $\bar{V}$

Max.:  $\text{trace} \left[ (I - \beta P)^{-1} (A\bar{U}^0\bar{V}^T + (\Gamma - \Delta)\bar{V}\bar{V}^T) \right]$

subj. to:  $\|\bar{\mathbf{v}}_i\|_2^2 \leq 1$ , for all  $i \in [n]$

**Social welfare:** Expected total utility over all users

**Global Recommendation Problem**

# Global Recommendation

Max.:  $\text{trace} \left[ (I - \beta P)^{-1} (A\bar{U}^0\bar{V}^\top + (\Gamma - \Delta)\bar{V}\bar{V}^\top) \right]$

subj. to:  $\|\bar{\mathbf{v}}_i\|_2^2 \leq 1$ , for all  $i \in [n]$



- Variables to solve:  $\bar{V}$
- Quadratically-Constrained Quadratic Optimization Problem (QCQP)
- Not convex, in general ☹️
- Our solution strategy: Relaxation

# SDP Relaxation

- Global Recommendation: **Semi-Definite Program (SDP)** with a **rank-1 constraint**
- **Relaxation**: Drop rank-1 constraint → SDP only
- Solve the SDP relaxation
  - IF (rank-1): done!
  - ELSE: there exists a randomized algorithm giving a  $4/7$  approximation
- **Observation**: In our experiments, all solution matrices are rank-1, hence optimal 😊

# Experiments

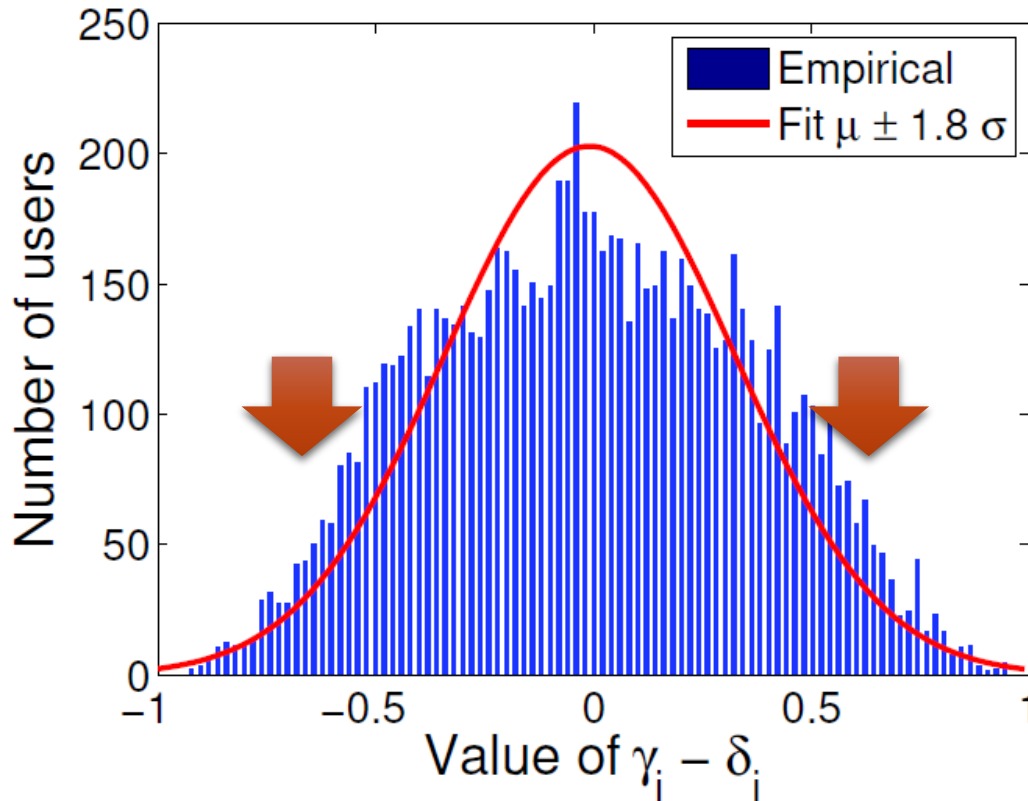
## Datasets

	Flixster	FilmTipSet	MovieLens
#users	4.6K	0.4K	8.9K
#items	25K	4.3K	3.8K
#ratings	1.8M	118K	1.3M
#edges	44K	N/A	N/A

## Objectives

- Find evidence of attraction and aversion from data
- Evaluate SDP solutions
- Baseline (MF-Local): Recommend based on inherent profiles only

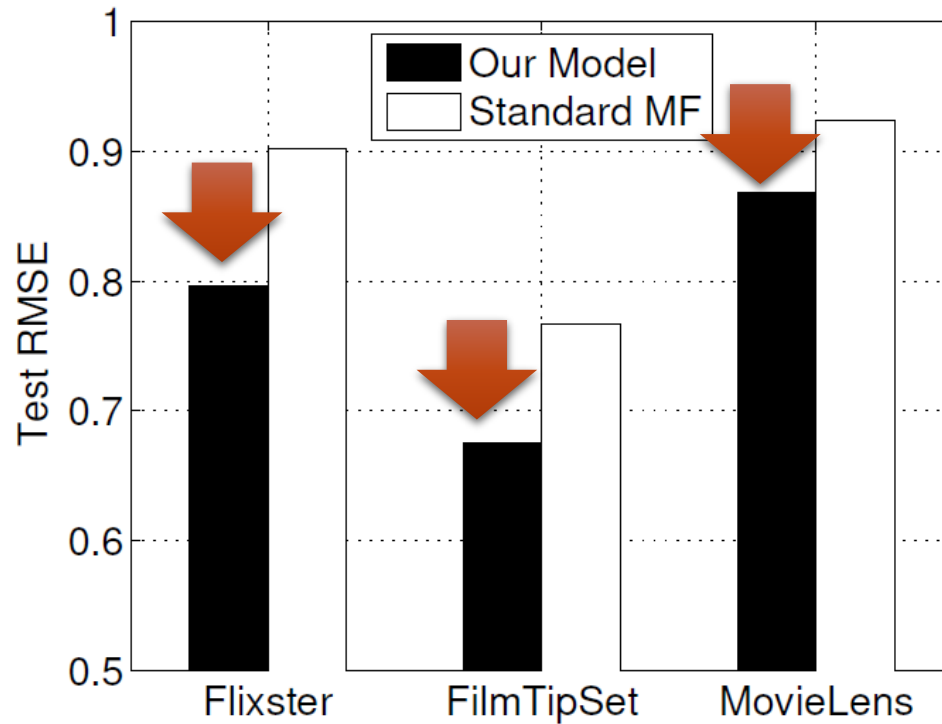
# Finding evidence of attraction & aversion



MovieLens

Heavy tail:  
existence of  
strongly attracted  
and aversive users

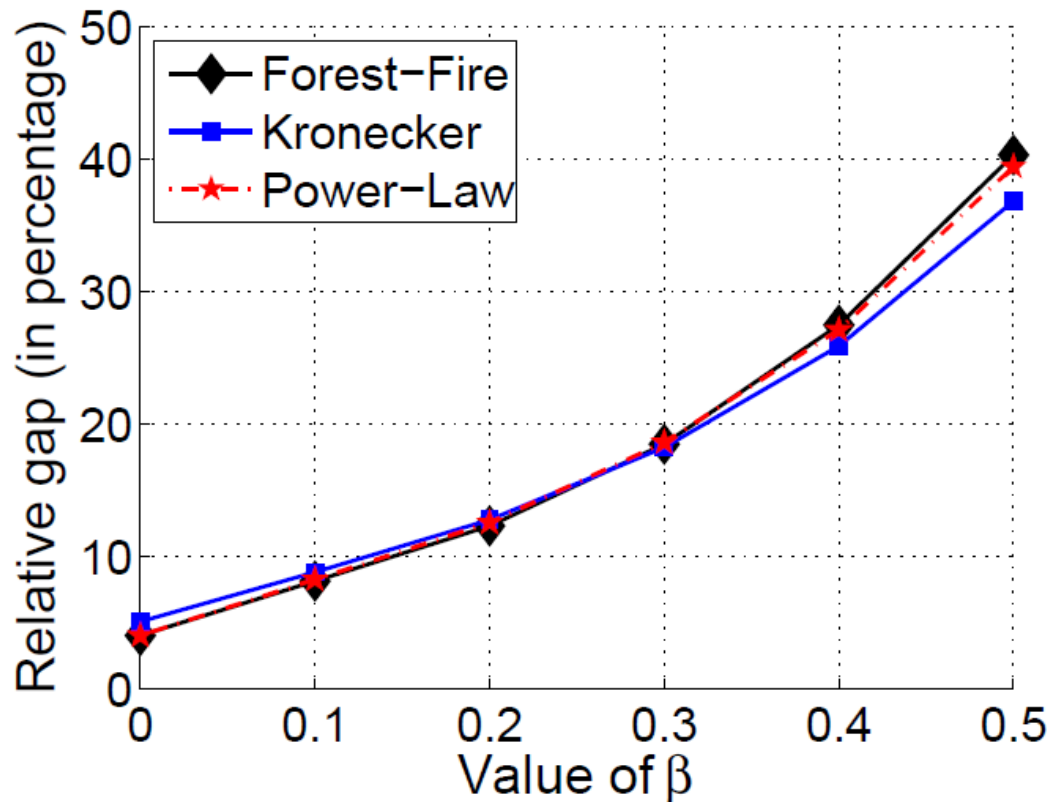
# Finding evidence of attraction & aversion



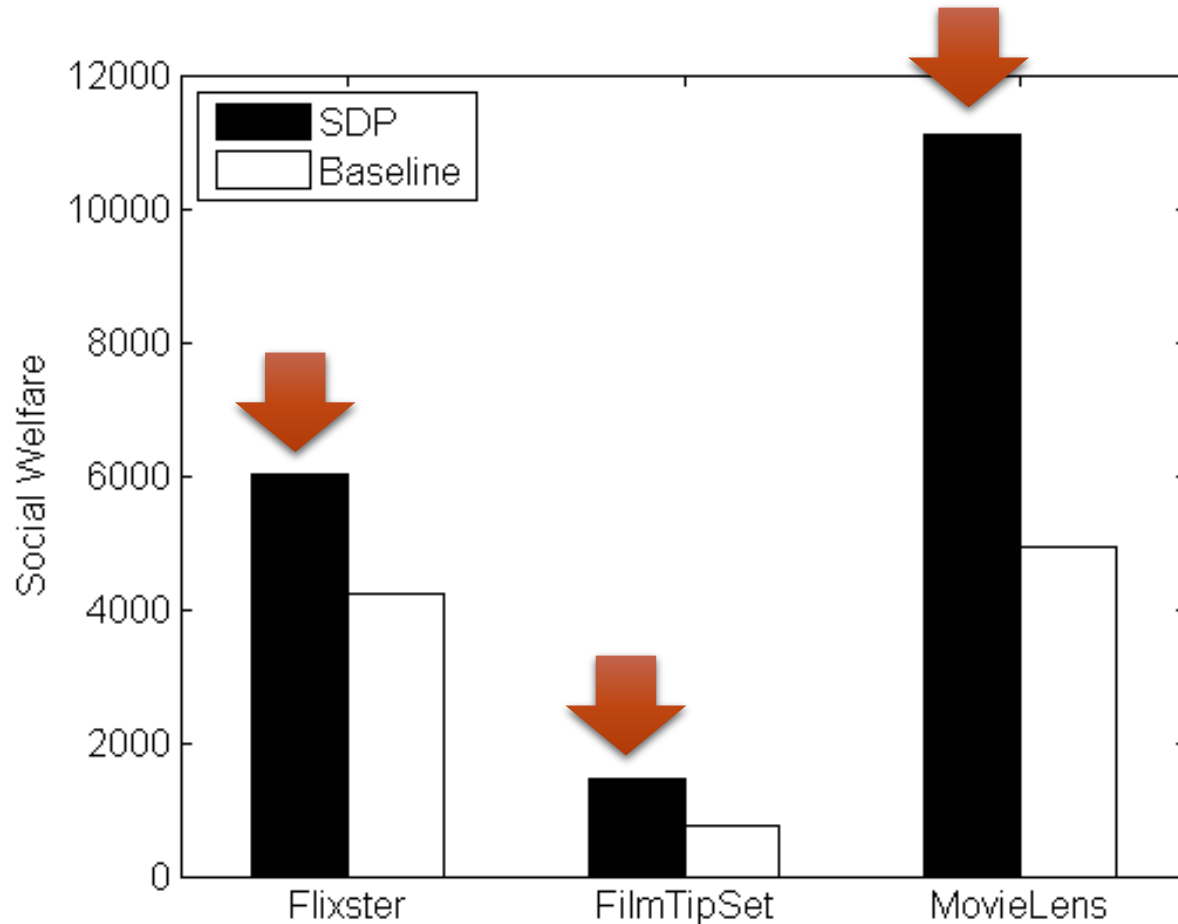
Incorporating  
evolution probabilities  
into Matrix  
Factorization leads to  
better predictions

# Varying Social Effect $\beta$ (Synthetic)

- Synthetic SN: Forest-Fire, Kronecker, Power-law
- Y-axis:  $\frac{SDP\ solution - baseline}{baseline} * 100\%$



# Social Welfare on Real Data



SDP outperforms baseline on three real-world datasets, in terms of Social Welfare



# Future Work

- Study the optimality of SDP relaxation in theory
- Improve scalability of SDP-based algorithms by exploiting special structural features
- Study other factors for interest evolution



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# Thank you!



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