the **social** side of **recommendation** systems: how **groups** shape our **decisions**

Allison J.B. Chaney
IC Postdoctoral Fellow
Princeton University

Influencing Deliberation

Influencing Deliberation

Tools for **Knowledge** Creation

How can we make it easier to create knowledge?

Influencing Deliberation

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How can we make it easier to create knowledge?

Understanding **Decision** Processes

How do people decide which choices to make?

Tools for **Knowledge** Creation

How can we make it easier to create knowledge?

data → **unsupervised machine learning**

domain expertise → **unsupervised machine learning**

unsupervised machine learning → **hidden patterns**

hidden patterns → **visualization & exploration**

Tools for **Knowledge** Creation

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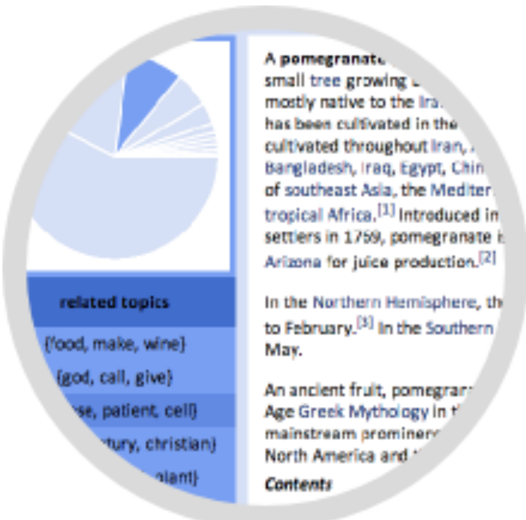

Visualizing topic models.
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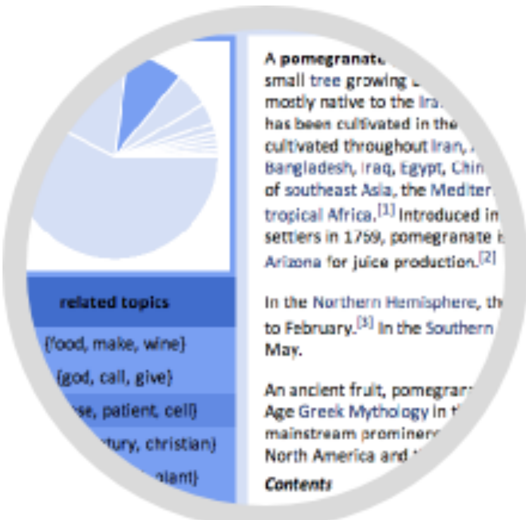

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open source

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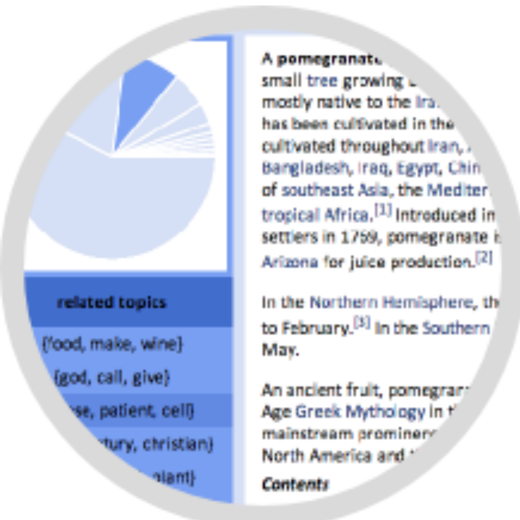

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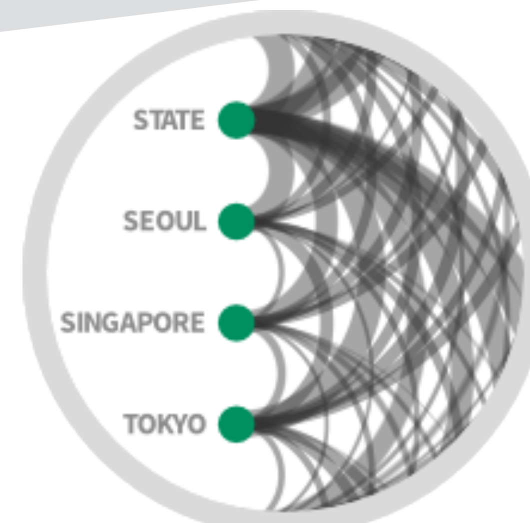

open source Tools for **Knowledge** Creation

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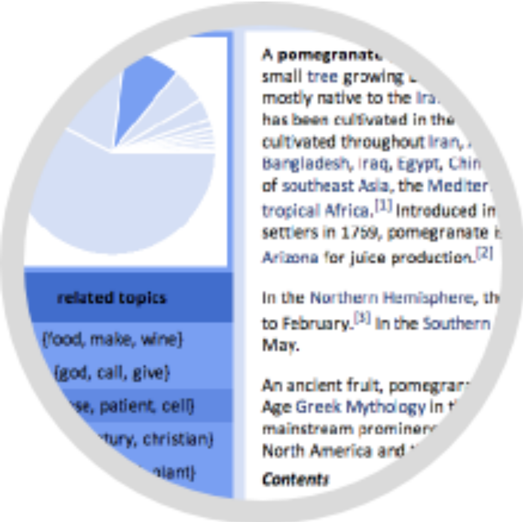

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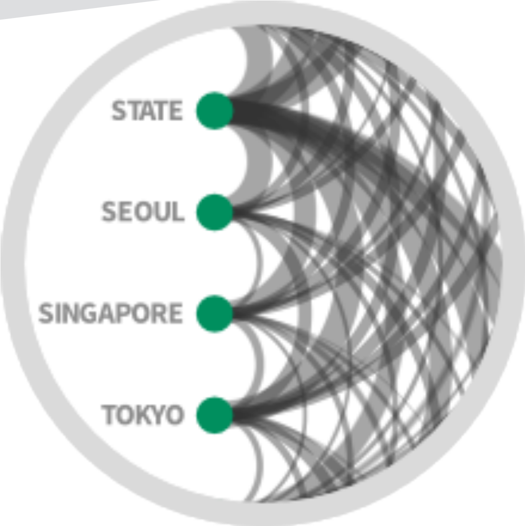

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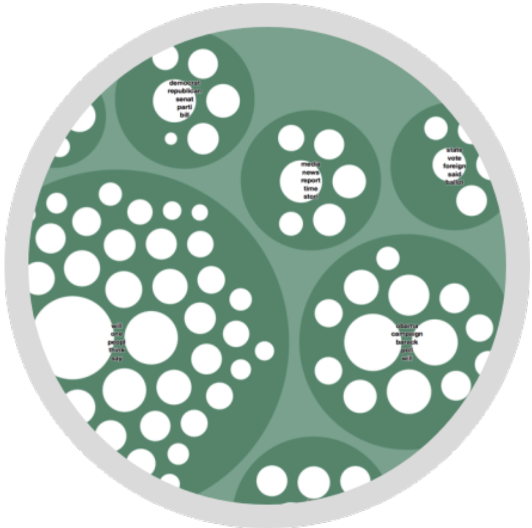

The Power of Aggregation for Topic Models Used For Measurement.
Chaney, Shiraito, Stewart. Text as Data, 2017.

open source

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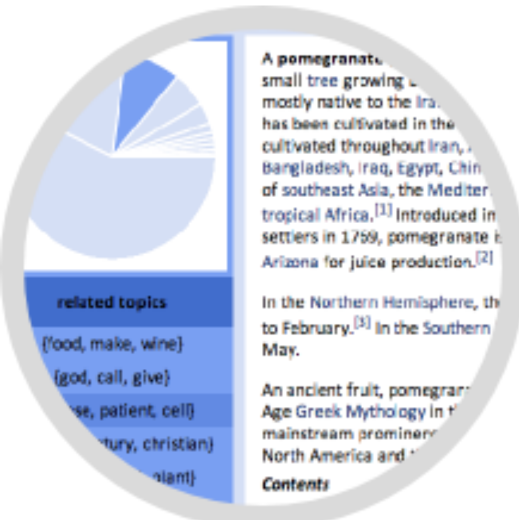

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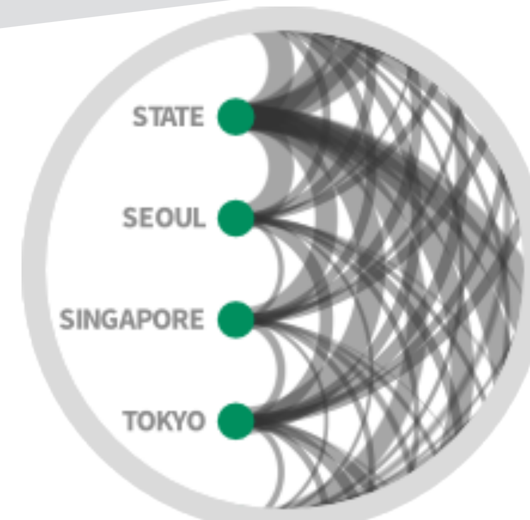

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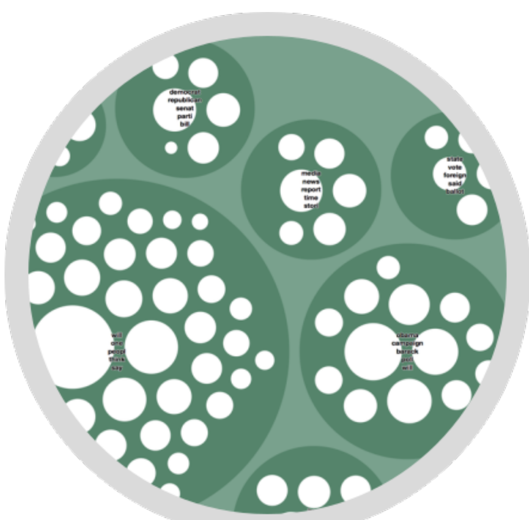

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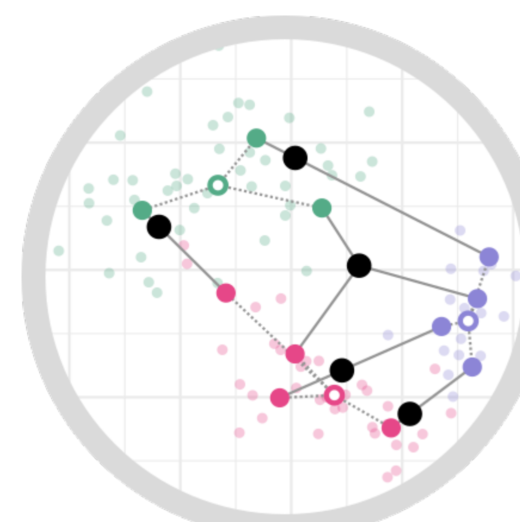

Generalized Nonparametric Deconvolution Models
Chaney, Verma, Lee, and Engelhardt. In Progress.

Understanding **Decision** Processes

How do people decide what choices to make?

What do decisions look like?

Understanding **Decision** Processes

How do people decide what choices to make?

amazon
NETFLIX
pandora
Etsy
facebook
Spotify

What do decisions look like?

The Washington Post
THE WALL STREET JOURNAL.
The New York Times
Bing
Google

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Chameleon Preferences

How do the decisions people make depend on the people around them?

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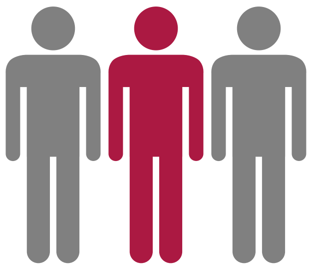
Algorithmic Personalization isn't Personal



How do recommendations alter group behavior?

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A large-scale exploration of group viewing patterns. Chaney, Gartrell, Hofman, Guiver, Koenigstein, Kohli, and Paquet. ACM TVX, 2014.


?
MOVIE
1
2
3

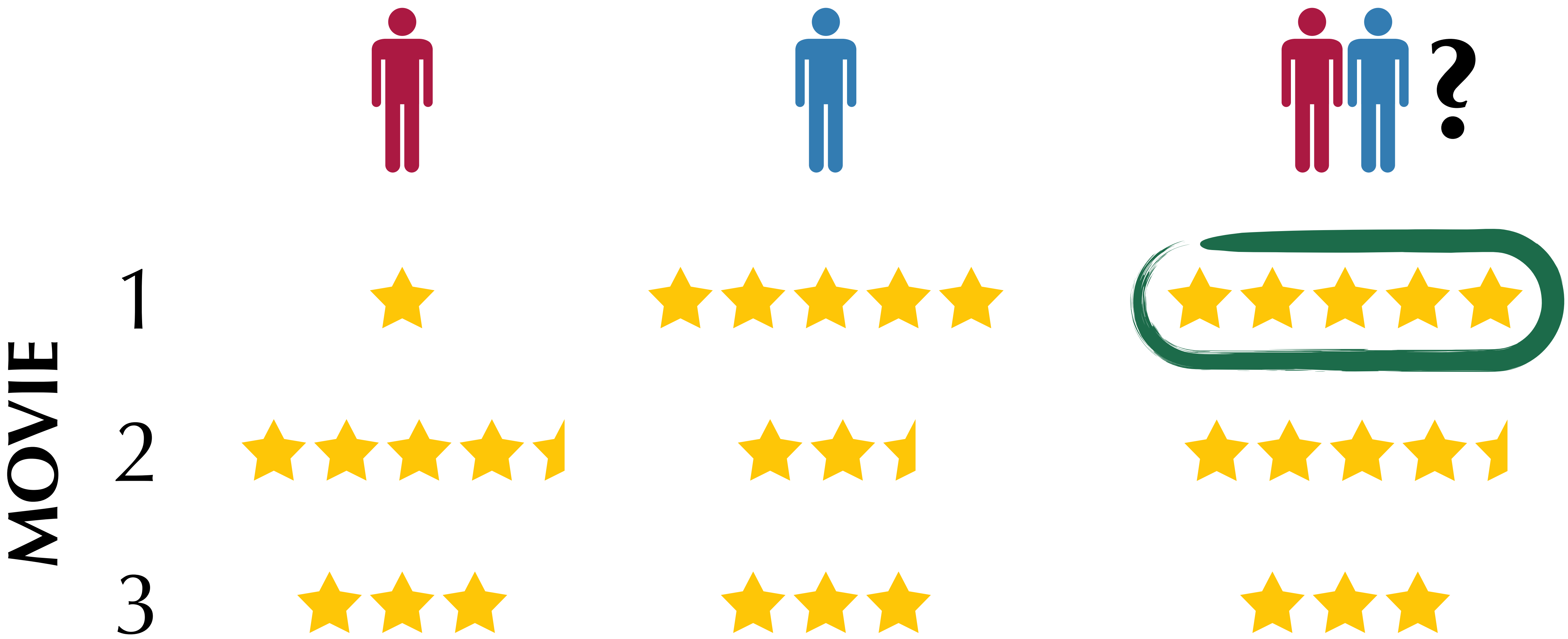
average satisfaction

average satisfaction

least misery

least misery

maximum satisfaction



maximum satisfaction

June 2012

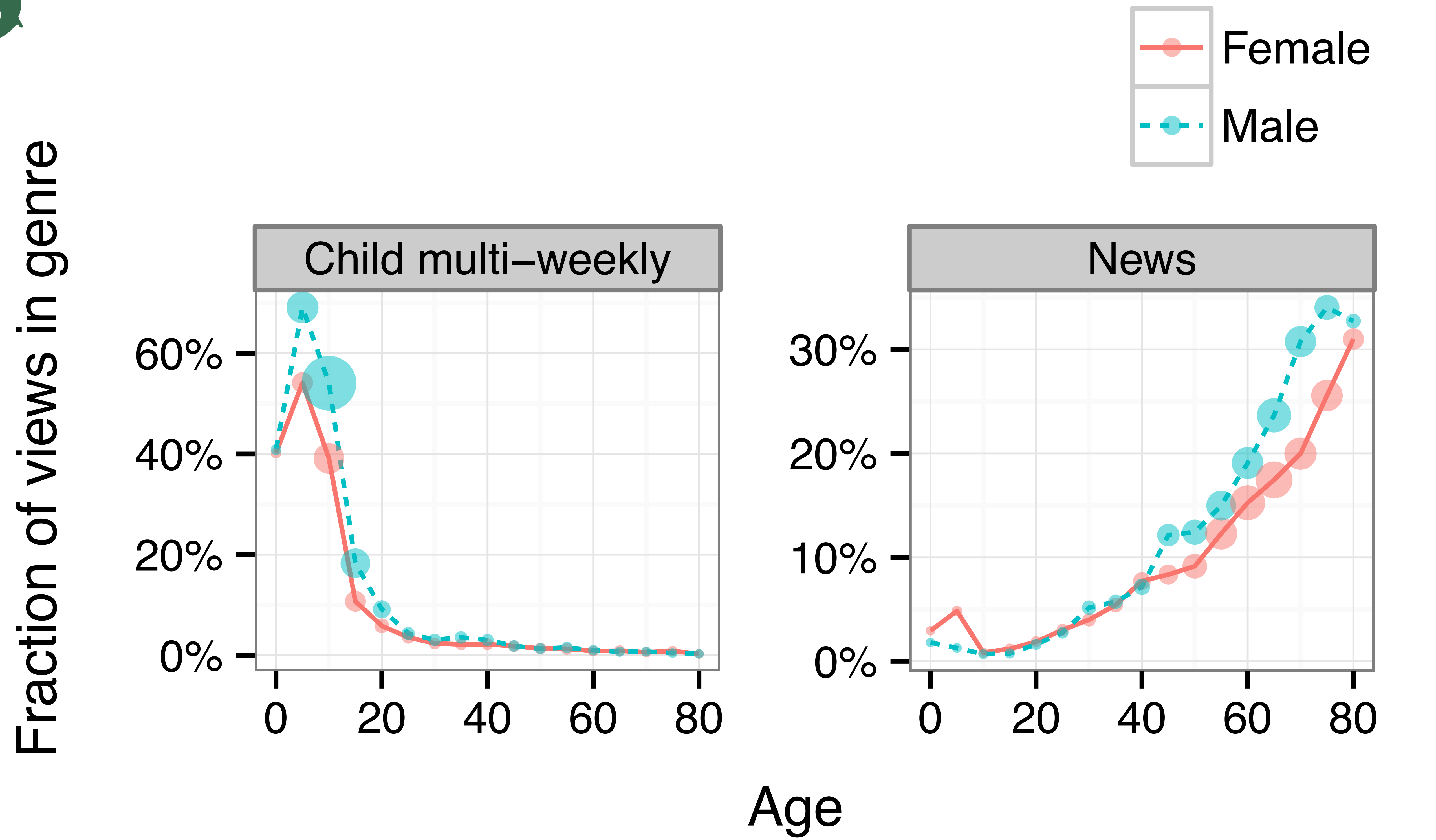
50,200 users

2,417 TV shows; 16,546 telecasts

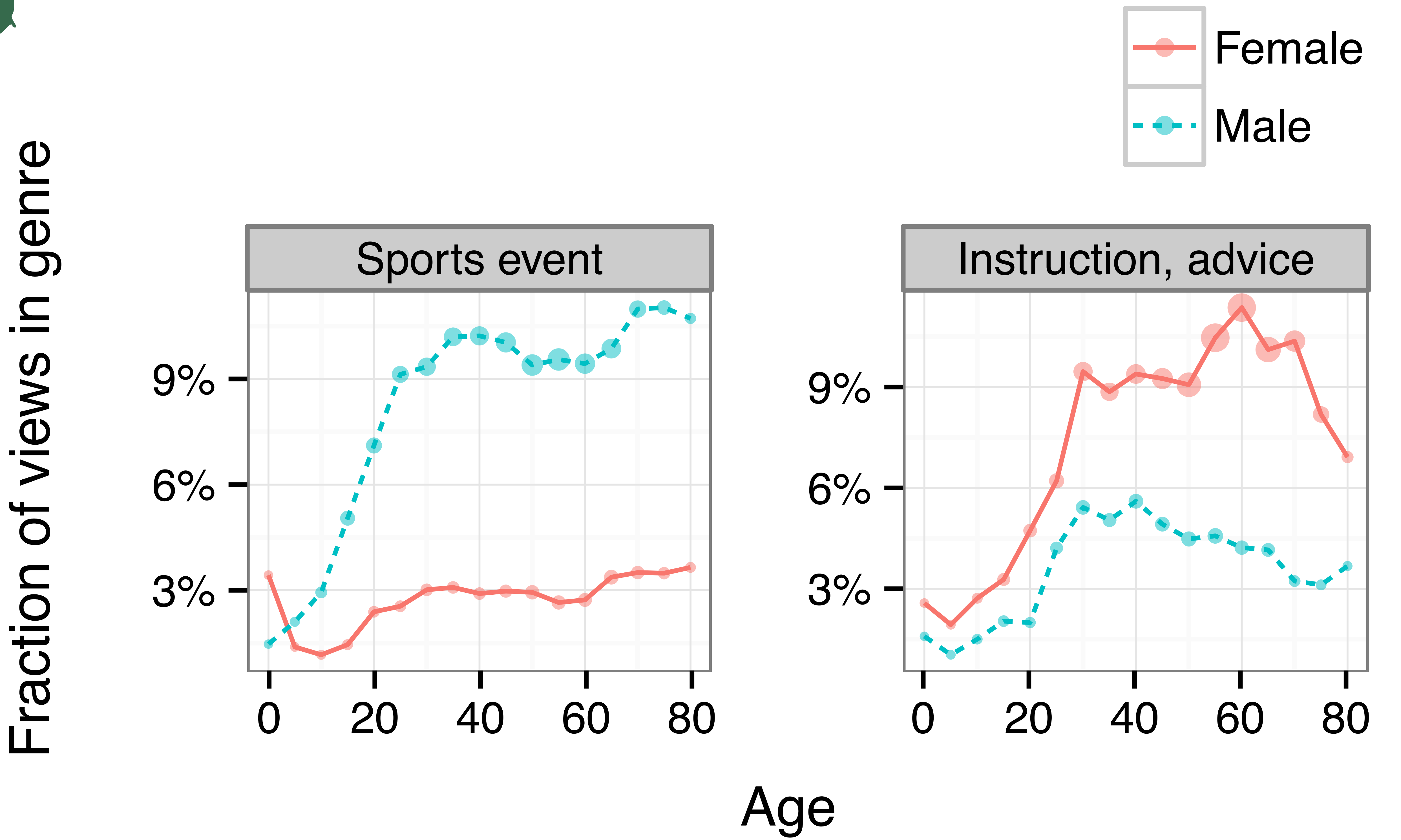
~1.1 million TV program views

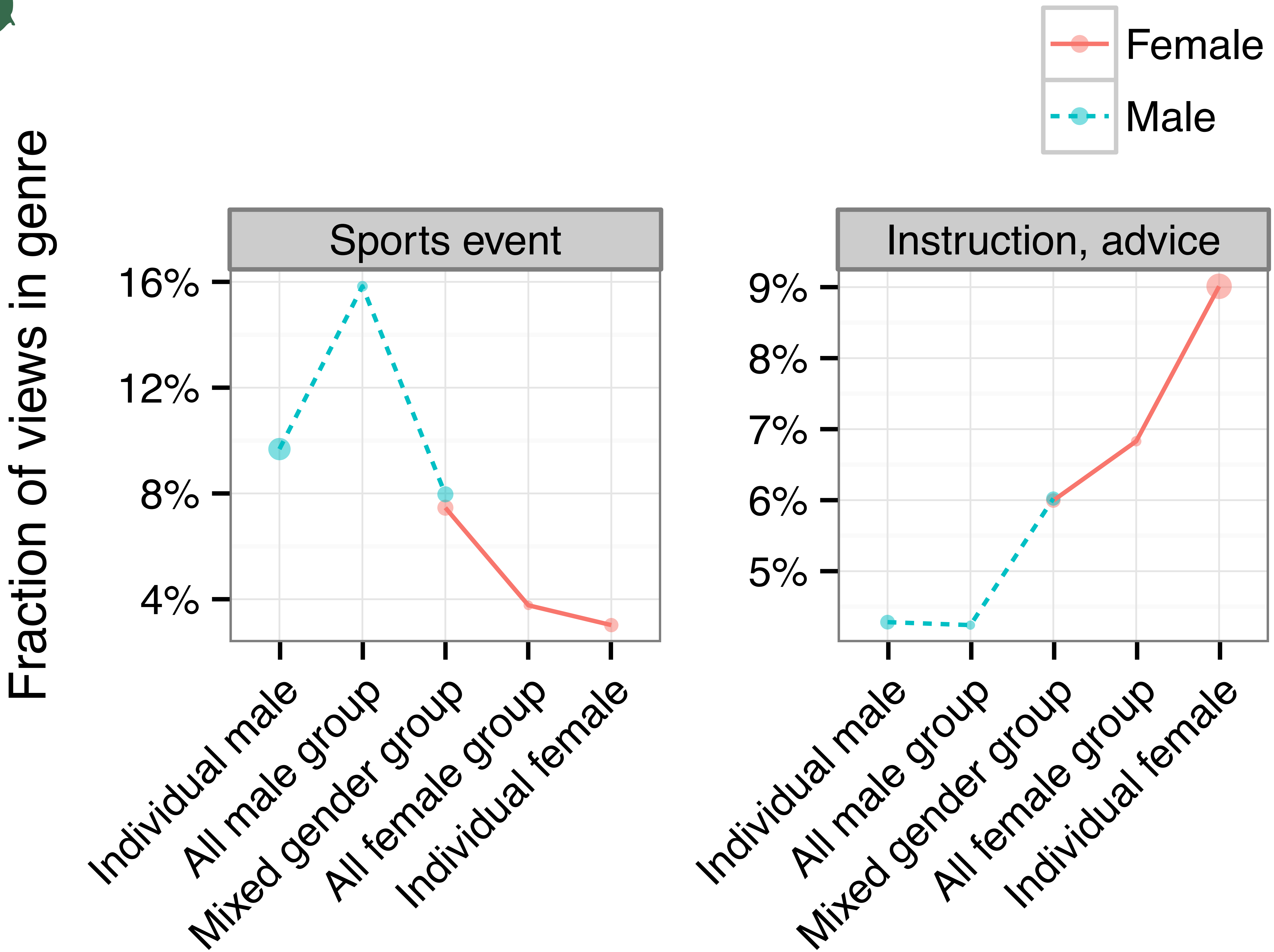
813,615 individual views

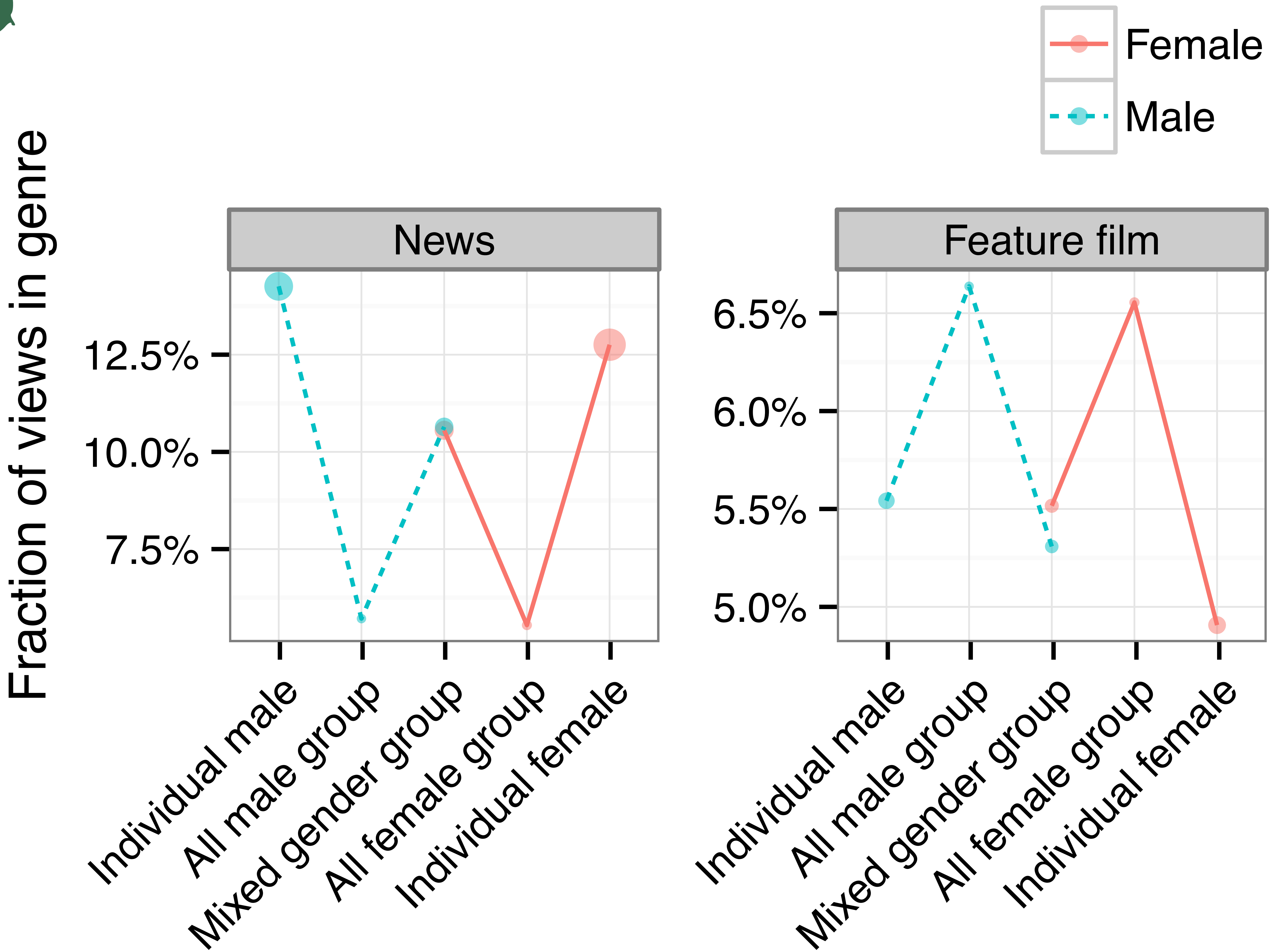
279,546 group views

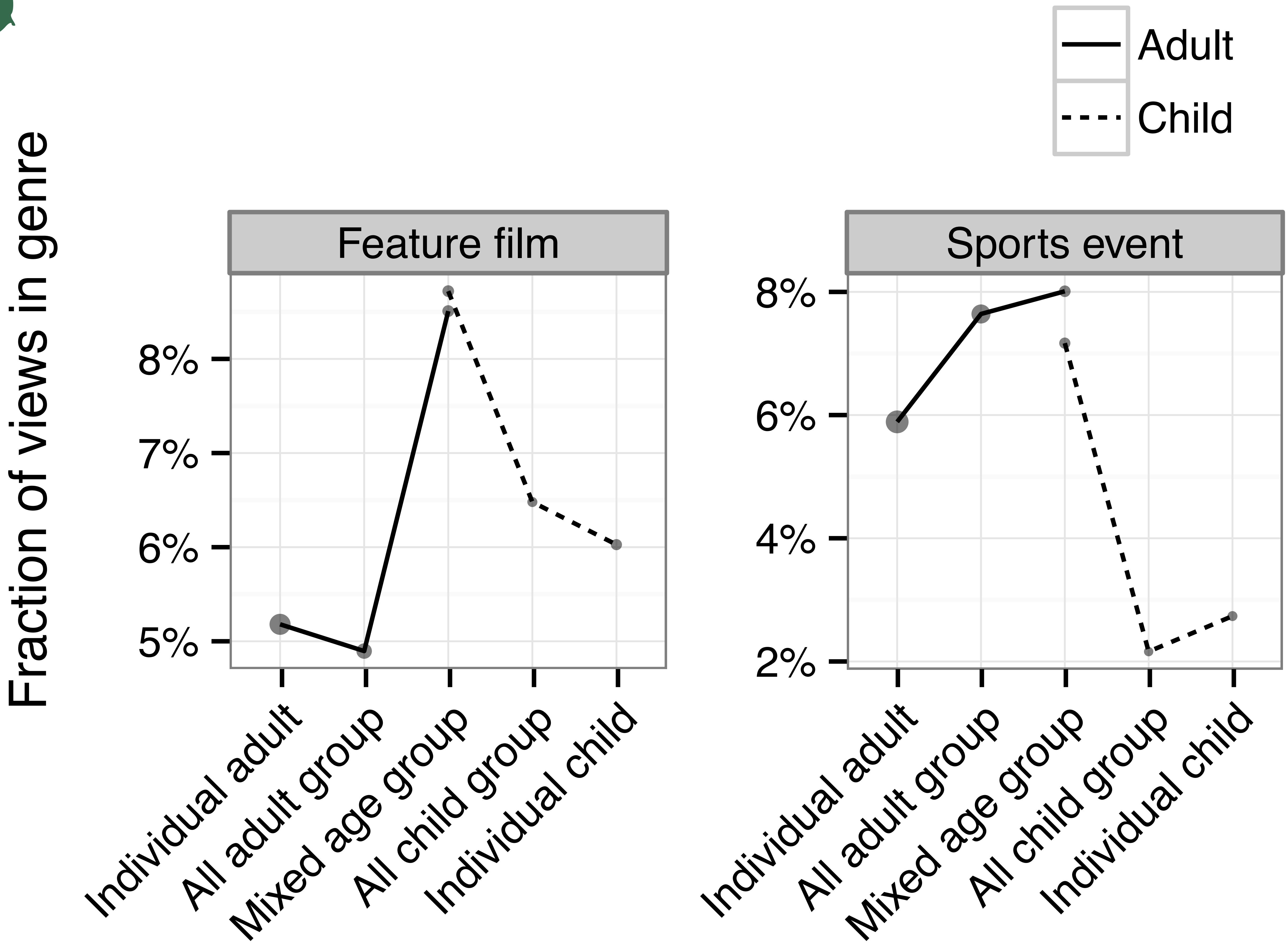


Female
Male
Child multi–weekly
News
Fraction of views in genre
0%
20%
40%
60%
0%
10%
20%
30%
0
20
40
60
80
Age


Female
Male
Sports event
Instruction, advice
9%
6%
3%
0
20
40
60
80
Fraction of views in genre
Age

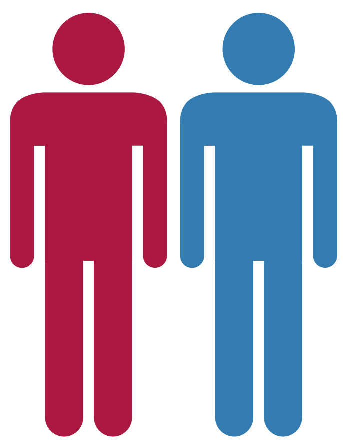

Female
Male
Fraction of views in genre
Sports event
16%
12%
8%
4%
Instruction, advice
9%
8%
7%
6%
5%
Individual male
All male group
Mixed gender group
All female group
Individual female
Individual male
All male group
Mixed gender group
All female group
Individual female


Female
Male
Fraction of views in genre
News
12.5%
10.0%
7.5%
Individual male
All male group
Mixed gender group
All female group
Individual female
Feature film
6.5%
6.0%
5.5%
5.0%
Individual male
All male group
Mixed gender group
All female group
Individual female

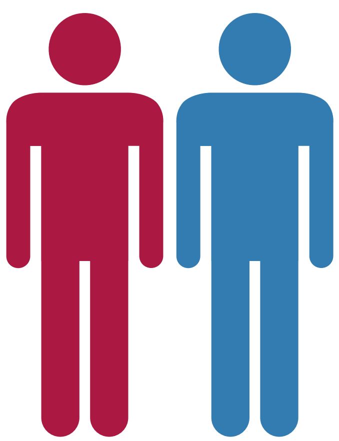


Adult
Child
Fraction of views in genre
Feature film
8%
7%
6%
5%
Sports event
8%
6%
4%
2%
Individual adult
All adult group
Mixed age group
All child group
Individual child
Individual adult
All adult group
Mixed age group
All child group
Individual child

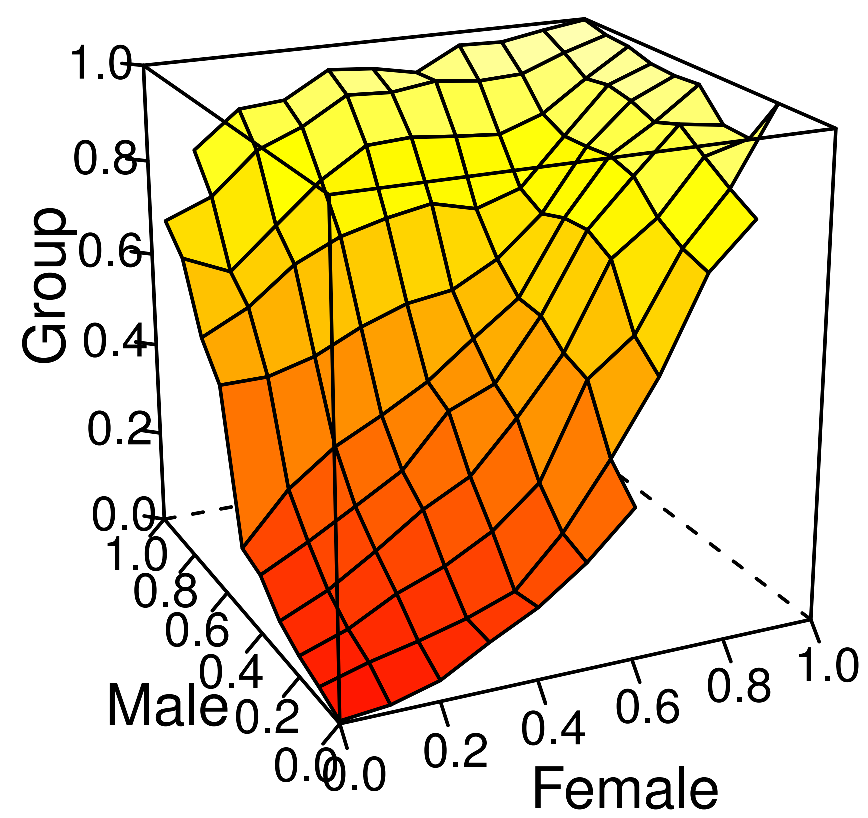
two-person mixed-gender adult groups



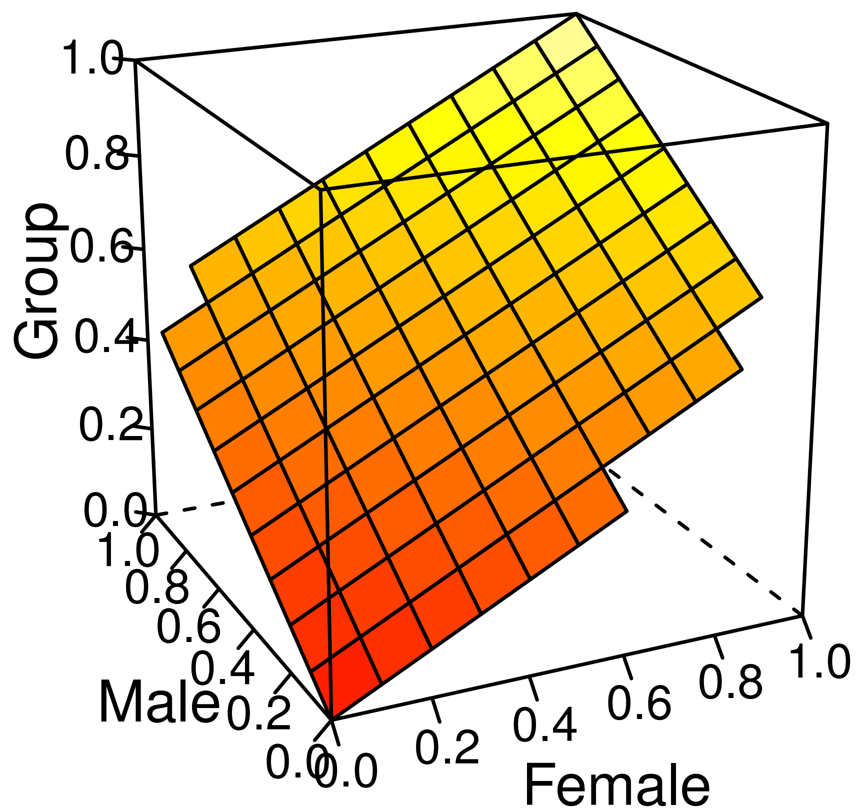
two-person mixed-gender adult groups



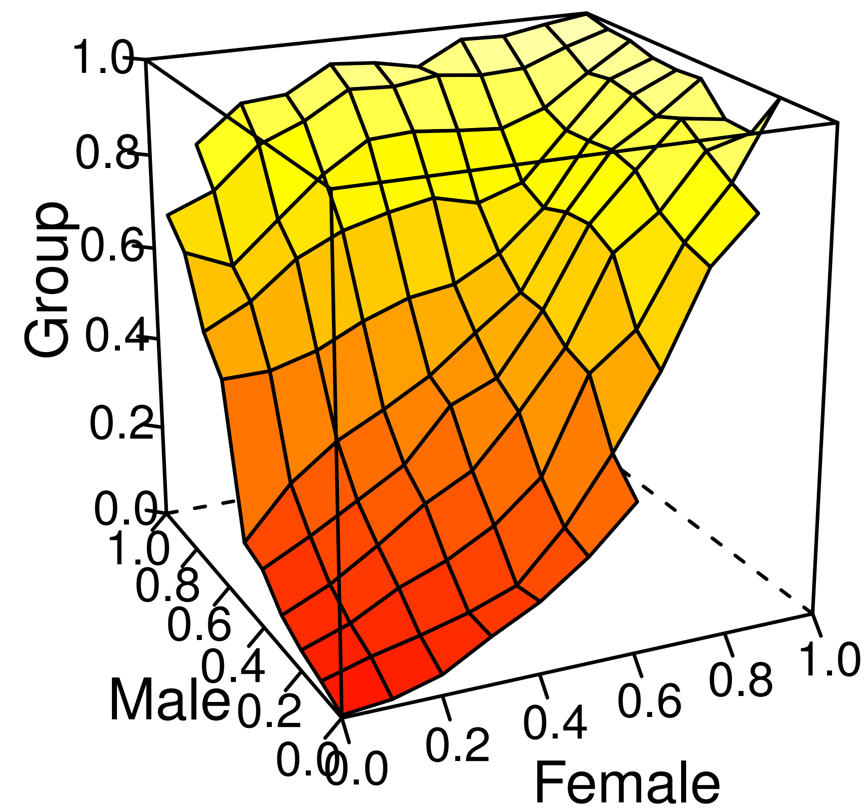
empirical

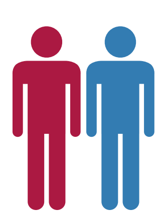
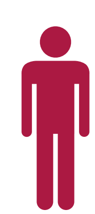


average satisfaction

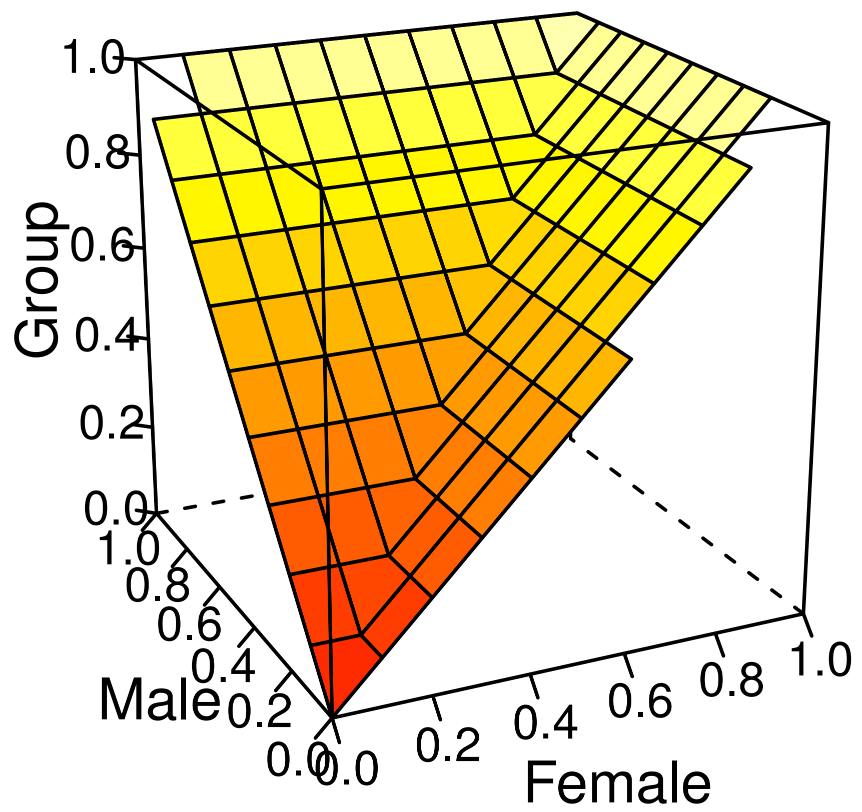


empirical

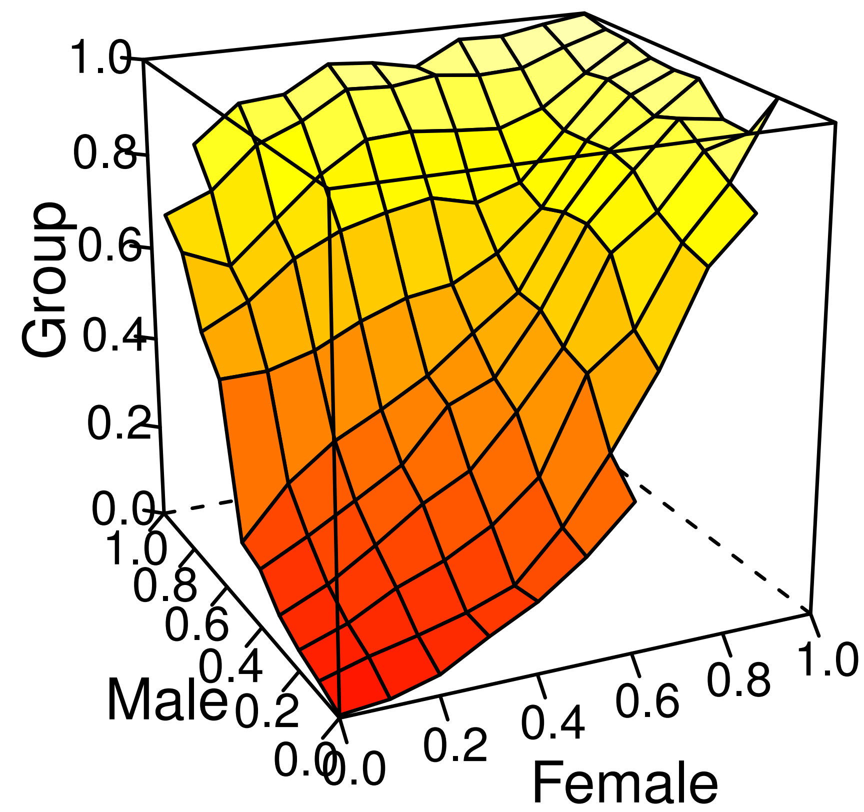


 = mean( , )

maximum satisfaction



empirical



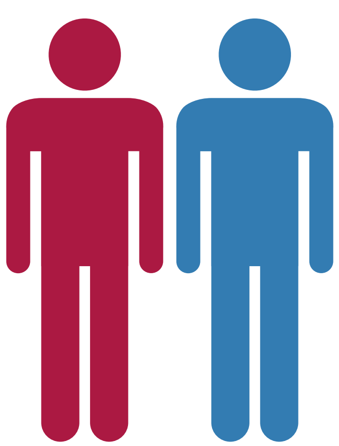
group view model

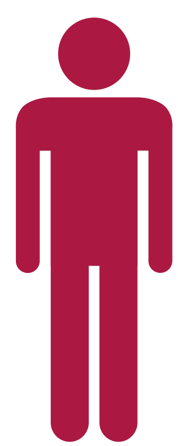
Probability of **group** view

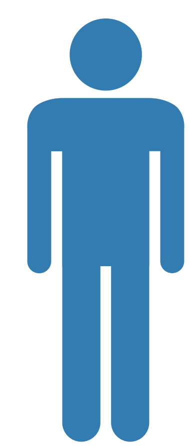
Probability of **female** individual view

Probability of **male** individual view

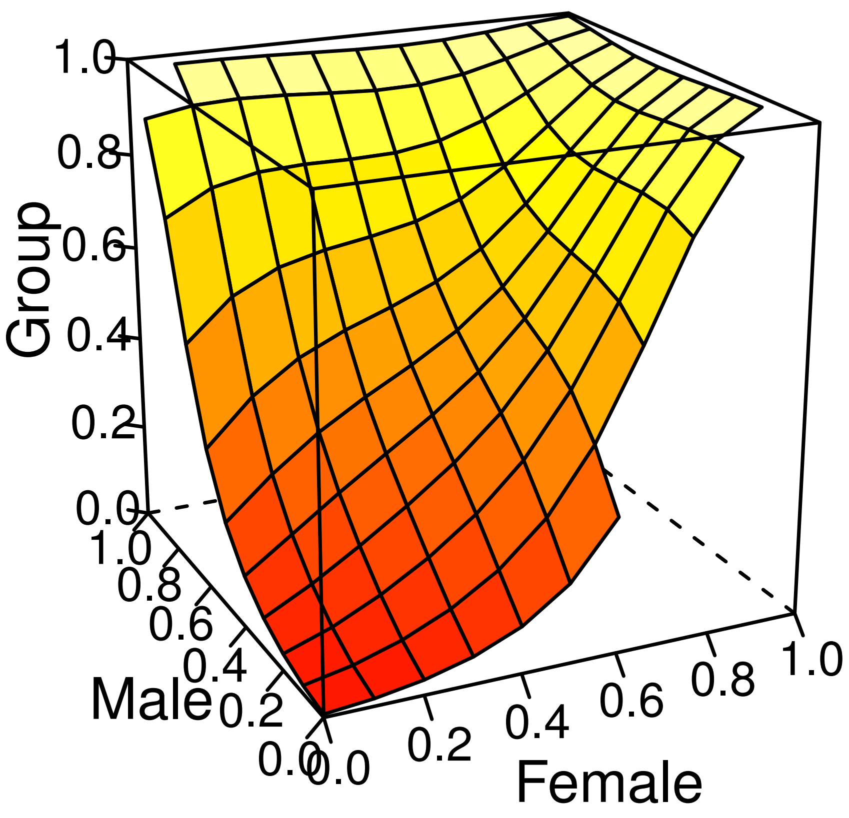
$$\log \frac{p_G}{1 - p_G} = \alpha_0 + \alpha_f p_f + \alpha_m p_m + \beta_f p_f^2 + \beta_m p_m^2 + \gamma_f p_f^3 + \gamma_m p_m^3 + \delta p_f p_m$$



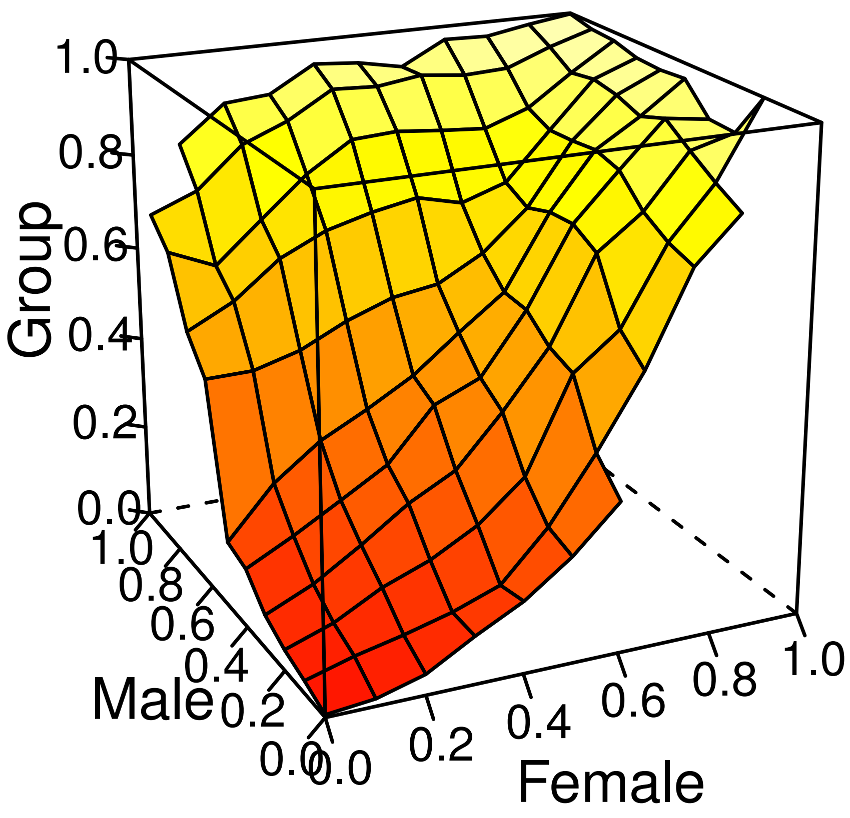




group view model



empirical



evaluation on random 20% held out data

	AUC
average satisfaction	82.7%
maximum satisfaction	82.9%
group view model	**83.1%**

Chameleon Preferences

How do the
decisions people make
depend on the
people around them?

Chameleon Preferences

social influence has complex effects on the way people express **preferences**

Chameleon Preferences

viewing habits shift substantially between **individual** and **group** contexts

groups display markedly different aggregate **preferences** depending on their **demographics**

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How do people decide what choices to make?

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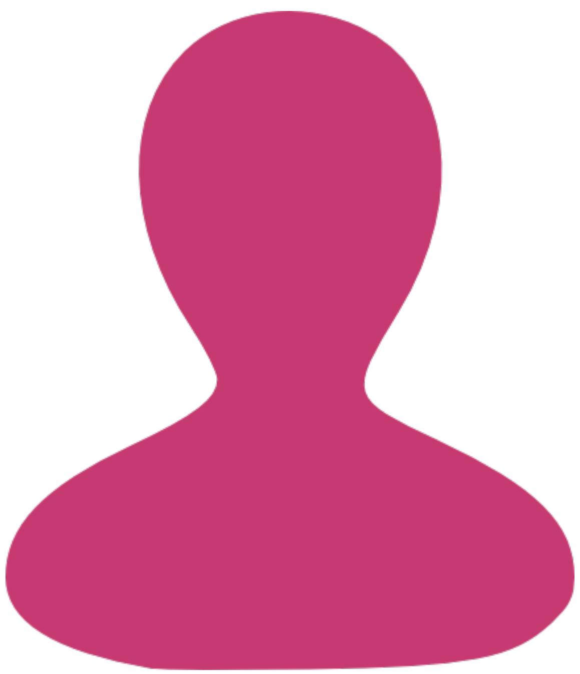
A probabilistic model for using social networks in personalized item recommendation. Chaney, Blei, Eliassi-Rad. ACM RecSys, 2015.

Personalized Item Recommendation



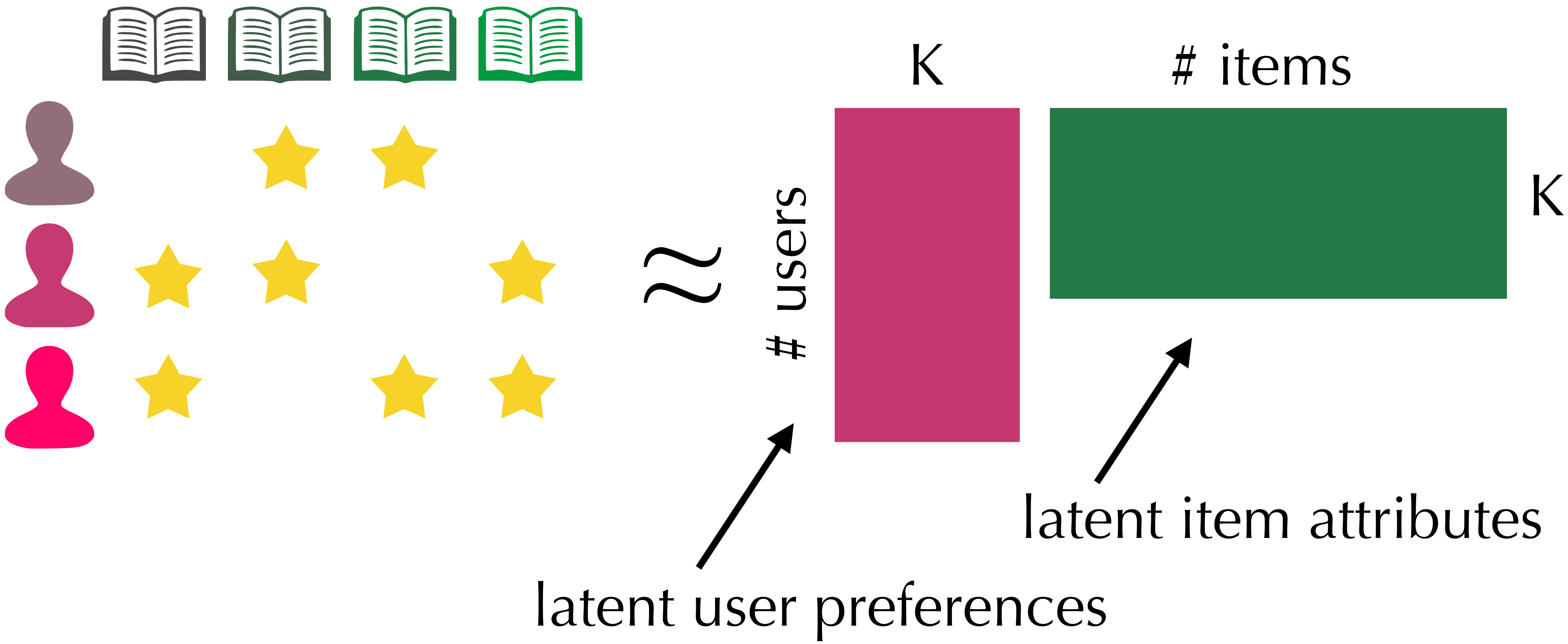
Anna Karenina

Winter’s Tale

East of Eden

???

Matrix Factorization



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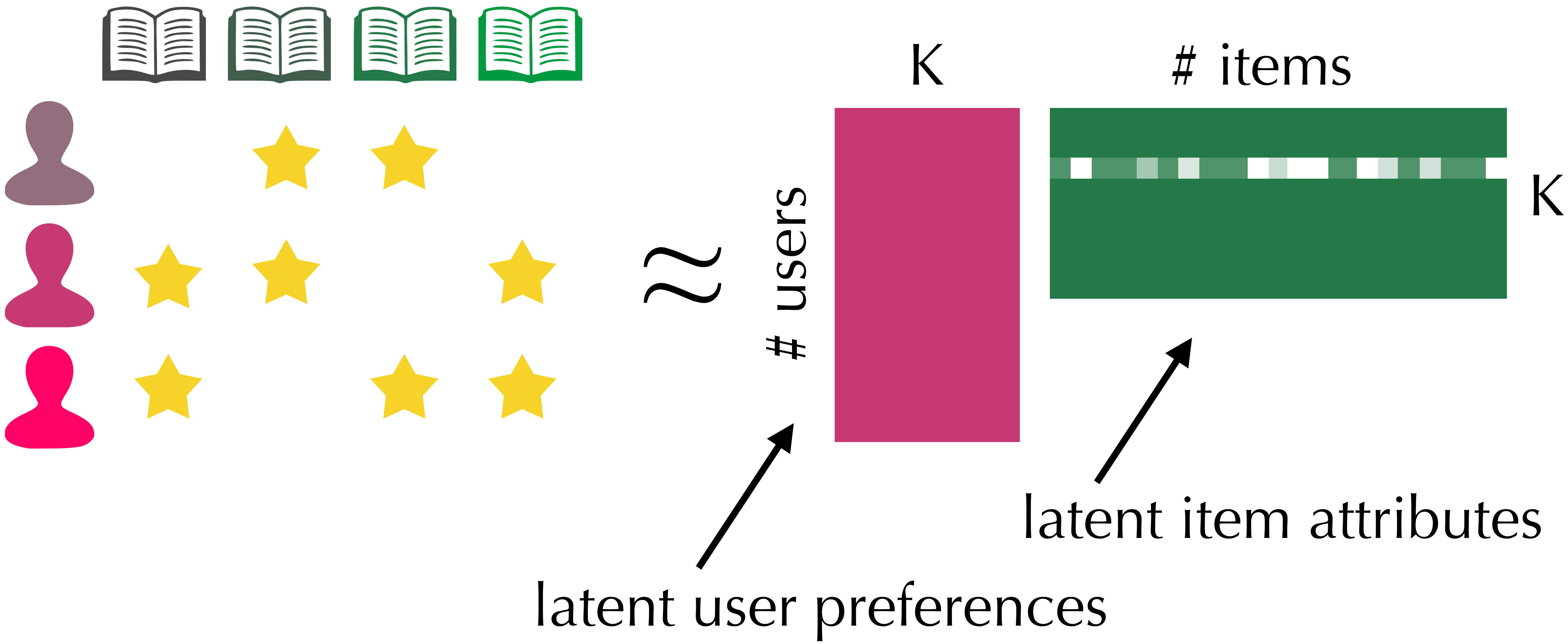

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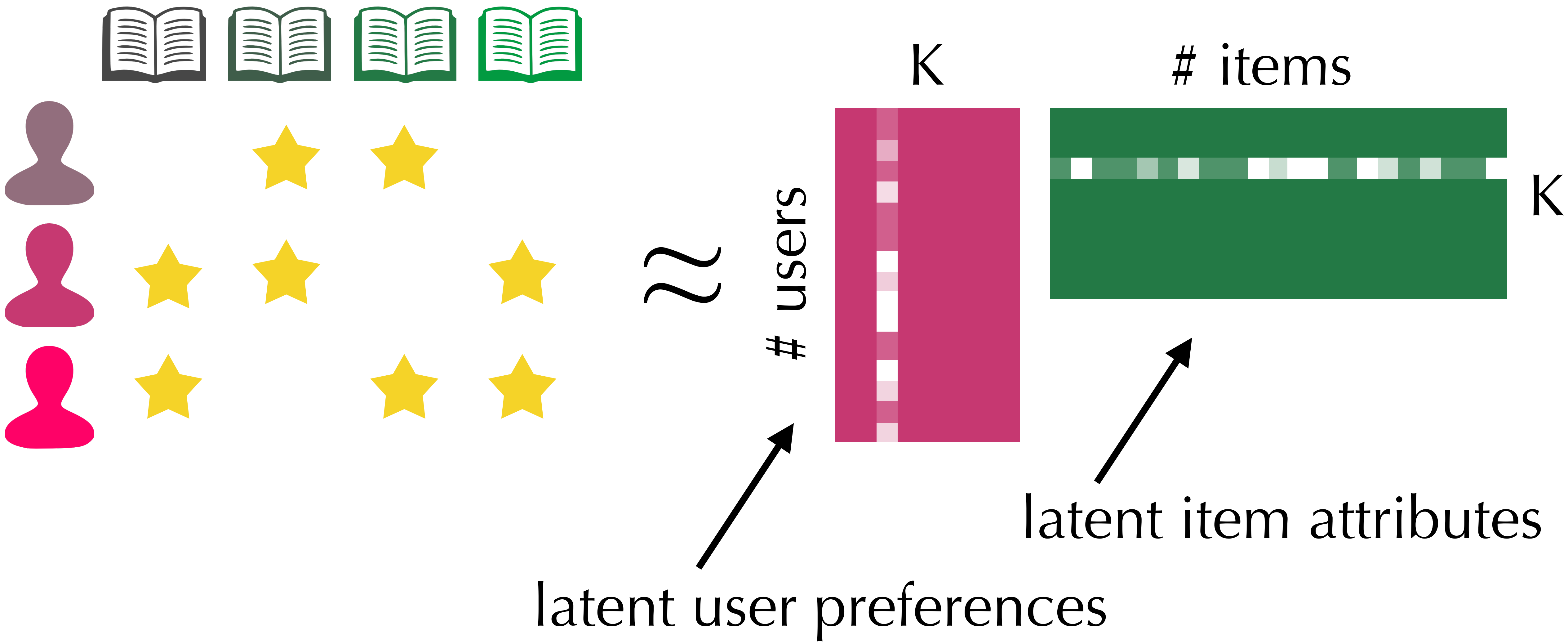
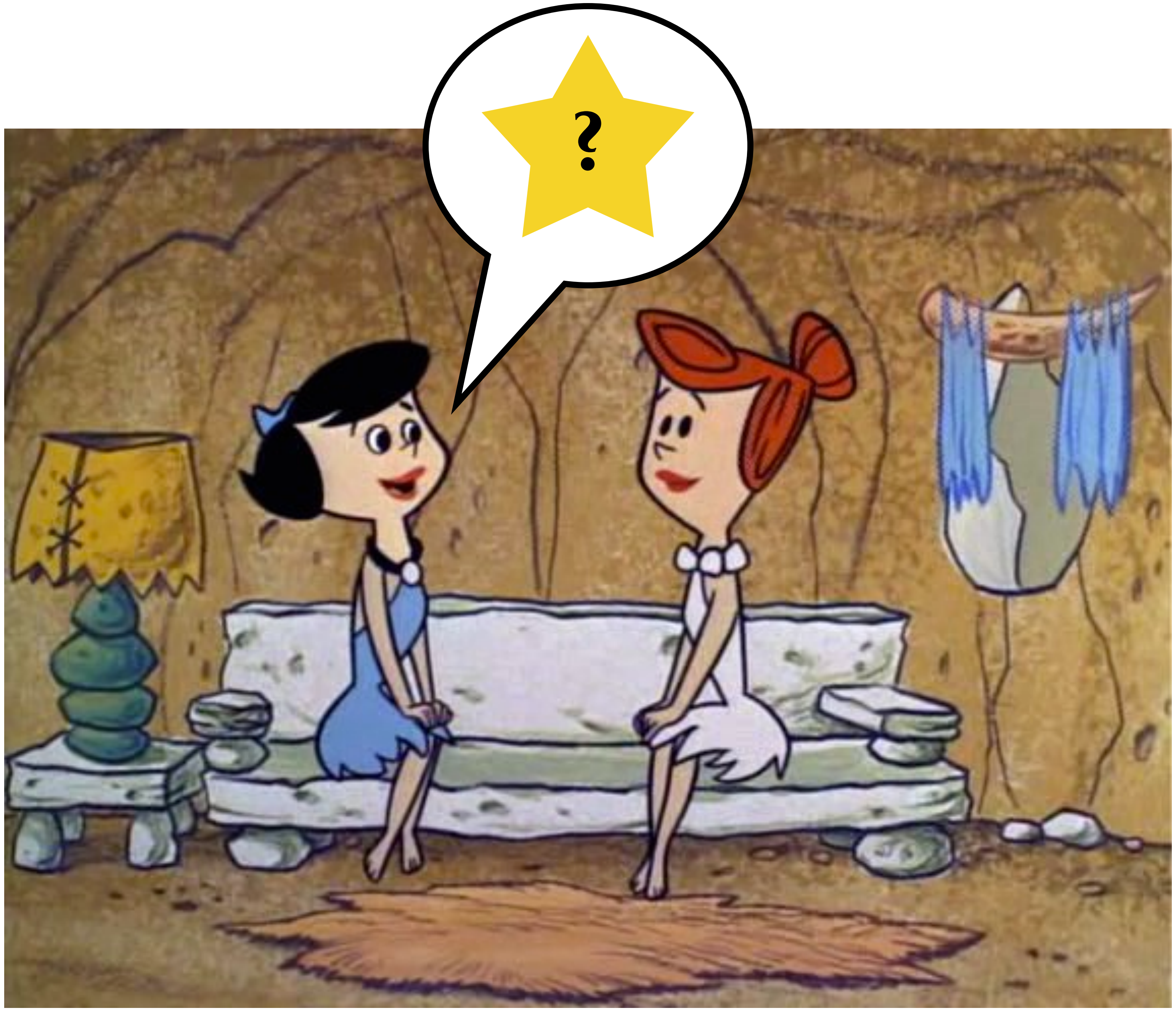


Including Social Networks



Other Methods for Including Social Networks

SoRec	SoRec: Social Recommendation Using Probabilistic Matrix Factorization. Ma et al., SIGIR, 2008.
RSTE	Learning to Recommend with Social Trust Ensemble. Ma et al., SIGIR, 2009.
SocialMF	A Matrix Factorization Technique with Trust Propagation for Recommendation in Social Networks. Jamali and Ester, RecSys, 2010.
TrustMF	Social Collaborative Filtering by Trust. Yang et al., IJCAI, 2013.
TrustSVD	TrustSVD: Collaborative Filtering with Both the Explicit and Implicit Influence of User Trust and of Item Ratings. Guo et al., AAAI, 2015.

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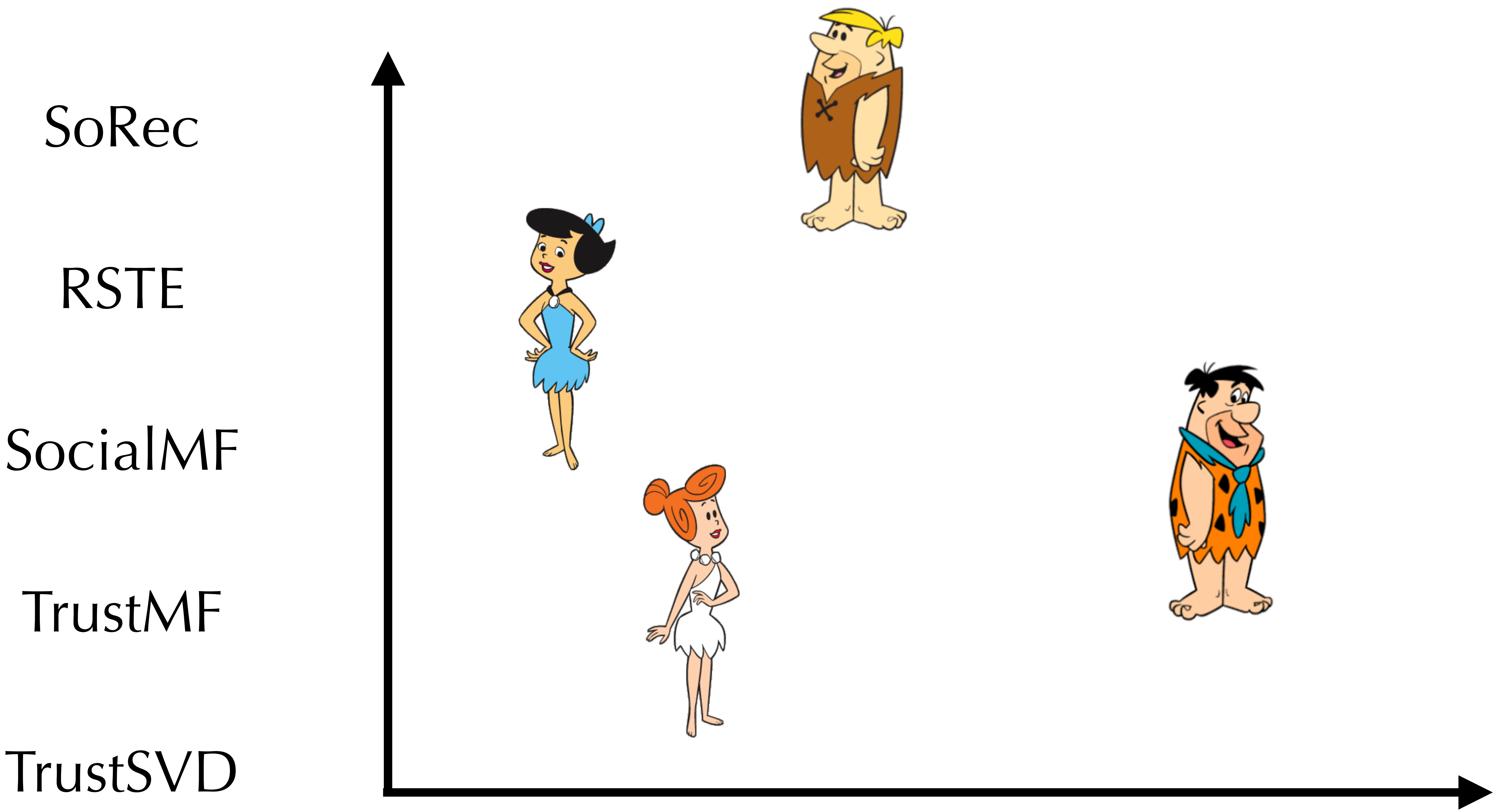

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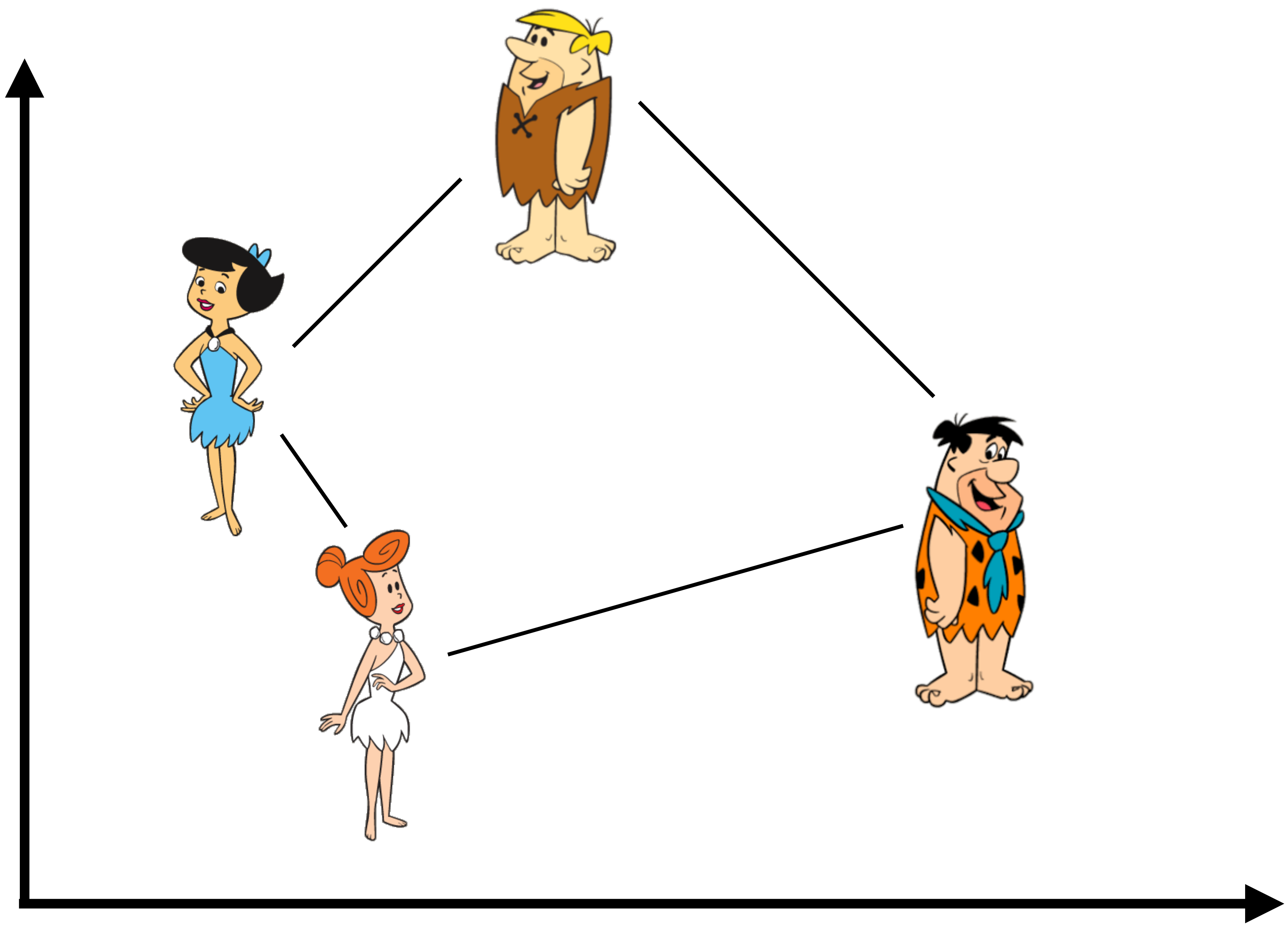
TrustSVD



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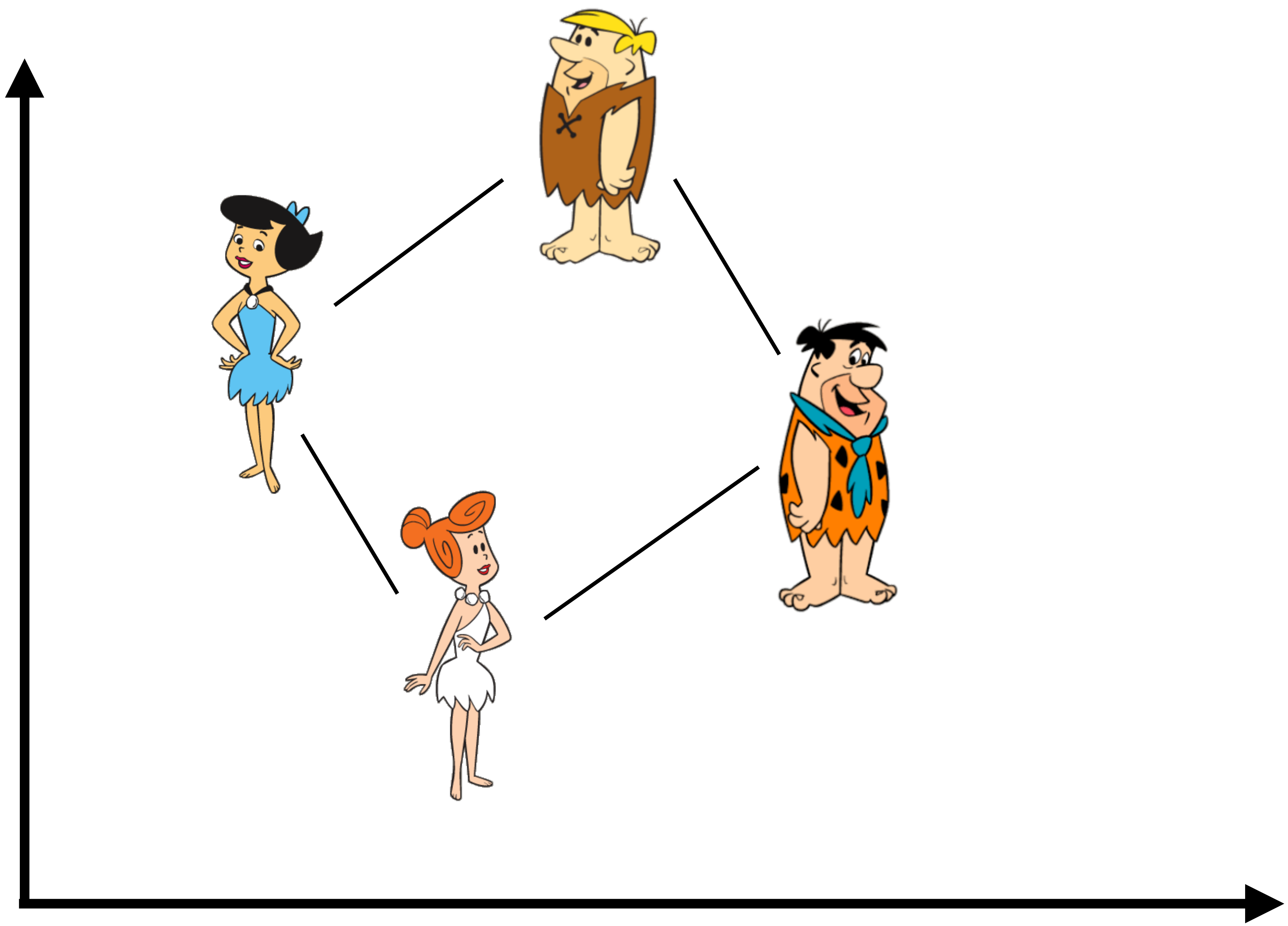

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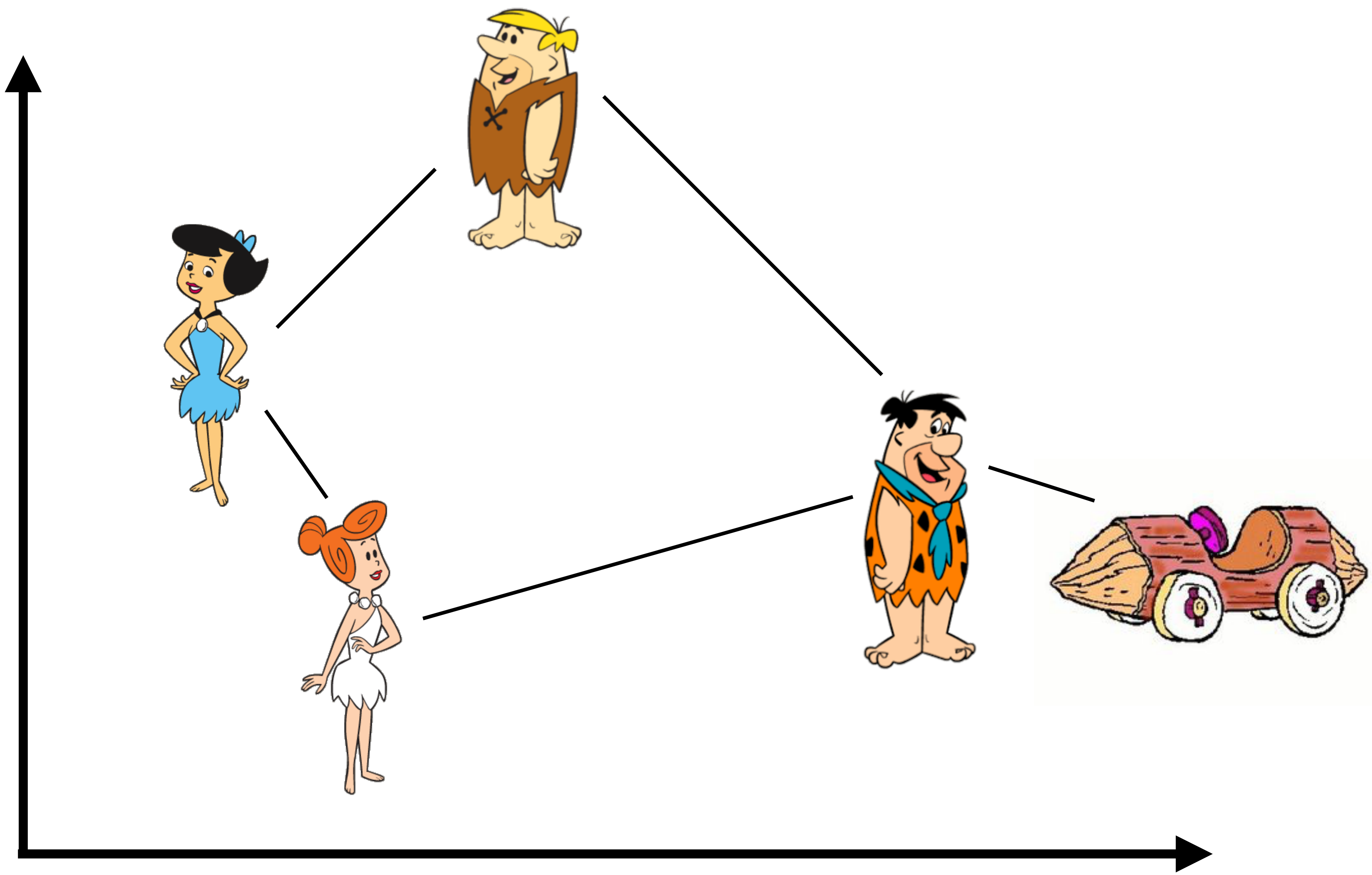

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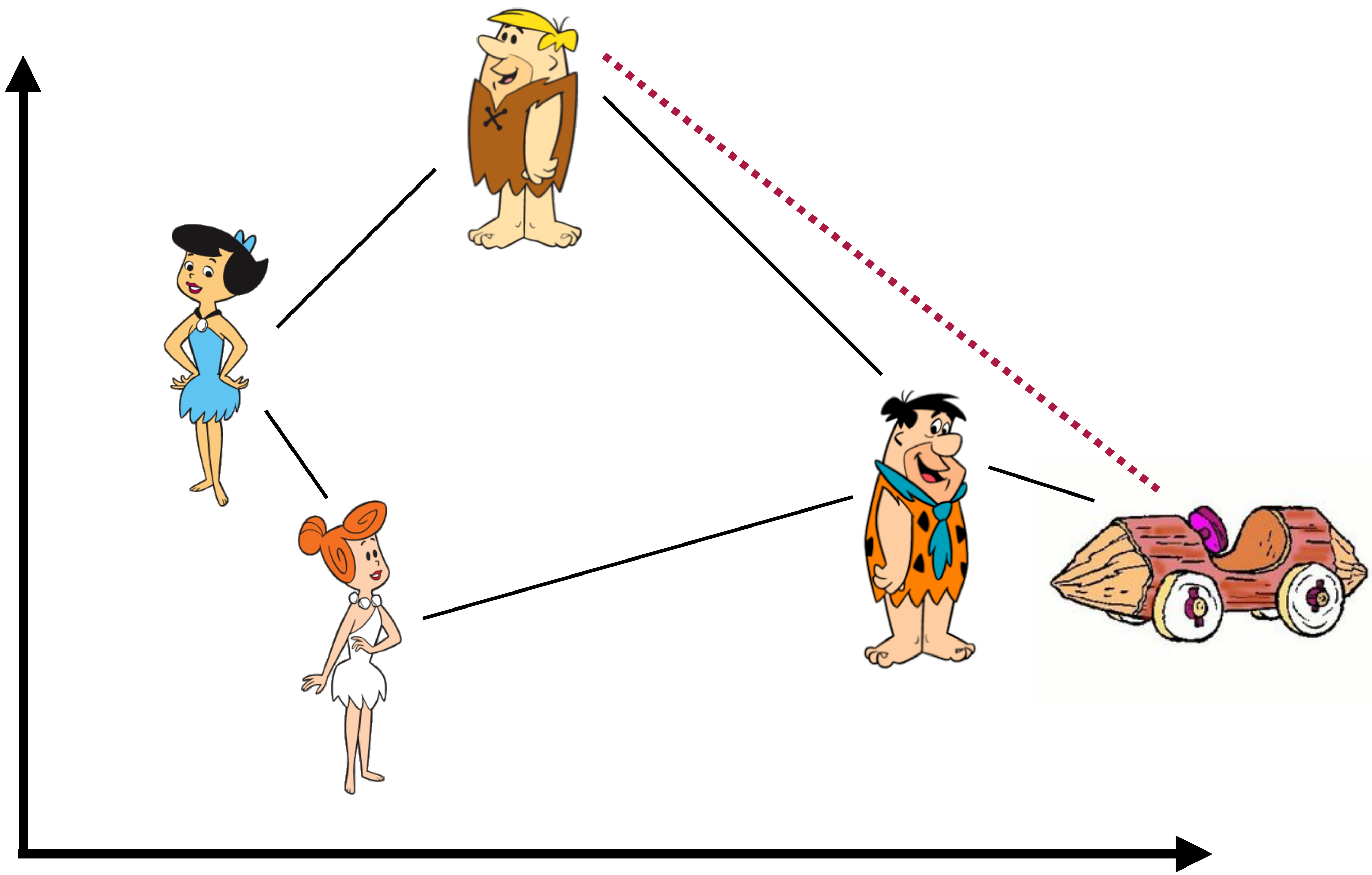

An Example Etsy User

An Example Etsy User

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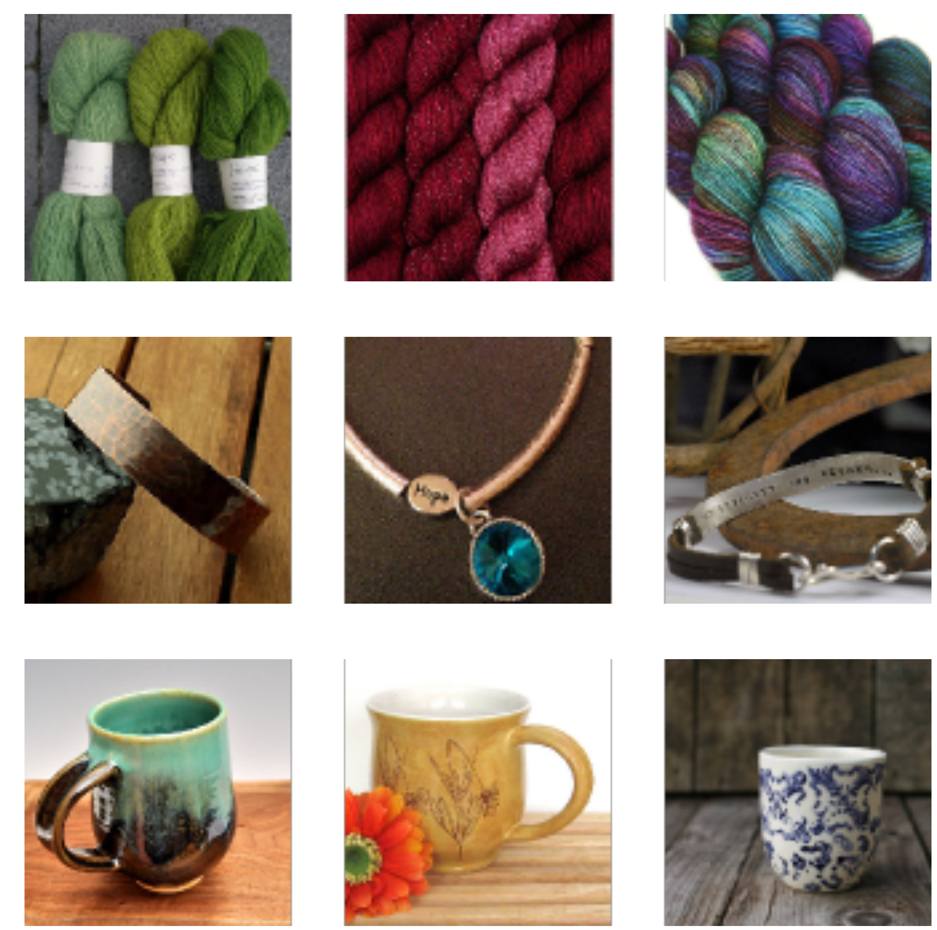

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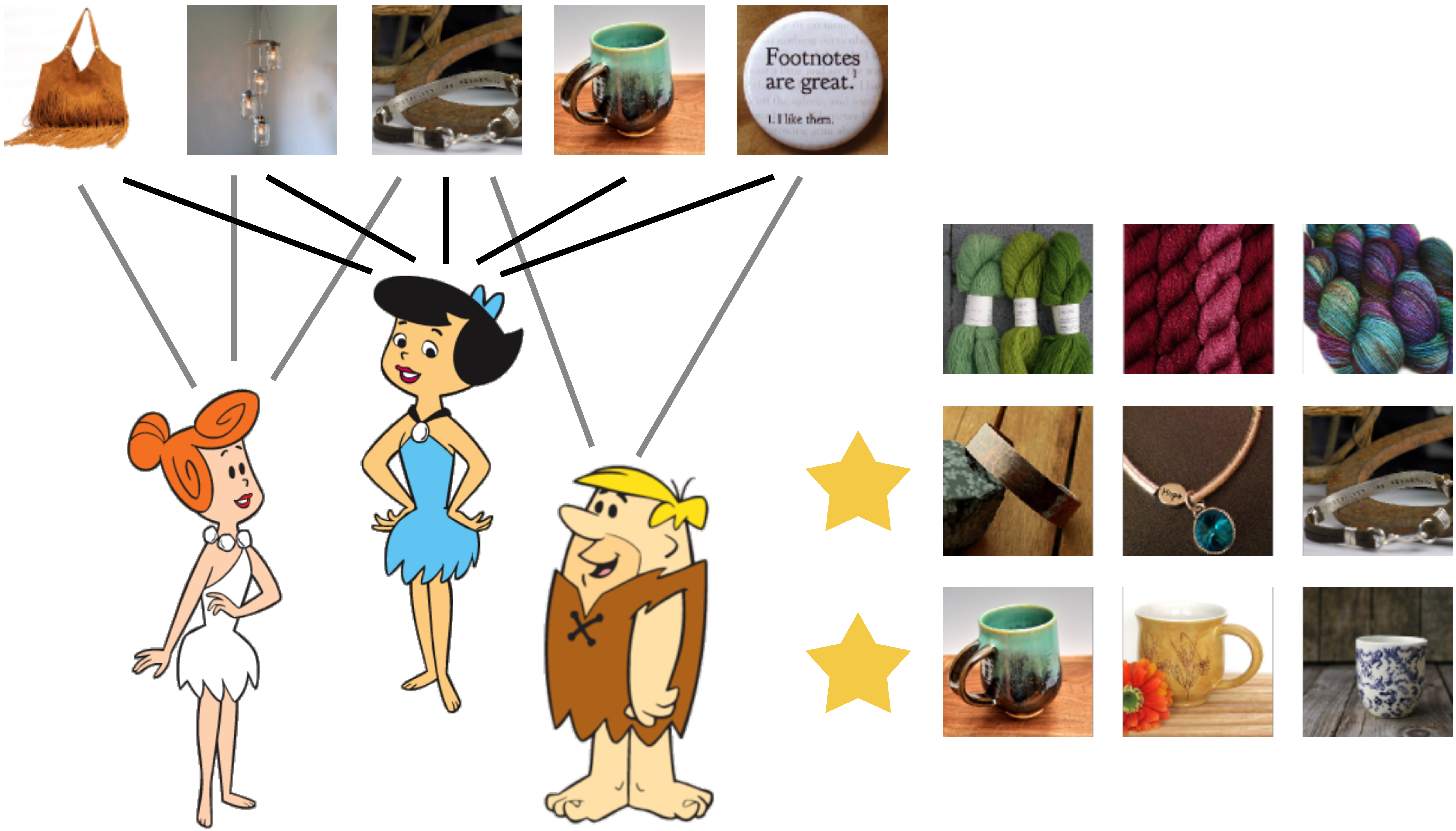

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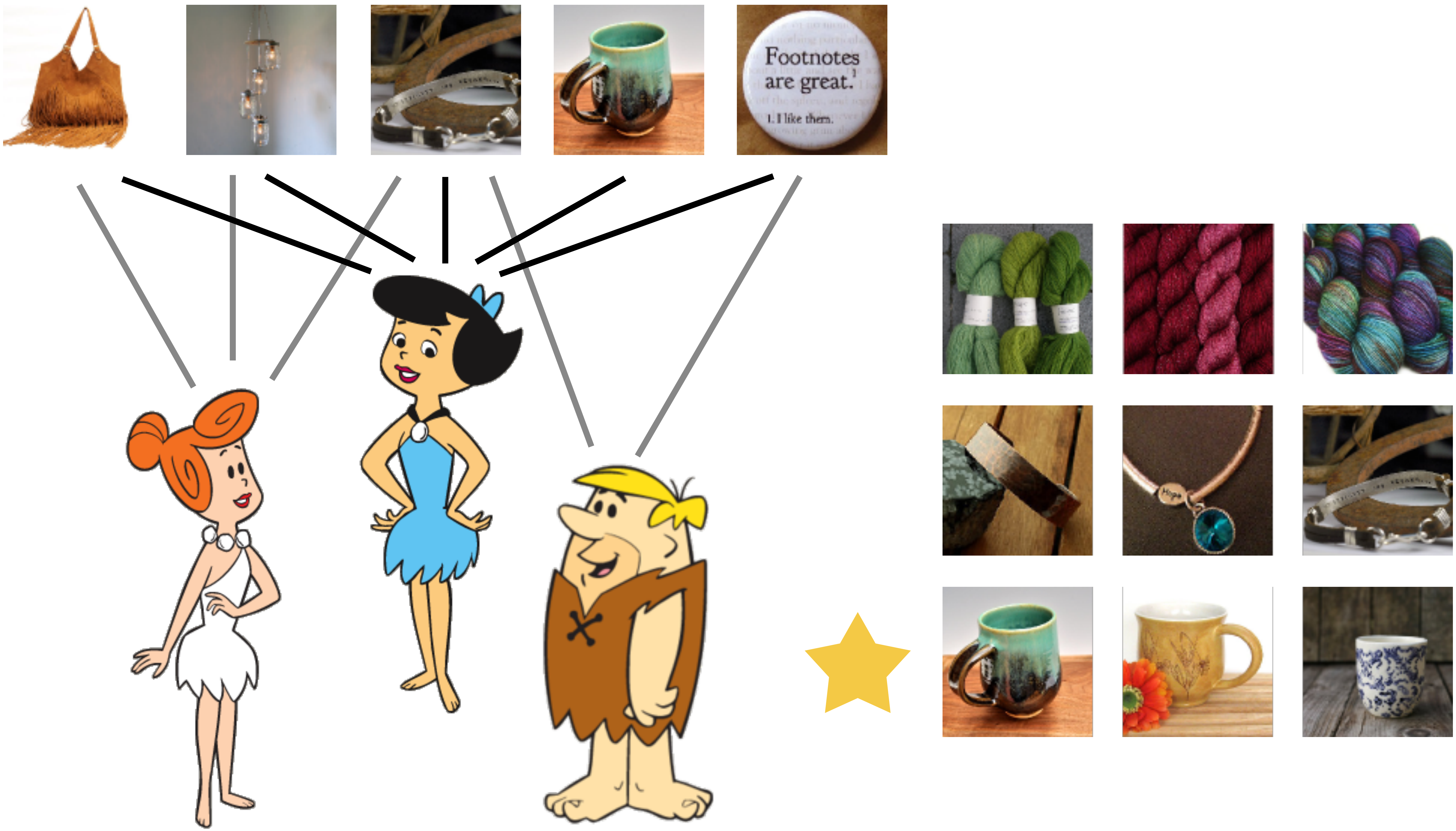

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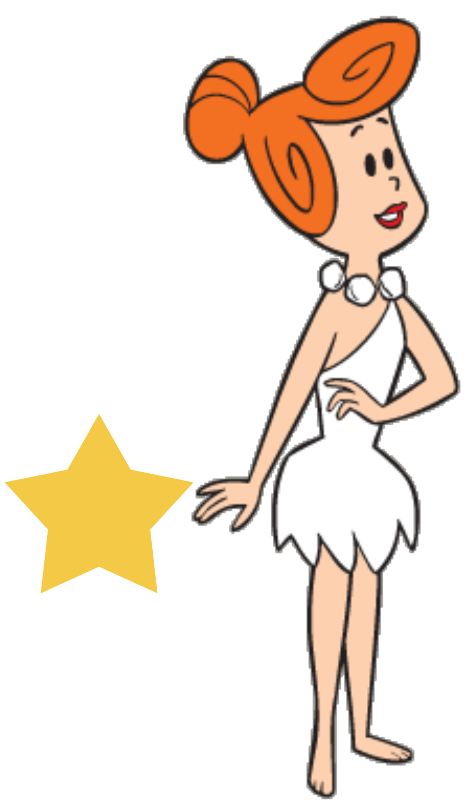




An Example Etsy User








An Example Etsy User

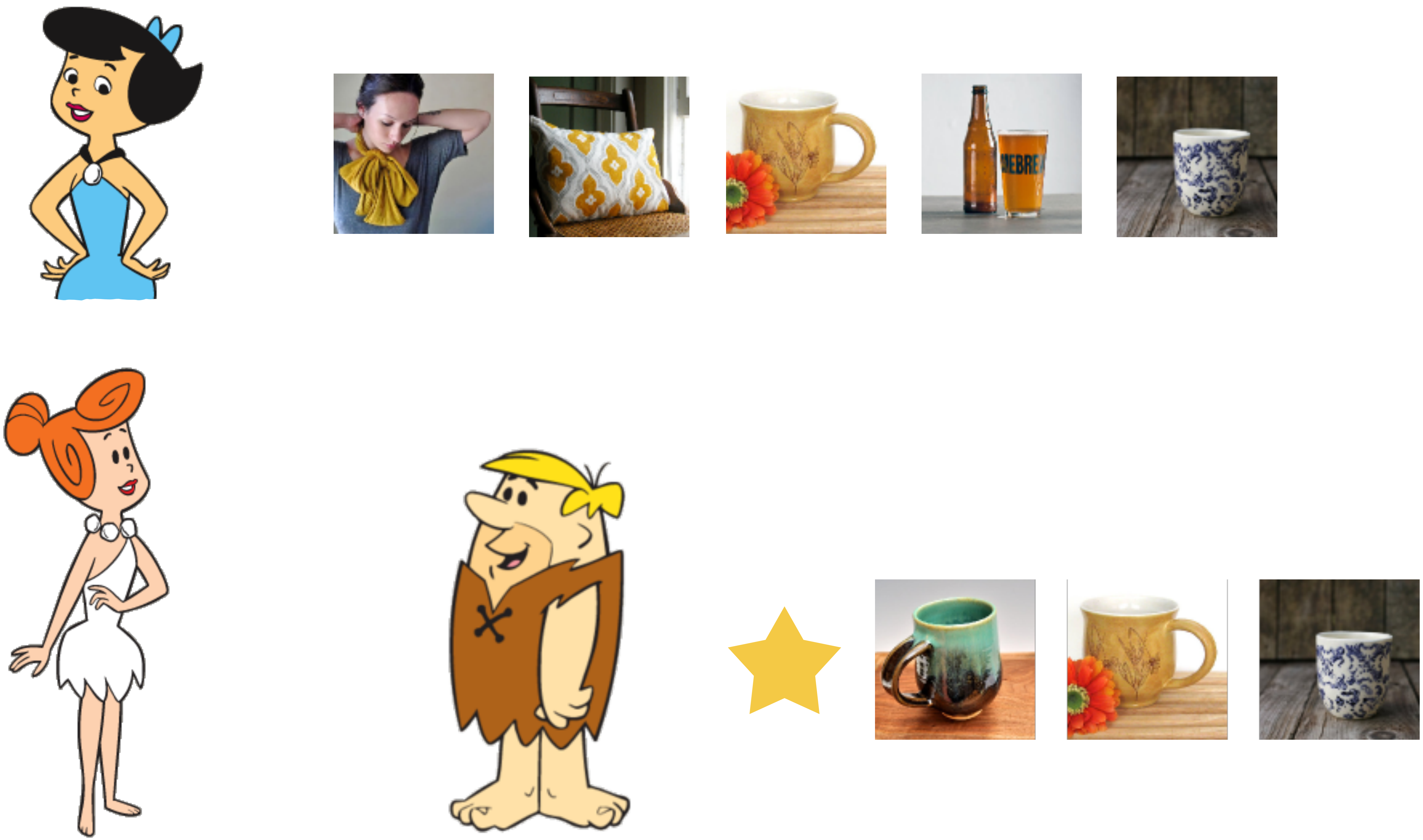









An Example Etsy User



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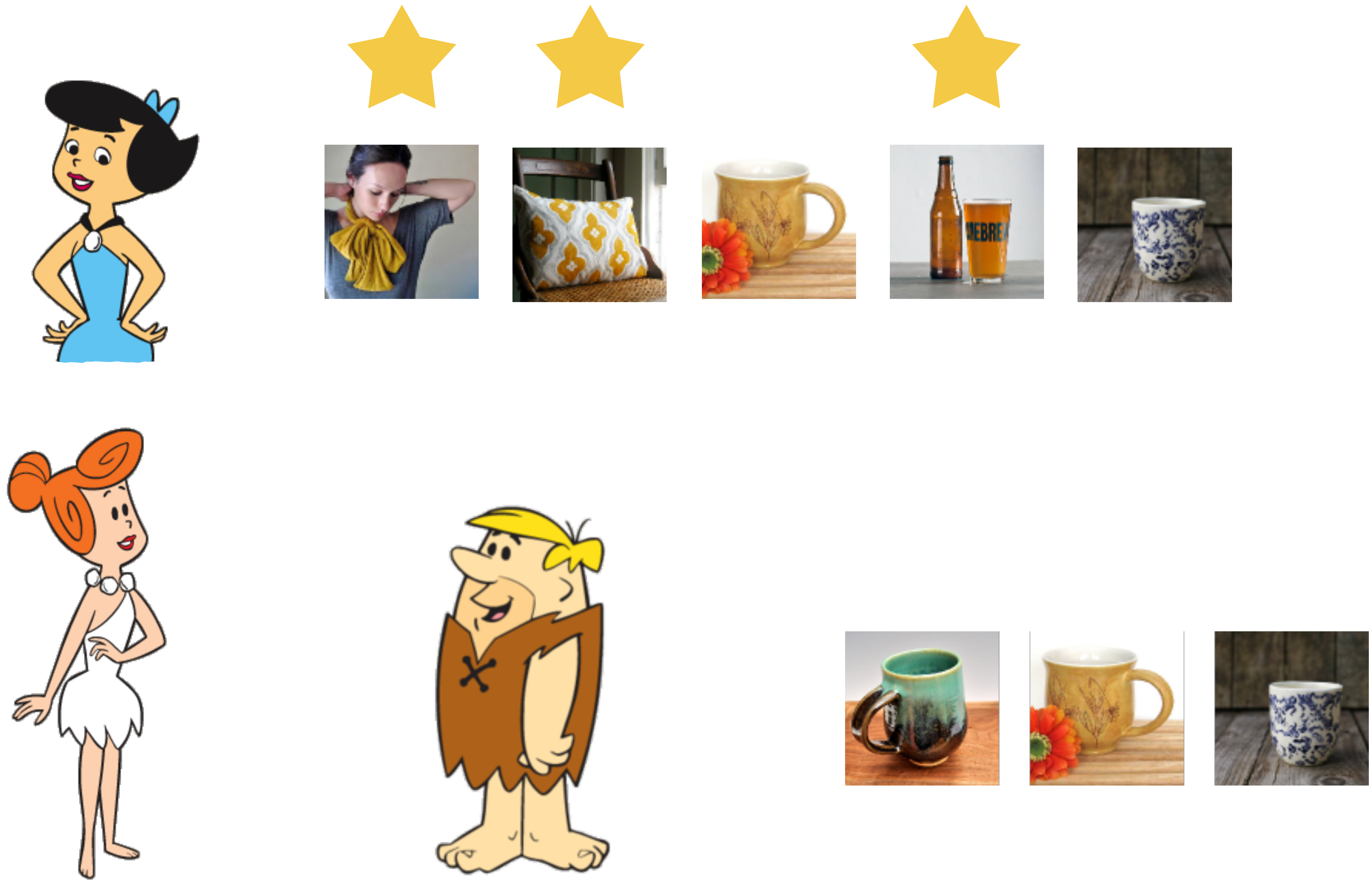
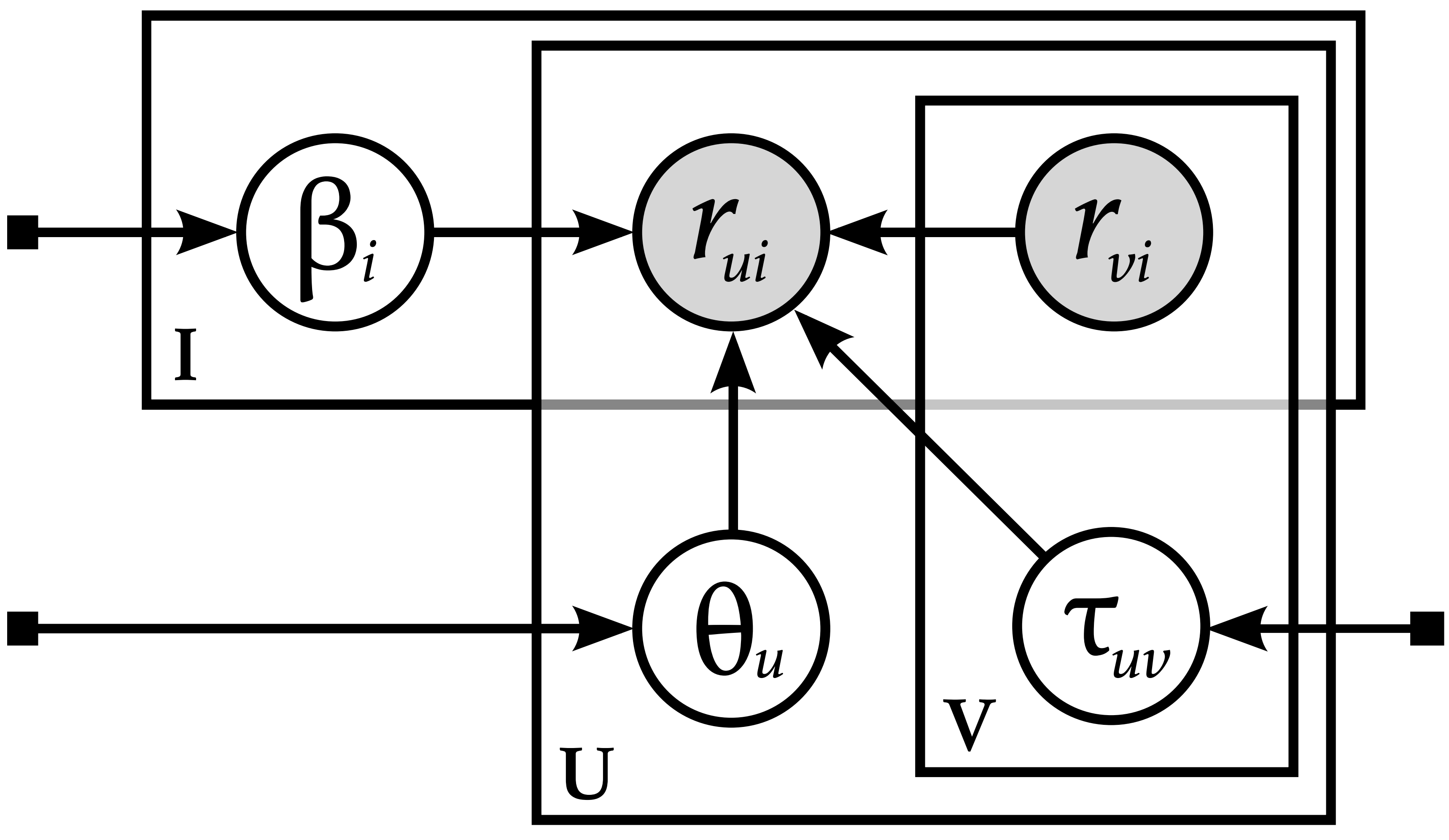
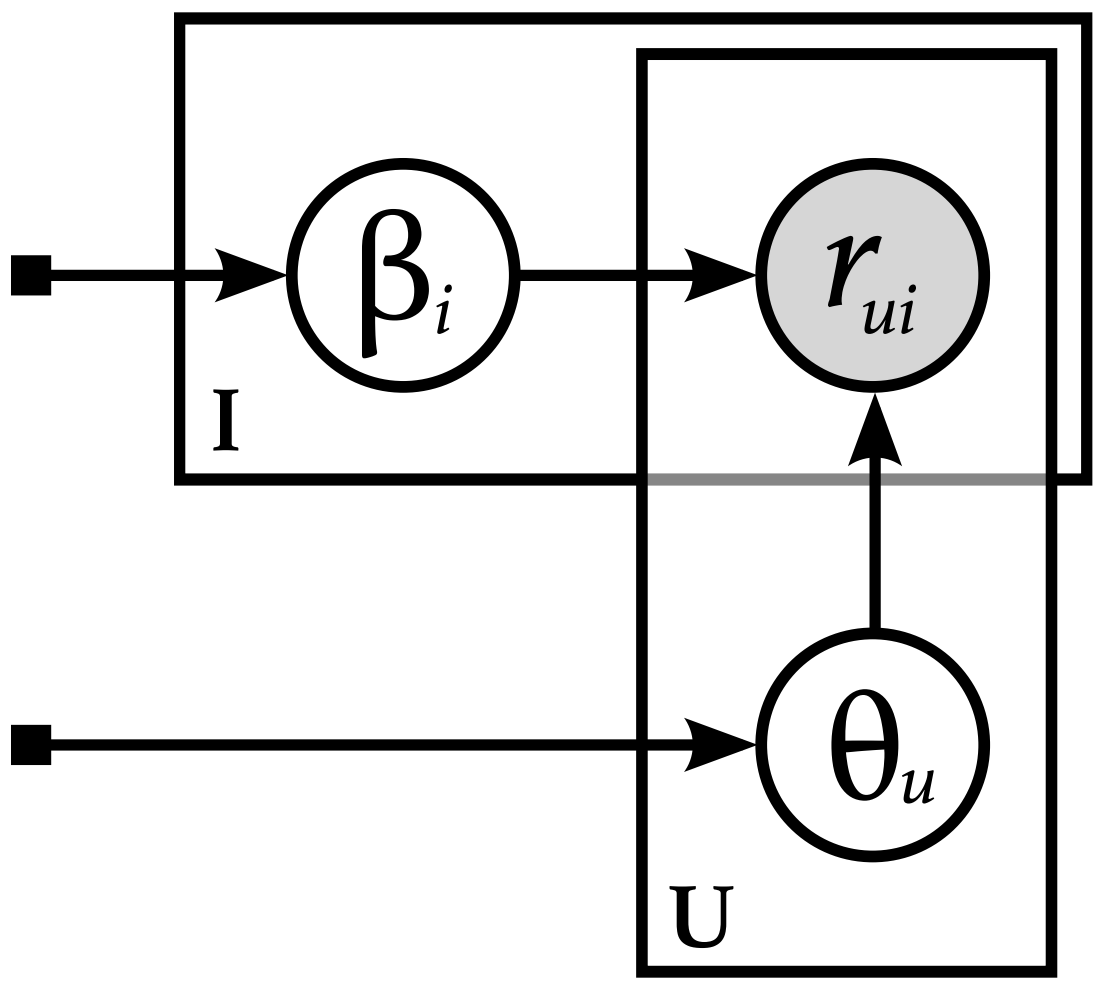


Social Poisson Factorization



Matrix Factorization



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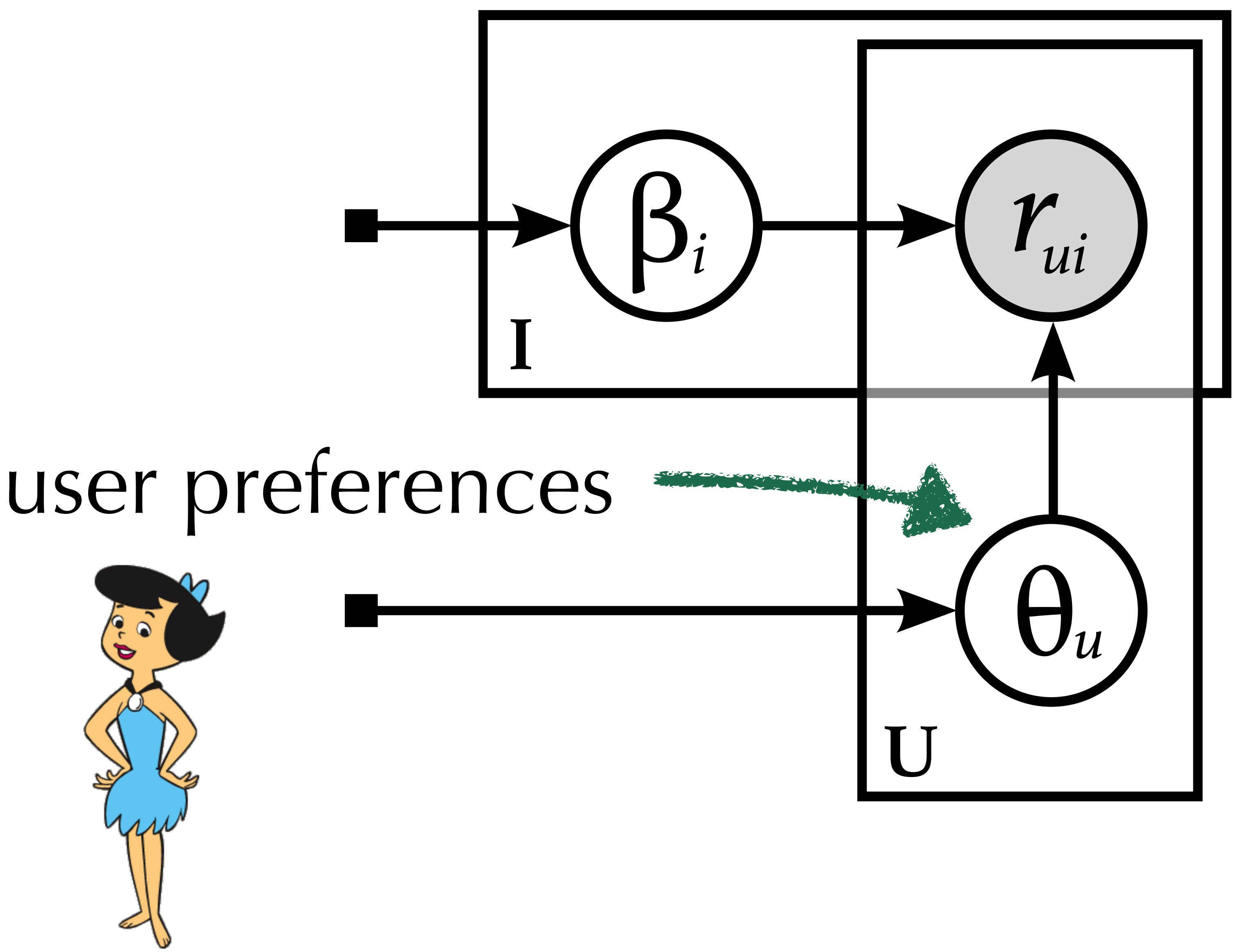

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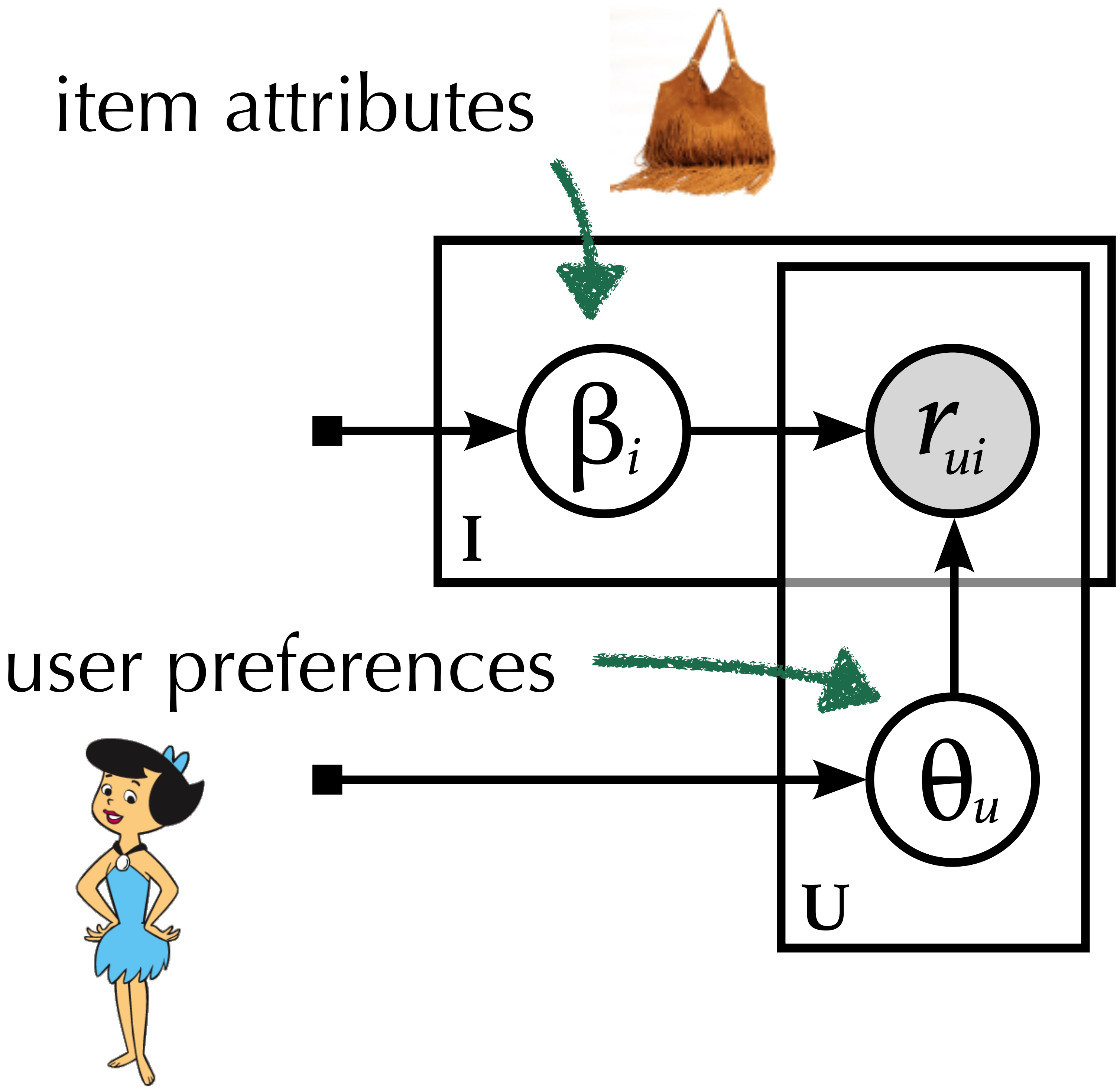

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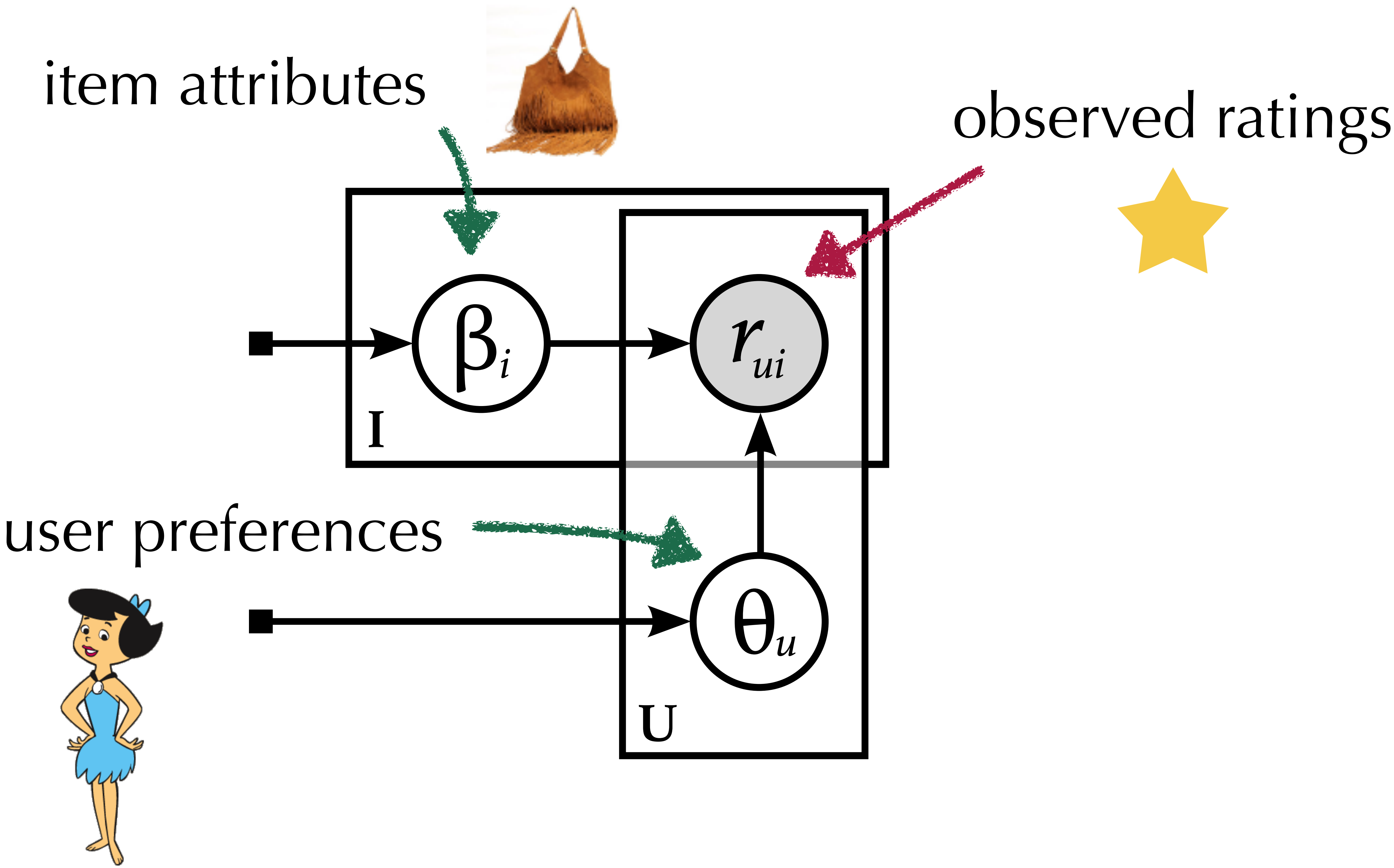
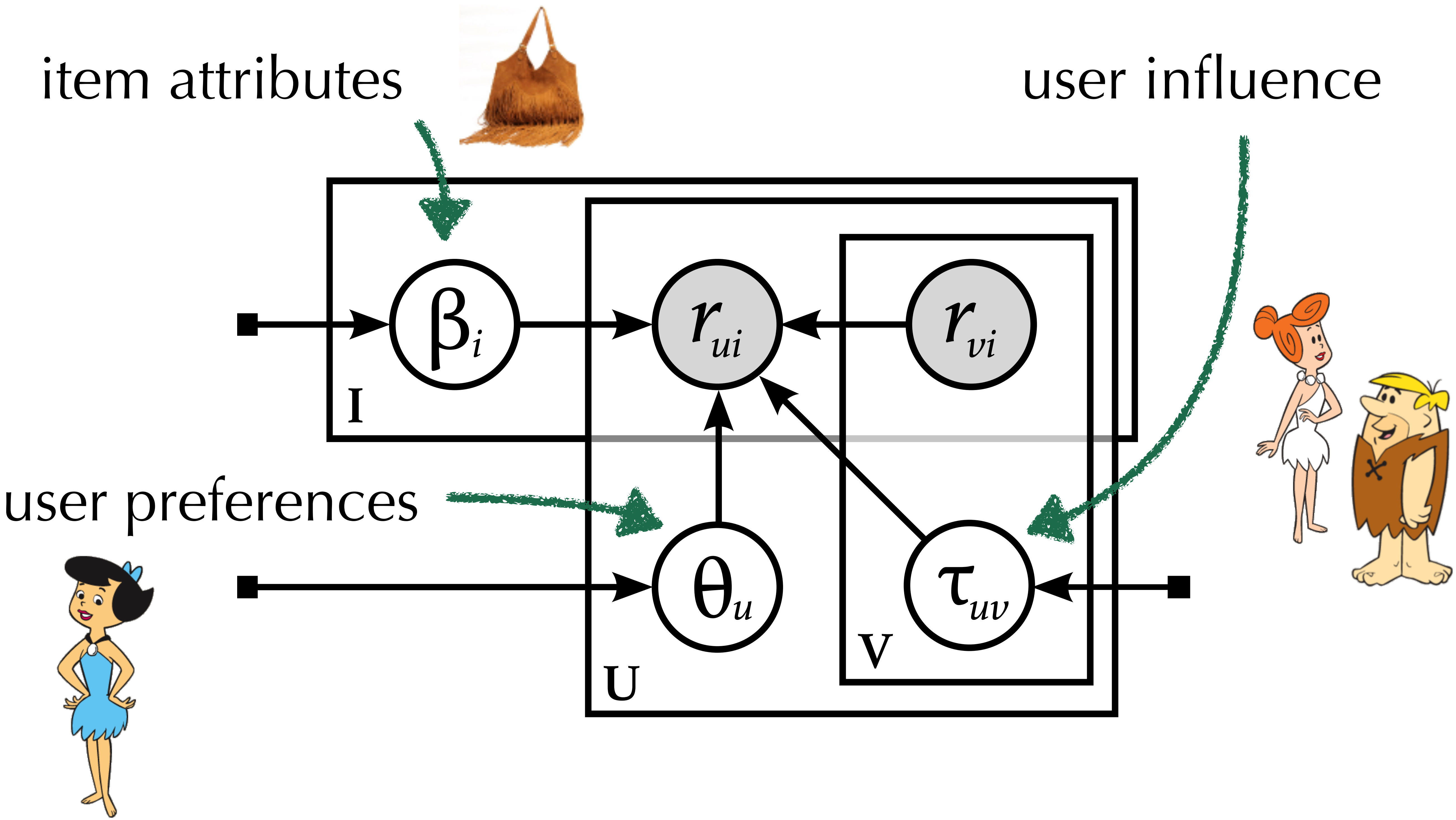
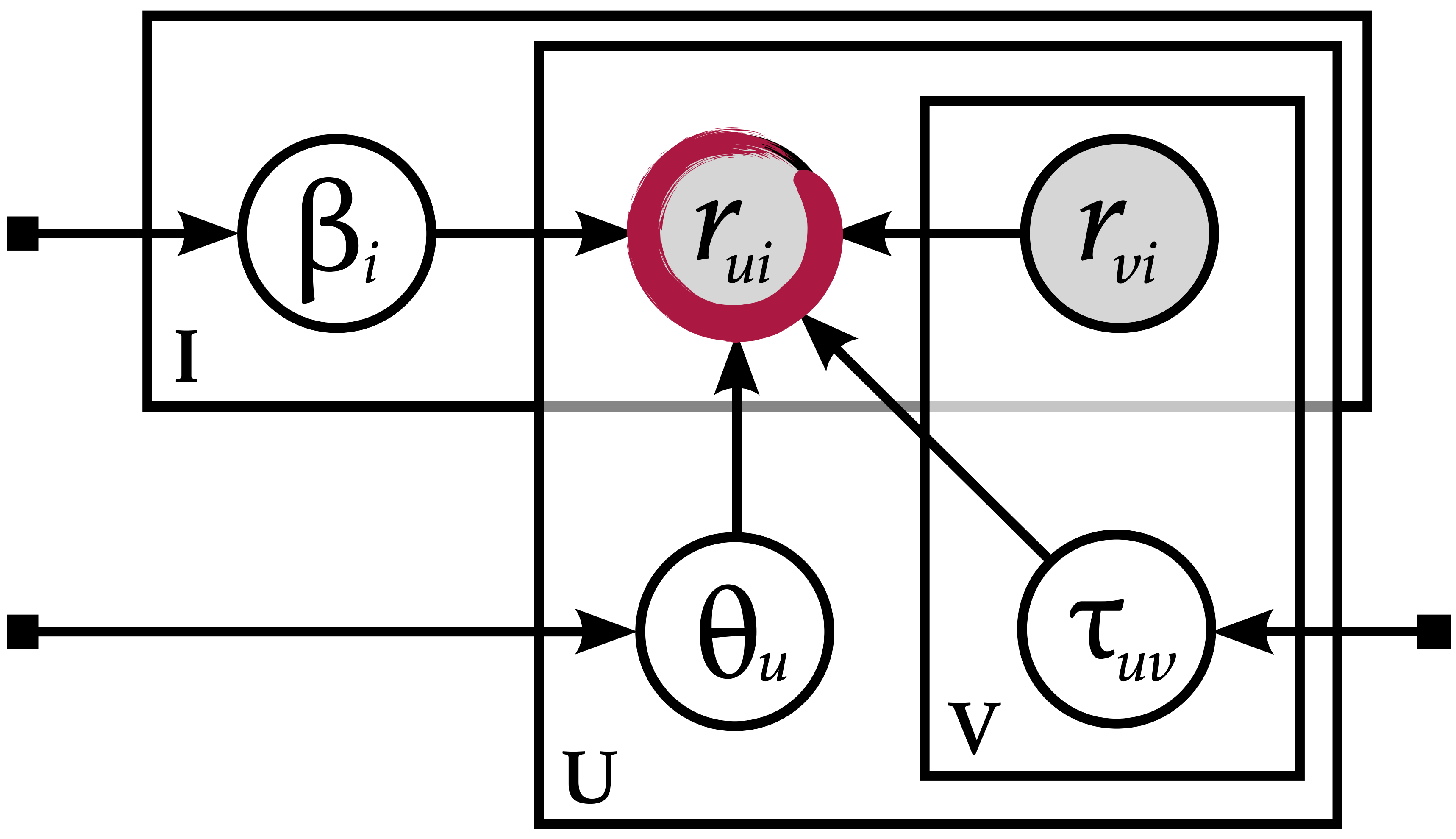


Social Poisson Factorization



$$r_{ui} \mid r_{-u,i} \sim \text{Poisson}\left(\theta_u^\top \beta_i + \sum_{v \in N(u)} \tau_{uv} r_{vi}\right)$$



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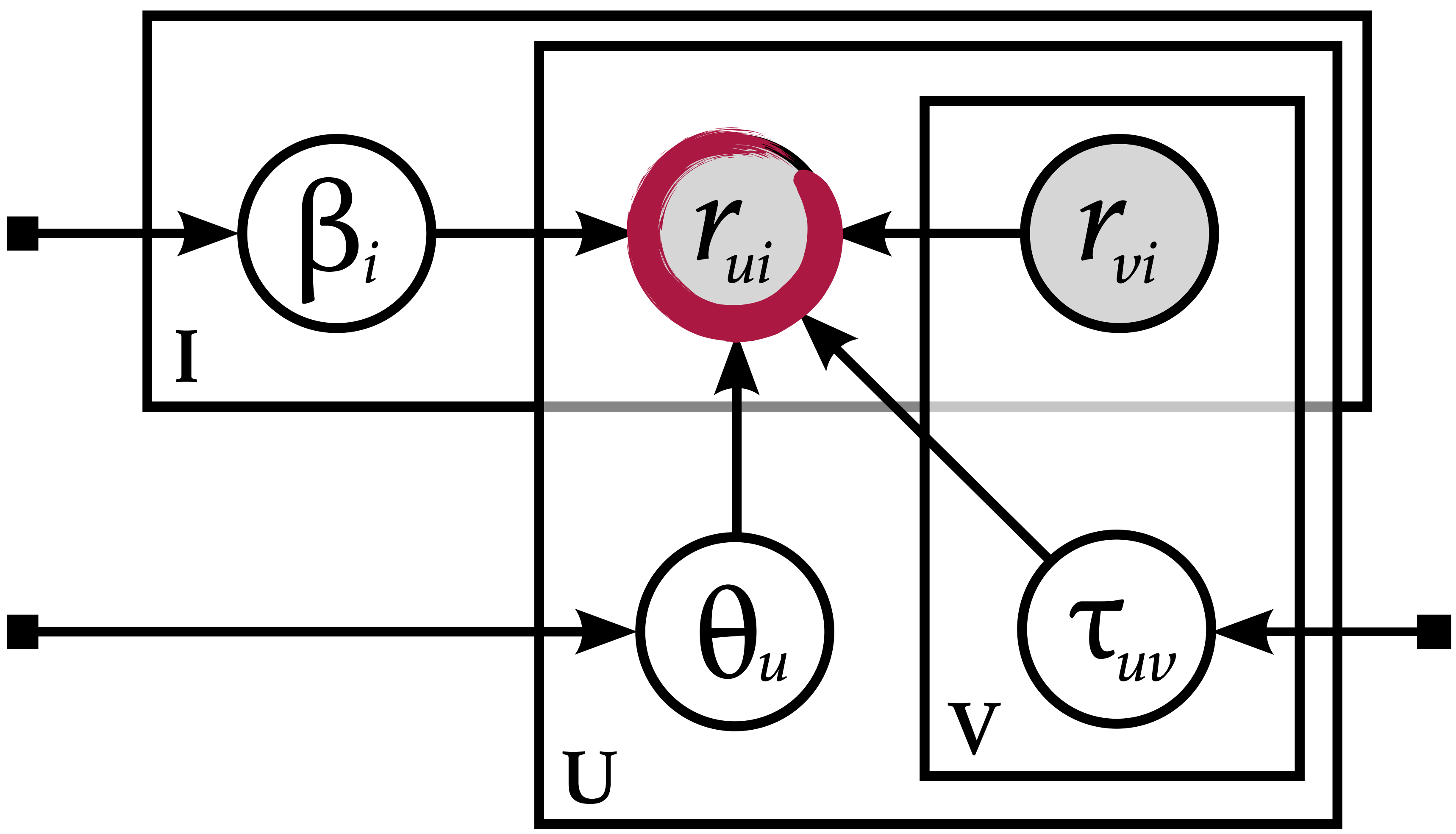

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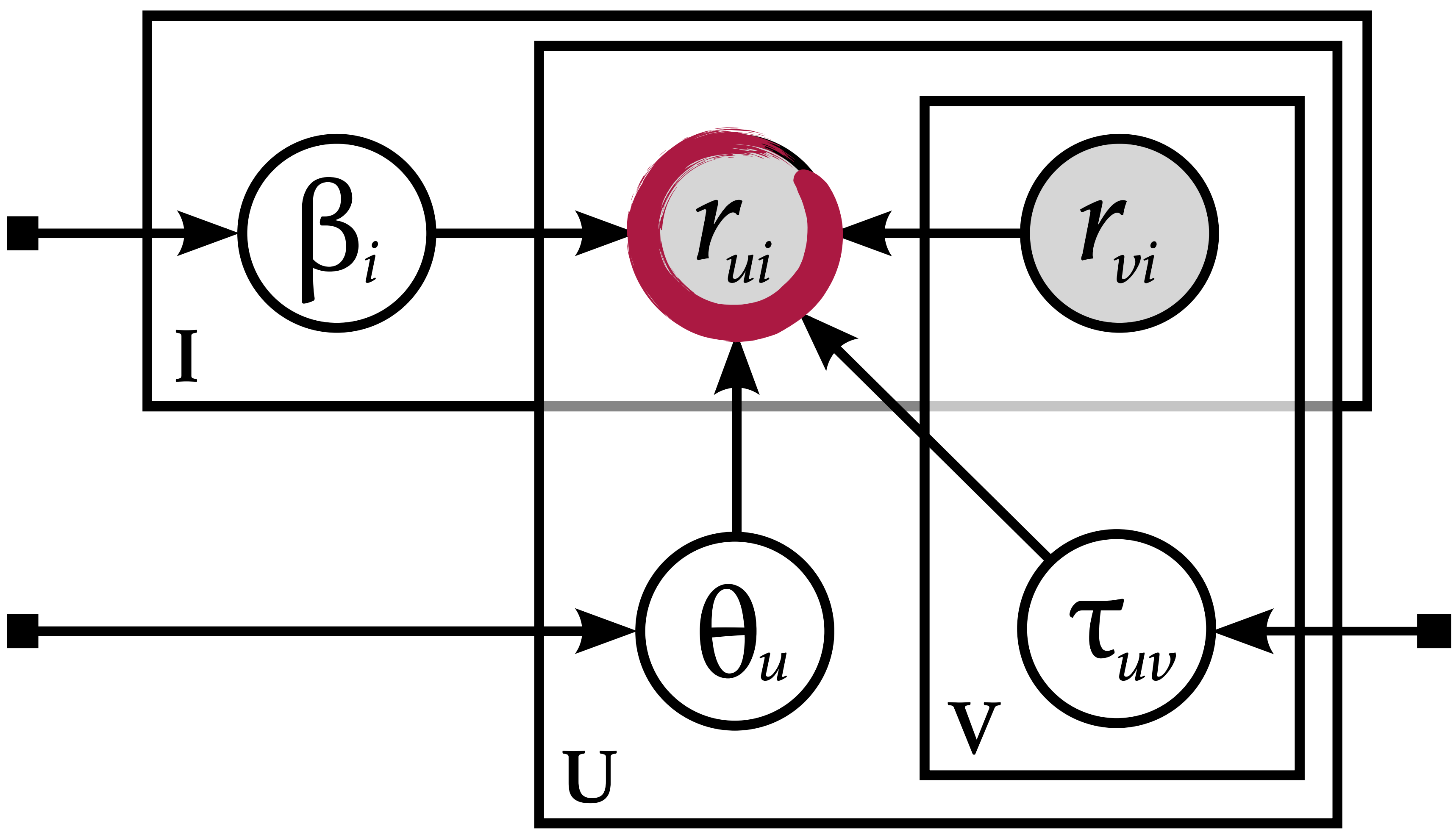

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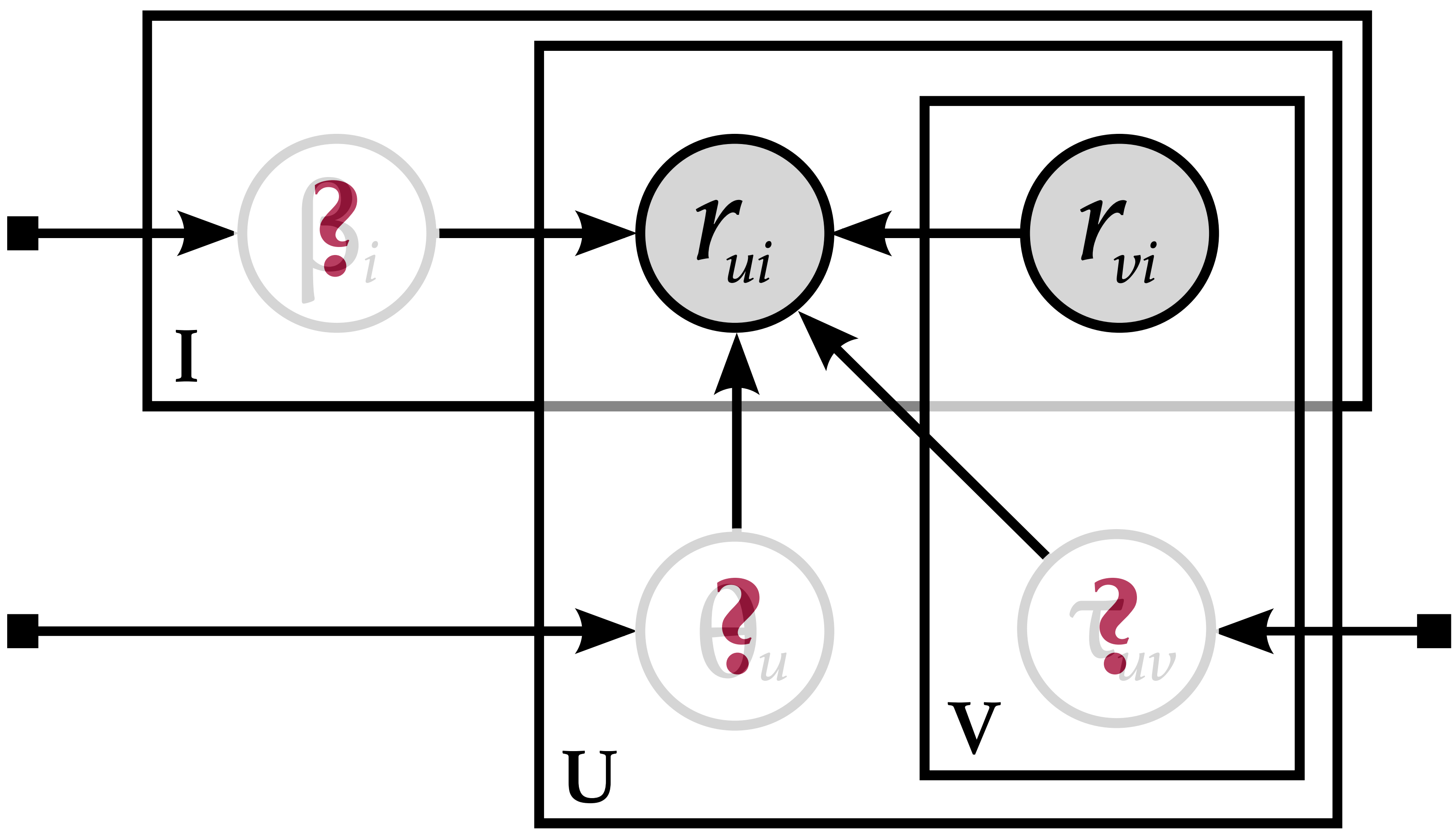


Posterior Distribution

latent model parameters

easy to compute

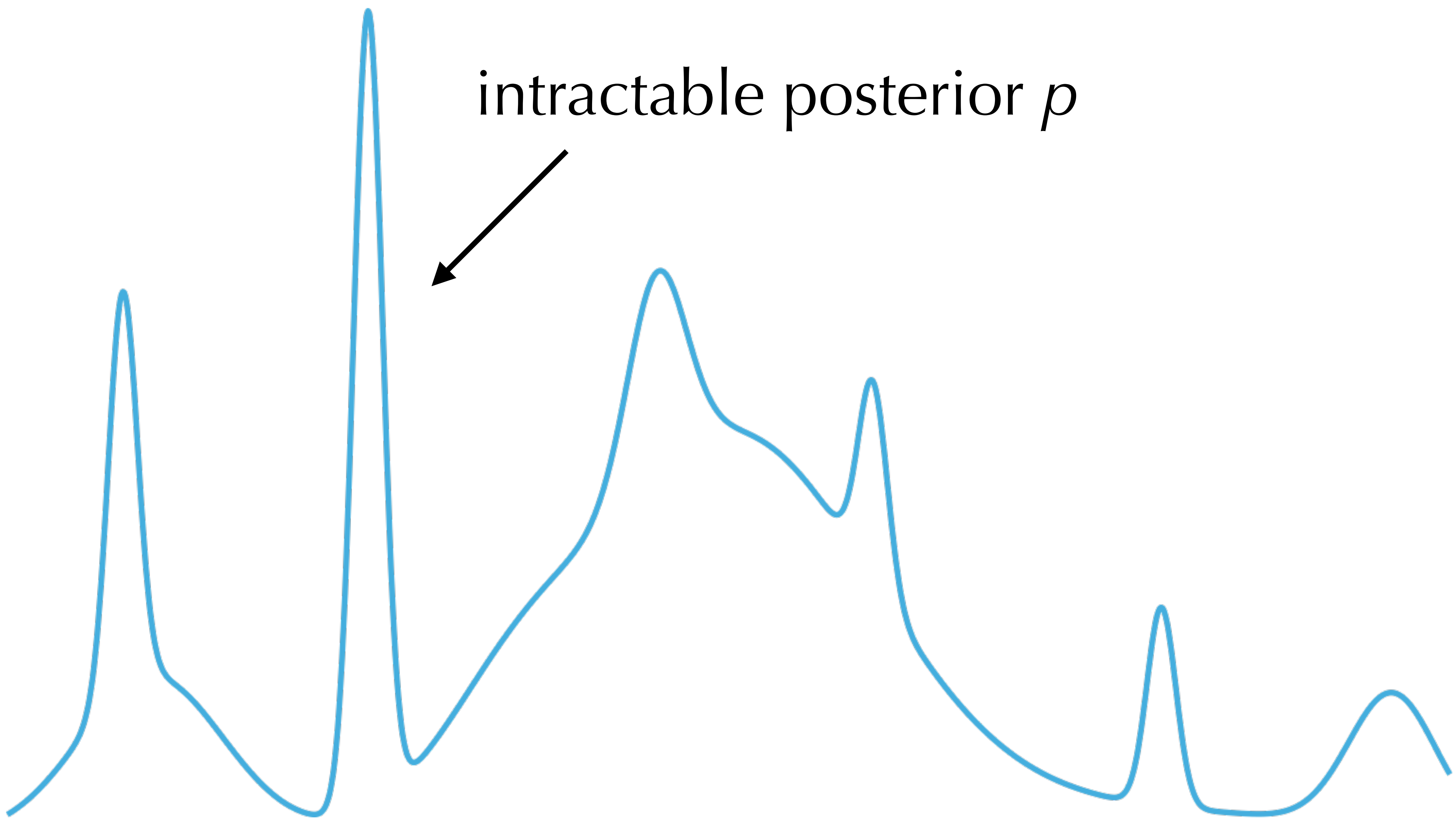
$$p(\beta, \theta, \tau \mid \mathbf{R}, \mathbf{N}, \mu) = \frac{p(\beta, \theta, \tau, \mathbf{R}, \mathbf{N} \mid \mu)}{\int_\beta \int_\theta \int_\tau p(\beta, \theta, \tau, \mathbf{R}, \mathbf{N} \mid \mu)}$$

observed data

intractable

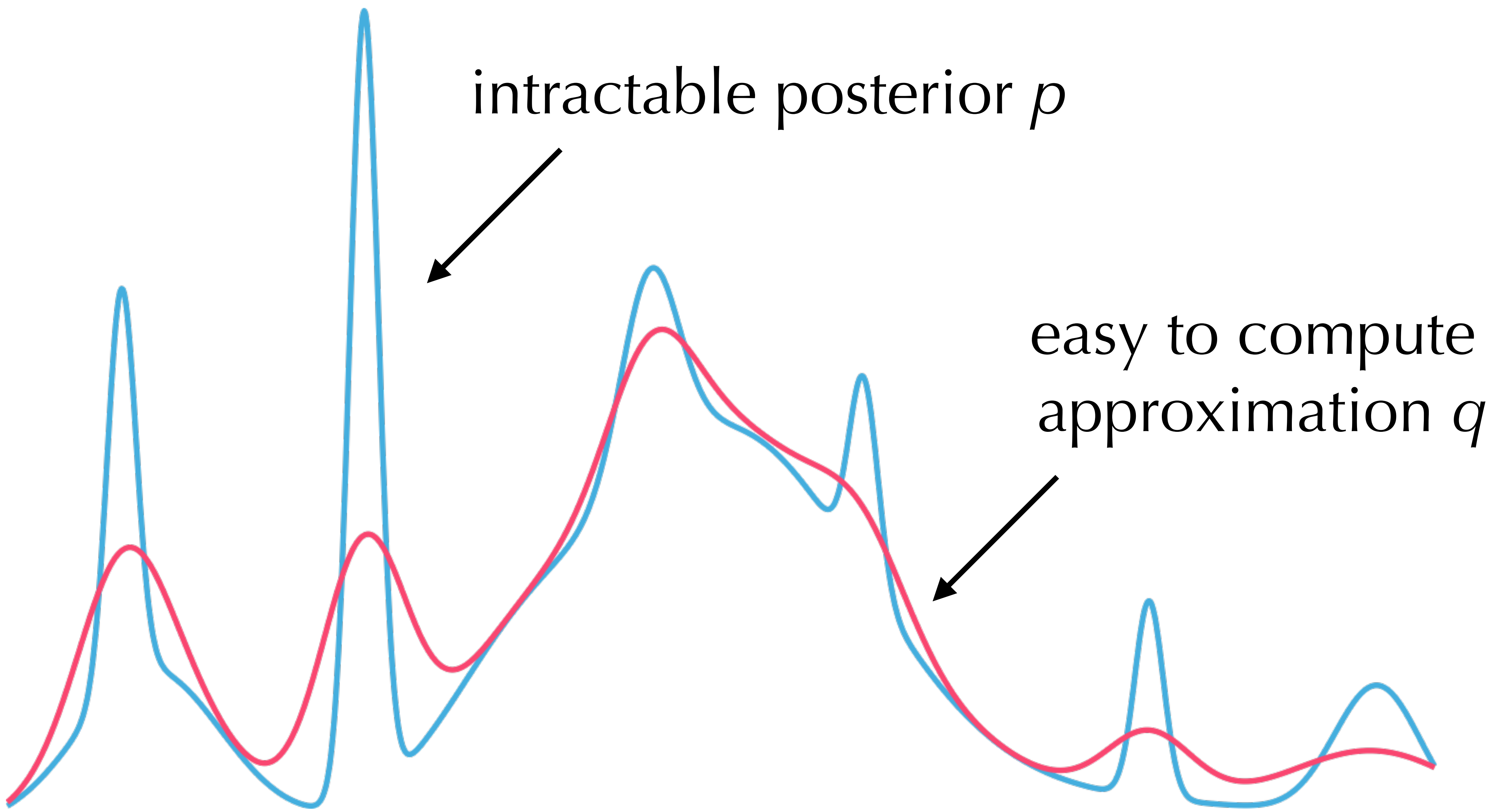
model hyperparameters

Variational Inference



$$p(\beta, \theta, \tau \mid \mathbf{R}, \mathbf{N}, \mu)$$

Variational Inference



$$p(\beta, \theta, \tau \mid \mathbf{R}, \mathbf{N}, \mu) \;\approx\; q(\beta \mid \lambda_\beta)\, q(\theta \mid \lambda_\theta)\, q(\tau \mid \lambda_\tau)$$

Inference Details

$$r_{ui} \,|\, r_{-u,i} \sim \text{Poisson}\left(\theta_u^\top \beta_i + \sum_{v \in N(u)} \tau_{uv} r_{vi}\right)$$

$$z_{uik}^M \sim \text{Poisson}(\theta_{uk}\beta_{ik}) \qquad z_{uiv}^S \sim \text{Poisson}(\tau_{uv} r_{vi})$$

$$r_{ui} \mid r_{-u,i} = \sum_{k=1}^{K} z_{uik}^M + \sum_{v=1}^{V} z_{uiv}^S$$

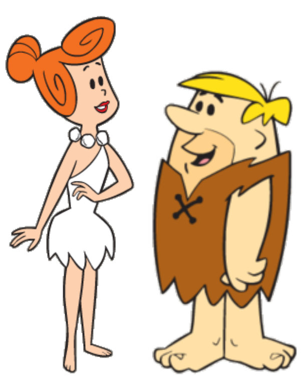
Complete Conditional Distributions

user preferences

$$\theta_{uk} \mid \beta, \tau, z, \mathbf{R}, \mathbf{N} \sim \text{Gamma}\left(a_\theta + \sum_i z^M_{uik},\ b_\theta + \sum_i \beta_{ik}\right)$$

item attributes

$$\beta_{ik} \mid \theta, \tau, z, \mathbf{R}, \mathbf{N} \sim \text{Gamma}\left(a_\beta + \sum_u z^M_{uik},\ b_\beta + \sum_u \theta_{uk}\right)$$



user influence

$$\tau_{uv} \mid \theta, \beta, z, \mathbf{R}, \mathbf{N} \sim \text{Gamma}\left(a_\tau + \sum_i z^S_{uiv},\ b_\tau + \sum_i r_{vi}\right)$$

Inference Highlights

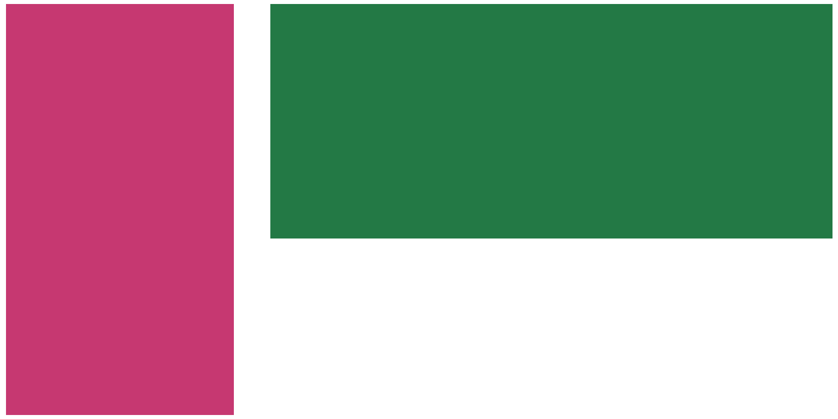
Inference Highlights

no need to
sample zeros

Inference Highlights

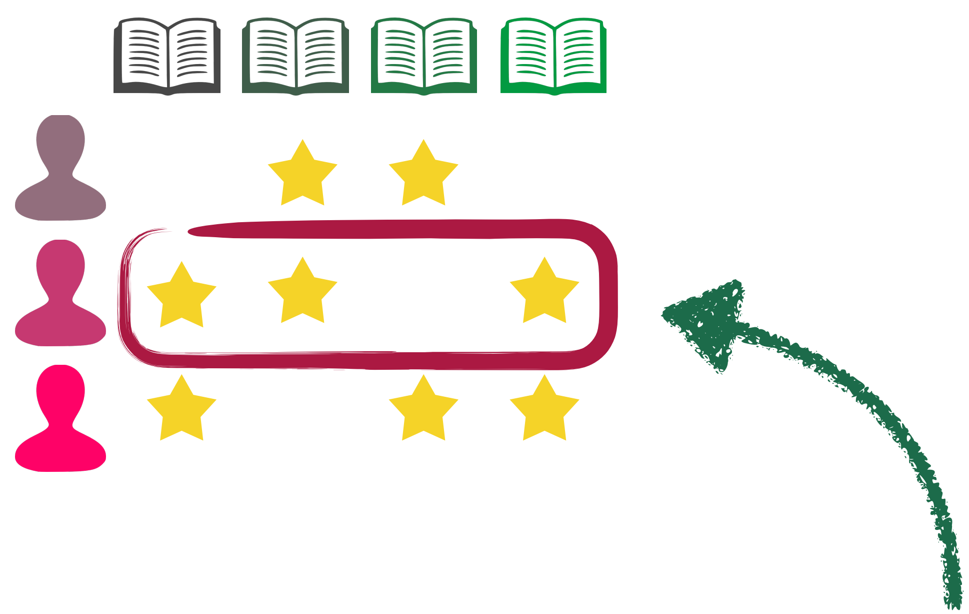
no need to
sample zeros

initialization
requires noise



Inference Highlights

no need to
sample zeros



initialization
requires noise

sample rows for
stochastic updates
(scalability)

Recommendation

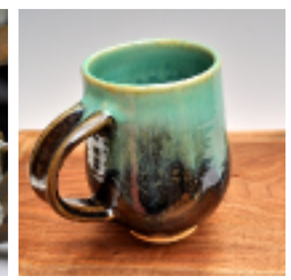
$$\mathbf{E}[r_{ui}] = \mathbf{E}[\theta_u]^\top \mathbf{E}[\beta_i] + \sum_{v \in N(u)} \mathbf{E}[\tau_{uv}] r_{vi}$$

Evaluation

Evaluation

training set






test set



Evaluation

training set

test set

ranked
predictions

Evaluation

training set

test set

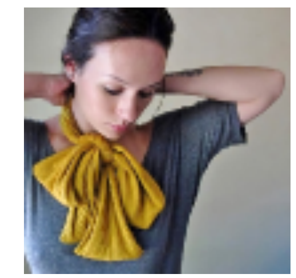
ranked predictions

Evaluation

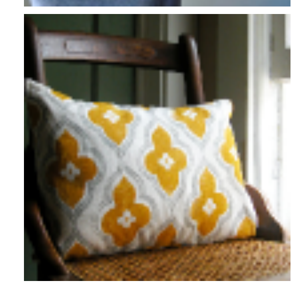
$$CRR(user) = \sum_{n=1}^{N} \frac{\mathbf{1}[rec_n \in \mathcal{H}]}{n} = \sum_{i \in \mathcal{H}} \frac{1}{rank(i)}$$

$$NCRR(user) = \frac{CRR(user)}{\text{ideal } CRR(user)}$$

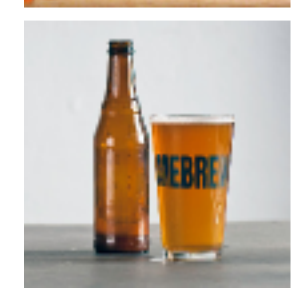
ranked predictions



1/1



1/2



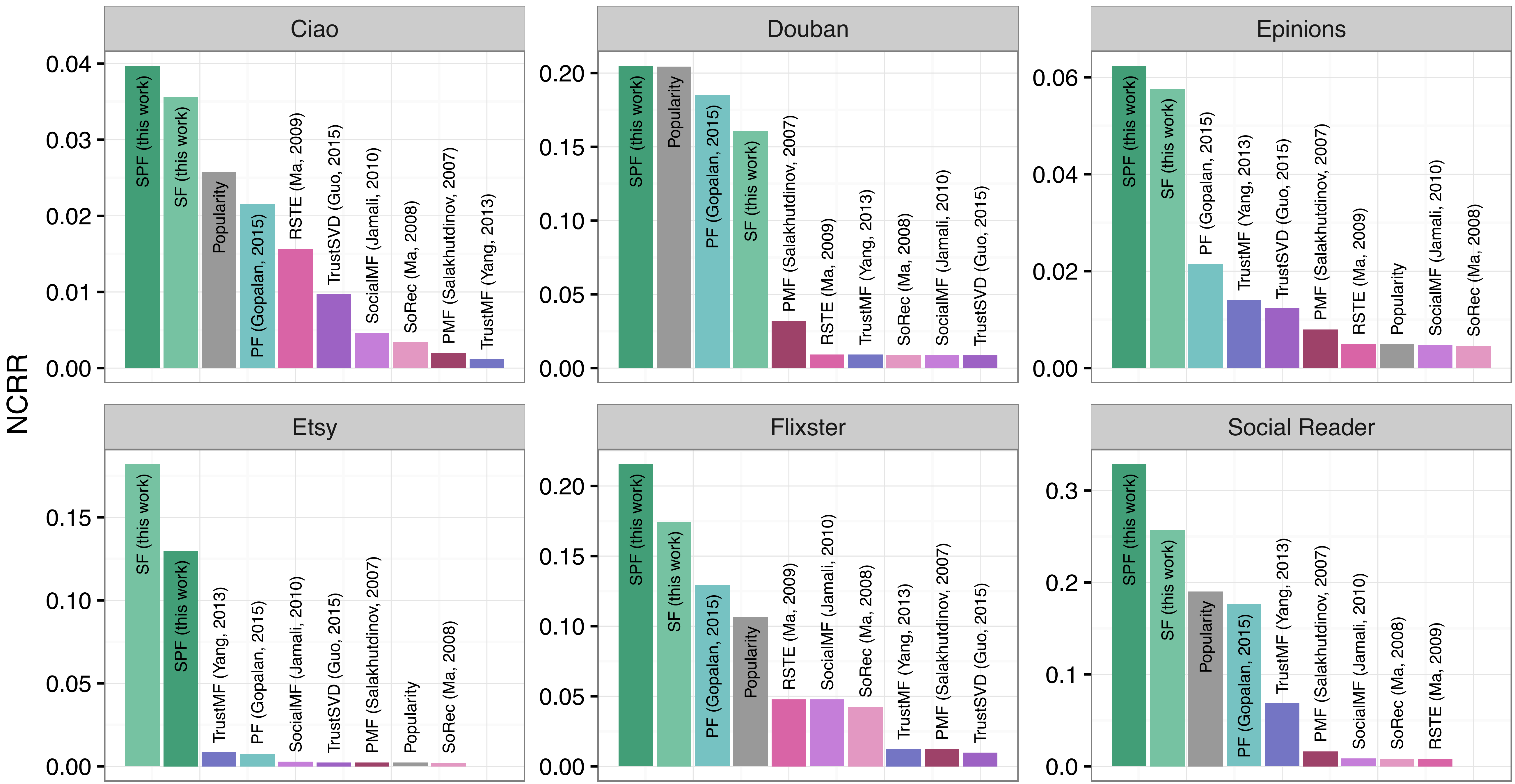
1/4

Data

source	# users	# items	% ratings	% edges
Ciao	7,000	98,000	0.038%	0.103%
Epinions	39,000	131,000	0.012%	0.011%
Flixster	132,000	42,000	0.122%	0.006%
Douban	129,000	57,000	0.221%	0.016%
Social Reader	122,000	6,000	0.065%	0.001%
Etsy	40,000	5,202,000	0.009%	0.300%

etsy.com and librec.net/datasets.html

SPF Held-out Evaluation



Our Friends Inspire Us

How do we leverage **social** behavior to find better things to **recommend** for people?

Our Friends Inspire Us

infer how much **friends** exert **social influence** on each other and include that in making **recommendations**

Understanding **Decision** Making

How do people decide what choices to make?

Chameleon Preferences

How do the decisions people make depend on the people around them?

Our Friends Inspire Us

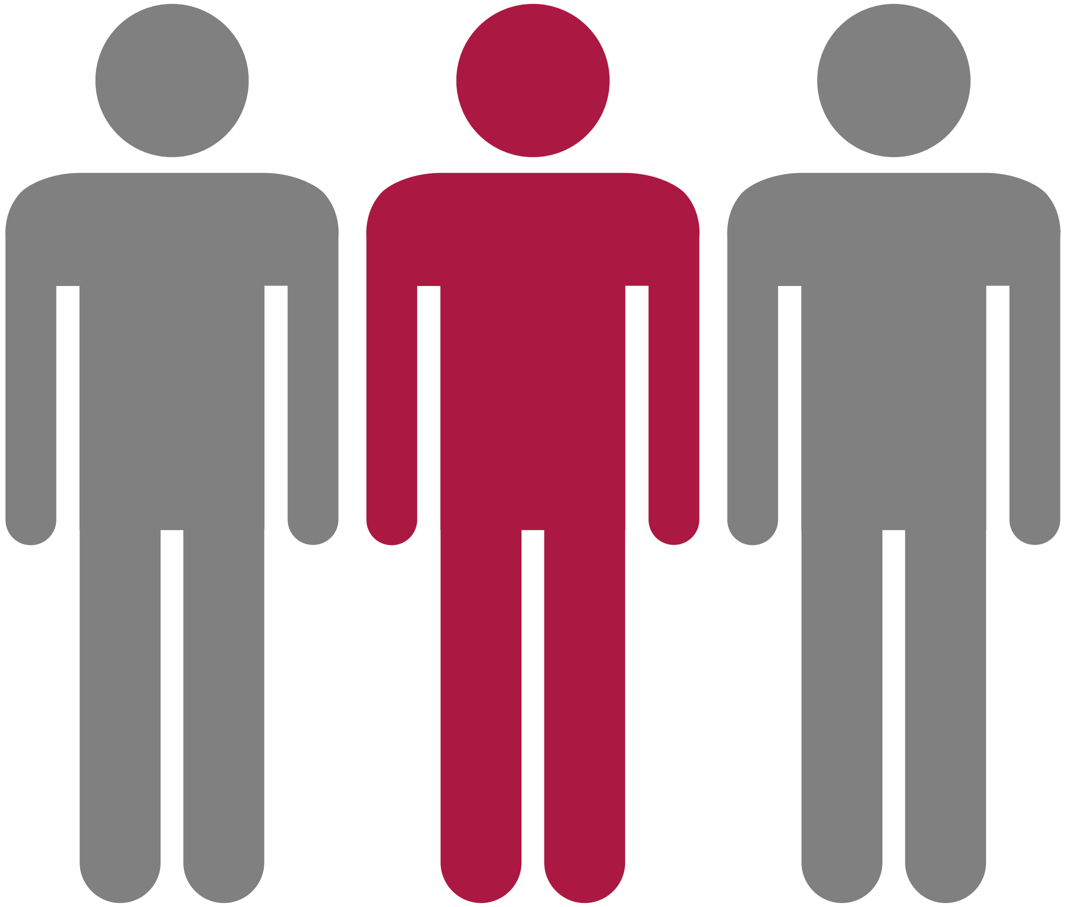
How do we leverage social behavior to find better things to recommend for people?

Algorithmic Personalization isn't Personal

How do recommendations alter group behavior?

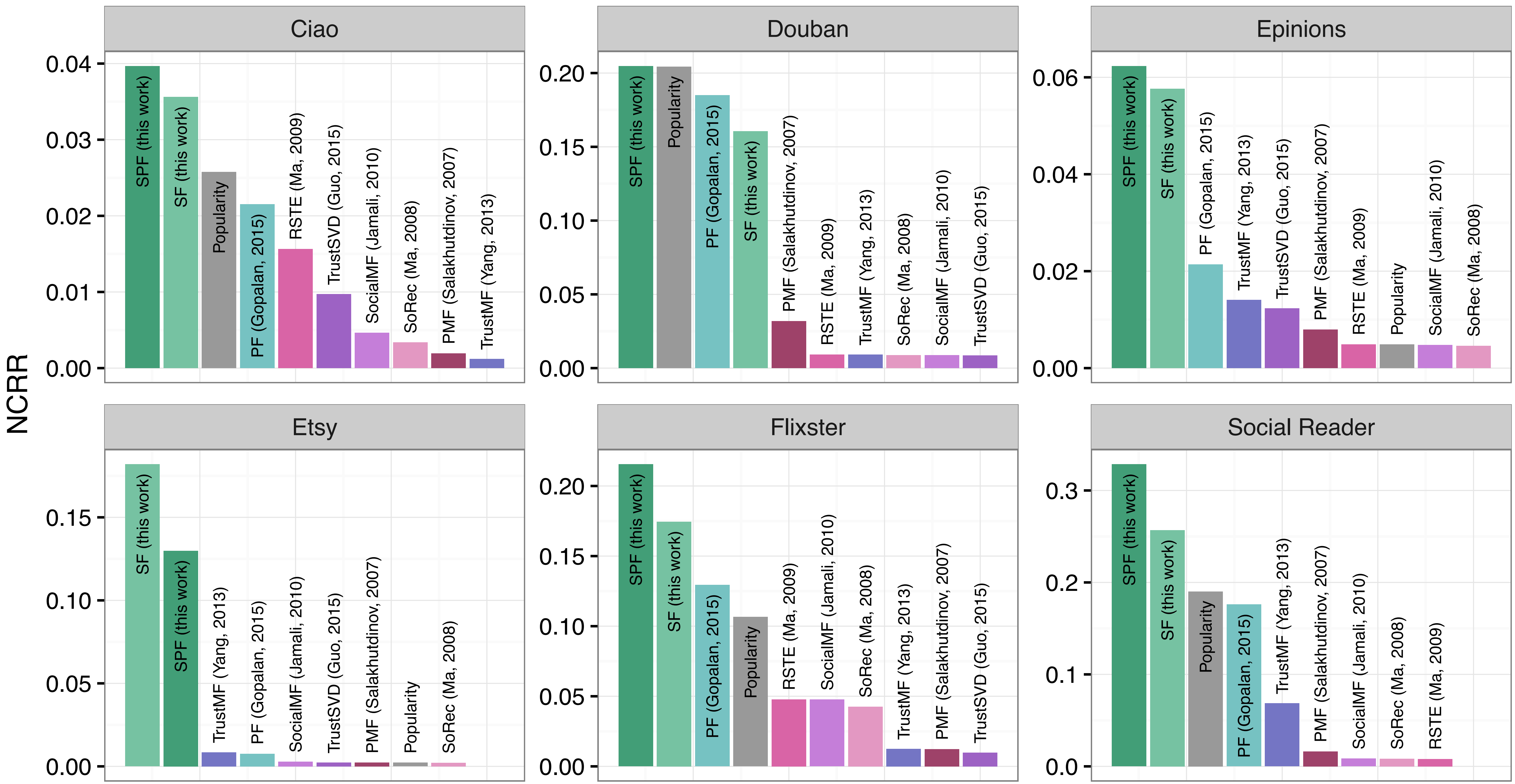
Algorithmic Personalization isn't Personal

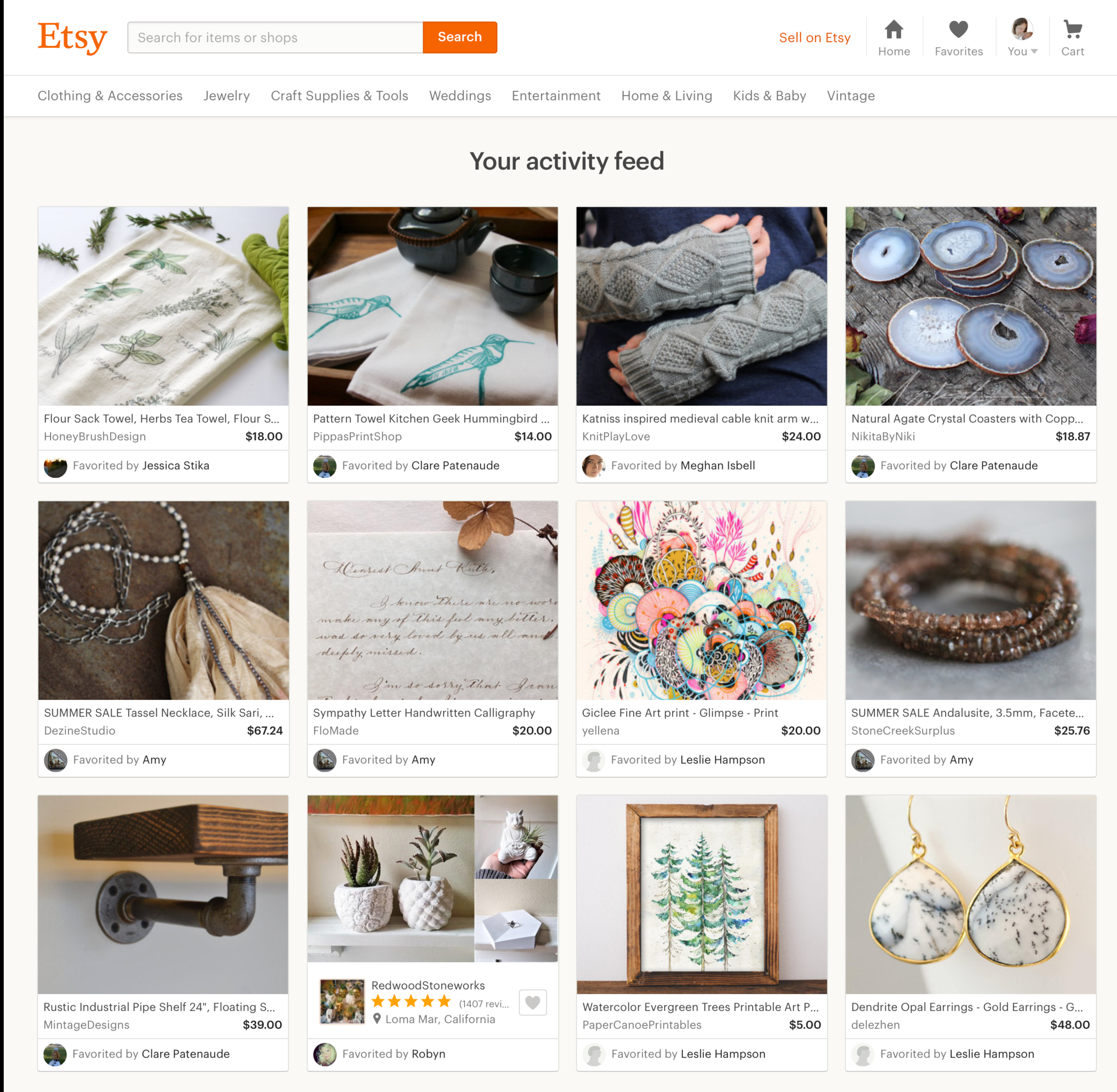
How do **recommendations** alter **group** behavior?



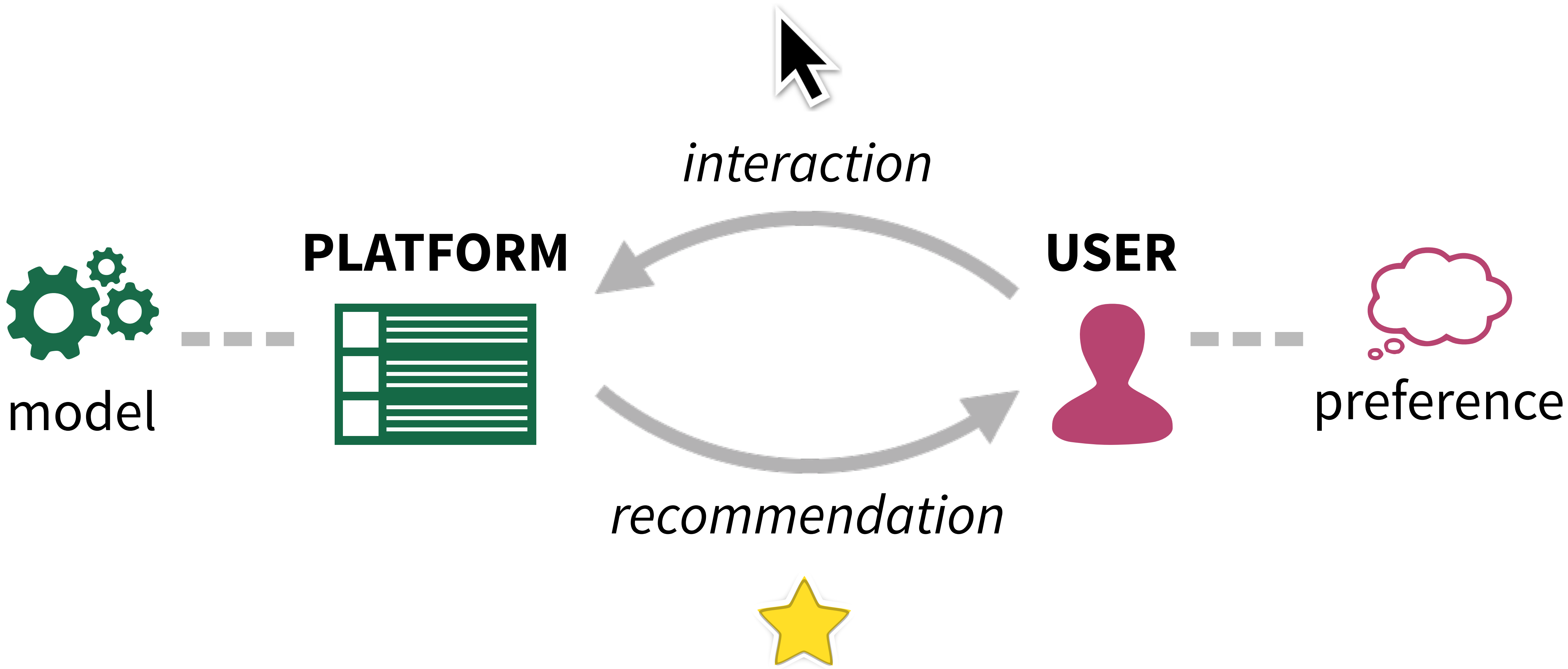
How Algorithmic Confounding in Recommendation Systems Increases Homogeneity and Decreases Utility.
Chaney, Stewart, Engelhardt.
arXiv, 2017.

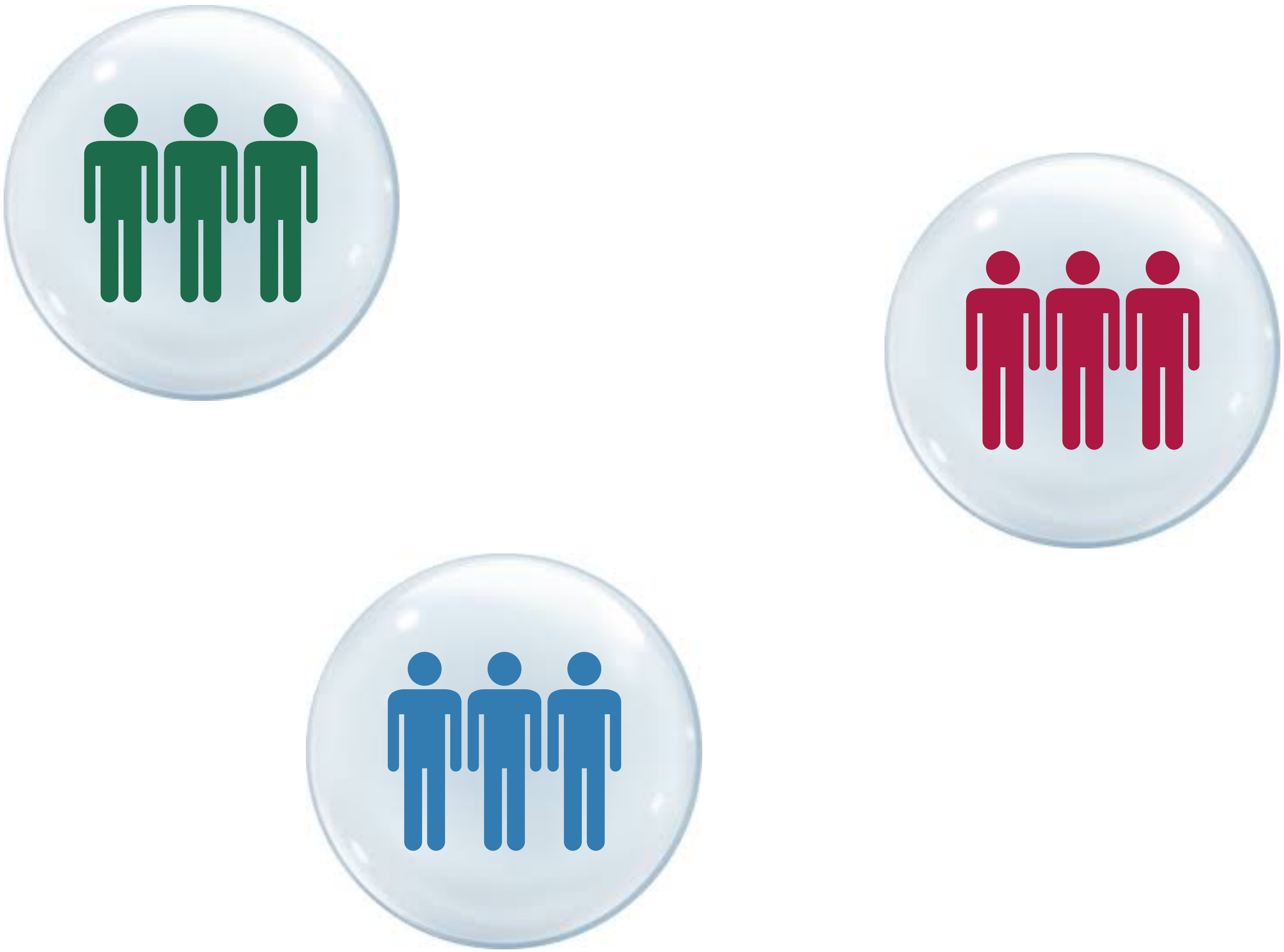
SPF Held-out Evaluation



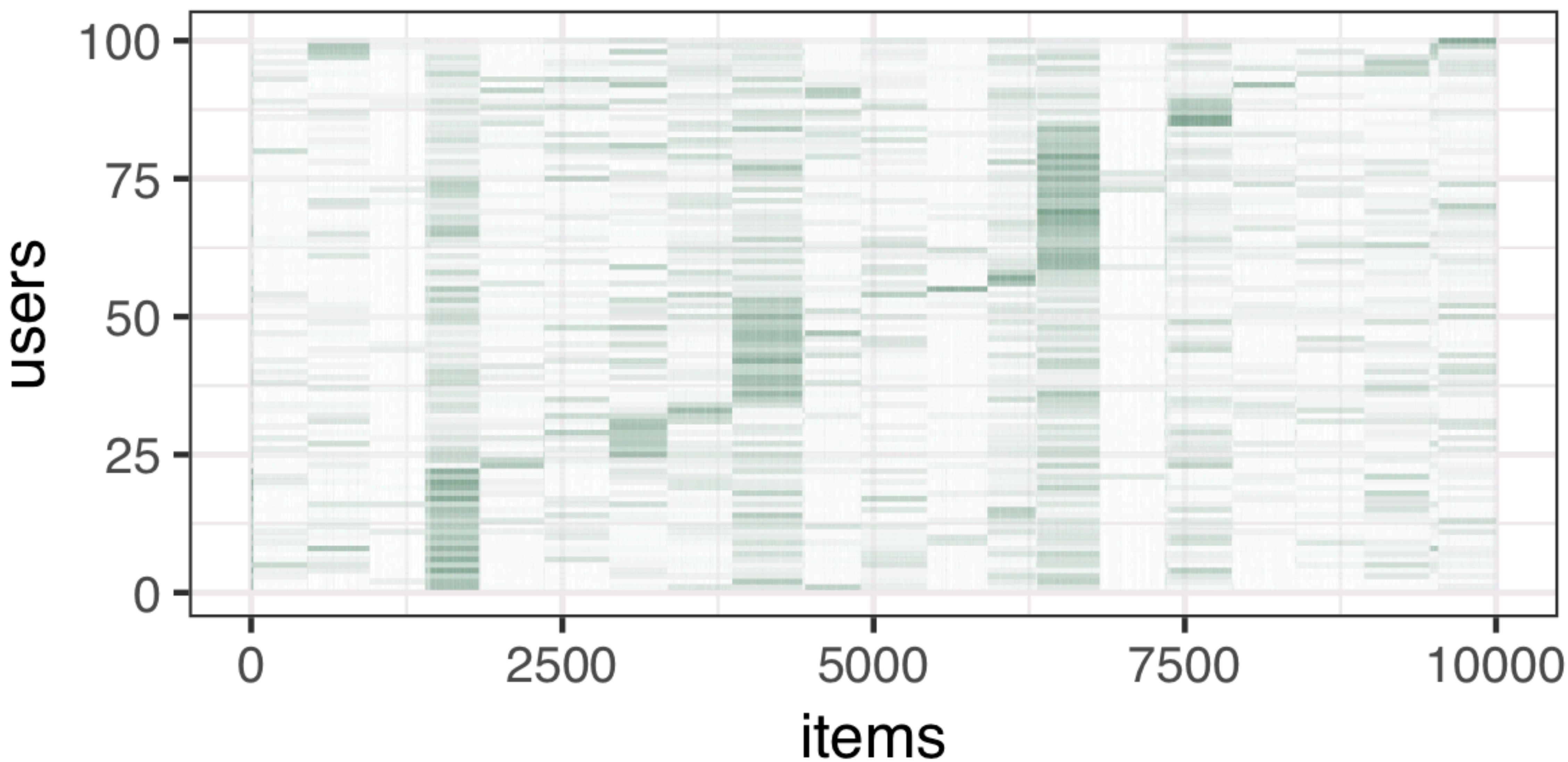

Etsy
Search for items or shops
Search
Sell on Etsy
Home
Favorites
You
Cart
Clothing & Accessories
Jewelry
Craft Supplies & Tools
Weddings
Entertainment
Home & Living
Kids & Baby
Vintage
Your activity feed
Flour Sack Towel, Herbs Tea Towel, Flour S...
HoneyBrushDesign
$18.00
Favorited by Jessica Stika
Pattern Towel Kitchen Geek Hummingbird ...
PippasPrintShop
$14.00
Favorited by Clare Patenaude
Katniss inspired medieval cable knit arm w...
KnitPlayLove
$24.00
Favorited by Meghan Isbell
Natural Agate Crystal Coasters with Copp...
NikitaByNiki
$18.87
Favorited by Clare Patenaude
SUMMER SALE Tassel Necklace, Silk Sari, ...
DezineStudio
$67.24
Favorited by Amy
Sympathy Letter Handwritten Calligraphy
FloMade
$20.00
Favorited by Amy
Giclee Fine Art print - Glimpse - Print
yellena
$20.00
Favorited by Leslie Hampson
SUMMER SALE Andalusite, 3.5mm, Facete...
StoneCreekSurplus
$25.76
Favorited by Amy
Rustic Industrial Pipe Shelf 24", Floating S...
MintageDesigns
$39.00
Favorited by Clare Patenaude
RedwoodStoneworks
(1407 revi...
Loma Mar, California
Favorited by Robyn
Watercolor Evergreen Trees Printable Art P...
PaperCanoePrintables
$5.00
Favorited by Leslie Hampson
Dendrite Opal Earrings - Gold Earrings - G...
delezhen
$48.00
Favorited by Leslie Hampson

The Feedback Loop





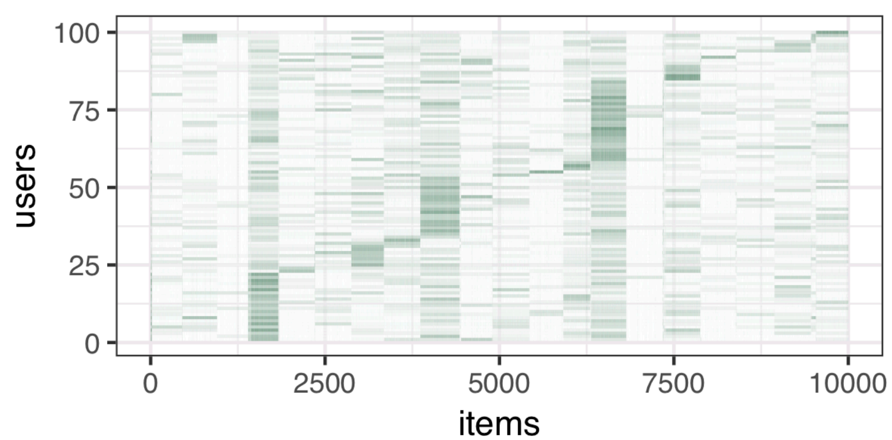
Simulation Setup



Simulation Setup

alternative realities

“world”



content filtering

social filtering

matrix factorization

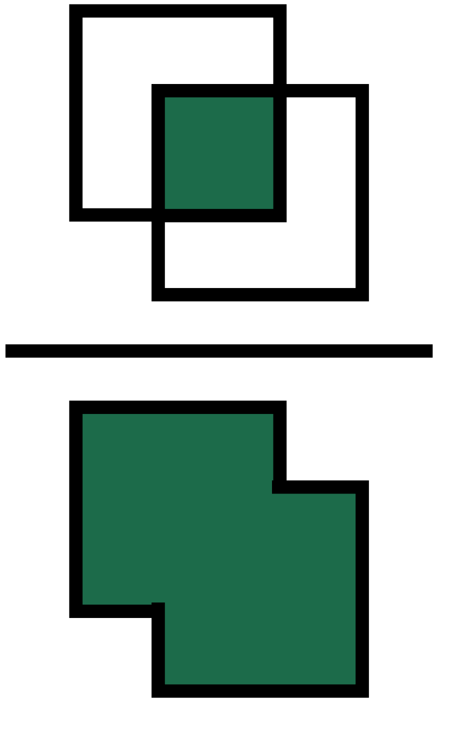
popularity

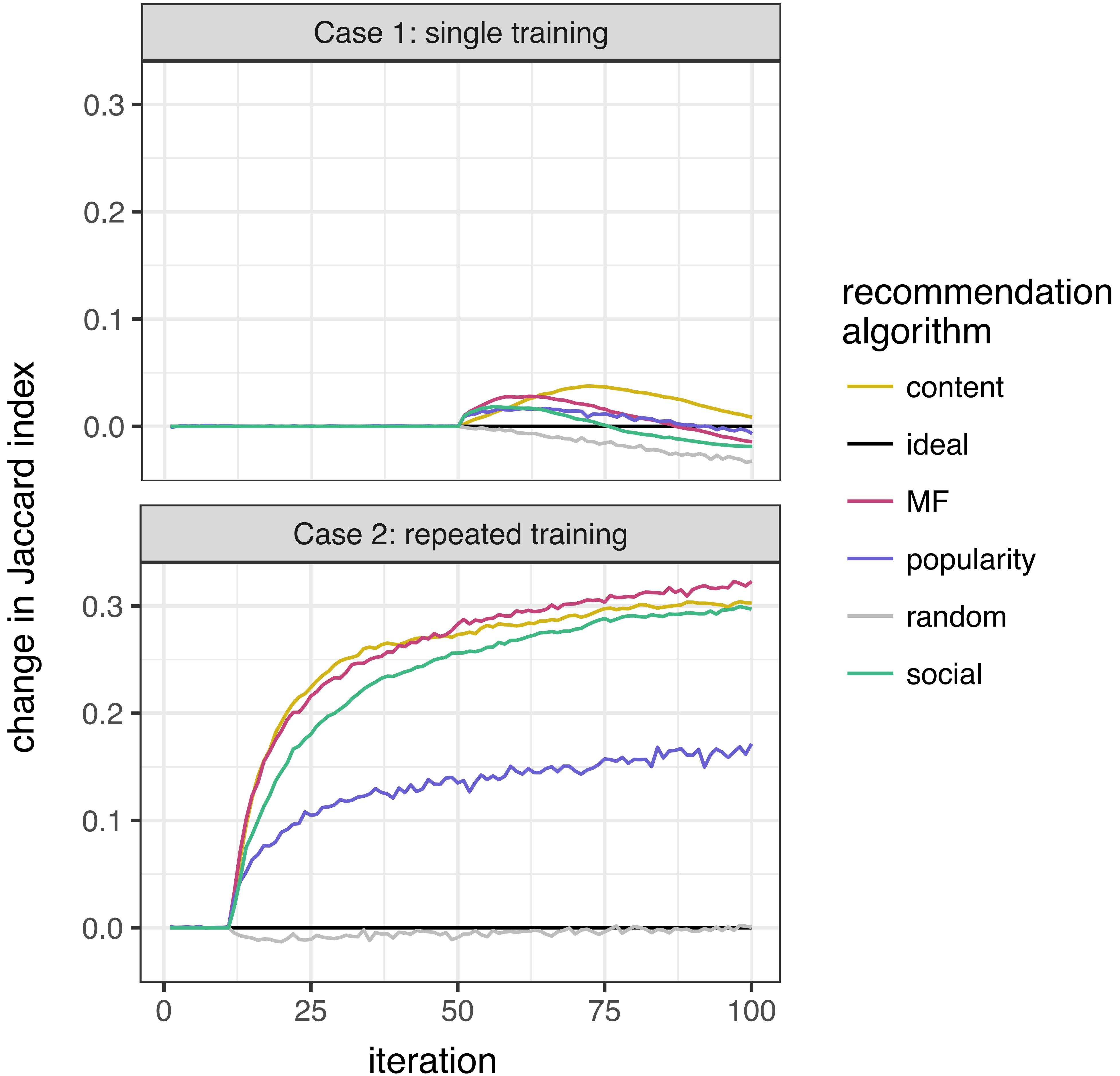
random

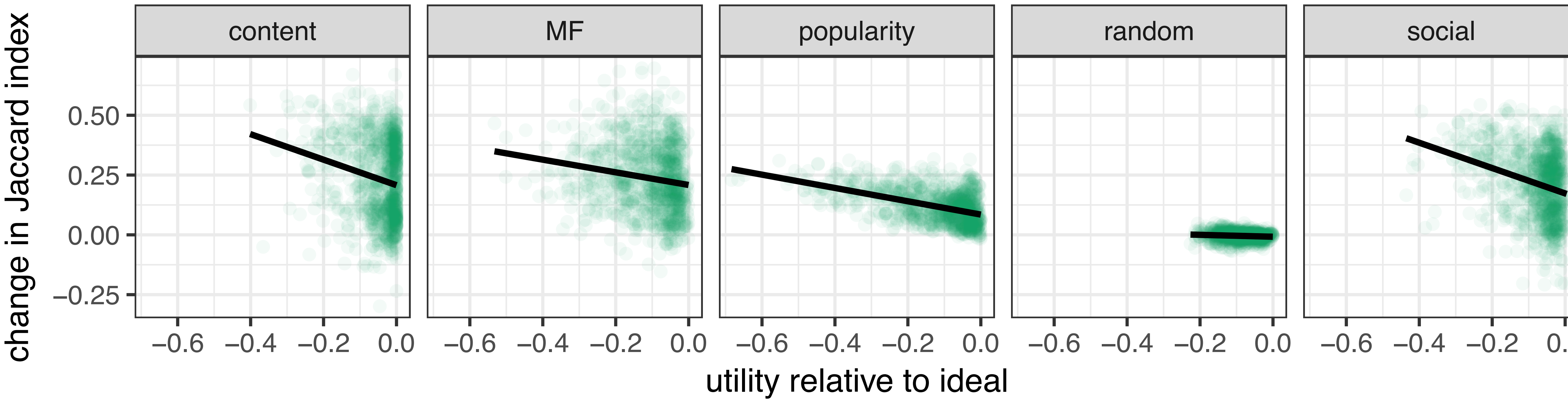
ideal

Jaccard Index

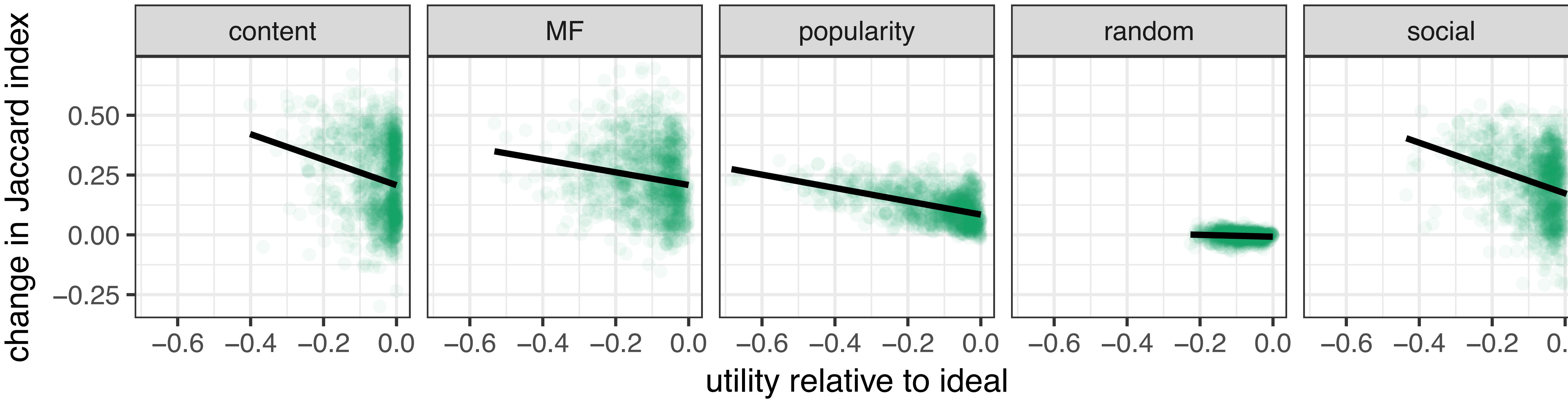
$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} =$$




Case 1: single training
Case 2: repeated training
0.3
0.2
0.1
0.0
0
25
50
75
100
change in Jaccard index
iteration
recommendation algorithm
content
ideal
MF
popularity
random
social



content
MF
popularity
random
social
change in Jaccard index
0.50
0.25
0.00
−0.25
−0.6
−0.4
−0.2
0.0
utility relative to ideal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MF
popularity
random
social
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0.25
0.00
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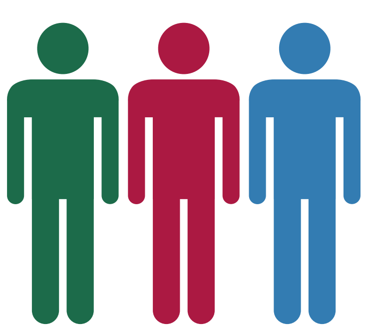
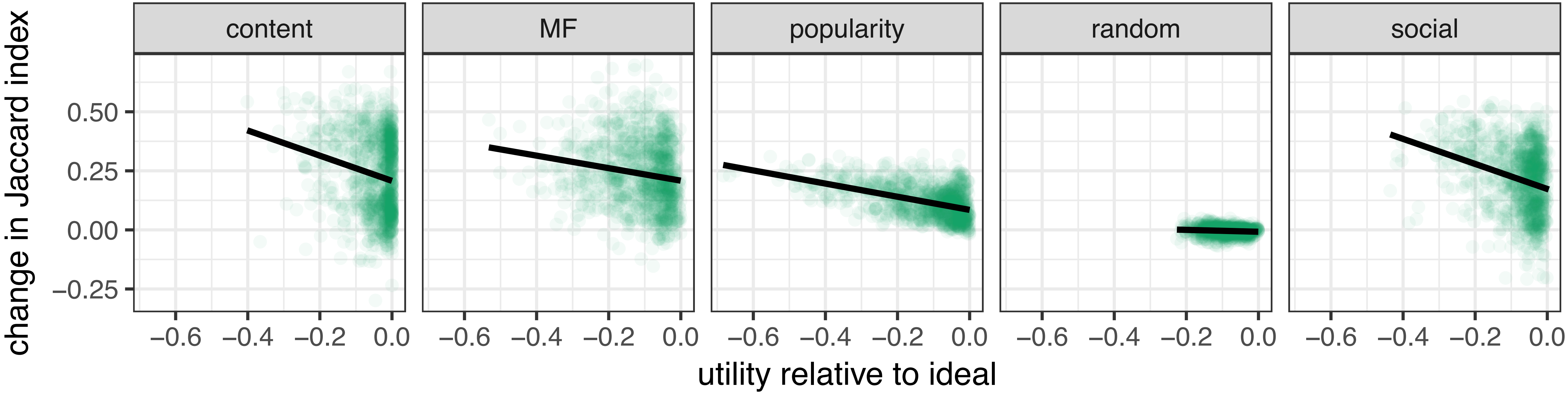
−0.4
−0.2
0.0
utility relative to ideal

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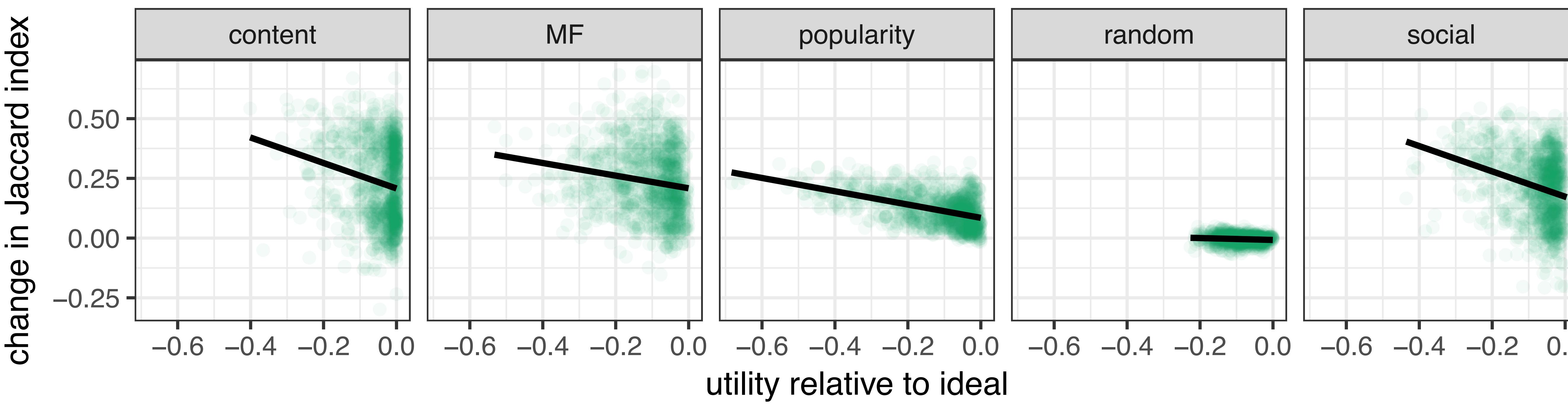
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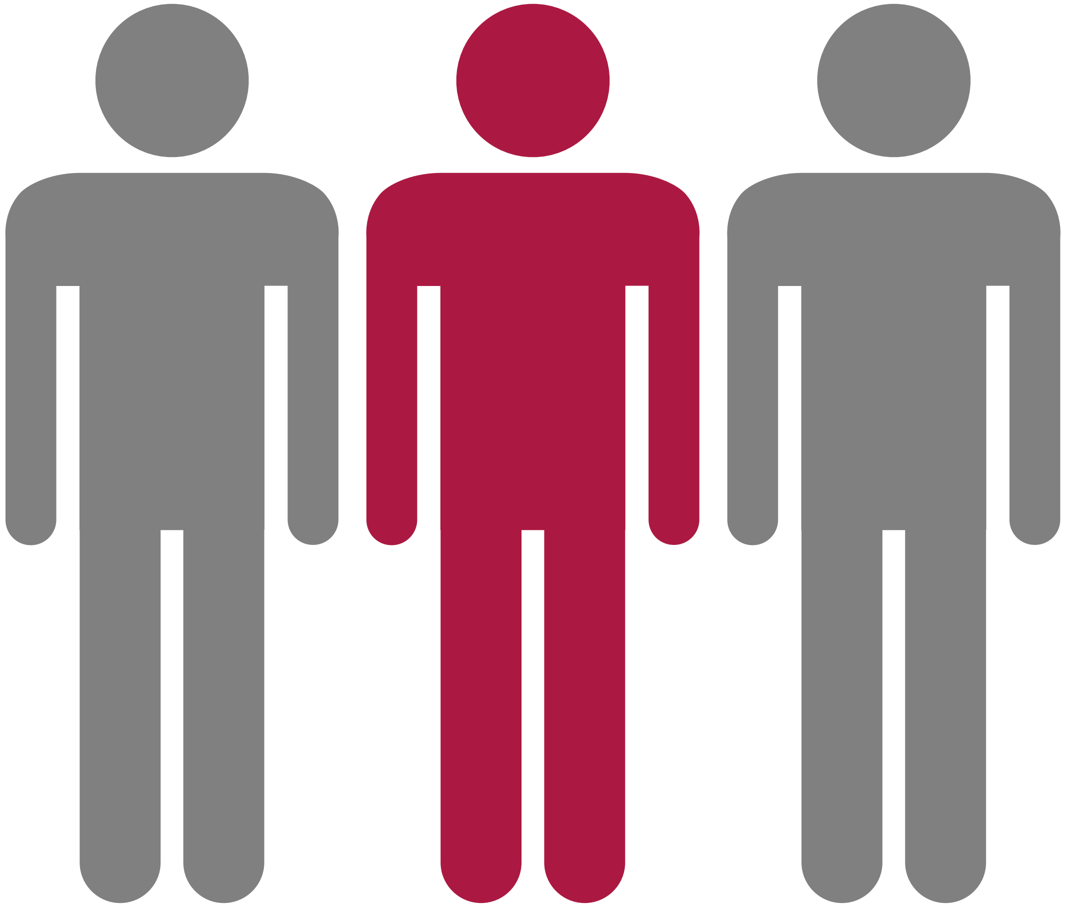
0.25
0.00
−0.25
−0.6
−0.4
−0.2
0.0
utility relative to ideal

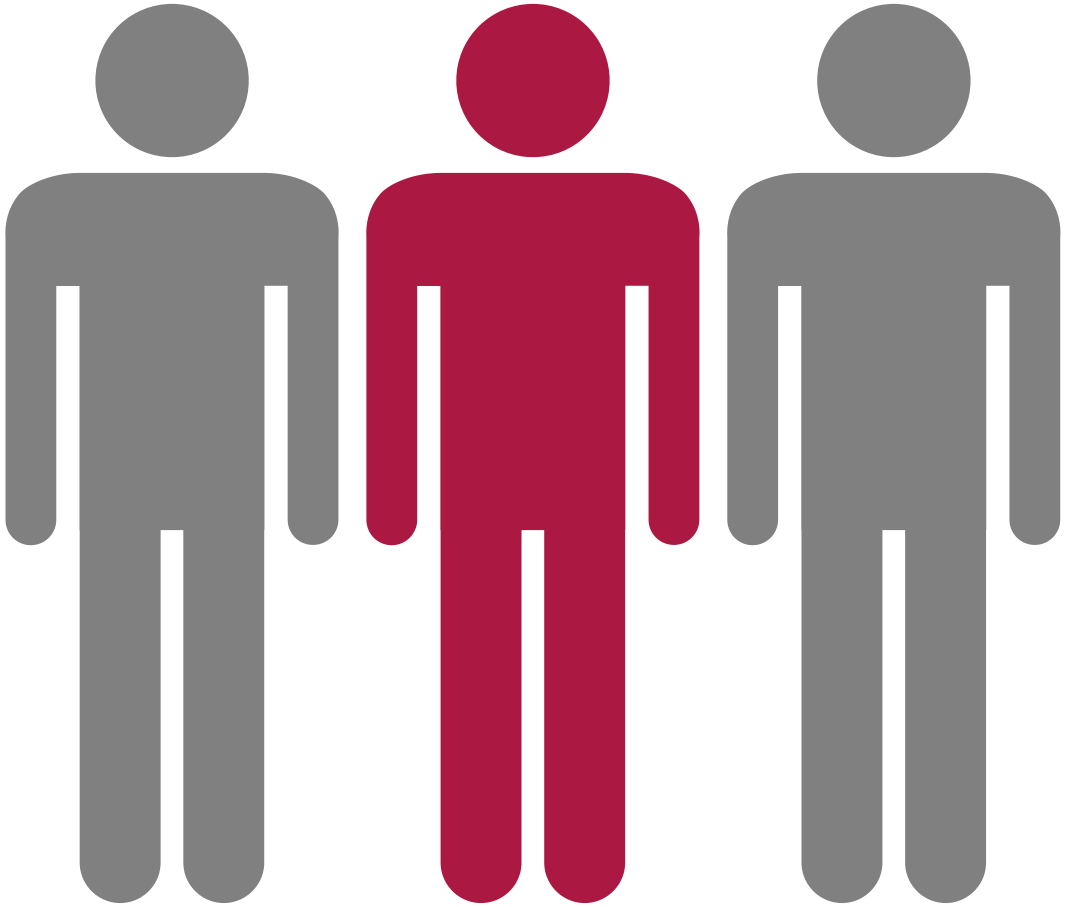
Algorithmic Personalization isn't Personal

How do **recommendations** alter **group** behavior?



Algorithmic Personalization isn't Personal

Recommendations systems push **groups** of users to have more **homogenous** behavior than they'd ideally have



Understanding **Decision** Processes

How do people decide what choices to make?

Chameleon Preferences

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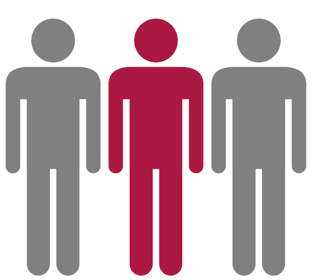
Our Friends Inspire Us

How do we leverage social behavior to find better things to recommend for people?

Algorithmic Personalization isn't Personal



How do recommendations alter group behavior?

Influencing Deliberation

Tools for **Knowledge** Creation

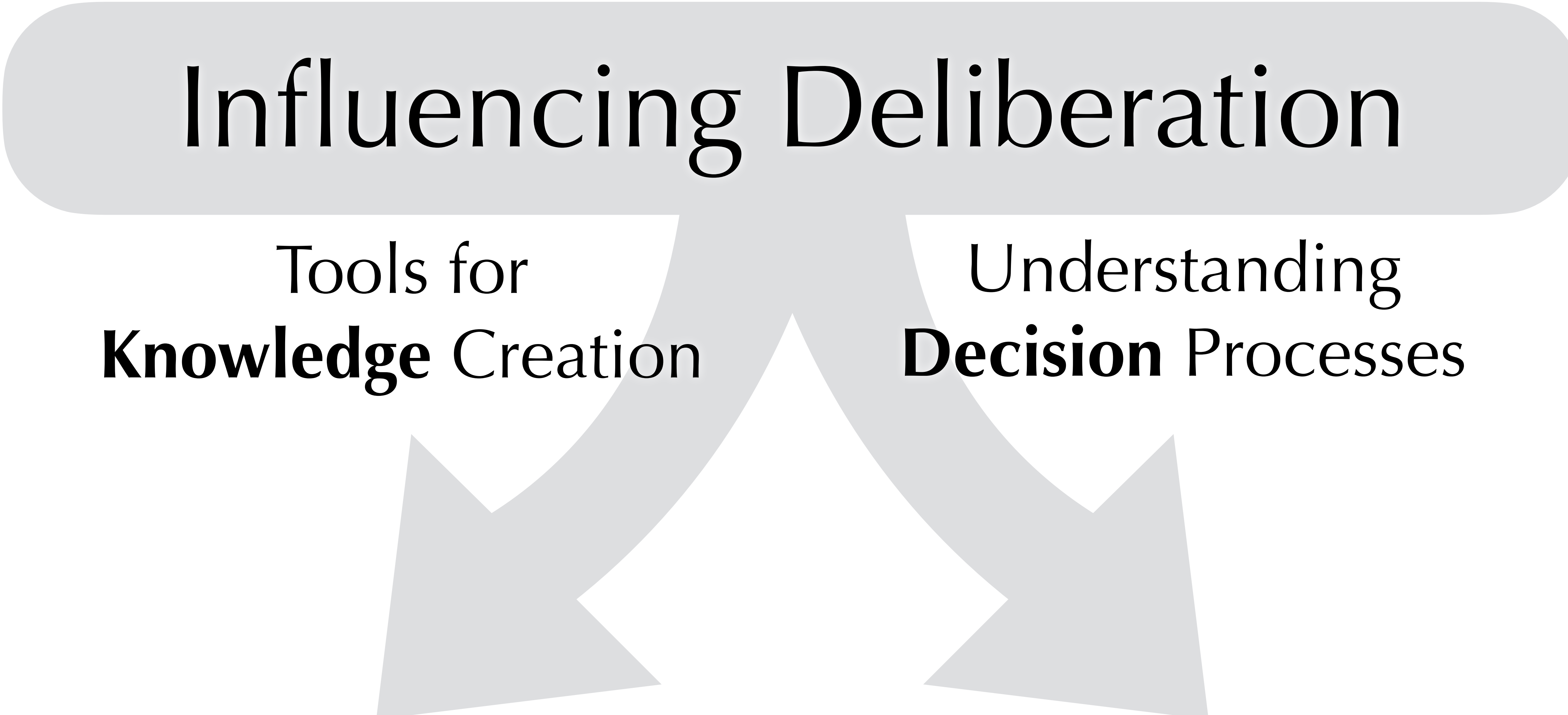
How can we make it easier to create knowledge?

Understanding **Decision** Processes

How do people decide which choices to make?

Influencing Deliberation

Tools for **Knowledge** Creation	Understanding **Decision** Processes
work with domain experts	identify impacts of algorithmic confounding
develop new unsupervised machine learning	build recommendation systems
build interactive visualizations	explore issues of fairness, accountability, and transparency


Influencing Deliberation
Tools for **Knowledge** Creation
Understanding **Decision** Processes

Influencing Deliberation

Tools for
Knowledge Creation

identifying
propaganda

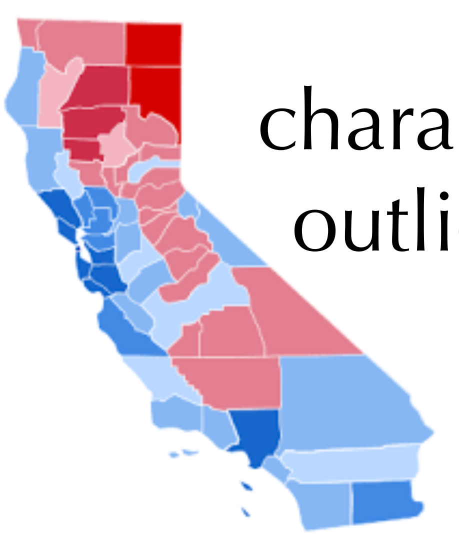
Understanding
Decision Processes

Influencing Deliberation

Tools for **Knowledge** Creation

Understanding **Decision** Processes

identifying propaganda

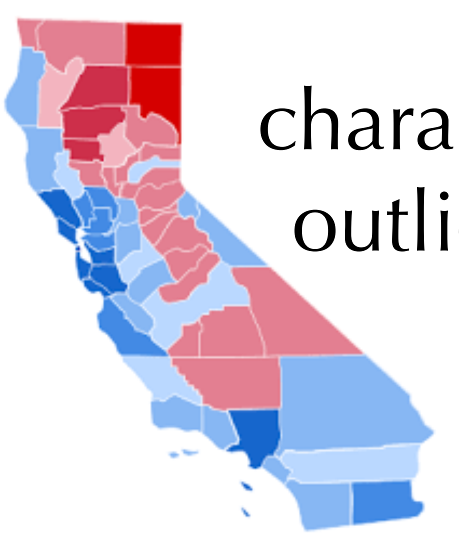


characterizing outlier votes

Influencing Deliberation

Tools for **Knowledge** Creation

identifying propaganda



characterizing outlier votes

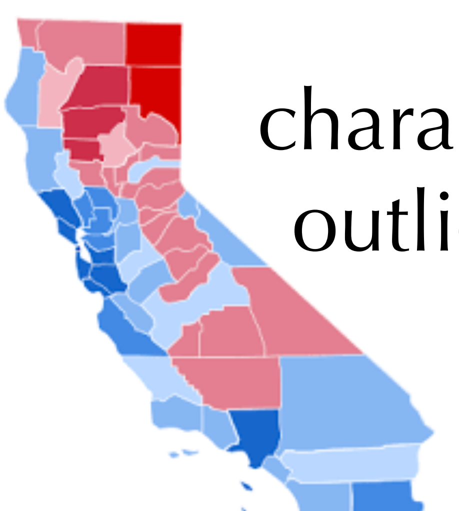
Understanding **Decision** Processes

model preferences over time

Influencing Deliberation

Tools for **Knowledge** Creation

identifying propaganda



characterizing outlier votes

Understanding **Decision** Processes

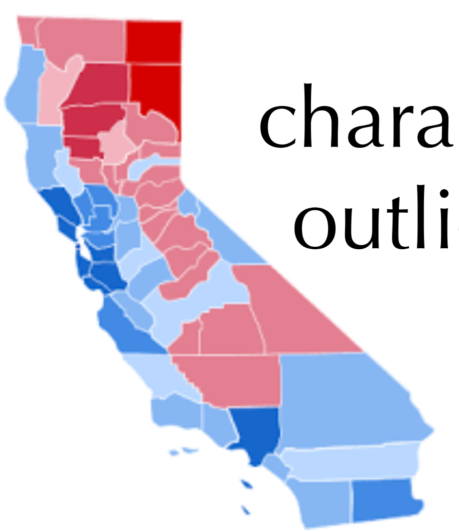
model preferences over time

disproportionate impact

Influencing Deliberation

Tools for **Knowledge** Creation

identifying propaganda



characterizing outlier votes

education & healthcare recommendations

Understanding **Decision** Processes

model preferences over time

disproportionate impact

thank you!

for papers & code, visit **ajbc.io**

Princeton Center for Information Technology Policy Seed Grant
IC Postdoctoral Research Fellowship Program (ORISE, DOE & ODNI)