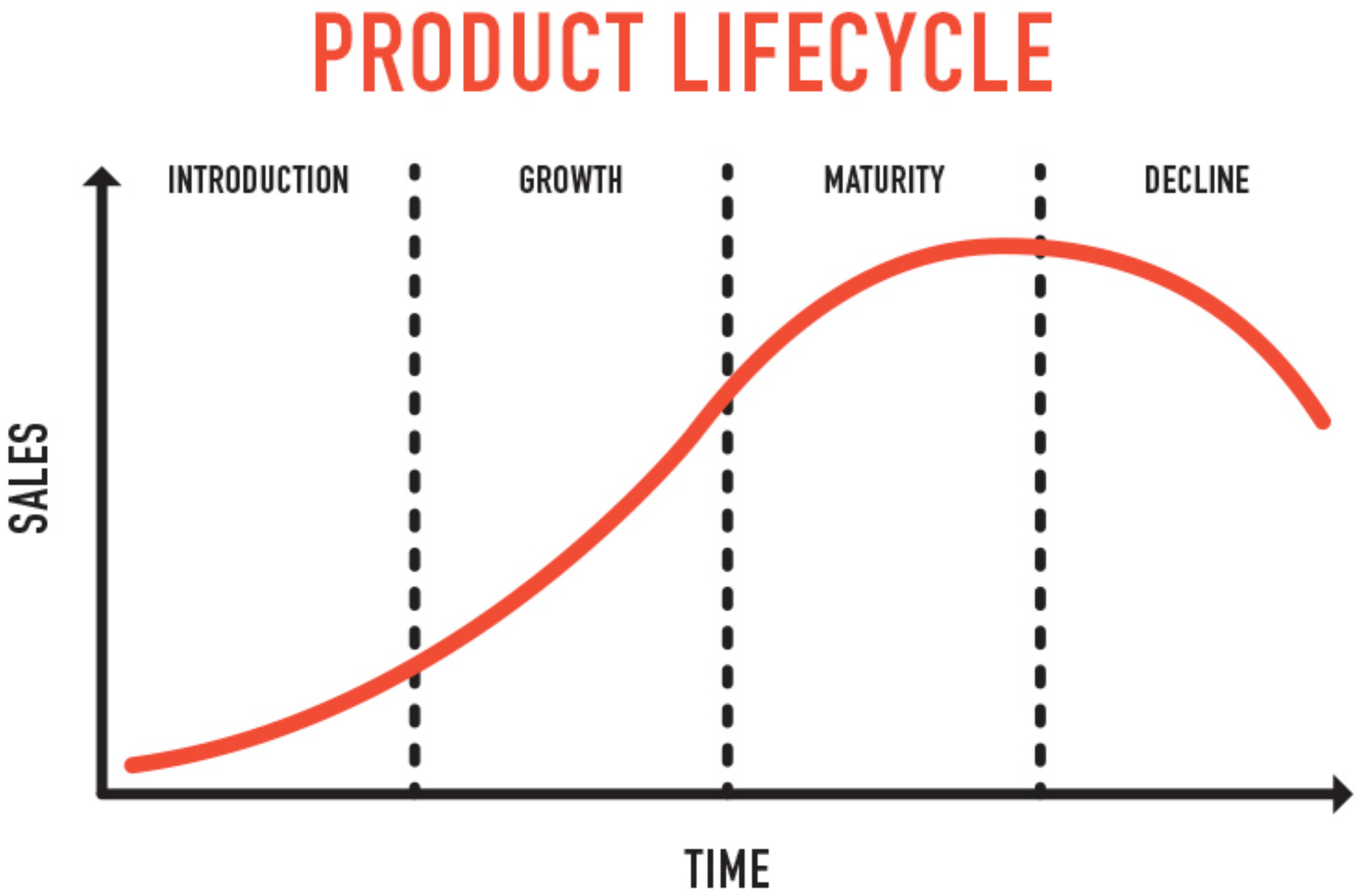
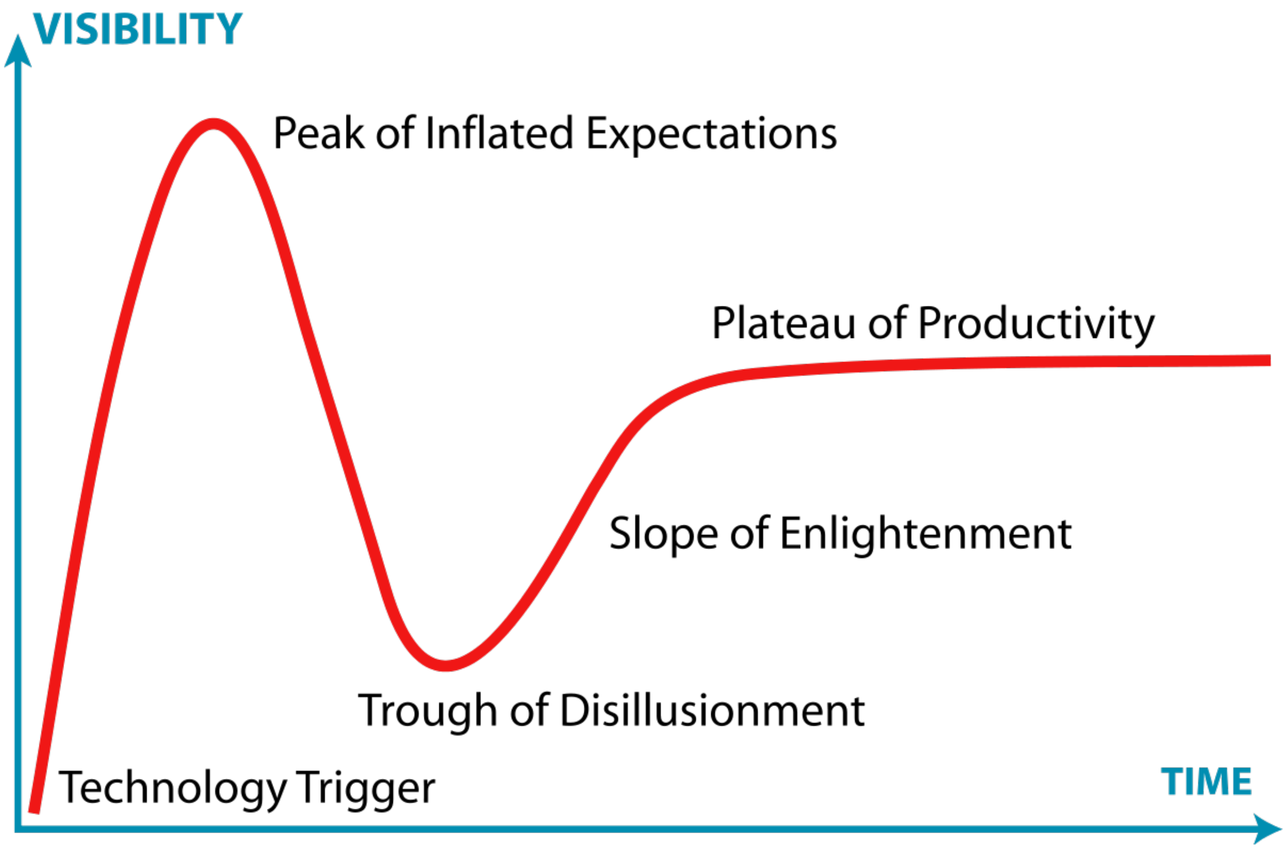
BiCycle: Item Recommendation with Life Cycles

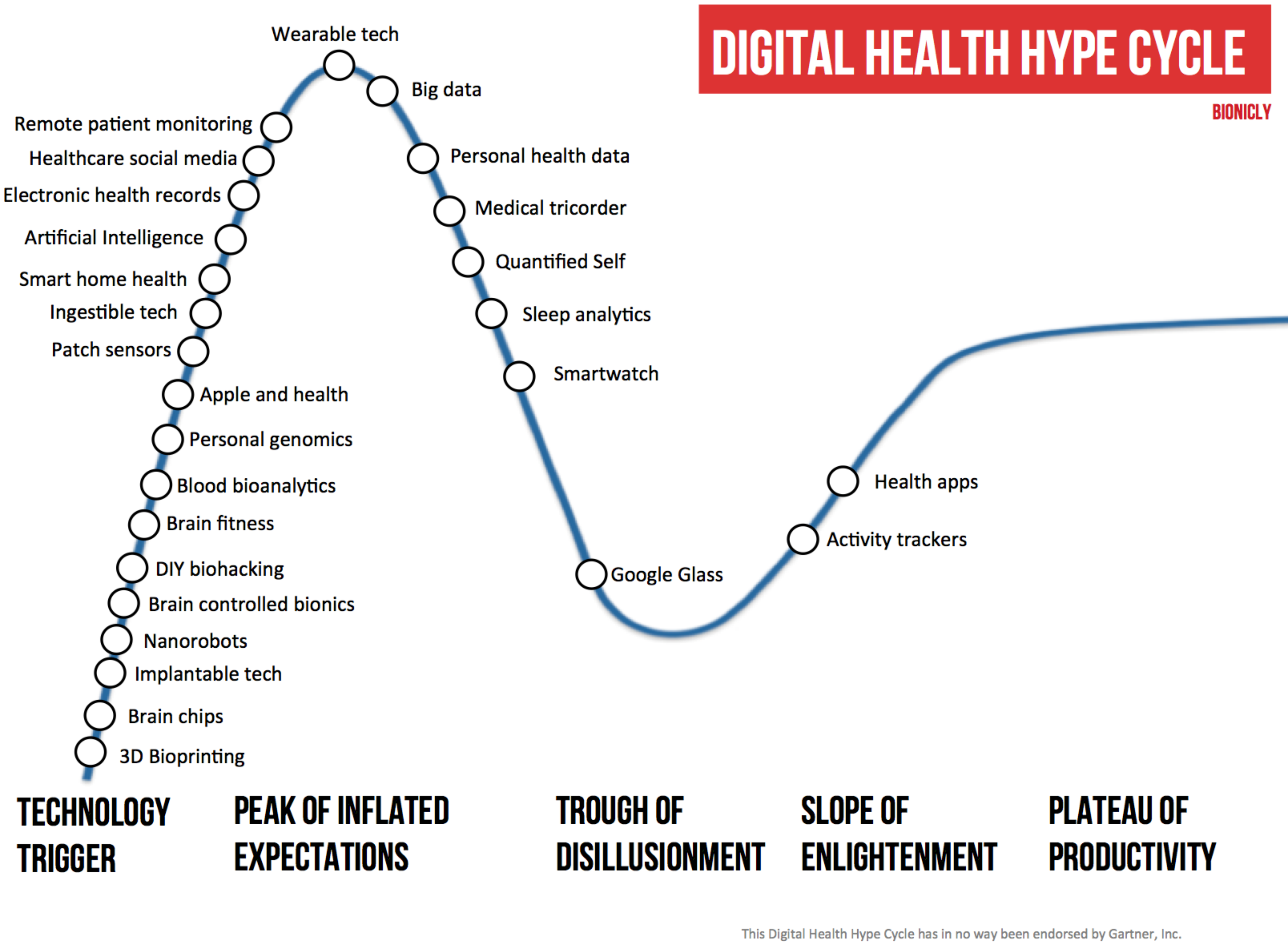
Xinyue Liu[*], Yuanfang Song[#], Charu Aggarwal[§],
Yao Zhang[‡], Xiangnan Kong[*],

[*] Worcester Polytechnic Institute [#] University of Wisconsin-Madison
[§] IBM T.J. Watson Research Center [‡] Fudan University

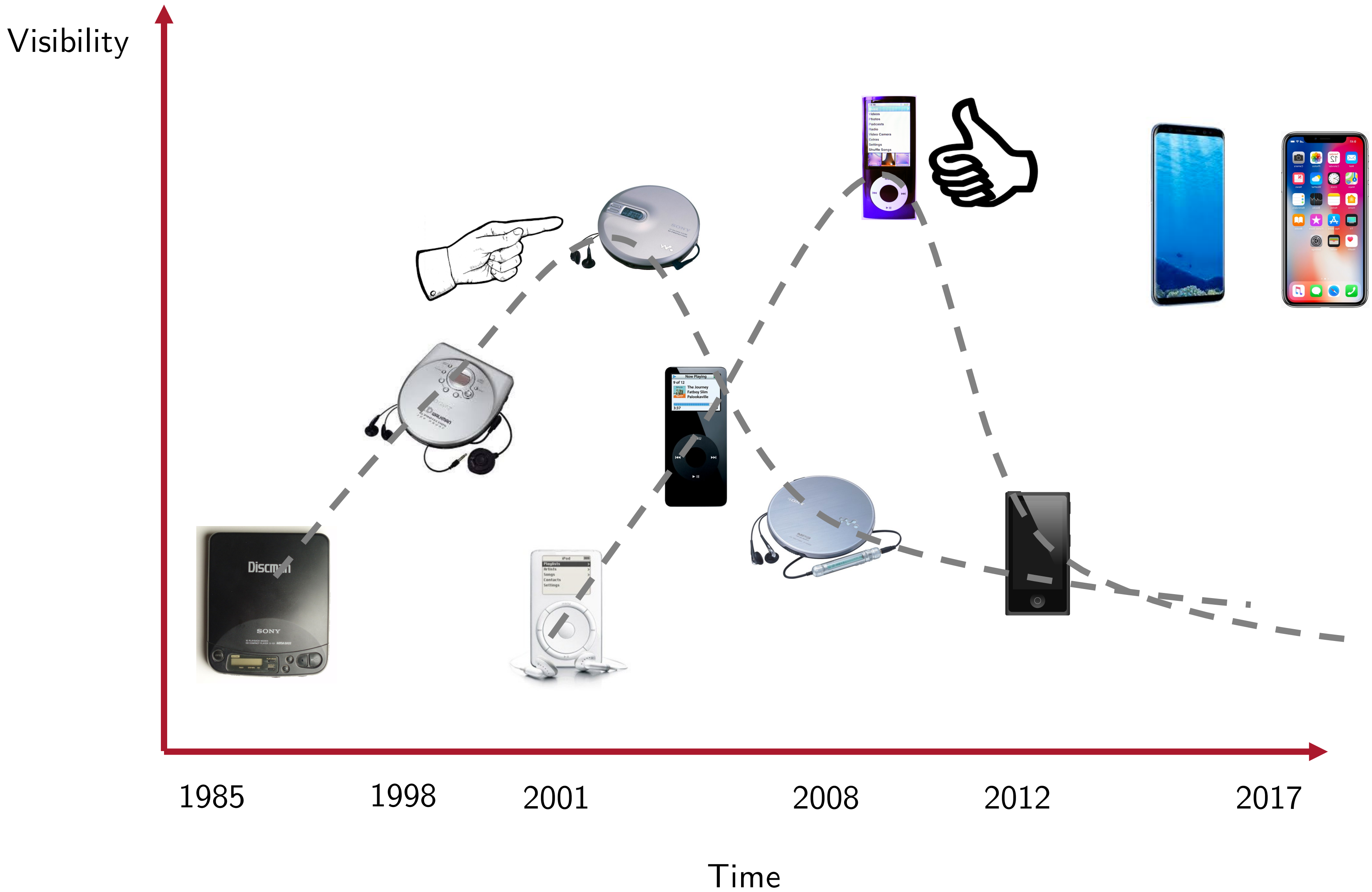

PRODUCT LIFECYCLE
INTRODUCTION
GROWTH
MATURITY
DECLINE
SALES
TIME

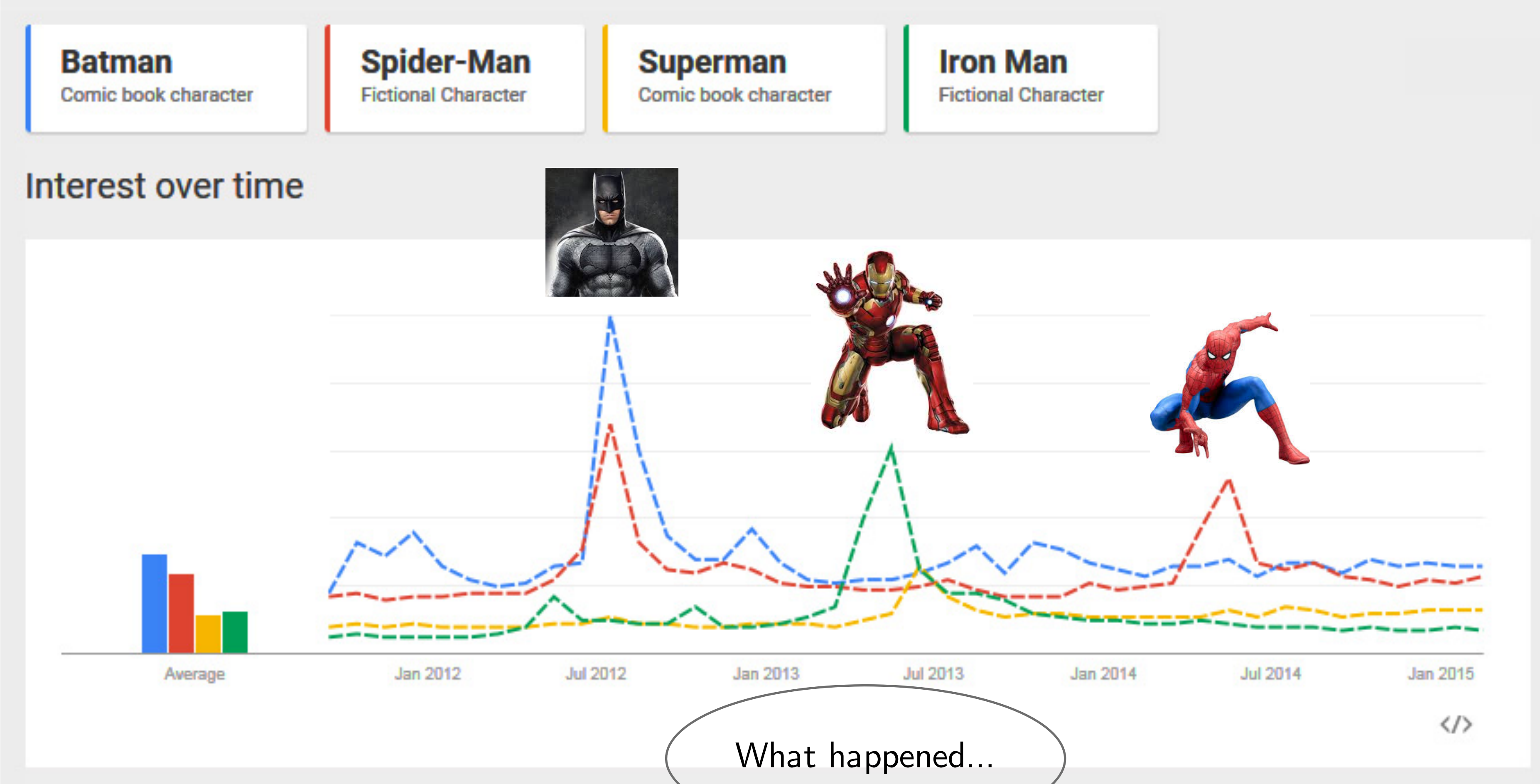
Hype Circle [Gartner]




DIGITAL HEALTH HYPE CYCLE
BIONICLY
Wearable tech
Big data
Remote patient monitoring
Healthcare social media
Electronic health records
Artificial Intelligence
Smart home health
Ingestible tech
Patch sensors
Apple and health
Personal genomics
Blood bioanalytics
Brain fitness
DIY biohacking
Brain controlled bionics
Nanorobots
Implantable tech
Brain chips
3D Bioprinting
Personal health data
Medical tricorder
Quantified Self
Sleep analytics
Smartwatch
Google Glass
Activity trackers
Health apps
TECHNOLOGY TRIGGER
PEAK OF INFLATED EXPECTATIONS
TROUGH OF DISILLUSIONMENT
SLOPE OF ENLIGHTENMENT
PLATEAU OF PRODUCTIVITY
This Digital Health Hype Cycle has in no way been endorsed by Gartner, Inc.

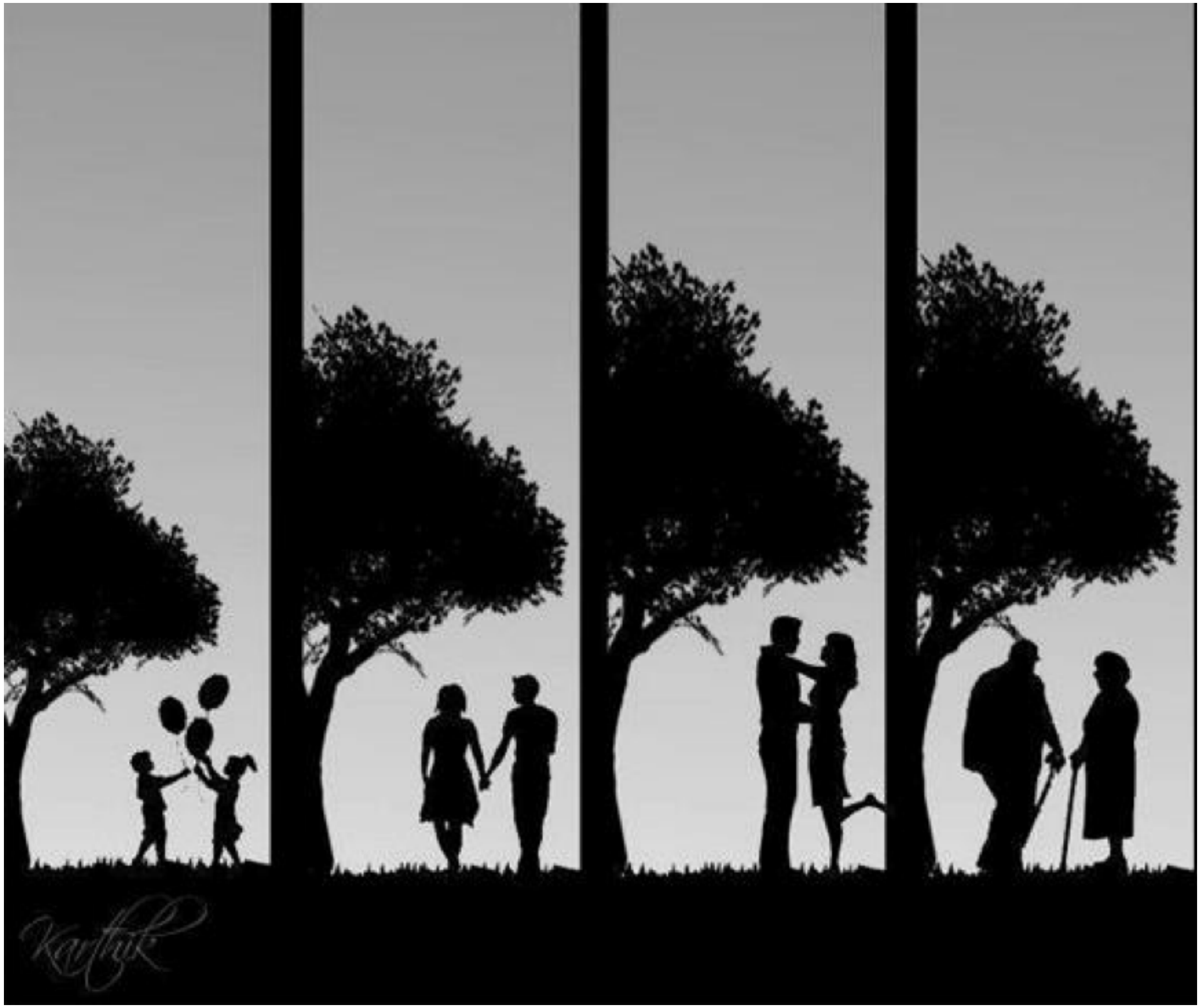
Life Cycle of Portable Music Player





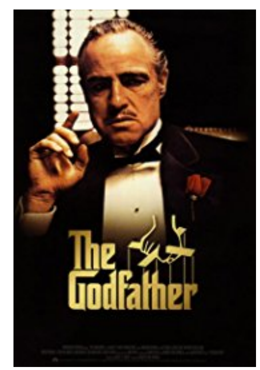
What happened...

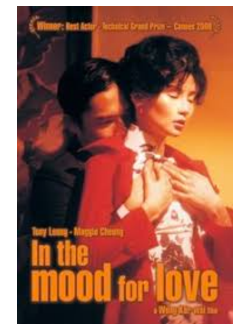
Human Life Cycle

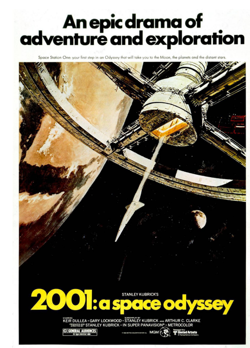


Movies

Rookie Professional Connoisseur

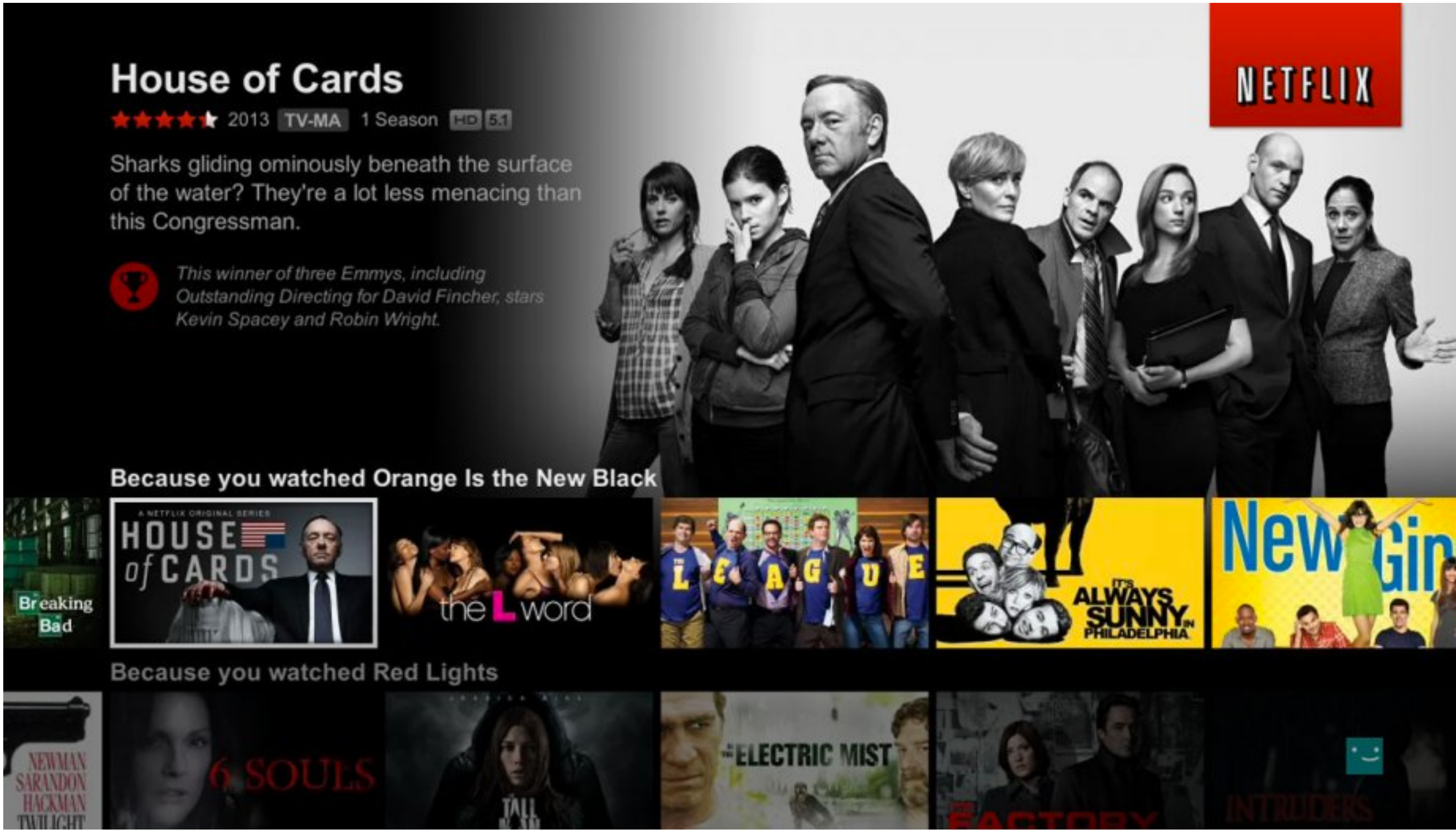






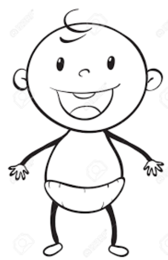
Young Mature Aged

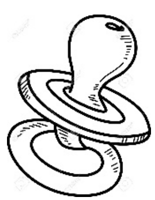
Item Recommendation



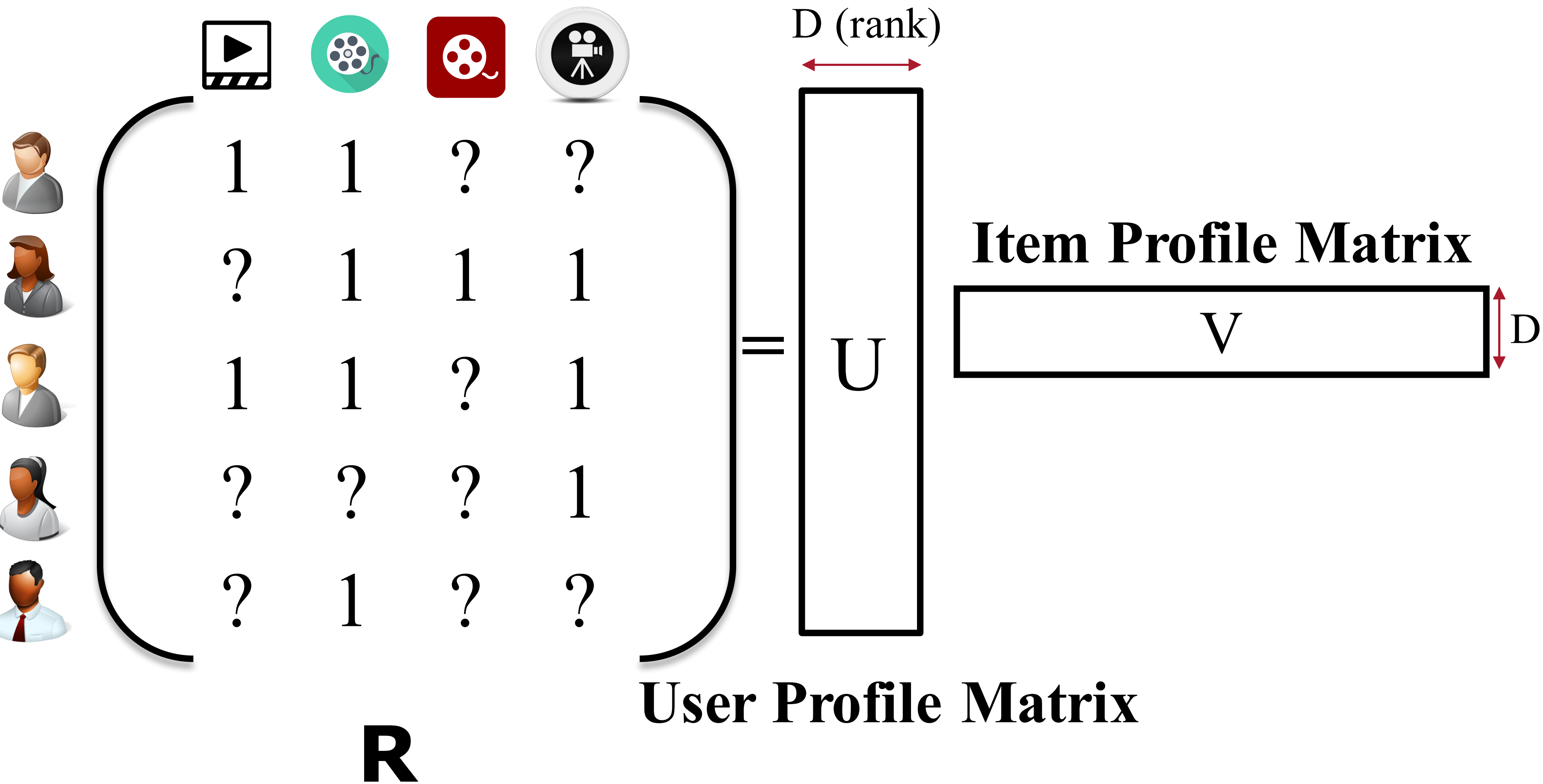
Problem Studied

Recommend items to users
by considering their life cycles






Low Rank Matrix Factorization



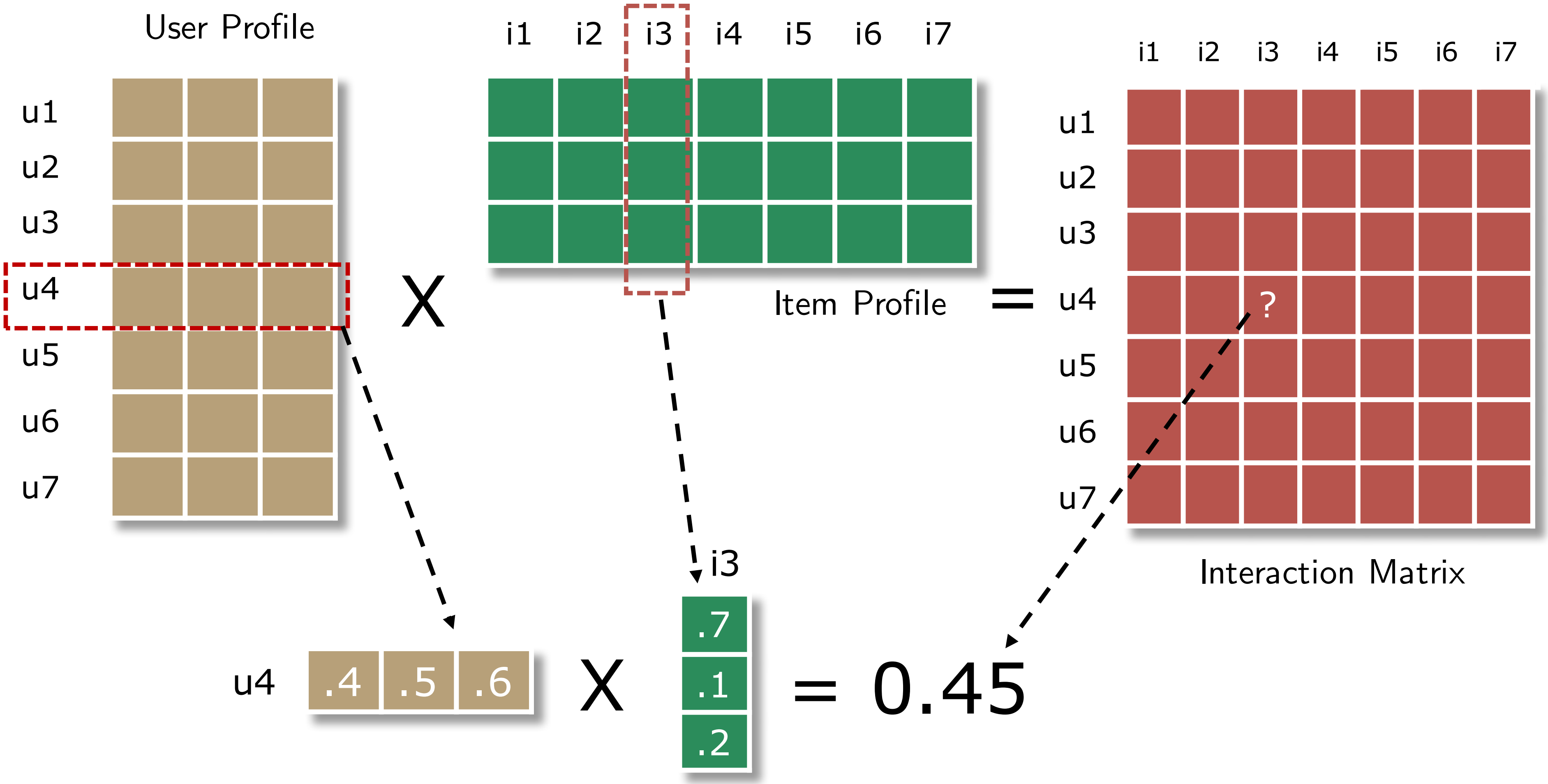
Low Rank Matrix Factorization

Reconstruction Error

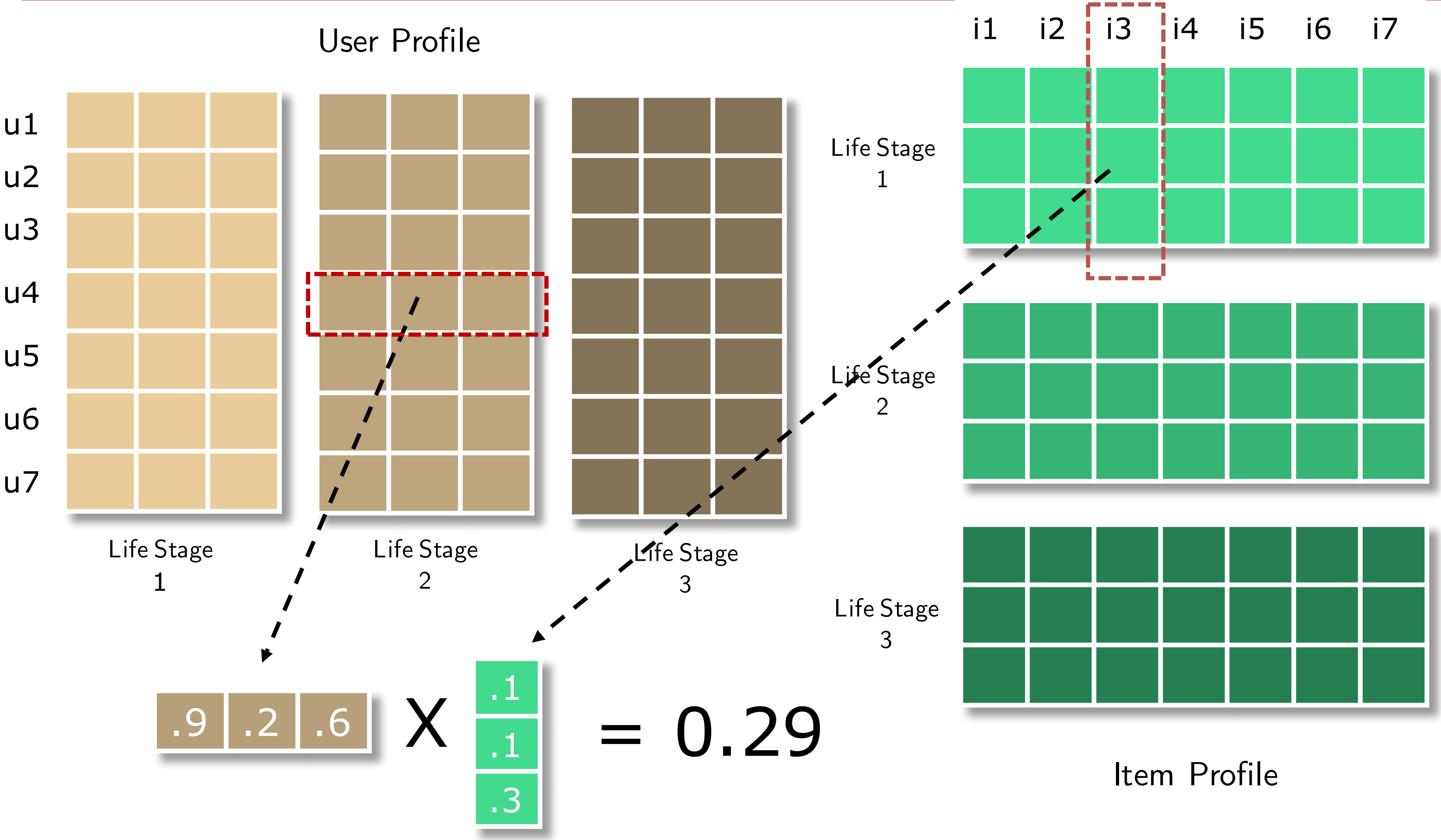
$$\underset{\mathbf{U},\mathbf{V}}{\text{minimize}} \boxed{\frac{1}{2}||\mathbf{R} - \mathbf{U}^\top \mathbf{V}||_F^2} + \boxed{\frac{\lambda}{2}(||\mathbf{U}||_F^2 + ||\mathbf{V}||_F^2)}$$

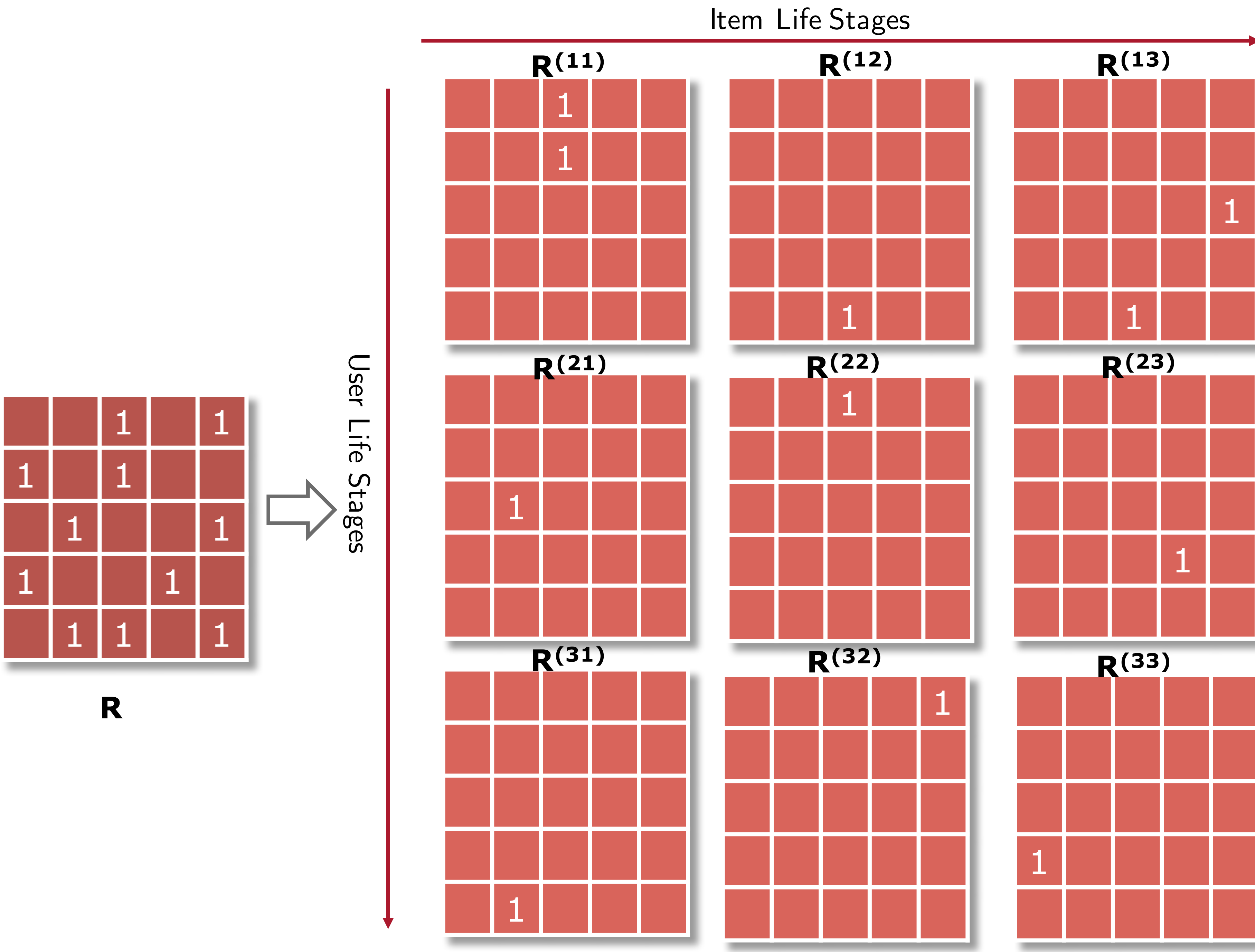
Regularization
Prevent over-fitting

Profile Matrix



Profile Matrix in Life Cycle

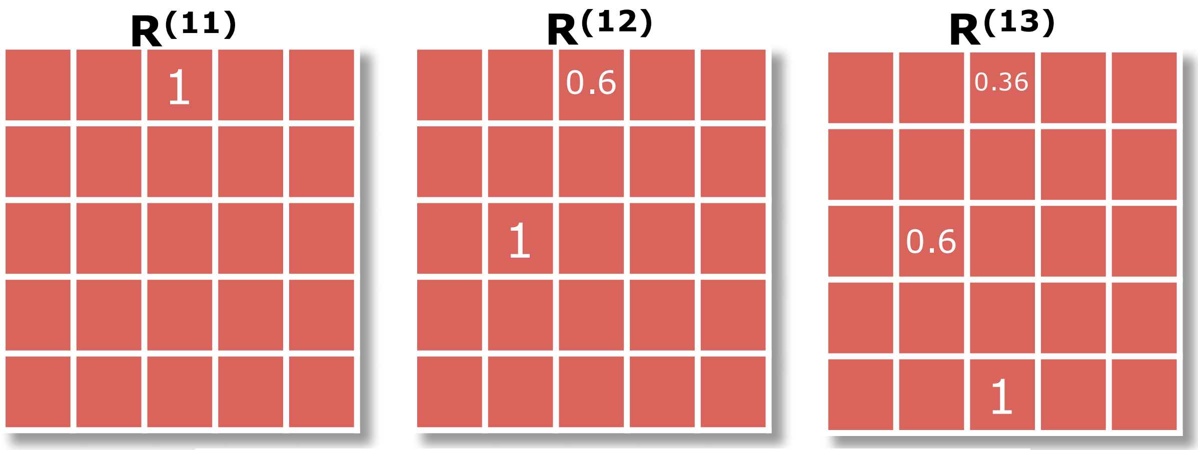



Item Life Stages
User Life Stages
R
R(11)
R(12)
R(13)
R(21)
R(22)
R(23)
R(31)
R(32)
R(33)

Smoothing on Interaction Matrix

Declay along the life cycle

Declay along the life cycle



$$\ldots \quad \tilde{\mathbf{R}}^{(pq)} = \begin{cases} \mathbf{R}^{(pq)}, \text{ if } p = q = 1. \\ \mathbf{R}^{(pq)} + \mu \tilde{\mathbf{R}}^{((p-1),q)}, \text{ if } q = 1 \text{ and } p \geq 2 \\ \mathbf{R}^{(pq)} + \pi \tilde{\mathbf{R}}^{(p,(q-1))}, \text{ if } p = 1 \text{ and } q \geq 2 \\ \mathbf{R}^{(pq)} + \mu \tilde{\mathbf{R}}^{((p-1),q)} + \pi \tilde{\mathbf{R}}^{(p,(q-1))}, \text{ otherwise} \end{cases} \quad ..$$

Forget Coefficient $\pi = 0.6$

Matrix Factorization with Life Cycle

Reconstruction Error

$$\min_{\{\mathbf{U}^{(p)}\},\{\mathbf{V}^{(q)}\}} \boxed{\frac{1}{2}\sum_{p=1}^{M}\sum_{q=1}^{N}||\tilde{\mathbf{R}}^{(pq)} - \mathbf{U}^{(p)}(\mathbf{V}^{(q)})^\top||_F^2}$$

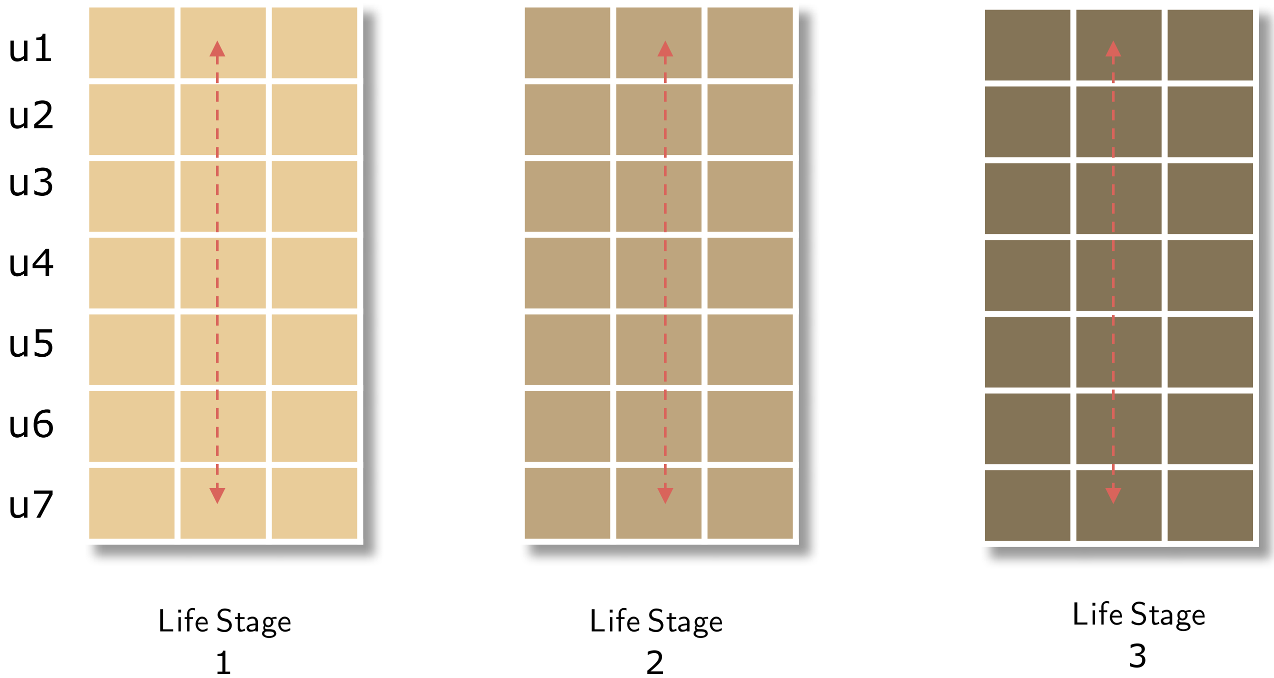
$$\boxed{+\frac{\lambda}{2}(\sum_{p=1}^{M}||\mathbf{U}^{(p)}||_F^2 + \sum_{q=1}^{N}||\mathbf{V}^{(q)}||_F^2)}$$

Regularization

- M user stages, N item stages

In-Stage Variance Regularization

User/Item characters in the same life stage are similar



$$L_v(\mathbf{U}^{(1)}, \dots, \mathbf{U}^{(M)}, \mathbf{V}^{(1)}, \dots, \mathbf{V}^{(N)})$$

$$= \boxed{\sum_{p=1}^{M} ||\mathbf{U}^{(p)} - \frac{1}{m}\mathbf{J}^{m \times m}\mathbf{U}^{(p)}||_F^2}$$

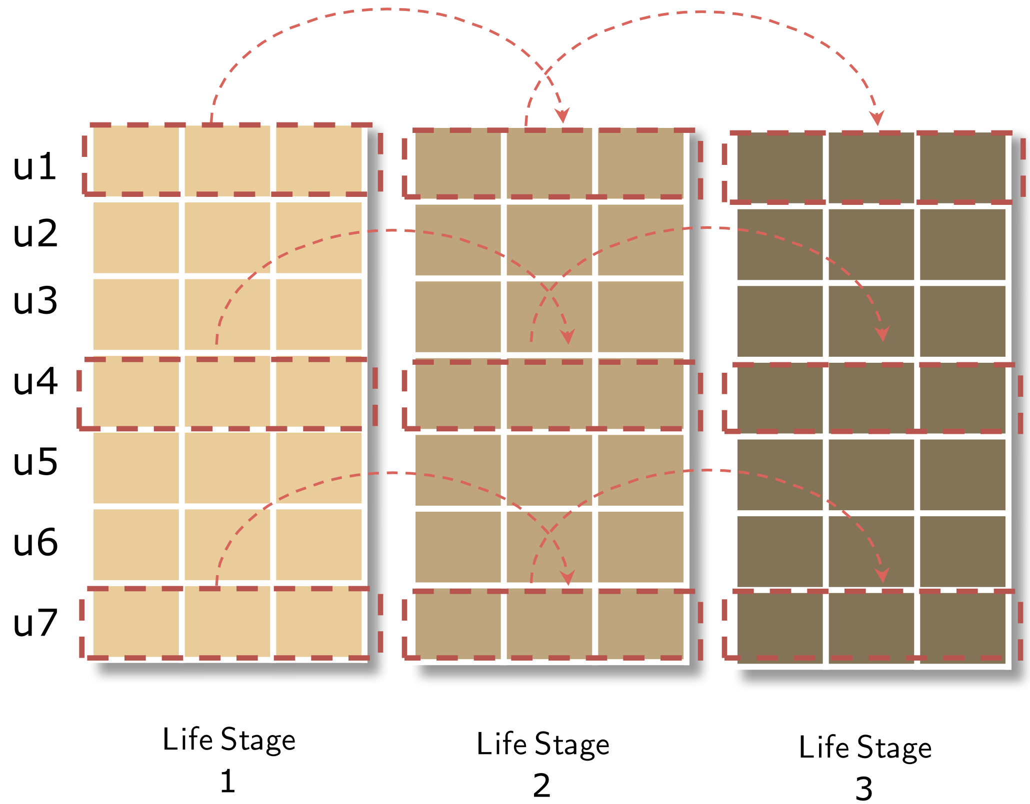
Overall in-stage variance of user profile

$$+ \boxed{\sum_{q=1}^{N} ||\mathbf{V}^{(q)} - \frac{1}{n}\mathbf{J}^{n \times n}\mathbf{V}^{(q)}||_F^2}$$

Overall in-stage variance of item profile

Inter-Stage Fused Regularization

Characters evolve gradually across life stages



$$L_f(\mathbf{U}^{(1)}, \ldots, \mathbf{U}^{(M)}, \mathbf{V}^{(1)}, \ldots, \mathbf{V}^{(N)}) = \sum_{p=1}^{M-1} ||\mathbf{U}^{(p+1)} - \mathbf{U}^{(p)}||_F^2 + \sum_{q=1}^{N-1} ||\mathbf{V}^{(q+1)} - \mathbf{V}^{(q)}||_F^2$$

Objective Function

Minimize the error for observed data

$$\min_{\{\mathbf{U}^{(p)}\},\{\mathbf{V}^{(q)}\}} \frac{1}{2}\sum_{p=1}^{M}\sum_{q=1}^{N} ||\mathbf{R}^{(pq)} - \mathbf{U}^{(p)}(\mathbf{V}^{(q)})^\top||_F^2$$

Not too complicated

$$+\frac{\lambda}{2}(\sum_{p=1}^{M}||\mathbf{U}^{(p)}||_F^2 + \sum_{q=1}^{N}||\mathbf{V}^{(q)}||_F^2)$$

To be similar
in same life stage

$$+\frac{\alpha}{2}L_v(\mathbf{U}^{(1)},\ldots,\mathbf{U}^{(M)},\mathbf{V}^{(1)},\ldots,\mathbf{V}^{(N)})$$

Evolve gradually
across life stages

$$+\frac{\beta}{2}L_f(\mathbf{U}^{1)},\ldots,\mathbf{U}^{(M)},\mathbf{V}^{(1)},\ldots,\mathbf{V}^{(N)})$$

Data Sets

- DBLP: author – keywords data set
- Epinions: product review data set
- ML100K: movie rating data set

Compared Methods

- Pop[1]: Recommend the popular items
- MF[2]: Low-rank matrix factorization
- SVD++[3]: Couples SVD with neighborhood model
- TimeSVD++[4]: Time-aware factorization model

- ItemCycle: Only consider life cycle of items
- UserCycle: Only consider life cycle of users
- <u>BiCycle</u>: Proposed Method

[1] X. Yu, X. Ren, Y. Sun, Q. Gu, B. Sturt, U. Khandelwal, B. Norick, and J. Han, "Personalized entity recommendation: A heterogeneous information network approach,"
[2] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender system"
[3] Y. Koren, "Factorization meets the neighborhood: a multifaceted collaborative filtering model,"
[4] Y. Koren, "Collaborative Filtering with Temporal Dynamics"

Evaluation Metrics

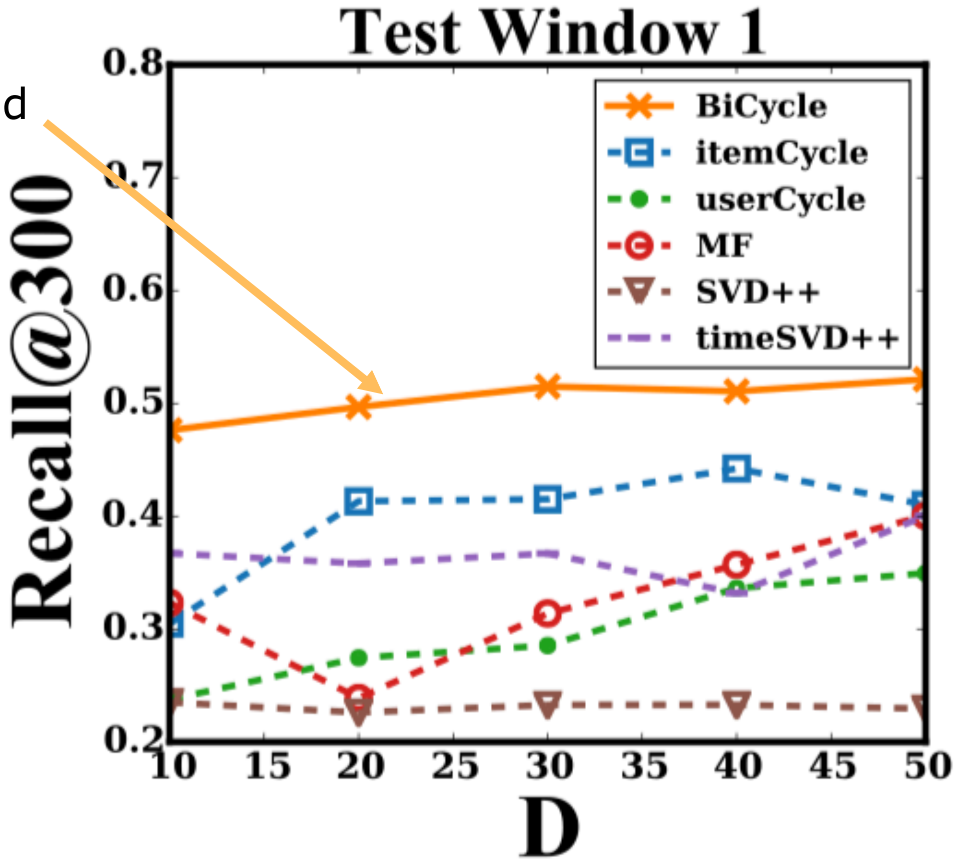
- Precision@k
- Recall@k
- MRR (Mean Reciprocal Rank)

Experimental Results

Dataset	Methods	Prec@1	Prec@5	Prec@10	MRR
DBLP-Terms	BiCycle	**0.2874** (1)	**0.1767** (1)	**0.1336** (1)	**0.1434** (1)
	USERCYCLE	0.2781 (3)	0.1749 (3)	0.1286 (4)	0.1365 (3)
	ITEMCYCLE	0.2848 (2)	0.1754 (2)	0.1318 (2)	0.1407 (2)
	MF	0.2741 (4)	0.1762 (4)	0.1306 (3)	0.1357 (4)
	SVD++	0.1992 (5)	0.1538 (5)	0.1152 (6)	0.1114 (6)
	TIMESVD	0.1738 (6)	0.1441 (6)	0.1178 (5)	0.1143 (5)
	POP	0.0067 (7)	0.0043 (7)	0.0040 (7)	0.0062 (7)
ML100K	BiCycle	**0.2800** (1)	**0.2000** (1)	**0.1680** (1)	**0.1311** (1)
	USERCYCLE	0.2200 (3)	0.1880 (2)	0.1620 (3)	0.1282 (3)
	ITEMCYCLE	**0.2800** (1)	0.1880 (2)	0.1640 (2)	0.1296 (2)
	MF	0.2200 (3)	0.1680 (4)	0.1540 (4)	0.1237 (4)
	SVD++	0.1800 (5)	0.1360 (5)	0.1240 (5)	0.0920 (5)
	TIMESVD	0.1800 (5)	0.1320 (6)	0.1080 (6)	0.0740 (6)
	POP	0.0200 (7)	0.0080 (7)	0.0060 (7)	0.0098 (7)

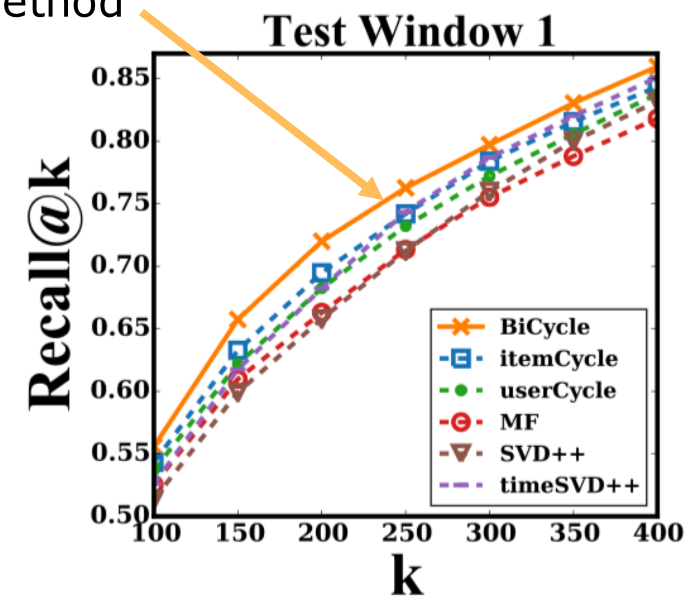
Experimental Results (Epinions)

Our Method

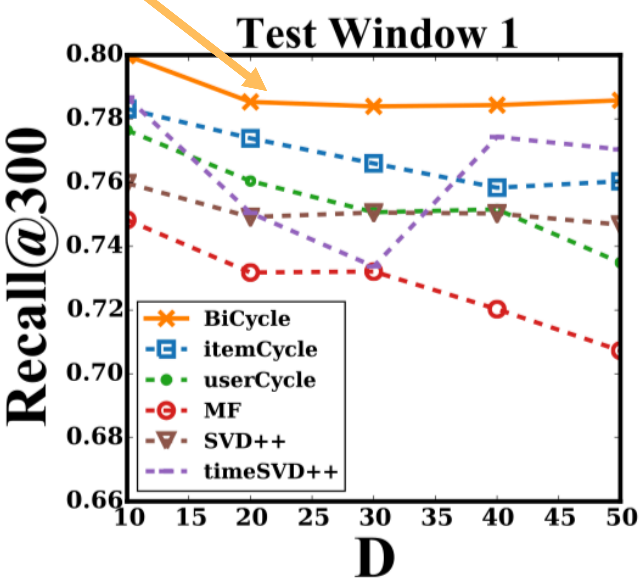


Experimental Results (DBLP)

Our Method

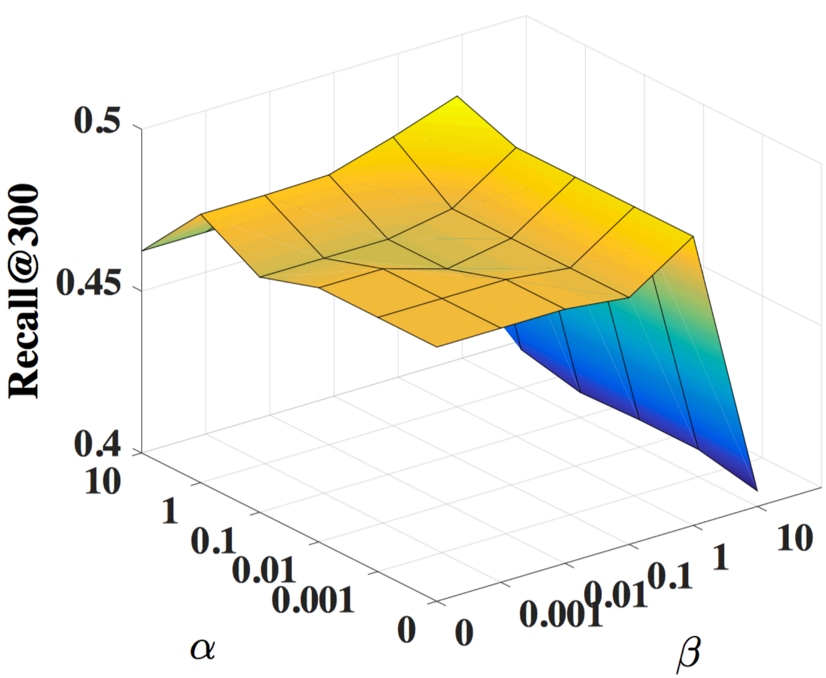


Our Method

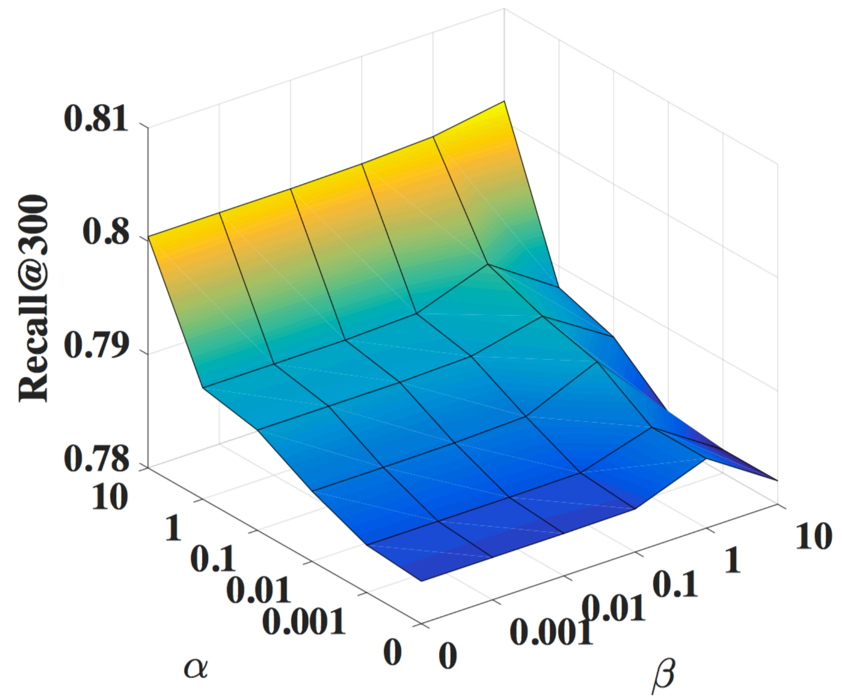


Parameter Study

Balance between variance regularization and fused regularization



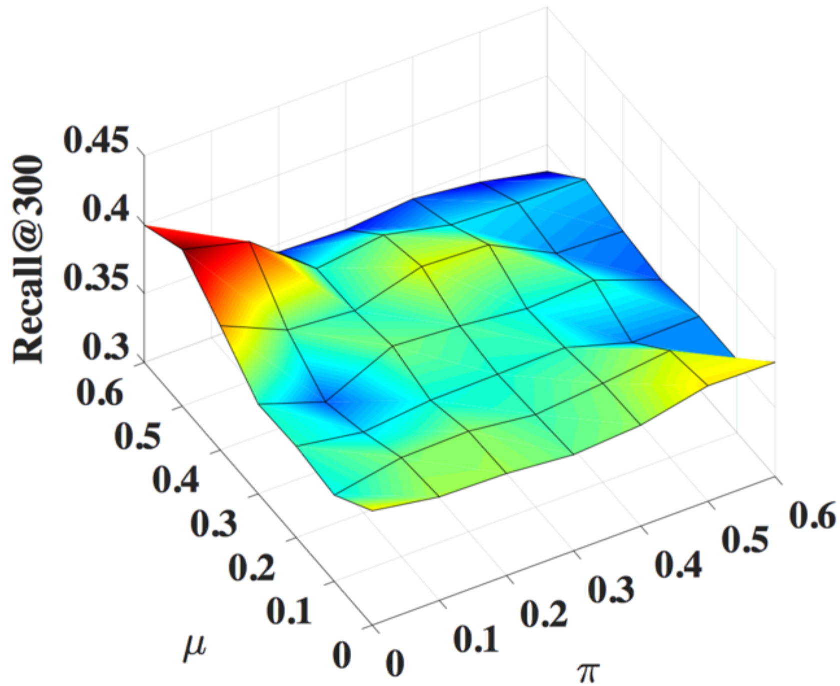
(a) Epinions



(b) DBLP-Terms

Parameter Study

On smoothing coefficients [π(users) and μ (items)]

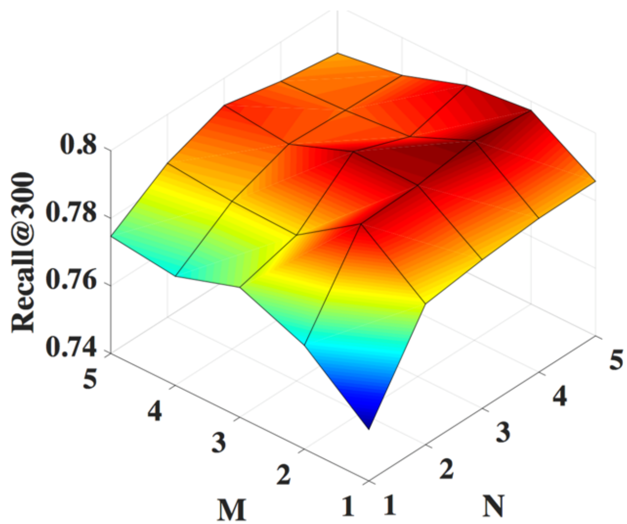


(a) Epinions (on μ and π)

- Effective on user side
- Not very sensitive on item side

Parameter Study

On number of life stages



(b) DBLP (on M and N)

- The best # of user life stages are smaller than best # of item life stages
- When M=1 and N=1, the model degenerates to pure MF

Summary

- Proposed Life-Cycle Aware Item Recommendation Method
  - Considering the life cycles of both users and items
  - Users(items) at same life stage share similar pattern
  - Users (items) evolve gradually across life stages
- Conclusion
  - The inherent life cycles of users and items helps the recommendation
  - Using life cycles with appropriate parameters beats Time-aware CF using wall time

WPI

Q&A

Contact Authors: Xinyue Liu, Xiangnan Kong

xliu4@wpi.edu, xkong@wpi.edu