User Novelty driven Personalized Item Recommendation

CHEN, Jun (陈俊)

PhD Graduate

Tsinghua University

Outline

- User Novelty driven Personalized Item Recommendation
  - User novelty classification
  - Repeat recommendation *(with **low** user novelty)*
  - Novel recommendation *(with **high** user novelty)*
  - Intransitive preference modeling *(beyond a single angle of uesr novelty)*

Background

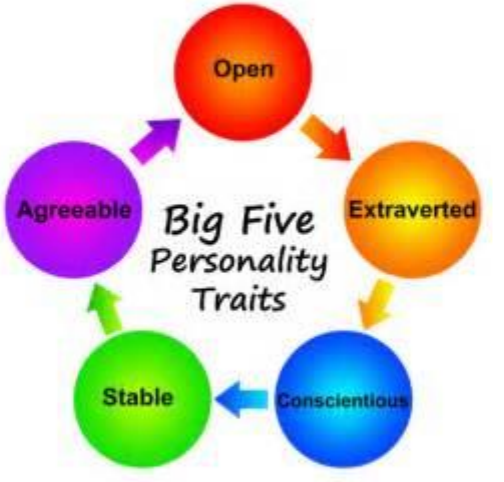
- **In a conventional way to build RecSys**
  - Obtain user feedbacks, e.g., views/clicks/ratings.
  - Fit data with a model, e.g. CF, MF, LTR, NN.
  - Predict unseen items of potential user interests.
  - Constraints: time, social relations, geo locations, etc.
- **Task in this study**
  - Given user's previous consumption history with timestamps, predict what (s)he will consume next.

$$\text{Predict } x^u_t \quad \text{s.t. } \{x^u_1, x^u_2, x^u_3, \ldots, x^u_{t-1}\}$$

- **Some potential methods**
  - Markov Chain model
  - Tensor factorization
  - Neural networks for sequence learning (GRU/LSTM)
- **Regardless of user's intention on x^u_t**

Background

- **In this study, user's intention matters**
  - In psychology, the *openness* in the *Big Five Personality Traits* model describes people's willingness to accept unknown things.
  - ***User novelty*** as a metric of openness: low – familiar, high – novel.
  - User's selection is a reflection of their **intentions**: repeat familiar items or explore novel items.
- **Problem breakdown**
  A. User novelty classification
  B. Repeat recommendation (*low user novelty*)
  C. Novel recommendation (*high user novelty*)
  D. Intransitive preference modeling



A. User novelty classification

Motives

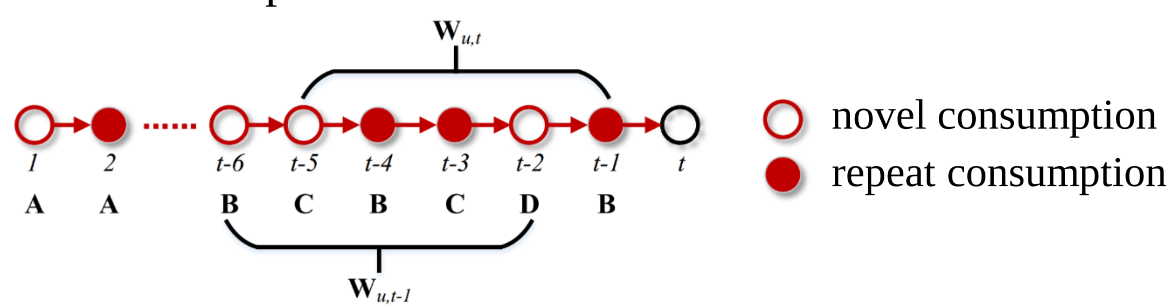
- Understand user's intentions of consumptions.
- Divide the candidate itemset for recommendations.

Problem

- Given the time window **W** of user *u*'s consumption behaviors before time *t*, predict whether *u* will choose the consumed items in **W** at *t*.
- User novelty: $\mathrm{P}(x_t^u \notin \mathbf{W})$

Examples

- Given *u*'s recent playlist of songs **W**, predict if *u* will repeat listening to a song in **W** at next time step.
- Given the sequence of *u*'s recent POI check-ins **W**, predict if *u* will revisit a POI in **W** at next time step.



A. User novelty classification

- **In a binary classification scheme**
  - **Feature extraction**
    A. Average normalized item popularity
    B. Average normalized item reconsumption ratio
    C. User reconsumption ratio
    D. Window repeat ratio

A. $$h_{IP}(v) = \frac{\ln(1 + freq(v))}{\max_{x \in \mathcal{V}} \ln(1 + freq(x))}, \quad h_{IP}(\mathbf{W}_{u,t}) = \frac{1}{|\mathbf{W}_{u,t}|} \sum_{v \in \mathbf{W}_{u,t}} h_{IP}(v)$$

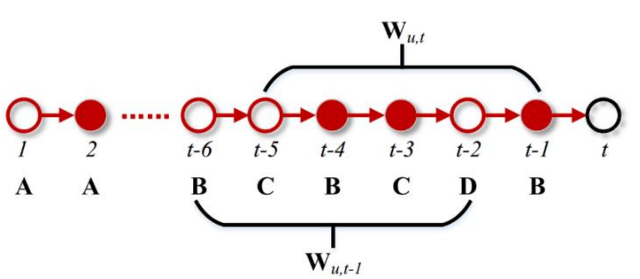
B. $$h_{AIRR}(v) = \ln\left(1 + \frac{\sum_{u \in \mathcal{U}} \sum_{x_t^u \in \mathcal{X}^u} \mathbb{1}_{x_t^u = v \wedge x_t^u \in \mathbf{W}_{u,t}}}{\sum_{u \in \mathcal{U}} \sum_{x_t^u \in \mathcal{X}^u} \mathbb{1}_{x_t^u = v}}\right)$$

$$h_{IRR}(v) = \frac{h_{AIRR}(v)}{\max_{x \in \mathcal{V}} h_{AIRR}(x)}$$

$$h_{IRR}(\mathbf{W}_{u,t}) = \frac{1}{|\mathbf{W}_{u,t}|} \sum_{v \in \mathbf{W}_{u,t}} h_{IRR}(v)$$

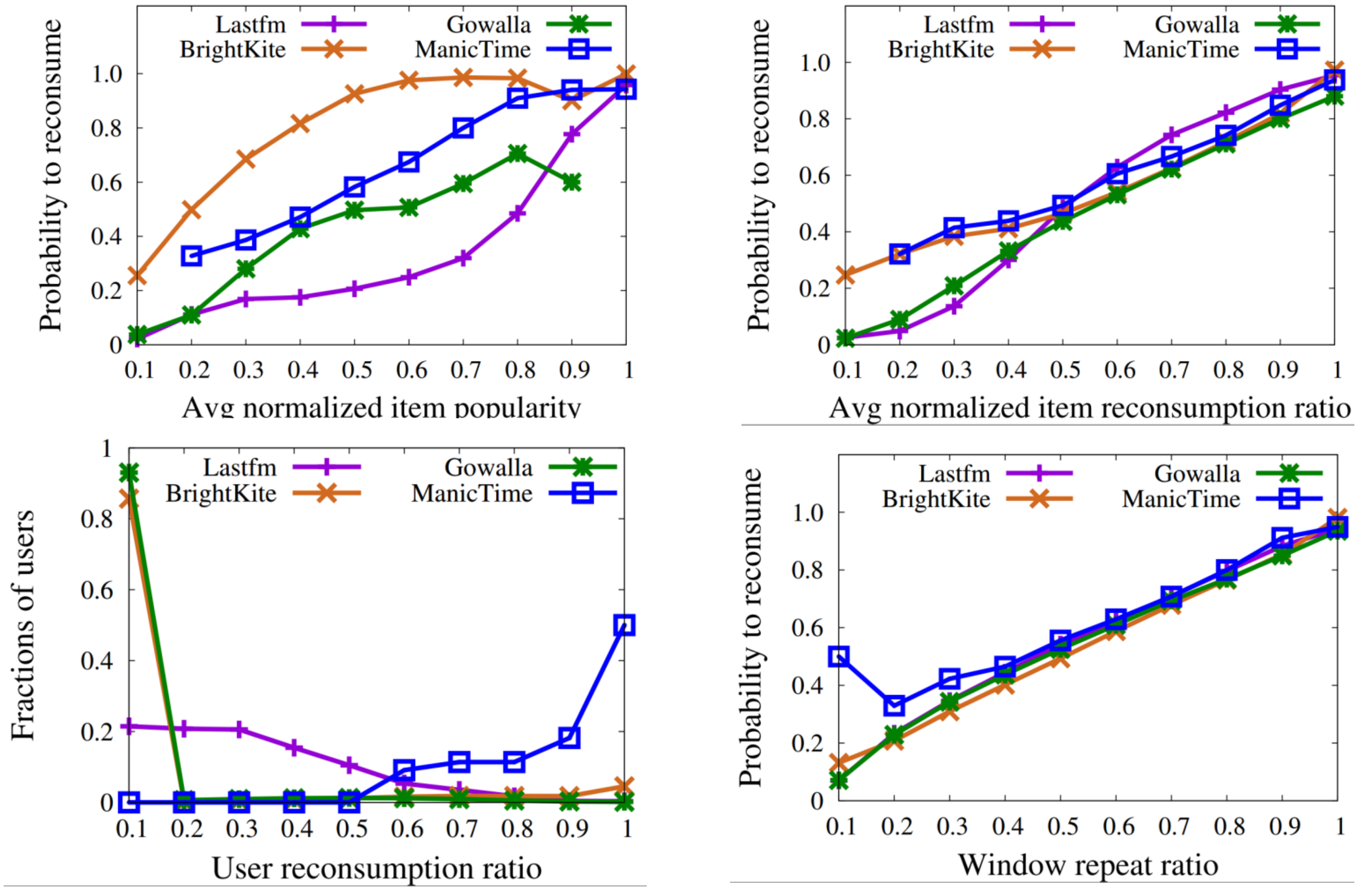
C. $$h_{URR}(u) = \frac{\sum_{x_t^u \in \mathcal{X}^u} \mathbb{1}_{x_t^u \in \mathbf{W}_{u,t}}}{|\mathcal{X}^u|}$$

D. $$h_{WRR}(\mathbf{W}_{u,t}) = 1 - \frac{|DS(\mathbf{W}_{u,t})|}{|\mathbf{W}_{u,t}|}$$



A. User novelty classification

- **Feature significance**



A. User novelty classification

- **In a binary classification scheme**
  - **Classifiers**

Lasso classifier

$$\Pr_{\mathcal{L}}(u,t) = \mathbf{w}^T \mathbf{x}_{u,t}$$

$$\operatorname*{argmin}_{\mathbf{w}_{\mathcal{L}}^*} \mathcal{L}(\mathbf{w}) = \sum_{u \in \mathrm{U}} \sum_{t \in T_u} (\mathbf{w}^T \mathbf{x}_{u,t} - \mathbb{I}_{t \in W_k^{u,t}})^2 \quad s.t. \sum_i \mathbf{w}_i = \mathbf{1}$$

$$\operatorname*{argmin}_{\mathbf{w}_{\mathcal{L}}^*} \mathcal{L}(\mathbf{w}) = \sum_{u \in \mathrm{U}} \sum_{t \in T_u} (\mathbf{w}^T \mathbf{x}_{u,t} - \mathbb{I}_{t \in W_k^{u,t}})^2 + \lambda \sum_i \mathbf{w}_i$$

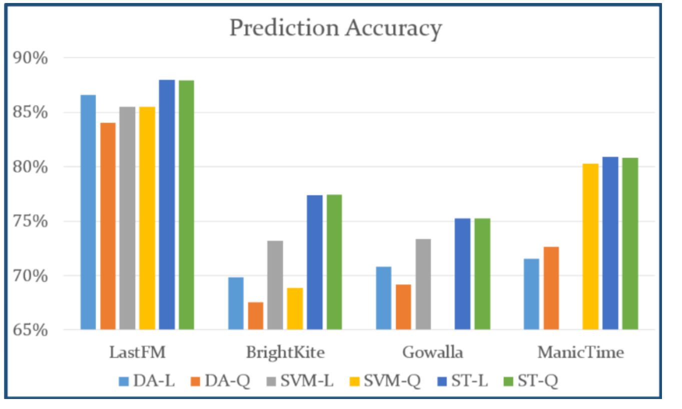
Quadratic classifier

$$\Pr_{\mathcal{Q}}(u,t) = \sqrt{\mathbf{w}^T diag(\mathbf{x}_{u,t})^2 \mathbf{w}}$$

$$\operatorname*{argmin}_{\mathbf{w}_{\mathcal{Q}}^*} \mathcal{Q}(\mathbf{w}) = \sum_{u \in \mathrm{U}} \sum_{t \in T_u} \left(\sqrt{\mathbf{w}^T diag(\mathbf{x}_{u,t})^2 \mathbf{w}} - \mathbb{I}_{t \in W_k^{u,t}}\right)^2 \quad s.t.\ \mathbf{w}^T \mathbf{w} = \mathbf{1}$$

$$\operatorname*{argmin}_{\mathbf{w}_{\mathcal{Q}}^*} \mathcal{Q}(\mathbf{w}) = \sum_{u \in \mathrm{U}} \sum_{t \in T_u} \left(\sqrt{\mathbf{w}^T diag(\mathbf{x}_{u,t})^2 \mathbf{w}} - \mathbb{I}_{t \in W_k^{u,t}}\right)^2 + \lambda \mathbf{w}^T \mathbf{w}$$

- **Experiments**
  - Publish the ManicTime dataset (https://github.com/chenjun082/manictime).
  - Average 80% accuracy on *Last.fm*, *Gowalla*, *BrightKite* and *ManicTime* dataset.

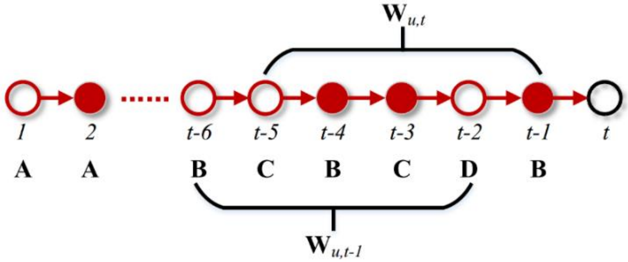


J. Chen, et al. Will you reconsume the near past? fast prediction on short-term reconsumption behaviors. **AAAI**, 2015.

B. Repeat recommendation

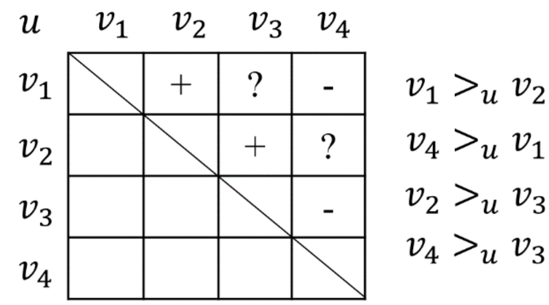
- **Motives**
  - Repeat consumptions are common
    - e.g. 77% in Last.fm [Kapoor, WSDM2015]
  - Some people have ***low user novelty*** at sometimes.
  - A lack of study in repeat recommendation.
- **Problem**
  - Precondition: *u*'s user novelty is low at time *t*.
  - Given the time window **W** of user *u*'s consumption behaviors before time *t*, recommend items from **W** to *u* at time *t*.
- **Examples**
  - Recommend a preferred pop song listened several days before.
  - Recommend a nice steak house visited months before.

Indeed, it is a ranking problem with implicit user feedback !

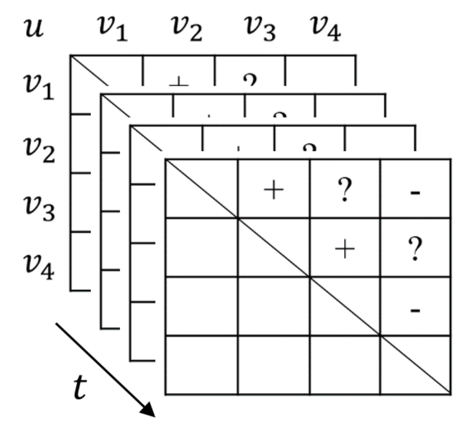


B. Repeat recommendation

- **Bayesian Personalized Ranking**
  - u's preference on v, $r_{uv} = \mathbf{u} \cdot \mathbf{v}$.
  - Observed pairwise comparison $v_i >_u v_j$.
  - Maximize: $\Pi\, \sigma(\mathbf{u} \cdot \mathbf{v}_\mathrm{i} - \mathbf{u} \cdot \mathbf{v}_\mathbf{j})$.
  - Estimate **u** for all users, **v** for all items.
  - SGD on log loss.



- **Time Sensitive**
  - User's preference at each time step is different.
  - Reconsumed *v.s.* non-consumed (temporal pairwise comparisons).
  - Tensor factorization may not work since the latent factors of the next step is unknown.



How to capture user's preference for repeat consumption?

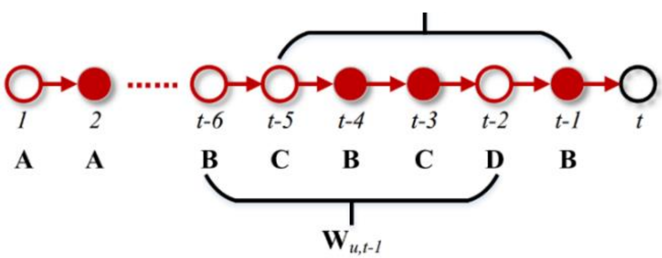
B. Repeat recommendation

- **Time-Sensitive Personalized Pairwise Ranking**
  - Incorporate time-sensitive features $\mathbf{f}_{uvt}$:

$$r_{uvt} = \mathbf{u}^\top \mathbf{v} + \mathbf{u}^\top \mathbf{A}_u \mathbf{f}_{uvt} = \mathbf{u}^\top (\mathbf{v} + \mathbf{A}_u \mathbf{f}_{uvt})$$

  - $\mathbf{f}_{uvt}$ is extracted from u's previous interactions with v in $\mathbf{W}$.
  - $\mathbf{A}_u$ is a personalized feature space transform matrix.
  - r_{uvt} balances u's static and temporal preference on v.
  - The probability of u preferring v_i to v_j:

$$\begin{aligned} p(v_i >_{ut} v_j) &= \sigma(r_{uv_it} - r_{uv_jt}) \\ &= \sigma(\mathbf{u}^\top(\mathbf{v}_i + \mathbf{A}_u \mathbf{f}_{uv_it} - \mathbf{v}_j - \mathbf{A}_u \mathbf{f}_{uv_jt})) \\ &= \sigma(\mathbf{u}^\top(\mathbf{v}_i - \mathbf{v}_j + \mathbf{A}_u(\mathbf{f}_{uv_it} - \mathbf{f}_{uv_jt}))) \\ &= \frac{1}{1 + e^{-\mathbf{u}^\top(\mathbf{v}_i - \mathbf{v}_j + \mathbf{A}_u(\mathbf{f}_{uv_it} - \mathbf{f}_{uv_jt}))}}. \end{aligned}$$

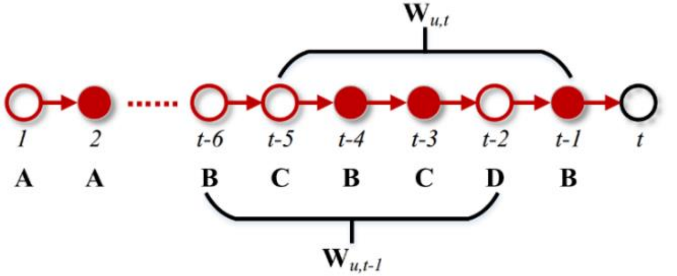


B. Repeat recommendation

- **Time-Sensitive Personalized Pairwise Ranking**
  - Objective (log loss with L-2 regularization):

$$\mathcal{J} = \sum_{(u,v_i,v_j,t)\in\mathcal{D}} -\ln p(v_i >_{ut} v_j) + \frac{\lambda}{2}\sum_u \|\mathbf{A}_u\|_F^2 + \frac{\gamma}{2}(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2)$$

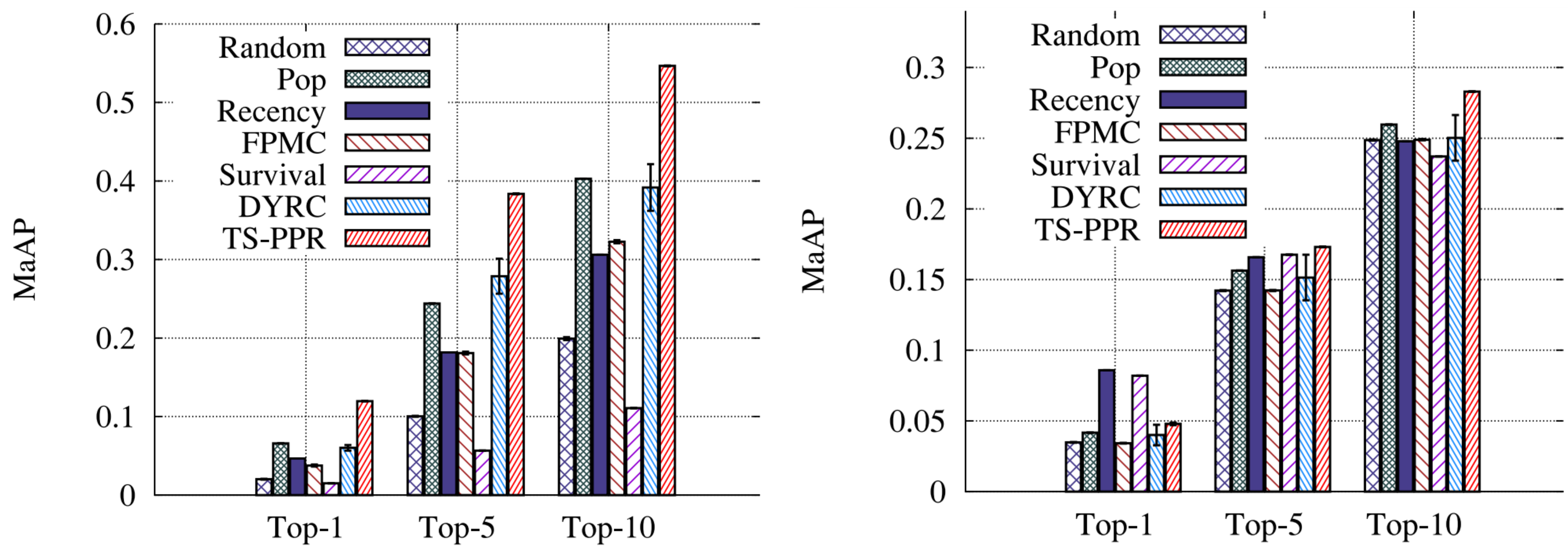
  - Training with SGD.
  - Negative sampling
    - For each repeat consumption on v_i at time t, randomly sample s (e.g. 5) negative items v_j w.r.t. time window $\mathbf{W}$.
  - Recommend repeat items v by ranking with r_{uvt}.
  - Codes: https://github.com/chenjun082/ts-ppr
- **Time-sensitive Features**
  - Normalized item quality
  - Item reconsumption ratio
  - Recency feature
  - Dynamic familiarity



B. Repeat recommendation

Experiments

- Evaluation conducted on Last.fm and Gowalla datasets.

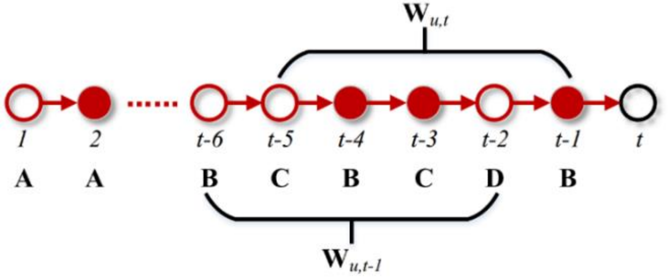


(a) Gowalla (b) Lastfm

1. J. Chen, et al. Recommendation for repeat consumption from user implicit feedback. **IEEE TKDE** 2016.
2. J. Chen, et al. Recommendation for repeat consumption from user implicit feedback (Extended Abstract). **IEEE ICDE** 2017.

C. Novel recommendation

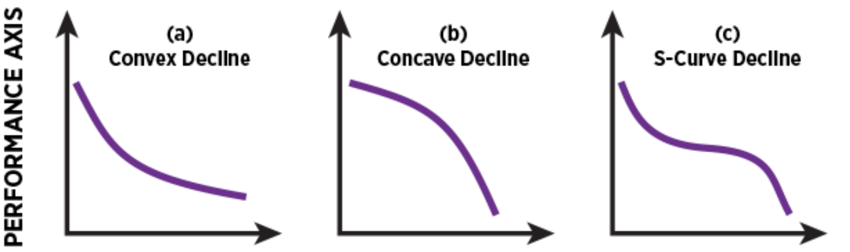
- **Motives**
  - Some people have ***high user novelty*** at sometimes.
  - One of the hottest topics in RecSys.
  - Building a memory-aware RecSys is less explored before.
- **Problem**
  - Given the time window **W** of user *u*'s previous consumptions before time *t*, recommend items to *u* at *t* ***regardless of previous consumptions or not***.
- **Main contributions**
  - Modeling user's temporal interest on a given item as a process of ***memory forgetting and enhancement*** towards building an intelligent RecSys.
  - Simplify the variable-order Markov Chain model with a weighted first-order Markov Chain model.



C. Novel recommendation

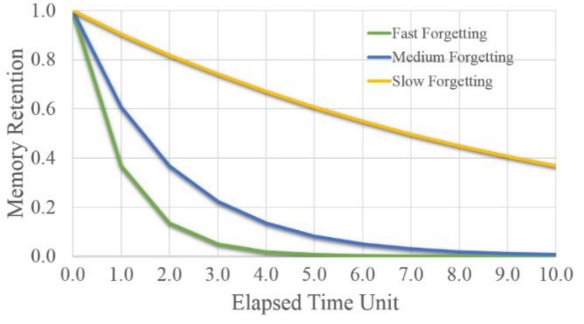
Memory forgetting as a human nature

Ebbinghaus forgetting curve

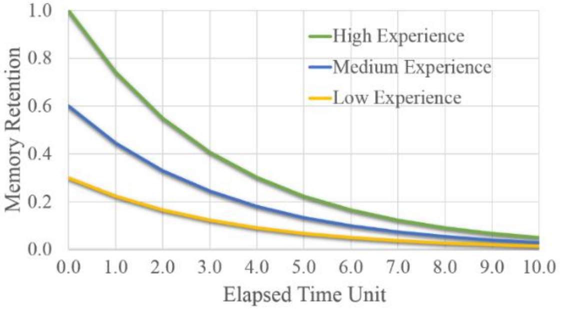


More forgetting curves

Personalized memory forgetting patterns



Personalized forgetting speed



Personalized initial memory

Intelligent RecSys

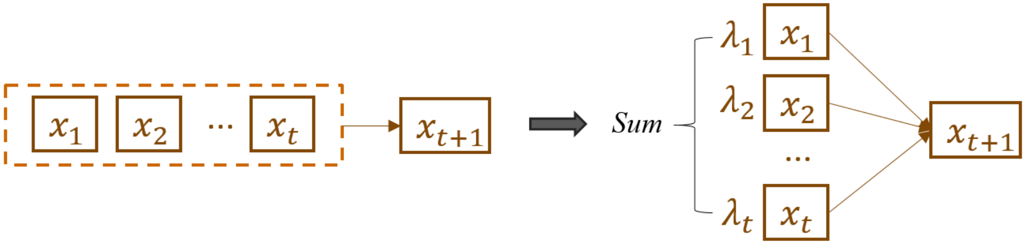
C. Novel recommendation

- **Interest-forgetting Markov model**
  - In a conventional variable-order Markov model, the probability of consuming *v* at *t* is the ***conditional probability*** of all previous consumptions.

$$\mathrm{P}(v|\mathcal{X}^{u,t}) = \mathrm{P}(v|x^u_{t-\Delta}, \ldots, x^u_{t-2}, x^u_{t-1})$$

  - The proposed (simplified) model,

$$\mathrm{P}(v|\mathcal{X}^{u,t}) = \mathrm{P}(v|x^u_{t-\Delta}, \ldots, x^u_{t-2}, x^u_{t-1}) = \sum_{i=1}^{\Delta} \mathrm{P}(v|x^u_{t-i})\lambda(u,t,i)$$

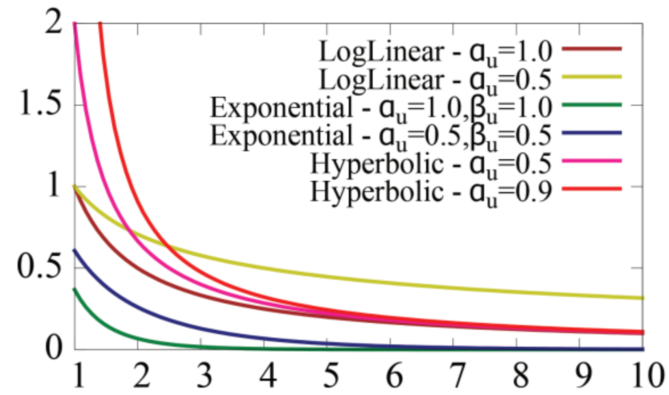


  - The forgetting and enhancement of interest is implanted in *λ(u,t,i)*,

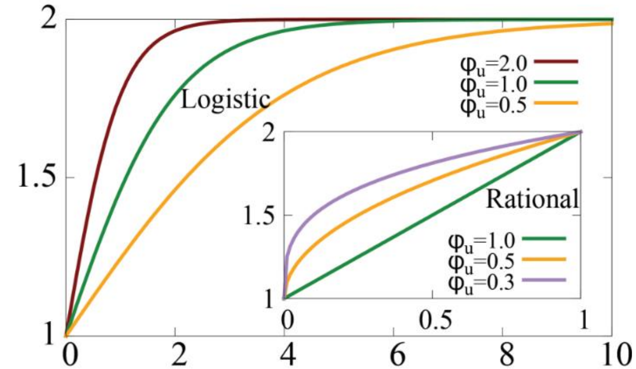
$$\lambda(u,t,i) = \Phi(u,t,i)\Upsilon(u,t,x^u_{t-i})$$

C. Novel recommendation

- **Interest forgetting**
  - To measure the interest retention Φ.
    - Log-linear, $\Phi = c_u \Delta t^{-\alpha_u}$
    - Exponential, $\Phi = c_u \Delta t^{-\alpha_u} e^{-\beta_u \Delta t}$
    - Hyperbolic, $\Phi = \frac{c_u}{\Delta t - \alpha_u}$
  - Personalized parameters to estimate
    - α_u, β_u, c_u



- **Interest enhancement**
  - To measure the accumulative interest
    - Logistic, $\Upsilon = \frac{2}{1+e^{-\phi_u f(u,v,t)}}$
    - Rational, $\Upsilon = 1 + f(u,v,t)^{\phi_u}$
  - Personalized parameters to estimate
    - ϕ_u



C. Novel recommendation

- **One-step transition probability**

$$\mathrm{P}(v|\mathcal{X}^{u,t}) = \sum_{i=1}^{\Delta} \mathrm{P}(v|x^u_{t-i})\lambda(u,t,i)$$

  - Maximum likelihood estimation
    - $\mathrm{P}(v|x) = f(v, x) / f(x)$
  - Matrix factorization

$$\underset{\mathbf{R},\mathbf{Q}}{\operatorname{argmin}} \sum_{\mathbf{P}[x,v]>0} (\mathbf{R}[x]\cdot\mathbf{Q}[v] - \mathbf{P}[x,v])^2 + \frac{\gamma}{2}(\|\mathbf{R}\|_F^2 + \|\mathbf{Q}\|_F^2)$$

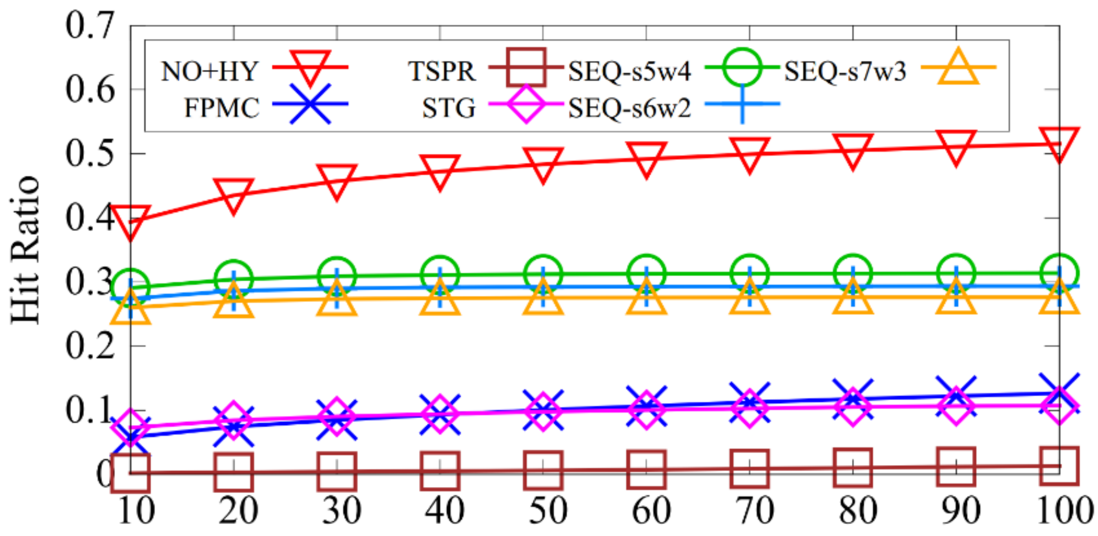
- **Objective (log loss)**

$$\Theta^* = \underset{\Theta}{\operatorname{argmin}}\, \mathcal{L} = -\sum_u \sum_{\tilde{x},\mathcal{X}^{u,t}} \ln P(\tilde{x}|\mathcal{X}^{u,t};\Theta)$$
$$= -\sum_u \sum_{\tilde{x},\mathcal{X}^{u,t}} \ln\left(\sum_{i=1}^{\Delta} \mathrm{P}(\tilde{x}|x^u_{t-i})\Phi(u,t,i)\Upsilon(u,t,x^u_{t-i})\right),$$
$$s.t.\quad 1 \le \Upsilon(u,t,x^u_{t-i}) \le 2,\ 0 \le \Phi(u,t,i) \le 1,\ 0 \le \mathrm{P}(\tilde{x}|x^u_{t-i}) \le 1.$$

- **GD training to get** α_u, β_u, c_u and ϕ_u.
- **Recommend by ranking with** $\mathrm{P}(v|\mathcal{X}^{u,t})$

C. Novel recommendation

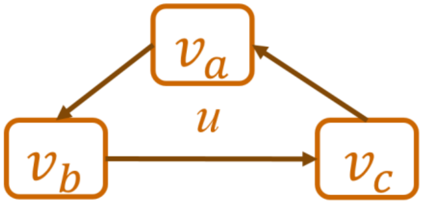
- **Experiments**
  - Evaluation conducted on Last.fm dataset.
  - Much higher accuracy in Top-*k* recommendations.



1. J. Chen, et al. A personalized interest-forgetting Markov model for recommendations. **AAAI** 2015, **oral presentation**.
2. J. Chen, et al. Modeling the interest-forgetting curve for music recommendation. **ACM Multimedia** 2014.

D. Intransitive preference modeling

- **Motives**
  - The assumption of transitive preference is over-simplified sometimes.
  - Intransitive preference was observed in pairwise comparisons[Tversky, 1969].
  - There lacks computational models for intransitive preference.
- **Problem**
  - Given many pairwise comparisons $\{v_i >_u v_j\}$ (***intransitivity may exist***), find a function $f(u,v_x,v_y)$ that can predict if u prefers v_x over v_y or otherwise for an unseen triplet (u,v_x,v_y).
- **Impact of intransitive preference models**
  - Transitive preference models (RankNet[Burges, 2005], BPR[Rendle, 2009], MF[Koren, 2009]) fail due to the partial order of scalar preference values.
  - A more complext comparison schema is required.
  - Find the cause of intransitive preference.



preference circle

D. Intransitive preference modeling

- **Major argument**
  - User has different judging criteria for different pairwise comparisons.
  - The different selections of judging criteria lead to intransitive preference.
- **Image as an example**
  - Judging criteria: colors, salience objects, theme, etc.
  - If comparing A and B using colors, comparing B and C using salience objects, and comparing A and C using image theme, the pairwise comparison reults can be intransitive.
  - What if more than one judging criterion are used in a single comparison?

No.	A	B	C	D
Images				
Color	Blue, Green, White	Green, Grey, White	Yellow, Orange, Red	Blue, Grey, White
Object	Mountain, Grass, Cow	Tree, Water, Rock	Sunset, Cloud, Sea	Sea, Tree, Beach
Theme	Country Life	Primitive Forest	Overseas Scenery	Beach View

D. Intransitive preference modeling

- **Multi-Criterion (MuCri) Preference Models**
  - **Main idea**: for a given (user, item) pair, compute multiple preference values with ***multiple criteria*** to form ***a preference vector***.
  - Latent MuCri (L-MuCri) Model
    - Represent a/an user/item with multiple **latent** vectors (*i.e. criteria*).
      - $\mathbf{u} = \{\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_D\}$, $\mathbf{h} = \{\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_D\}$
    - The Top-*F* criteria under which user *u* prefers item *a*.

$$\underset{1 \le x \le D_{lt}}{\overset{F_{lt}}{\operatorname{argmax}}}\ \mathbf{u}_x^\top \mathbf{h}_x^a$$

    - The joint set of criteria that *u* uses to compare item *a* and *b*,

$$\mathcal{C}_{uab}^{lt} = \Big(\underset{1 \le x \le D_{lt}}{\overset{F_{lt}}{\operatorname{argmax}}}\ \mathbf{u}_x^\top \mathbf{h}_x^a \Big) \cup \Big(\underset{1 \le y \le D_{lt}}{\overset{F_{lt}}{\operatorname{argmax}}}\ \mathbf{u}_y^\top \mathbf{h}_y^b \Big)$$

    - *u*'s preference on item *a* **when comparing *a* and *b*** (may change when *u* compare *a* and *c* or others),

$$r_{ua|b}^{lt} = \frac{1}{|\mathcal{C}_{uab}^{lt}|} \sum_{x \in \mathcal{C}_{uab}^{lt}} \mathbf{u}_x^\top \mathbf{h}_x^a.$$

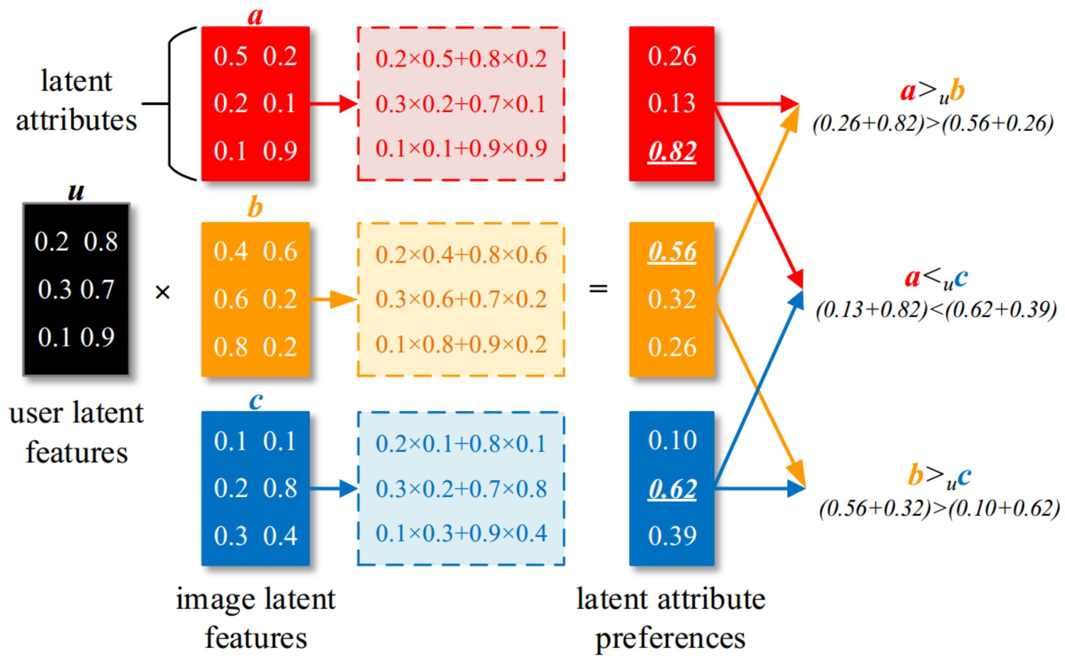
D. Intransitive preference modeling

Multi-Criterion (MuCri) Preference Models

- The probability of u preferring a to b in pairwise comparison,

$$p_{lt}(a >_u b) = \frac{e^{r^{lt}_{ua|b}}}{e^{r^{lt}_{ua|b}} + e^{r^{lt}_{ub|a}}} = \frac{1}{1 + e^{-(r^{lt}_{ua|b} - r^{lt}_{ub|a})}}$$

- An illustration



D. Intransitive preference modeling

- **Multi-Criterion (MuCri) Preference Models**
  - Objective,

$$\mathcal{O} = \sum_{u} \sum_{(a,b)\in\mathcal{R}_u} -\ln p(a >_u b) + \frac{\lambda}{2}(\|\mathbf{U}\|_F^2 + \|\mathbf{H}\|_F^2) + \frac{\gamma}{2}\|\hat{\mathbf{U}}\|_F^2$$

  - Content-based MuCri (C-MuCri) Model
    - $\mathbf{f}^a$ are the extracted content features of item *a*.
    - For images, we extracted RGB, SIFT, GIST, LBP and deep features.

$$C_{uab}^{ct} = \Big(\operatorname*{argmax}_{1\le x\le D_{ct}}^{F_{ct}} \hat{\mathbf{u}}_x^\top \mathbf{f}_x^a\Big) \cup \Big(\operatorname*{argmax}_{1\le y\le D_{ct}}^{F_{ct}} \hat{\mathbf{u}}_y^\top \mathbf{f}_y^b\Big)$$

  - Hybrid MuCri (H-MuCri) Model
    - Max: $p(a >_u b) = max(p_{lt}(a >_u b), p_{ct}(a >_u b))$
    - Mean: $p(a >_u b) = \frac{1}{2}(p_{lt}(a >_u b) + p_{ct}(a >_u b))$
    - Product: $p(a >_u b) = p_{lt}(a >_u b)p_{ct}(a >_u b)$
  - Codes: https://github.com/chenjun082/mucri

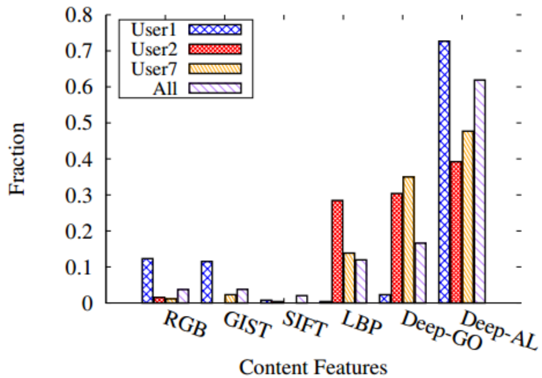
D. Intransitive preference modeling

- **Evaluation**
  - Publish a new pairwise scenery image comparison dataset (INRIA Holidays).
    - https://github.com/chenjun082/holidays
  - Accuracy performance

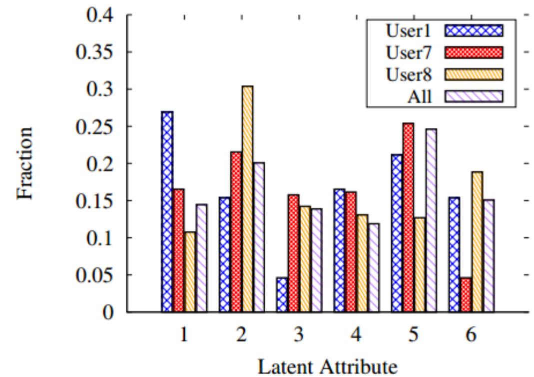
Data Sets	Models	Accuracy			AUC		
		2-fold	5-fold	10-fold	2-fold	5-fold	10-fold
INRIA Holidays	**BRP** [14]	0.7436$\pm$0.0047	0.7488$\pm$0.0088	0.7497$\pm$0.0152	0.7408$\pm$0.0044	0.7463$\pm$0.0092	0.7465$\pm$0.0158
	GBPR [15]	0.7167$\pm$0.0134	0.7319$\pm$0.0094	0.7334$\pm$0.0192	0.7138$\pm$0.0123	0.7289$\pm$0.0109	0.7310$\pm$0.0196
	BC-Inner [27]	0.7291$\pm$0.0030	0.7327$\pm$0.0119	0.7404$\pm$0.0120	0.7267$\pm$0.0030	0.7306$\pm$0.0127	0.7378$\pm$0.0118
	BC-Dist [27]	0.7152$\pm$0.0050	0.7173$\pm$0.0038	0.7244$\pm$0.0193	0.7137$\pm$0.0058	0.7148$\pm$0.0035	0.7217$\pm$0.0194
	L-MuCri	0.7622$\pm$0.0050	0.7829$\pm$0.0097	0.7832$\pm$0.0110	0.7602$\pm$0.0048	0.7809$\pm$0.0107	0.7813$\pm$0.0111
	C-MuCri	0.7525$\pm$0.0056	0.7772$\pm$0.0072	0.7842$\pm$0.0107	0.7641$\pm$0.0064	0.7765$\pm$0.0172	0.7830$\pm$0.0099
	H-MuCri-Max	0.7535$\pm$0.0013	0.7686$\pm$0.0026	0.7708$\pm$0.0130	0.7520$\pm$0.0017	0.7672$\pm$0.0026	0.7690$\pm$0.0132
	H-MuCri-Mean	**0.7746**$\pm$0.0071	0.7896$\pm$0.0100	0.7902$\pm$0.0101	0.7732$\pm$0.0071	**0.7880**$\pm$0.0096	0.7887$\pm$0.0113
	H-MuCri-Prod	0.7690$\pm$0.0100	**0.7927**$\pm$0.0064	**0.7905**$\pm$0.0076	**0.7758**$\pm$0.0033	0.7858$\pm$0.0105	**0.7890**$\pm$0.0082
Aesthetics	**BRP** [14]	0.7159$\pm$0.0018	0.7243$\pm$0.0072	0.7250$\pm$0.0112	0.7158$\pm$0.0018	0.7242$\pm$0.0072	0.7248$\pm$0.0112
	GBPR [15]	0.7059$\pm$0.0004	0.7104$\pm$0.0034	0.7116$\pm$0.0030	0.7059$\pm$0.0003	0.7103$\pm$0.0034	0.7115$\pm$0.0030
	BC-Inner [27]	0.6795$\pm$0.0029	0.6859$\pm$0.0024	0.6881$\pm$0.0051	0.6795$\pm$0.0028	0.6858$\pm$0.0025	0.6880$\pm$0.0050
	BC-Dist [27]	0.6788$\pm$0.0009	0.6786$\pm$0.0018	0.6787$\pm$0.0067	0.6785$\pm$0.0010	0.6783$\pm$0.0018	0.6783$\pm$0.0067
	L-MuCri	**0.7789**$\pm$0.0011	**0.7997**$\pm$0.0031	**0.8052**$\pm$0.0044	**0.7788**$\pm$0.0011	**0.7997**$\pm$0.0031	**0.8052**$\pm$0.0045
	C-MuCri	0.7222$\pm$0.0002	0.7469$\pm$0.0079	0.7504$\pm$0.0081	0.7222$\pm$0.0002	0.7469$\pm$0.0079	0.7504$\pm$0.0081
	H-MuCri-Max	0.6079$\pm$0.0006	0.6179$\pm$0.0032	0.6174$\pm$0.0111	0.6078$\pm$0.0006	0.6175$\pm$0.0030	0.6173$\pm$0.0109
	H-MuCri-Mean	0.7748$\pm$0.0003	0.7937$\pm$0.0029	0.8005$\pm$0.0039	0.7747$\pm$0.0002	0.7937$\pm$0.0029	0.8005$\pm$0.0039
	H-MuCri-Prod	0.7744$\pm$0.0002	0.7960$\pm$0.0021	0.8012$\pm$0.0048	0.7743$\pm$0.0002	0.7960$\pm$0.0020	0.8011$\pm$0.0048

D. Intransitive preference modeling

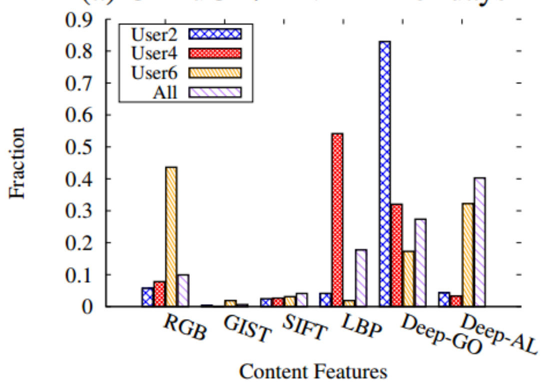
- **Evaluation**
  - Users' top preferred latent or content criteria in pairwise image comparisons.



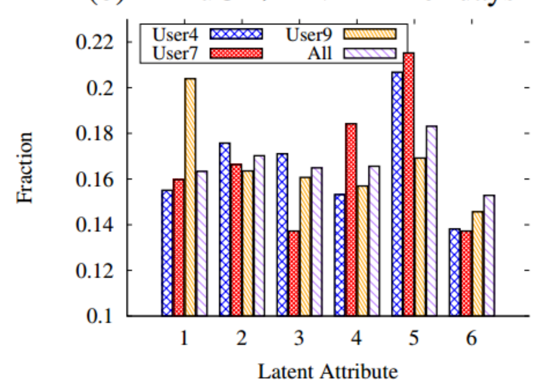
(a) C-MuCri，INRIA Holidays



(b) L-MuCri，INRIA Holidays



(c) C-MuCri，Aesthetics



(d) L-MuCri，Aesthetics

D. Intransitive preference modeling

- **More information**
  - https://github.com/chenjun082/mucri
  - https://github.com/chenjun082/holidays
  - J. Chen, et al. Learning the personalized intransitive preferences of images. **IEEE Transactions on Image Processing**, 26(9), 2017.
  - J. Chen, et al. Modeling the intransitive pairwise image preference from multiple angles. **ACM Multimedia**, 2017.

User Novelty driven Personalized Item Recommendation

CHEN, Jun (陈俊)

PhD Graduate

Tsinghua University