Experience aware Item Recommendation in Evolving Review Communities

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Recommendation System

	i_1	i_2	...	i_k	...	i_n
U_1	5	?	...	3	...	4
U_2	?	?	...	4	...	5
⋮	...	...	...	...	...	...
U_k	2	5	...	?	...	3
⋮	...	...	...	...	...	...
U_m	5	4	...	2	...	?

$$rec(u,i) = \beta_g + \beta_u + \beta_i + \langle \alpha_u, \phi_i \rangle$$

user preferences　　item properties

Use-Case: Camera

- Recommend camera [Canon EOS Rebel EF-S DSLR]
- Facet of interest: *lens*

  - *My first DSLR. Excellent camera, take great pictures with high definition, without a doubt it makes honor to its name. (5)*

  - *The EF 75-300 mm lens is only good to be used outside. The 2.2X HD lens can only be used for specific items; filters are useless if ISO, AP,... are correct. The short 18-55mm lens is cheap and should have a hood to keep light off lens. (3)*

Use-Case: Movies

- Recommend Christopher Nolan movie
- Facet of interest: *non-linear narrative* style

  - **Memento (2001)**: “Backwards told is thriller noir-art empty ultimately but compelling and intriguing this.”

  - **The Dark Knight (2008)**: Memento was very complicated. The Dark Knight was flawless. Heath Ledger rocks !

  - **Inception (2010)**: “Inception is to some extent a triumph of style over substance. It is complex only in a structural way, not in terms of plot. It doesn't <u>*unravel*</u> in the way \`Memento' does.

- Prior work: McAuley and Leskovec (WWW 2013) exploiting *rating behavior* evolution over time

Our Contribution:

- Analyze influence of different factors like *writing style*, *facet preferences*, *rating behavior* and maturing *rate* on user experience progression over *time*

- Model a *smooth* temporal progression in experience

- Derive an experience-aware language model to give *interpretations*

Objective

- Recommend item to a user based on his level of experience in consuming the item, which we learn from his ratings and reviews over time

- Train a system with his reviews till time '*t*' and predict user assigned item rating at time '*t+1*'

User Experience Level: Factors

- Experienced users have similar *facet preferences*, exhibited in similar *rating behavior*
  - *Even though the ratings may appear temporally apart*
  - E.g. Experienced users would find *Memento* to be good at first view

- Experienced users have a sophisticated *writing style* and *vocabulary*

User Experience Progression: Factors

- Maturing rate - *community activity*
- Facet preference – *acquired taste*
- Writing style - *language model*
- Posting Time difference
- Experience level difference
  - *Smooth progression*

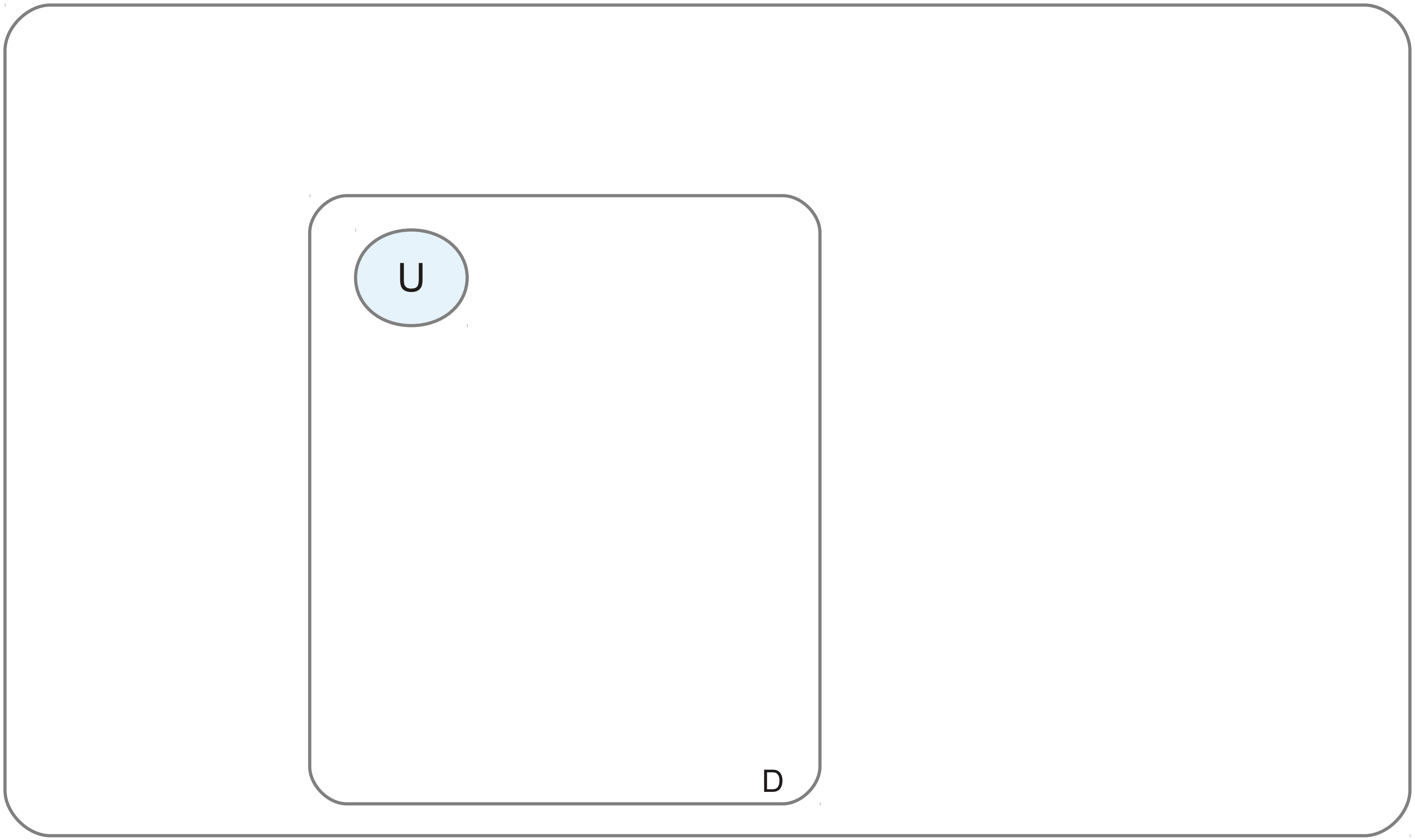
Model

- *Latent Dirichlet Allocation* to model similar facet preferences (*acquired taste)* and writing style (*language model) of users at similar levels of experience*

- Experience level difference
  - *Smooth progression* over time
  - *Hidden Markov Model - at each time step, the user stays at current level 'e' or moves to 'e+1'*
  - *Decision made by the joint interactions*

- Time is not modeled explicitly
  - Instead we model experience, as a latent variable, which evolves over time

Generative Model: HMM-LDA



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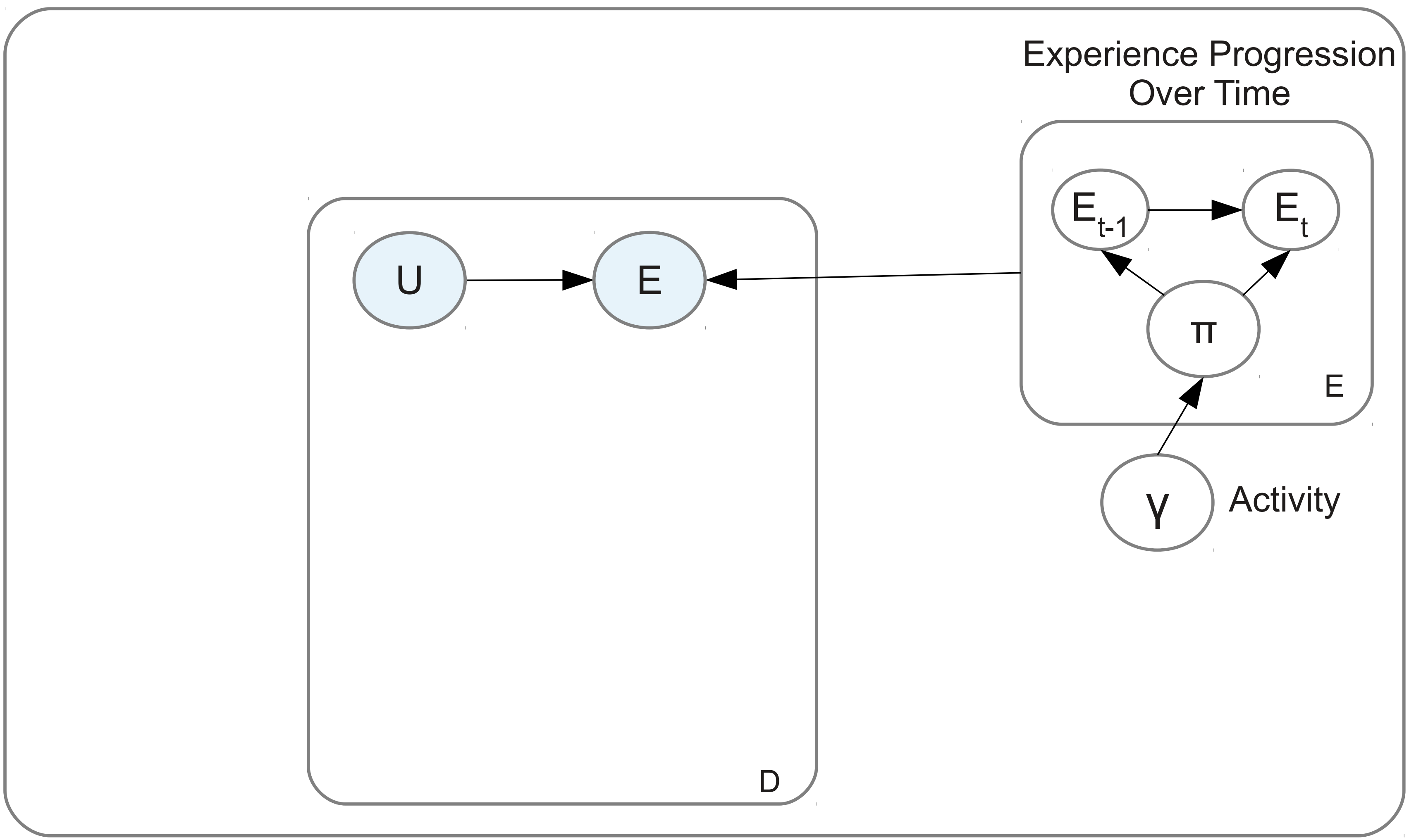

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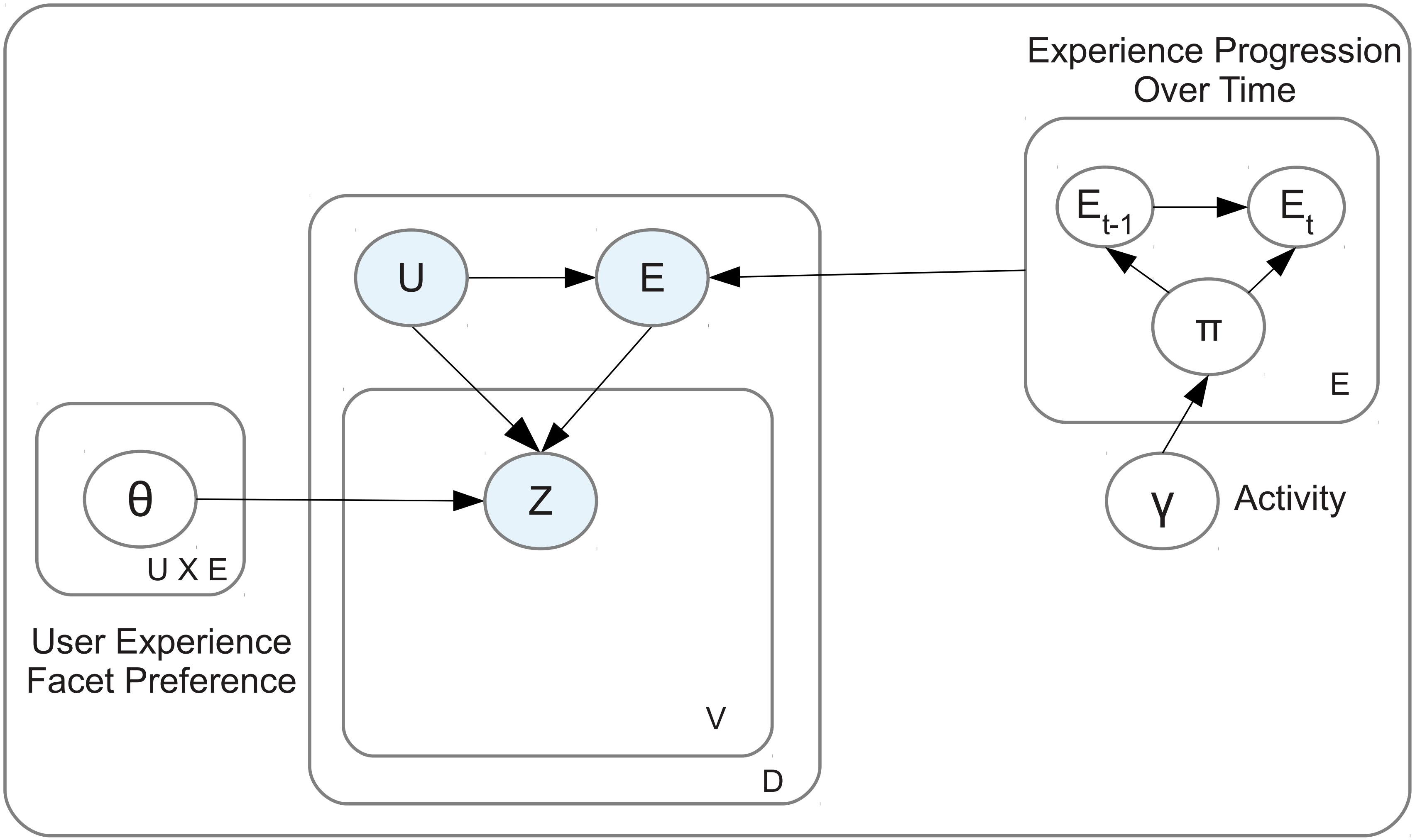

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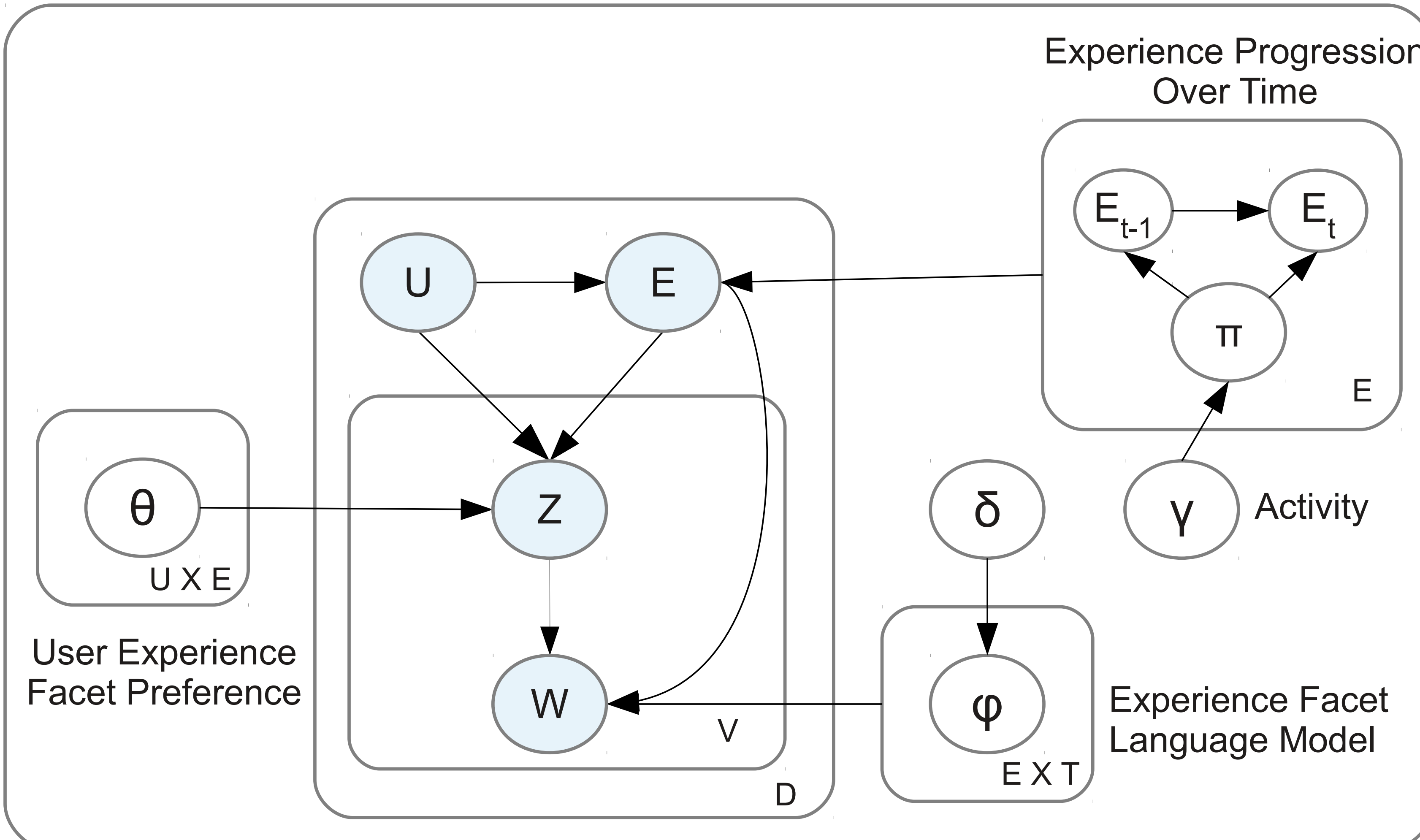

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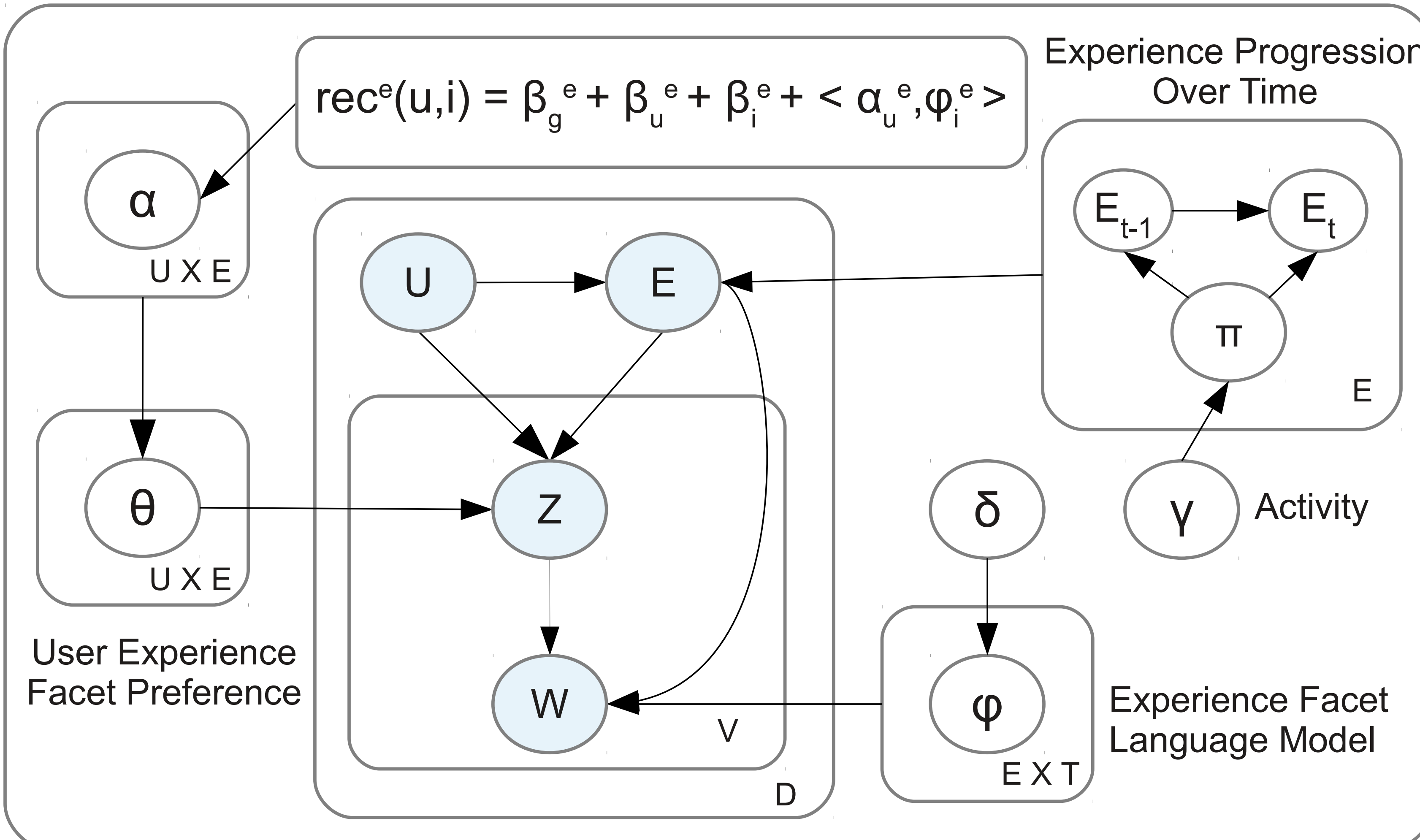


Joint Probability Distribution

$$P(U,E,Z,W,\theta,\phi,\pi;\alpha,\delta,\gamma) = \prod_{u=1}^{U}\prod_{e=1}^{E}\prod_{i=1}^{D_u}\prod_{z=1}^{Z}\prod_{j=1}^{N_{d_u}}\{$$

$$\underbrace{P(\pi_e;\gamma^u)\times P(e_i|\pi_e)}_{\text{experience transition distribution}} \times \underbrace{P(\theta_{u,e};\alpha_{u,e})\times P(z_{i,j}|\theta_{u,e_i})}_{\text{user experience facet distribution}}$$

$$\times \underbrace{P(\phi_{e,z};\delta)\times P(w_{i,j}|\phi_{e_i,z_{i,j}})}_{\text{experience facet language distribution}} \}$$

EM Algorithm (1/3)

- E-Step via Collapsed Gibbs Sampling:
  - Estimate P(E|U, Z, W)

    $\propto$ P(E|U) X P (Z|E, U) X P (W |Z, E)

EM Algorithm (1/3)

- E-Step via Collapsed Gibbs Sampling:
  - Estimate P(E|U, Z, W)

    ∝ P(E|U) X P (Z|E, U) X P (W |Z, E)

$$\textbf{E-Step 1: } P(e_i = e | e_{i-1}, u_i = u, \{z_{i,j} = z_j\}, \{w_{i,j} = w_j\}, e_{-i}) \propto$$

$$P(e_i | u, e_{i-1}, e_{-i}) \times \prod_j P(z_j | e_i, u, e_{-i}) \times P(w_j | z_j, e_i, e_{-i}) \propto$$

$$\frac{m_{e_i}^{e_{i-1}} + I(e_{i-1} = e_i) + \gamma^u}{m_{\cdot}^{e_{i-1}} + I(e_{i-1} = e_i) + E\gamma^u} \times$$

$$\prod_j \frac{n(u, e, ., z_j, .) + \alpha_{u,e,z_j}}{\sum_{z_j} n(u, e, ., z_j, .) + \sum_{z_j} \alpha_{u,e,z_j}} \times \frac{n(., e, ., z_j, w_j) + \delta}{\sum_{w_j} n(., e, ., z_j, w_j) + V\delta}$$

EM Algorithm (2/3)

- E-Step via Collapsed Gibbs Sampling:
  - Estimate P(Z|W, E)

E-Step 2: $P(z_j = z | u_d = u, e_d = e, w_j = w, z_{-j}) \propto$

$$\frac{n(u, e, ., z, .) + \alpha_{u,e,z}}{\sum_z n(u, e, ., z, .) + \sum_z \alpha_{u,e,z}} \times \frac{n(., e, ., z, w) + \delta}{\sum_w n(., e, ., z, w) + V\delta}$$

EM Algorithm (3/3)

- M-Step via Support Vector Regression:
  - Minimize MSE to optimize parameters and predict ratings

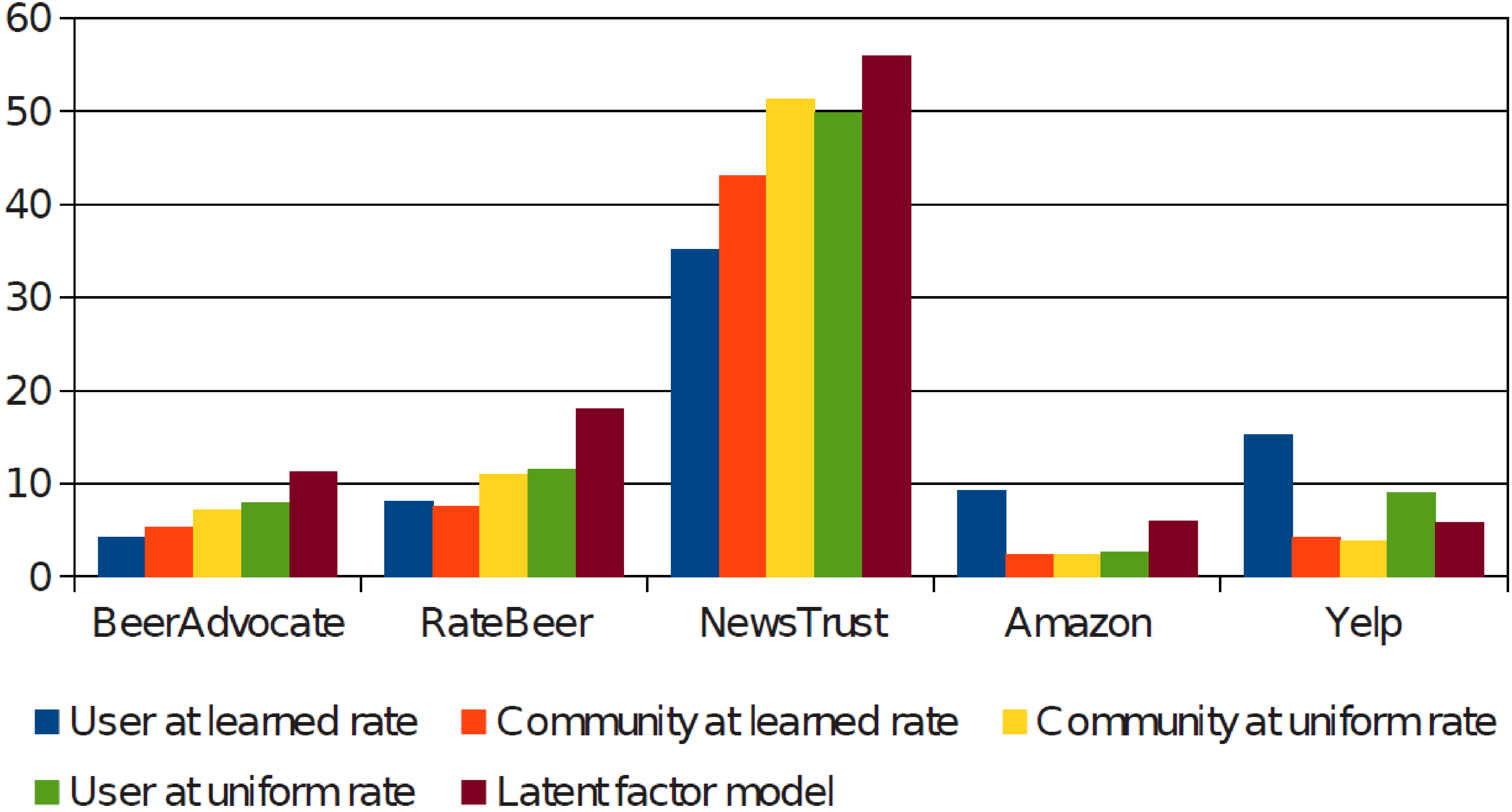
$$\textbf{M-Step:}\ \min_{\alpha_{u,e}} \frac{1}{2}{\alpha_{u,e}}^T \alpha_{u,e} + C \times$$

$$\sum_{d=1}^{D_u} (max(0, |r_d - {\alpha_{u,e}}^T < \beta_g(e), \beta_u(e), \beta_i(e), \phi_{e,z}(d) > | - \epsilon))^2$$

Dataset Statistics

Dataset	#Users	#Items	#Ratings
Beer (BeerAdvocate)	33,387	66,051	1,586,259
Beer (RateBeer)	40,213	110,419	2,924,127
Movies (Amazon)	759,899	267,320	7,911,684
Food (Yelp)	45,981	11,537	229,907
Media (NewsTrust)	6,180	62,108	134,407
TOTAL	885,660	517,435	12,786,384

JERTM: MSE Improvement over Baselines



From Amateurs to Connoisseurs: Modeling the Evolution of User Expertise through Online Reviews: McAuley and Leskovec et. al (WWW 2013)

Evolution Effect

Models	Beer Advocate	Rate Beer	News Trust	Amazon	Yelp
Our model (most recent experience level)	0.363	0.309	0.373	1.174	1.469
Our model (past experience level)	0.375	0.362	0.470	1.200	1.642

Experience Language Model for Beer Facet "*Taste*"

Experience Level 1: drank, bad, maybe, terrible, dull, shit
Experience Level 2: bottle, sweet, nice hops, bitter, strong light, head, smooth, good, brew, better, good
Expertise Level 3: sweet alcohol, palate down, thin glass, malts, poured thick, pleasant hint, bitterness, copper hard
Experience Level 4: smells sweet, thin bitter, fresh hint, honey end, sticky yellow, slight bit good, faint bitter beer, red brown, good malty, deep smooth bubbly, damn weak
Experience Level 5: golden head lacing, floral dark fruits, citrus sweet, light spice, hops, caramel finish, acquired taste, hazy body, lacing chocolate, coffee roasted vanilla, creamy bitterness, copper malts, spicy honey

Experience Language Model for Movie Facet "*Plot*" and "*Narrative Style*"

Level 1: stupid people supposed wouldnt pass bizarre totally cant
Level 2:storyline acting time problems evil great times didnt money ended simply falls pretty
Level 3: movie plot good young epic rock tale believable acting
Level 4: script direction years amount fast primary attractive sense talent multiple demonstrates establish
Level 5: realism moments filmmaker visual perfect memorable recommended genius finish details defined talented visceral nostalgia
Level 1: film will happy people back supposed good wouldnt cant
Level 2: storyline believable acting time stay laugh entire start funny
Level 3 & 4: narrative cinema resemblance masterpiece crude undeniable admirable renowned seventies unpleasant myth nostalgic
Level 5: incisive delirious personages erudite affective dramatis nucleus cinematographic transcendence unerring peerless fevered