Experience aware Item Recommendation in Evolving Review Communities

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Recommendation System

<table>
<thead>
<tr>
<th></th>
<th>$i_1$</th>
<th>$i_2$</th>
<th>$\cdots$</th>
<th>$i_k$</th>
<th>$\cdots$</th>
<th>$i_n$</th>
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</thead>
<tbody>
<tr>
<td>$U_1$</td>
<td>5</td>
<td>?</td>
<td>$\cdots$</td>
<td>3</td>
<td>$\cdots$</td>
<td>4</td>
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<tr>
<td>$U_2$</td>
<td>?</td>
<td>?</td>
<td>$\cdots$</td>
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<td>$\cdots$</td>
<td>5</td>
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</tr>
<tr>
<td>$U_k$</td>
<td>2</td>
<td>5</td>
<td>$\cdots$</td>
<td>?</td>
<td>$\cdots$</td>
<td>3</td>
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<td>$\vdots$</td>
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<tr>
<td>$U_m$</td>
<td>5</td>
<td>4</td>
<td>$\cdots$</td>
<td>2</td>
<td>$\cdots$</td>
<td>?</td>
</tr>
</tbody>
</table>

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

- 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 *unravel* 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
Generative Model: HMM-LDA
Generative Model: HMM-LDA

User Experience Facet Preference

Experience Progression Over Time

User Experience Preference

Activity
Generative Model: HMM-LDA
Generative Model: HMM-LDA

\[ \text{rec}^e(u,i) = \beta_g^e + \beta_u^e + \beta_i^e + \langle \alpha_u^e, \phi_i^e \rangle \]
Joint Probability Distribution

\[ P(U, E, Z, W, \theta, \phi, \pi; \alpha, \delta, \gamma) = \prod_{u=1}^{U} \prod_{e=1}^{E} \prod_{d_u}^{D_u} \prod_{z=1}^{Z} \prod_{j=1}^{N_{d_u}} \{ \\
\times P(\pi_e; \gamma^u) \times P(e_i|\pi_e) \\
\times P(\theta_u,e; \alpha_{u,e}) \times P(z_{i,j}|\theta_u,e_i) \\
\times P(\phi_{e,z}; \delta) \times P(w_{i,j}|\phi_{e_i,z_{i,j}}) \} \]

- experience transition distribution
- user experience facet distribution
- experience facet language distribution
EM Algorithm (1/3)

➢ E-Step via Collapsed Gibbs Sampling:
  ➢ Estimate $P(E|U, Z, W)$
    $\propto P(E|U) \times P(Z|E, U) \times P(W|Z, E)$
EM Algorithm (1/3)

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

**E-Step 1:**

$$P(e_i = e|e_{i-1}, u_i = u, \{z_{i,j} = z_j\}, \{w_{i,j} = w_j\}, e_{-i}) \propto P(e_i|u, e_{i-1}, e_{-i}) \times \prod_j P(z_j|e_i, u, e_{-i}) \times P(w_j|z_j, e_i, e_{-i}) \propto \frac{m_{e_i-1}^{e_i} + I(e_{i-1} = e_i) + \gamma^u}{m_{e_i-1}^{e_i} + I(e_{i-1} = e_i) + E\gamma_u} \times \prod_j \frac{n(u, e, .., z_j, .) + \alpha_{u,e,z_j}}{\sum_{z_j} n(u, e, .., z_j, .) + \sum_{z_j} \alpha_{u,e,z_j}} \times \frac{n(., e, .., z_j, w_j) + \delta}{\sum_{w_j} n(., e, .., z_j, w_j) + V\delta}$$
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

\[
\text{M-Step: } \min_{\alpha_{u,e}} \frac{1}{2} \alpha_{u,e}^T \alpha_{u,e} + C \times \\
\sum_{d=1}^{D_u} \left( \max(0, |r_d - \alpha_{u,e}^T \beta_g(e), \beta_u(e), \beta_i(e), \phi_{e,z}(d) > | - \epsilon) \right)^2
\]
## Dataset Statistics

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#Users</th>
<th>#Items</th>
<th>#Ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beer (BeerAdvocate)</td>
<td>33,387</td>
<td>66,051</td>
<td>1,586,259</td>
</tr>
<tr>
<td>Beer (RateBeer)</td>
<td>40,213</td>
<td>110,419</td>
<td>2,924,127</td>
</tr>
<tr>
<td>Movies (Amazon)</td>
<td>759,899</td>
<td>267,320</td>
<td>7,911,684</td>
</tr>
<tr>
<td>Food (Yelp)</td>
<td>45,981</td>
<td>11,537</td>
<td>229,907</td>
</tr>
<tr>
<td>Media (NewsTrust)</td>
<td>6,180</td>
<td>62,108</td>
<td>134,407</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td>885,660</td>
<td>517,435</td>
<td>12,786,384</td>
</tr>
</tbody>
</table>
From Amateurs to Connoisseurs: Modeling the Evolution of User Expertise through Online Reviews: McAuley and Leskovec et. al (WWW 2013)
## Evolution Effect

<table>
<thead>
<tr>
<th>Models</th>
<th>Beer Advocate</th>
<th>Rate Beer</th>
<th>News Trust</th>
<th>Amazon</th>
<th>Yelp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our model (most recent experience level)</td>
<td>0.363</td>
<td>0.309</td>
<td>0.373</td>
<td>1.174</td>
<td>1.469</td>
</tr>
<tr>
<td>Our model (past experience level)</td>
<td>0.375</td>
<td>0.362</td>
<td>0.470</td>
<td>1.200</td>
<td>1.642</td>
</tr>
</tbody>
</table>
**Experience Language Model for Beer Facet “Taste”**

<table>
<thead>
<tr>
<th>Experience Level 1</th>
<th>drank, bad, maybe, terrible, dull, shit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience Level 2</td>
<td>bottle, sweet, nice hops, bitter, strong light, head, smooth, good, brew, better, good</td>
</tr>
<tr>
<td>Expertise Level 3</td>
<td>sweet alcohol, palate down, thin glass, malts, poured thick, pleasant hint, bitterness, copper hard</td>
</tr>
<tr>
<td>Experience Level 4</td>
<td>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</td>
</tr>
<tr>
<td>Experience Level 5</td>
<td>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</td>
</tr>
</tbody>
</table>
Experience Language Model for Movie Facet “Plot” and “Narrative Style”

Level 1: stupid people supposed wouldn't pass bizarre totally cant
Level 2: storyline acting time problems evil great times didn't 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 wouldn't 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