ELIXIR: Learning from User Feedback on Explanations to Improve Recommender Models

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The Web Conference, 2021
Motivation

User $u$

Recommendation ($rec$):
- Fight Club

Explanation ($exp$):
- 7 years in Tibet
- The Prestige
- Pulp Fiction
Motivation

I want to stop seeing this item and the like.

I want to see more items like this.
Motivation

So far: item-level rating

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Recommendation ($rec$):

Fight Club

Explanation ($exp$):

7 years in Tibet

The Prestige

Pulp Fiction

What is it that you (dis)like about the $Fight\ Club$?

Brad Pitt

Surprise Ending

Violence

...
Motivation

The idea: Leverage feedback on pairs of explanations and recommendations

User $u$

I want to stop seeing this item and the like.

I want to see more items like this.

<table>
<thead>
<tr>
<th>Recommendation ($rec$)</th>
<th>Explanation ($exp$):</th>
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<tbody>
<tr>
<td>Fight Club</td>
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Similar aspect of ($rec$, $exp$):
- Cast: Brad Pitt
- Storyline: Surprise Ending
- Content: Violence

Feedback on ($rec$, $exp$):
- Like
- Dislike
ELIXIR

Efficient Learning from Item-level eXplanations In Recommenders
(Improving future recommendations through feedback on pairs of recommendation and explanation items)

User $u$

Recommendation ($rec$) at time $T$
- Fight Club
- 7 years in Tibet
- The Prestige
- Pulp Fiction

Explanation ($exp$):
- 7 years in Tibet
- The Prestige
- Pulp Fiction

Similar aspect of ($rec$, $exp$):
- Cast: Brad Pitt
- Storyline: Surprise Ending
- Content: Violence

Feedback on ($rec$, $exp$):
- Liked: Fight Club, The Prestige
- Disliked: 7 years in Tibet, Pulp Fiction

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Collect and densify Feedback
Incorporate Feedback

Recommendation ($rec$) at time $T+1$
- Ocean’s Eleven
ELIXIR: Feedback Matrix

Recommendation (\(\text{rec}\)) at time \(T\)

Explanation (\(\text{exp}\)):

Do you like the similarity between \((\text{rec}, \text{exp})\)?

\[
\begin{pmatrix}
0 & 1 & 1 & -1 \\
1 & \ddots & & \\
1 & & \ddots & \\
-1 & & & \\
\end{pmatrix}
\]
ELIXIR: Feedback Densification

★ Label propagation [Zhu and Ghahramani, 2002] on pairs of items to mitigate sparsity \( \Rightarrow F^d_u \)

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★ Present pairs $(\vec{v}_i, \vec{v}_j)$ with pseudo-items (geometric mean of two vectors)

$$\vec{v}_{ij} = (\vec{v}_i \otimes \vec{v}_j)^{\frac{1}{2}}$$

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★ The affinity matrix $W$ encodes pair-pair similarity. This makes $W$ huge! ($W \in \mathbb{R}^{\mid I \mid^2 \times \mid I \mid^2}$, $I$ is the set of items)

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ELIXIR: Feedback Densification

- Label propagation [Zhu and Ghahramani, 2002] on pairs of items to mitigate sparsity $\Rightarrow F_u^d$
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- The affinity matrix $W$ encodes pair-pair similarity. This makes $W$ huge! ($W \in \mathbb{R}^{||I||^2 \times ||I||^2}, I$ is the set of items)

- Propagate labels only on kNN of the labeled pairs
  - naive approach: $O(||I||^2)$
  - our approach:
    - find kNN of $v_{ij}$ among the items in $I$ using locality sensitive hashing (LSH), we call this set $kNN_{ij}^I$.
    - Search for kNN of $v_{ij}$ in $kNN_{ij}^I \times kNN_{ij}^I$.
    - This reduces the time complexity to $O(||I||)$ for small $k$.

ELIXIR: Feedback Incorporation

*The Idea:* Learn user-specific parameters $\vec{w}_u$ of a mapping function $g$ to produce user-specific item representations.

$$\min_{\vec{w}_u} \frac{1}{m} \sum_{u, v_j} F_u^d (v_i, v_j) \cdot (\text{sim}(\vec{v}_i, \vec{v}_j) - \text{sim}(g(\vec{v}_i, \vec{w}_u), g(\vec{v}_j, \vec{w}_u))) + \gamma ||\vec{w}_u||^2$$

No. feedback pairs $\rightarrow$ similarity function

Similarity of items in **negative** (positive) pairs **decreases** (increases).
ELIXIR: Feedback Incorporation

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After feedback incorporation

User $u$

Distance of items to user's profile
Instantiation of ELIXIR

★ We instantiated our framework with RecWalk\textsuperscript{PR} [Nikolakopoulos and Karypis, WSDM’19]

\[
\overrightarrow{PPR}(u, .) = \alpha \cdot \overrightarrow{e}_u + (1 - \alpha) \cdot \overrightarrow{PPR}(u, .) \cdot [\beta A + (1 - \beta)S]
\]

★ Explanations generated by PRINCE [Ghazimatin et al., WSDM’20]
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★ Explanations generated by PRINCE [Ghazimatin et al., WSDM’20]

★ Learning \( \vec{w}_u ( g(\vec{v}_i, \vec{w}_u) = \vec{v}_i + \vec{w}_u ) \):

\[
\min \frac{1}{m} \sum_{v_i, v_j} F^d_u (v_i, v_j) \cdot (\cos(\vec{v}_i, \vec{v}_j) - \cos(\vec{v}_i + \vec{w}_u, \vec{v}_j + \vec{w}_u)) + \gamma ||\vec{w}_u||^2
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---

Nikolakopoulos and Karypis, RecWalk: Nearly uncoupled random walks for top-n recommendation, WSDM’19

Ghazimatin et al., PRINCE: Provider-side Interpretability with Counterfactual Explanations in Recommender Systems, WSDM’20
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\]

★ Updating the model:

\[ S_u(v_i, v_j) = \cos(\vec{v}_i + \vec{w}_u, \vec{v}_j + \vec{w}_u) \]

\[ PPR(u, \cdot) = \alpha \cdot \vec{e}_u + (1 - \alpha) \cdot PPR(u, \cdot) \cdot [\beta A + (1 - \beta)S_u] \]

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User Study for Data Collection

★ User studies in two domains: movies and books

★ Phase 1: Building users’ profiles
  ○ 50 liked movies selected from Movielens website
  ○ 50 liked books selected from Goodreads website

★ Phase 2: Collecting feedback on items and pairs
  ○ 30 recommendations (generated at time $T$)
    ■ generated by RecWalk
    ■ $S$: cosine similarity of item representations learned by applying NMF on item-feature matrix
  ○ 150 pairs corresponding to recommendations and their top 5 explanations
  ○ 150 pairs corresponding to recommendations and their bottom 5 explanations

★ Phase 3: Collecting feedback on final recommendations (evaluation at time $T+1$)

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Evaluation Configurations

★ Item-level feedback (baseline)

★ Pair-level feedback with explanations

★ Pair-level feedback with random items
  ○ explanation items are replaced by the least relevant items from user’s history

★ Item+pair-level feedback with explanations

★ Item+pair-level feedback with random items
  ○ explanation items are replaced by the least relevant items from user’s history
Results

Metrics: P@k, MAP@k, nDCG@k at time $T+1$

Key findings:
- Pair-level feedback improves recommendation.
Results

★ Metrics: P@k, MAP@k, nDCG@k at time $T+1$

★ Key findings:
  ○ Pair-level feedback improves recommendation.
  ○ Pair-level feedback is more discriminative than item-level.

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★ Metrics: P@k, MAP@k, nDCG@k at time $T+1$

★ Key findings:
  ○ Pair-level feedback improves recommendation.
  ○ Pair-level feedback is more discriminative than item-level.
  ○ Using explanations for pair-level feedback is essential.

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Some insights

★ Users give much more positive feedback than negative.
Some insights

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★ User behavior carries over from items to pairs (pearson correlation ≥ 0.5).
Some insights

- Users give much more positive feedback than negative.
- User behavior carries over from items to pairs (pearson correlation ≥ 0.5)
- Users mostly give feedback on shared genres/content between rec and exp

![Graphs showing mentions of different categories for Movies and Books](image-url)
ELIXIR

★ A human-in-the-loop framework that elicits lightweight user feedback on pairs of recommendation and explanation items.
★ Learns user-specific item representations based on user feedback.
★ Instantiated with recommenders based on random walks with restart.
★ Major gains in recommendation quality over item-level feedback, shown with real user studies.
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- Learns user-specific item representations based on user feedback.
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Thanks!
Explanations in Action

★ The role of explanations is mostly limited to improving user trust and satisfaction.

★ Critiqued-enabled recommenders [Jin et al., CIKM’19], [Luo et al., SIGIR’20]
  ○ Feedback on explicit and coarse-grained item properties
  ○ Negative feedback

★ ELIXIR
  ○ elicits lightweight user feedback on similarity of recommendation and explanation items.
  ○ supports both positive and negative feedback.

Jin et al., MusicBot: Evaluating Critiquing-Based Music Recommenders with Conversational Interaction, CIKM’19
Luo et al., Deep Critiquing for VAE-based Recommender Systems, SIGIR’20
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  ○ Feedback on explicit and coarse-grained item properties
  ○ Negative feedback
      ✔️ I want to stop seeing this item and the like.
      ✗ I want to see more items like this.

★ ELIXIR
  ○ elicits lightweight user feedback on similarity of recommendation and explanation items.
  ○ supports both positive and negative feedback.
      ✔️ I want to stop seeing this item and the like.
      ✔️ I want to see more items like this.

Jin et al., MusicBot: Evaluating Critiquing-Based Music Recommenders with Conversational Interaction, CIKM’19
Luo et al., Deep Critiquing for VAE-based Recommender Systems, SIGIR’20
## Anecdotal Examples

<table>
<thead>
<tr>
<th>History at time T (recs)</th>
<th>Recommendations</th>
<th>Feedback on recs</th>
<th>Explanations exp from h</th>
<th>Feedback on (recs, exp) pairs</th>
<th>(recs, exp) Similarity</th>
<th>Recommendation at time T+1 using only item-level feedback</th>
<th>Recommendation at time T+1 using both item and pair-level feedback</th>
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<tbody>
<tr>
<td><strong>Movies</strong></td>
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<td>Doctor Strange</td>
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<td>Space</td>
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<td>Harry Potter and the Deathly Hallows: Part 1</td>
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<td>Content: Based on a book, fantasy</td>
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Results

★ Metrics: P@k, MAP@k, nDCG@k at time $T+1$

★ Key findings:
  ○ Pair-level feedback improves recommendation.
Results

★ Metrics: P@k, MAP@k, nDCG@k at time T+1

★ Key findings:
- Pair-level feedback improves recommendation.
- Pair-level feedback is more discriminative than item-level.

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★ Metrics: P@k, MAP@k, nDCG@k at time $T+1$

★ Key findings:

○ Pair-level feedback improves recommendation.

○ Pair-level feedback is more discriminative than item-level.

○ Using explanations for pair-level feedback is essential.

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ELIXIR: Feedback Densification

Recommendation \((\text{rec})\) at time \(T\)

Explanation \((\text{exp})\):

Do you like the similarity between \((\text{rec}, \text{exp})\):

★ Label propagation [Zhu and Ghahramani, 2002] on pairs of items to mitigate sparsity ⇒ \(F_u^d\)
  ○ defining pseudo-items, selecting unlabeled pairs, using locality-sensitive hashing (LSH) for efficiency, ...

ELIXIR: Feedback Incorporation

**The Idea:** Learn user-specific parameters $\vec{w}_u$ of a mapping function $g$ to produce user-specific item representations

$$\min_{\vec{w}_u} \frac{1}{m} \sum_{v_i, v_j} F_u^d(v_i, v_j) \cdot (\text{sim}(v_i, v_j) - \text{sim}(g(v_i, \vec{w}_u), g(v_j, \vec{w}_u))) + \gamma ||\vec{w}_u||^2$$

No. feedback pairs $\leftarrow$ similarity function $\rightarrow$ Distance of items to user's profile
ELIXIR: Feedback Incorporation

**The Idea**: Learn user-specific parameters $\vec{w}_u$ of a mapping function $g$ to produce user-specific item representations

$$\min_{\vec{w}_u} \frac{1}{m} \sum_{v_i, v_j} F^d_u(v_i, v_j) \cdot (\text{sim}(v_i, v_j) - \text{sim}(g(v_i, \vec{w}_u), g(v_j, \vec{w}_u))) + \gamma ||\vec{w}_u||^2$$

No. feedback pairs $\rightarrow$ similarity function

After feedback incorporation

Distance of items to user’s profile
Translation vs. Scaling

Translation

Scaling
Diversity