Quality-Aware Neural Complementary Item Recommendation

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Item-to-Item Recommendation
Complementary Item Recommendation:
items that might be purchased together
Complementary Item Recommendation: Ground Truth

Complementary Item Recommendation: Challenges

1. How to define “complementary" distance?

2. How to balance quality vs. complementary relationship?

3. How to model complex interactions?

- Potential non-linear relationships between items features and quality.

Our Solution: ENCORE

1. Detect Complementary Items

2. Quality-Aware Recommendation

3. Transform via Neural Model

ENCORE: Neural COmplementary item REcommendation

Complement threshold
1. Detecting Complementary Items

- Influence factors

- Style-Based Complements:

  \[ d_{ji}^{(cm)}(I_i, I_j) = \| (m_i - m_j)^T E_M \|_2^2 \]

  - Image Feature Vector
  - Learned Low-ranked Embedding for image

- Functional Complements:

  \[ d_{ji}^{(ct)}(I_i, I_j) = \| (t_i - t_j)^T E_T \|_2^2 \]

  - Word2Vec
  - Learned Low-ranked Embedding for text

- Complementary relationship between items is influenced by style (image) and function (text) and this influence varies by items.
2. Quality-Aware Recommendation

- Complement relationship vs Item Quality

  ![Complement relationship vs Item Quality](image)

  Users may not choose the nearest complementary items but the highest-quality complementary items.

- Item Quality Estimation

  ![Item Quality Estimation](image)
3. Neural Complementary Item Recommendation

- Relationship

Complementary item recommendation is influenced by the complex interactions of item visual, textual and quality information.

- ENCORE Framework
Experiments

• **How well** does ENCORE perform versus baselines?

• What **impact** do the **design choices** of ENCORE have? (images, textual information, Non-linearity)

**Dataset**: Six categories in **Amazon** (Electronics, Cell Phones & Accessories (C & A), Clothing, Books, Digital Music, and Movies)

Experimental Setup: Baselines

- \( \text{LR}_A \): Logistic Regression with Average Rating
- \( \text{LR}_B \): Logistic Regression with Bayesian Rating
- \( \text{WNN} \): Weighted Nearest Neighbor
- \( \text{FNN} \): Feedforward Neural Network
- \( \text{LMT} \): Low-rank Mahalanobis Transform \[\text{McAuley SIGIR 2015}\]
- \( \text{Monomer} \) \[\text{He ICDM 2016}\]
- Variations of ENCORE (see paper)

**Metrics:** Accuracy, Precision at top-k

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* He, Ruining, Charles Packer, and Julian McAuley. "Learning compatibility across categories for heterogeneous item recommendation." Data Mining (ICDM), 2016.
Experiments: Recommendation Effectiveness

ENCORE outperforms state-of-the-art methods in accuracy, precision@5 and precision@10 for most situations, especially for Electronics and Clothing categories.
**Experiments:** Case Study

<table>
<thead>
<tr>
<th>Query Items</th>
<th>Complementary Items Recommended by ENCORE</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>(a)</em> IdeaPad U430</td>
<td>External DVD Writer Adapter Protection Plan Tablet</td>
</tr>
<tr>
<td><em>(b)</em> iPad Air</td>
<td>Screen Protector Screen Protector Case Protection Plan</td>
</tr>
<tr>
<td><em>(c)</em> Apple iPhone 5 Verizon Wireless</td>
<td>Screen Protector SIM Card Case &amp; Screen Protector Case</td>
</tr>
</tbody>
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Conclusions and Future Work

• Complementary relationships vary for different items. Items visual and textual information can help find complement items.

• Users may not choose the nearest complementary items but the highest-quality ones. Modeling item rating distribution by Bayesian inference can improve the accuracy and precision for complementary recommendation.

• Neural network structure in ENCORE provides improvement to the accuracy and precision of complement item recommendation

• Future work:
  • Personalized complementary item recommendation.
  • Effectively model textual information to improve the quality of recommendation.
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Thank you!