Learning a Hierarchical Embedding Model for Personalized Product Search

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Problem: Product Search

- **Product Search**: given a query submitted by a user, rank products so that the probability of a user purchase on one or multiple items in the result list can be maximized.
Personalization in Product Search

- Say I want a case for my phone and search “phone case”.

**Best sellers**

- **OtterBox COMMUTER SERIES Case for iPhone 7/8 Plus**
  - Rating: 4.5 stars
  - Price: $19.89 (prime)

- **iPhone 7 Plus Case, Matone Apple iPhone 7 Plus**
  - Rating: 4.5 stars
  - Price: $6.99 (prime)

- **Supcase Unicorn Beetle Hybrid Scratch Resistant Case for iPhone 5/5s**
  - Rating: 4.5 stars
  - Price: $15.99 (prime)

- **OtterBox DEFENDER SERIES Case for iPhone 5/5s**
  - Rating: 4.5 stars
  - Price: $18.95 (prime)

- **LifeProof FRE Waterproof Case for iPhone 6/6s**
  - Rating: 4.5 stars
  - Price: $36.59 (prime)

**If I have an iphone**

**If I have an android phone.**
Potentials of Personalization

- Purchase is a strong signal
  - Purchased items have high correlations with the user’s preference.

I purchased ...

I like ...
Potentials of Personalization

- Users write reviews for products.
  - Product reviews contain many details about user purchases.

A major design flaw: the headphone jack port opening. The added thickness on the top-end of the case creates enough of a gap to the Pixel's headphone jack that the metal insertion of certain headphones/aux cables will not be able to reach the jack to be inserted properly.

Saved my phone: I dropped my phone in the parking lot (3-foot fall) and it hit the pavement hard. Land on the corner, too! There is not a scratch on my Pixel. The case did suffer a crack from the fall, but I think that's from it absorbing and dispersing the impact force.
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Pitfalls of Personalization

• Vocabulary mismatch
  – Queries vs. Product descriptions

Search for “colorful light bulbs”

...10W RGB Color Changing Dimmable LED Light Bulbs...
Pitfalls of Personalization

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  – Reviews vs. Reviews

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...10W RGB Color Changing Dimmable LED Light Bulbs...

... this TV has a beautiful screen...

... it has a bright and colorful display...
Pitfalls of Personalization

• Vocabulary mismatch
  – Queries vs. Product descriptions
  – Reviews vs. Reviews

Search for “colorful light bulbs”

...10W RGB **Color Changing** Dimmable LED Light Bulbs...

... this TV has a **beautiful screen**...

... it has a **bright and colorful display**...
Pitfalls of Personalization

- **Data Sparsity**
  - Queries are formulated by users.
  - Items are purchased based on both query intents and user preferences.
  - Each user writes at most one review for a specific item.

\[
\text{not enough query per user}
\]

\[
\text{not enough item per } <u, q>\]

\[
\text{at most 1 review per } <u, i>\]

Users \rightarrow Queries

Reviews \leftarrow Items
Related Work

• Term-based Retrieval Model
  – Rank items based on the matching score between their descriptions and user’s queries [Nurmi et al., SIGIR’08].

\[
\text{score}(i, q) = \log p(i | q) \\
\propto \log p(i) + \log p(q | i)
\]

- **uniform distribution**
- **bag-of-words model (e.g. BM25, LM)**

No Personalization

Vocabulary Mismatch
Related Work

- **Latent Space Model**
  - Rank items based on the matching score between their descriptions and user’s queries [Gysel et al., CIKM’16].

```latex
tanh(W \cdot v + b)
```
Our Goal

Construct a *personalized* product retrieval model that maximizes the *probability of user purchases* in product search.
Optimization Objective

- Maximize user purchases in search
  - Rank items by $P(i|u, q)$
  - Maximize the likelihood of observed data:
    - User purchases
    - Review text

- Optimization objective

$$\mathcal{L}(R_u, R_i, u, i, q) = \log P(R_u, R_i, u, i, q)$$

$u$: user  $R_i$: reviews for $i$

$\text{observed} < u, q, i >$  $q$: query

$i$: item  $R_u$: reviews for $u$
Avoid Data Sparsity

• Problem 1: model of \( < R_{u,i,u,i} > \)
  – Reviews are dependent to users and items
  – Each user-item pair has at most 1 review.

• Assumption 1:
  *The review words are generated from user models and item models independently.*

\[
\mathcal{L}(R_u, R_i, u, i, q) = \log P(R_u, R_i, u, i, q)
\]
Avoid Data Sparsity

• Problem 2: model of $<u, q>$
  – Queries are dependent to users.
  – Items are dependent to users and queries.

• Assumption 2:

  Queries and users are independent. Item purchases are generated by the linear combination of query and user models.

$$
\mathcal{L}(R_u, R_i, u, i, q) = \log P(R_u, R_i, u, i, q) \\
= \log P(R_i|i) \cdot P(i|u, q) \cdot P(R_u|u, q) \cdot P(u, q)
$$
Avoid Vocabulary Mismatch

• Problem 3: model of term matching
  – Vocabulary gaps exist in queries and reviews.
  – Matching in semantic level is needed.

• Solution:
  
  *Project words, users, items and queries into a latent space with embedding-based language models.*
Avoid Vocabulary Mismatch

- Embedding-based language models:
  - Skip-gram models [Mikolov et al. arXiv’13, Le and Mikolov ICML’14]

\[
P(w|d) = \text{softmax}(\vec{w} \cdot \vec{d}) = \frac{\exp(\vec{w} \cdot \vec{d})}{\exp(\sum_{w' \in V_w} \vec{w'} \cdot \vec{d})}
\]
Avoid Vocabulary Mismatch

• Problem 3: model of term matching
  – Vocabulary gaps exist in queries and reviews.
  – Matching in semantic level is needed.

• Solution:

  Project words, users, items and queries into a latent space with embedding-based language models.

\[
P(R_u | u) = \prod_{w \in R_u} P(w | u)
= \prod_{w \in R_u} \frac{\exp(\vec{w} \cdot \vec{u})}{\sum_{w' \in \mathcal{V}_w} \exp(\vec{w'} \cdot \vec{u})}
\]
Hierarchical Embedding Model

\[
\begin{align*}
\mathcal{L}(R_u, R_i, u, i, q) &= \log \left( P(R_i|i)P(i|u, q)P(R_u|u) \right) \\
&= \log \left( P(i|\lambda q + (1 - \lambda)u) \right) + \sum_{w_i \in R_i} \log P(w_i|i) + \sum_{w_u \in R_u} \log P(w_u|u) \\
&\phi(w_q|w_q \in q) \quad \text{softmax}(\vec{w}_i \cdot \vec{i}) \quad \text{softmax}(\vec{w}_u \cdot \vec{u})
\end{align*}
\]
Query Model

\[ w_u \in R_u \implies \]

\[ w_q \in q \implies \phi\left(\begin{array}{c} w_q \\ w_q \\ w_q \end{array}\right) \rightarrow q \]

\[ u \]

\[ i \]

\[ w_i \]

\[ w_i \]

\[ w_i \]

\[ w_i \]

\[ \iff w_i \in R_i \]

\[ \text{Embedding look up} \]

\[ [\text{Vulic and Moens, SIGIR'15}] \text{ Mean} \]

\[ \phi(\{w_q | w_q \in q\}) = \frac{\sum_{w_q \in q} \bar{w}_q}{|q|} \]

\[ [\text{Gysel et al., CIKM'2016}] \text{ Projected Mean (pm)} \]

\[ \phi(\{w_q | w_q \in q\}) = \tanh(W \cdot \frac{\sum_{w_q \in q} \bar{w}_q}{|q|} + b) \]

\[ [\text{Palangi et al., ASLP'16}] \text{ RNN-LSTM} \]

\[ \phi(\{w_q | w_q \in q\}) = RNN(q) \]
Experiments

- Amazon Review Data [McAuley et al., SIGKDD’15]
  - 5-core data
  - Each user/item has at least 5 reviews

<table>
<thead>
<tr>
<th></th>
<th>Electronics</th>
<th>Kindle Store</th>
<th>CDs &amp; Vinyl</th>
<th>Cell Phones &amp; Accessories</th>
</tr>
</thead>
<tbody>
<tr>
<td>#items</td>
<td>63k</td>
<td>62k</td>
<td>64k</td>
<td>10k</td>
</tr>
<tr>
<td>#users</td>
<td>192k</td>
<td>68k</td>
<td>75k</td>
<td>28k</td>
</tr>
<tr>
<td>#reviews</td>
<td>1,689k</td>
<td>982k</td>
<td>1,097k</td>
<td>194k</td>
</tr>
<tr>
<td>#words per reviews</td>
<td>118.27</td>
<td>112.21</td>
<td>174.57</td>
<td>93.50</td>
</tr>
</tbody>
</table>
• Query Extraction
  – [Rowley, Journal of consumer marketing 17] :
    
    Users search for “a producer’s name, a brand or a set of terms which described the category of the product”.
  
  – Extract queries from category information [Gysel et al., CIKM’2016] :
    • >1 level category hierarchies
    • Stop words and duplicated words removed

Category: Camera, Photo -> Digital Camera Lenses

Query: photo digital camera lenses
Experiments

• Test data
  – Randomly hold:
    • 30% reviews (purchased $<u,i>$ pairs)
    • 30% queries
  – All $<u, i, q>$ triples in test set have not been observed in training

• Metrics
  – Mean Average Precision (MAP)
  – Mean Reciprocal Rank (MRR)
  – Normalized Discounted Cumulative Gain (NDCG)
Experiments

• **Baselines**
  - *QL*
    • Query Likelihood Model [Ponte and Croft, SIGIR’98]
  - *UQL*
    • Extended Query Likelihood with User Models *UQL*
  - *LSE*
    • Latent Semantic Entity

• **Our models**
  - *HEM*$_{mean}$
    • Hierarchical Embedding Model with Mean
  - *HEM*$_{pm}$
    • Hierarchical Embedding Model with Projected Mean
  - *HEM*$_{RNN}$
    • Hierarchical Embedding Model with RNN

*Source code can be accessed from* https://ciir.cs.umass.edu/downloads/HEM/
### Results

#### Retrieval performance:

<table>
<thead>
<tr>
<th>Model</th>
<th>Electronics MAP</th>
<th>Electronics MRR</th>
<th>Electronics NDCG</th>
<th>Kindle Store MAP</th>
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<th>CDs &amp; Vinyl MAP</th>
<th>CDs &amp; Vinyl MRR</th>
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<th>Cell Phones &amp; Accessories MAP</th>
<th>Cell Phones &amp; Accessories MRR</th>
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</tr>
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<tbody>
<tr>
<td>QL</td>
<td>0.289</td>
<td>0.289</td>
<td>0.316</td>
<td>0.011</td>
<td>0.012</td>
<td>0.013</td>
<td>0.009</td>
<td>0.011</td>
<td>0.010</td>
<td>0.081</td>
<td>0.081</td>
<td>0.092</td>
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<tr>
<td>UQL</td>
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<tr>
<td>LSE</td>
<td>0.233</td>
<td>0.234</td>
<td>0.239</td>
<td>0.006</td>
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<td>HEM&lt;sub&gt;mean&lt;/sub&gt;</td>
<td>0.071</td>
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#### Observations:

- Electronics are easier than Kindle Store and CDs & Vinyl
  - The queries/reviews language correlation is high.
  - #reviews per item is high.
  - The taste of users varied less.
## Results

- **Retrieval performance:**

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- **Observations:**
  - Term-based models vs. Latent space models
    - Vocabulary mismatch varies on datasets.
    - HEMs work well in all cases above.
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• Observations:
  – Relations between queries and words are non-linear
    • HEM<sub>mean</sub> performed worst.
    • HEM<sub>pm</sub> vs. HEM<sub>RNN</sub> depend on data characteristics
Summary

• A task of personalized product search

• A Hierarchical Embedding Model
  – A latent space model
  – Jointly modeling users, items and queries with review data

• Key takeaways from the experiments
  – Personalization is important for product search
  – The need varies in different scenarios
Thanks for listening!

Thanks SIGIR travel grants for supporting the presentation of this work

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http://www.cs.umass.edu/~aiqy/
https://ciir.cs.umass.edu/downloads/HEM/
Negative Sampling

- Proposed by Mikolov et al. [17], negative sampling is a technique that approximates the global objective of PV-DBOW by sampling “negative” terms from corpus:

\[
\ell = \sum_{w \in V_w} \sum_{d \in V_d} \#(w, d) \log(\sigma(\vec{w} \cdot \vec{d})) + \sum_{w \in V_w} \sum_{d \in V_d} \#(w, d) (k \cdot E_{w \sim P_V} [\log \sigma(-\vec{w} \cdot \vec{d})])
\]

- If we derived the local objective of a specific word-doc pair and let its partial derivative equal to zero. Then we have:

\[
\vec{w} \cdot \vec{d} = \log\left( \frac{\#(w, d)}{\#(d)} \cdot \frac{1}{P_V(w)} \right) - \log k
\]
Negative Sampling

- Approximates softmax with Negative Sampling:

\[ \log P(w_i|i) = \log \sigma(\vec{w}_i \cdot \vec{i}) + k \cdot \mathbb{E}_{w' \sim P_w} [\log \sigma(-\vec{w}' \cdot \vec{i})] \]

\[ \log P(w_u|u) = \log \sigma(\vec{w}_u \cdot \vec{u}) + k \cdot \mathbb{E}_{w' \sim P_w} [\log \sigma(-\vec{w}' \cdot \vec{u})] \]

\[ \log P(i|u, q) = \log \sigma(\vec{i} \cdot (\lambda \vec{q} + (1 - \lambda) \vec{u})) \]

\[ + k \cdot \mathbb{E}_{i' \sim P_i} [\log \sigma(-\vec{i}' \cdot (\lambda \vec{q} + (1 - \lambda) \vec{u}))] \]
## Appendix

Table 1: Statistics for the 5-core data for *Electronics, Kindle Store, CDs & Vinyl* and *Cell Phones & Accessories* [?].

<table>
<thead>
<tr>
<th></th>
<th>Electronics</th>
<th>Kindle Store</th>
<th>CDs &amp; Vinyl</th>
<th>Cell Phones &amp; Accessories</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Corpus</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of reviews</td>
<td>1,689,188</td>
<td>982,618</td>
<td>1,097,591</td>
<td>194,439</td>
</tr>
<tr>
<td>Review length</td>
<td>118.27±158.12</td>
<td>112.21±129.52</td>
<td>174.57±177.05</td>
<td>93.50±131.65</td>
</tr>
<tr>
<td>Number of items</td>
<td>63,001</td>
<td>61,934</td>
<td>64,443</td>
<td>10,429</td>
</tr>
<tr>
<td>Review per item</td>
<td>26.81±75.82</td>
<td>15.87±21.42</td>
<td>17.03±28.15</td>
<td>18.64±34.24</td>
</tr>
<tr>
<td>Number of users</td>
<td>192,403</td>
<td>68,223</td>
<td>75,258</td>
<td>27,879</td>
</tr>
<tr>
<td><strong>Queries</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of queries</td>
<td>989</td>
<td>4,603</td>
<td>694</td>
<td>165</td>
</tr>
<tr>
<td>Query length</td>
<td>6.40±1.64</td>
<td>7.07±1.89</td>
<td>5.71±1.62</td>
<td>5.93±1.57</td>
</tr>
<tr>
<td>Queries per item</td>
<td>1.02±0.23</td>
<td>5.08±2.04</td>
<td>4.04±1.92</td>
<td>1.11±0.38</td>
</tr>
<tr>
<td>Queries per user</td>
<td>8.13±5.84</td>
<td>35.65±37.48</td>
<td>21.75±16.53</td>
<td>4.95±2.60</td>
</tr>
<tr>
<td><strong>Train/Test</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of reviews</td>
<td>1,275,432/413,756</td>
<td>720,006/262,612</td>
<td>804,090/293,501</td>
<td>150,048/44,391</td>
</tr>
<tr>
<td>Number of queries</td>
<td>904/85</td>
<td>3313/1290</td>
<td>534/160</td>
<td>134/31</td>
</tr>
<tr>
<td>Number of user-query pairs</td>
<td>1,204,928/5,505</td>
<td>1,490,349/232,668</td>
<td>1,287,214/45,490</td>
<td>114,177/665</td>
</tr>
<tr>
<td>Relevant items per pairs</td>
<td>1.12±0.48/1.01±0.09</td>
<td>1.87±3.30/1.48±1.94</td>
<td>2.57±6.59/1.30±1.19</td>
<td>1.52±1.13/1.00±0.05</td>
</tr>
</tbody>
</table>
Experiments

- Amazon product review datasets
- Queries are extracted from product category information

Table 1: Example queries extracted following the paradigm proposed by Gysel et al. [?] from Amazon product data.

<table>
<thead>
<tr>
<th>Electronics:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- video games playstation accessory kit</td>
</tr>
<tr>
<td>- software operate system microsoft window</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Kindle Store:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- store kindle ebook cookbook food wine bake dessert</td>
</tr>
<tr>
<td>- books health fitness weight loss diet</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>CDs &amp; Vinyl:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- musical instrument general accessory sheet music folder</td>
</tr>
<tr>
<td>- digital music hard rock thrash speed metal</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cell Phones &amp; Accessories:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- cell phone accessory international charger</td>
</tr>
<tr>
<td>- cell phone accessory case sleeve</td>
</tr>
</tbody>
</table>

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Personalization Weights

**Electronics**

![Graph showing MAP versus lambda for Electronics](image)

**Kindle Store**

![Graph showing MAP versus lambda for Kindle Store](image)

**CDs & Vinyl**

![Graph showing MAP versus lambda for CDs & Vinyl](image)

**Cell Phones & Accessories**

![Graph showing MAP versus lambda for Cell Phones & Accessories](image)
Experiments

(a) Electronics  (b) Kindle Store  (c) CDs & Vinyl  (d) Cell Phones & Accessories

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