E-commerce in Your Inbox

Product Recommendations at Scale

M. Grbovic, V. Radosavljevic, N. Djuric, N. Bhamidipati (Yahoo Labs, Ad Targeting Team)
J. Savla, V. Bhagwan, D. Sharp (Yahoo, Inc., Yahoo Mail)
Introduction

● Distributed embeddings recently gained in popularity
● Tested in a number of applications at Yahoo
  ○ Search retargeting (WWW 2015)
  ○ Query categorization (WWW 2015)
  ○ Query rewriting  (SIGIR 2015)
  ○ Targeting at Tumblr (KDD 2015)
● This talk: Yahoo Mail (KDD 2015)
Introduction

- We can’t avoid ads in e-mail accounts
  - Improve user experience (and make more money) through product ads
Introduction

● Hundreds of millions of people around the world visit their e-mail inboxes daily
● Ads need to be highly relevant to overcome focus on the e-mail task
● Effective personalization and targeting is essential to tackling this problem
  ○ Higher revenue, better user experience
Inbound e-mails

- Still insufficiently explored and exploited area for the purposes of ad targeting
  - Only 10% of inbound volume represents human-generated e-mails
  - For remaining 90% of traffic, more than 22% represents e-mails related to online shopping
- A treasure trove of data
  - Standardized online receipts
  - Data from multiple commercial domains
Data set

- Includes receipts sent to users who opted-in for such research studies
  - March to October 2014
  - Extracted product names and purchase times
  - 280.7M purchases from 172 commercial domains made by 29M users
  - 2.1M unique bought products priced over $5
Data analysis

- Purchasing habits for different demographics
  a. Percentage of female online shoppers is higher
  b. Male users buy more expensive items
Data analysis

- Purchasing habits for different user cohorts
  a. Percentage of shoppers among online users
  b. Average number of purchases per user

![Maps showing purchasing habits for different age groups](image-url)
Data analysis

- Purchasing habits for different cohorts
  a. Average amount spent by a user
  b. Average price of purchased product
Recommending popular products

- Common and intuitive approach
- Lookback and lookahead parameters
Neural language models

- Neural language models induce low-$D$, distributed embeddings of words using neural networks
- Recently proposed word2vec gained popularity
  - Applied to sentences, graphs, app prediction, ...
- Can it help in product recommendation?
Proposed models

- prod2vec
- bagged-prod2vec
- user2vec
Proposed models

- Efficient product-level purchase prediction algorithm
  - Capable of scaling to millions of users and products
- Embed products to low-$D$ space using neural language model applied to a time series of user purchases
  - Clustering and nearest-neighbor search
Product-to-product models

- **prod2vec-topK**
  - Use each purchased item to recommend its $K$ neighbors to be shown to user

- **prod2vec-cluster**
  - Cluster the products, and empirically estimate probability that cluster $i$ follows cluster $j$
  - Retrieve nearest neighbors from each of the high-probability clusters
The neighbors are highly relevant to the query.

<table>
<thead>
<tr>
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<th>disney frozen lunch napkins</th>
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<td>disneys frozen party treat bags</td>
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Experiments

- Clustering results in more diverse recommendations
  - Example for product *cressi supernova dry snorkel*

<table>
<thead>
<tr>
<th>bagged-prod2vec-topK</th>
<th>bagged-prod2vec-cluster</th>
<th>cluster ID</th>
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<tr>
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<tr>
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<td>aqua sphere kayenne goggle with clear lens black</td>
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<td>nikon coolpix aw120 161 mp waterproof camera</td>
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<tr>
<td>us divers island dry snorkel</td>
<td>olympus stylus tg digital camera with 5x optical zoom</td>
<td></td>
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</table>
Recommending predicted products

- We fix lookback to 5 days
- Predicted products outperform popular ones
Experiments

- Bucket results

<table>
<thead>
<tr>
<th>Metric</th>
<th>Control (5% traffic)</th>
<th>Popular (5% traffic)</th>
<th>Predicted (5% traffic)</th>
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<tbody>
<tr>
<td>CTR</td>
<td>-</td>
<td>+ 8.33%</td>
<td>+ 9.81%</td>
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<tr>
<td>YR</td>
<td>n/a</td>
<td>-</td>
<td>+ 7.63%</td>
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- Implemented in production

Daily bucket test results
Conclusion

- Inbound e-mail data is underutilized
- Significant differences between various user cohorts
- Neural language models can directly be applied to the recommendation problem
  - Don’t count, predict!
- Look for our ads during this holiday season!