We Know What You Want to Buy: A Demographic-based System for Product Recommendation On Microblogs

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Background

- Recent years have witnessed a great success of e-commerce companies.

Product recommender systems play an important role to improve the sale of these companies.
Typical challenges

• Challenge I:
  – Can only provide **onsite recommendation service**
  – Cannot capture users’ instantaneous purchase intents outside those websites

A short status update (e.g. a tweet):
“Need your recommendation for my new phone!”

Current e-commerce recommender systems cannot capture such business opportunities.
Typical challenges

• Challenge II:
  – Know very little about “new users” (cold start)
  – Especially, it is hard to obtain important **demographic** information for recommendation
Our idea

• Online social media come to help
  – Important platforms where users **discuss their needs and desires**, and even disclose their purchase information

Users’ purchase intents can be discovered from real-time status messages in online social media
Our idea

• Online social media come to help
  – Usually containing **profile information** of the users

Contain public profiles of users, especially rich demographic data

Age = 15
Sex = Female
Work = Student
Interests = Music
...
A new paradigm for e-commerce recommender system

• Social media based recommender systems
  – Embedded recommender system ➔ Recommender systems on online social media

Social media accounts ➔ Users’ online identity
- Status update data: Monitor the status update messages for purchase intent detection
- Profile text data: Using profile information for user demographic modeling
Our system METIS

(A _MErchant_ Intent based recommendation System)

1.7 billion tweets from 5 million active users within a half-year time span

Three product types: laptop, camera and phone, containing 3,155 products and 1.13 million user reviews.

Social media platform  A linking bridge  E-commerce platform

We recommend products from e-commerce platform to users (in need) on microblogs
Overview of our system METIS

Monitor tweets and discover purchase-intent tweets

Social contents

“Need your recommendation for my new phone!”

Purchase intent detection

The key idea is to represent users and products in the same dimensions of demographic attributes.

Product demographic learning

Need=A phone
Age = 15
Sex = Female
Interests=Music

Product Recommendation

Big Data Analytics & Intelligence
Product Demographic Learning

- The product demographics, sometimes called the target audience, of a product or service is a collection of the characteristics of the people who buy that product or service.
  - **Online review**

21 of 24 people found the following review helpful

⭐⭐⭐⭐⭐ Love it!

By yourkm on December 28, 2012

**Verified Purchase**

My daughter is extremely happy with her new phone. As advertised, the phone is in great condition exceeding my expectations; thank you!

My daughter

Sex=female

Age= <15(probably)
Product Demographic Learning

• The product demographics, sometimes called the target audience, of a product or service is a collection of the characteristics of the people who buy that product or service.

  — Microblogs

We collect the demographics of the followers
Product Demographic Learning

• The product demographics, sometimes called the target audience, of a product or service is a collection of the characteristics of the people who buy that product or service.
  – Microblogs

We collect the demographics of the microbloging users who have published the positive comments on a product
Product Recommendation Framework

• Learning to Rank
  – A user’s need is viewed as a query (together with users’ profile data)
  – A candidate product is viewed as a candidate document
  – The recommendation score can be reflected by the “relevance score”
  – Given a user’s need, we rank products by their recommendation scores

Highlights:
- Demographic based features + traditional features (e.g. ratings and sale)
- Semi-automatic acquisition of training data
Feature vector construction

- Given a user and a candidate product

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEX</td>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td>AGE</td>
<td>0.1</td>
<td>0.4</td>
</tr>
<tr>
<td>INTERESTS</td>
<td>0.3</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Profiles

Age = 15
Sex = Female
Interests = Music

[ (SEX:0.7), (AGE:0.1), (INTERESTS:0.3) ]
Training data

• Semi-automatic acquisition of training data
  • Capturing the evidence of the user’s self-disclosure

Oct 1, 2012 Please recommend! I want to buy my son a Samsung phone.
Oct 4, 2012 Done! I have bought Galaxy II for my lovely son!
Deployment

• A demonstration system (in Chinese)
  – With real SINA Weibo and Jingdong data
  – http://sewm.pku.edu.cn/metis
Case I

• **A young girl** wants to buy a new phone & does not have special requirements
  - **White** iPhone and Samsung phones
Case II

- A young boy wants to buy a new phone & does not have special requirements
  - Black iPhone and Lenovo phones

Color changes to black from white with sex changing from female to male.
Case III

- A young boy wants to buy his girl-friend a phone as the birthday gift
  - **While** phones specially designed for high-quality photographing

Translations from Chinese: “I would like to buy my gf a new phone as the birthday gift.”

Accurate identification of the real buying target!
Not the boy but his gf.
Case IV

- A young girl who wants to buy cheap laptops (dislike Apple products)

In Chinese yuan
Summary

• The first public microblogging based product recommendation system in universities
• Learn product demographics from online reviews and microblogging data
• Automatic acquisition of the training data
• Demo systems and real service systems
Experiments

• Test collection

Table 4: Statistics of the dataset for product recommendation.

<table>
<thead>
<tr>
<th>Types</th>
<th>#brands</th>
<th>#models</th>
<th>#query-decision pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>phone</td>
<td>57</td>
<td>1,584</td>
<td>170</td>
</tr>
<tr>
<td>camera</td>
<td>25</td>
<td>724</td>
<td>496</td>
</tr>
<tr>
<td>laptop</td>
<td>25</td>
<td>829</td>
<td>437</td>
</tr>
</tbody>
</table>

• Evaluation metrics
  – NDCG
  – Precision @ k
Experiments

• Methods to compare
  – Simple baselines: sale, rating and polarity
  – Pointwise: MART, RandomForest (RF)
  – Pairwise: Ranksvm, RankBoost
  – Listwise: Listnet, AdaRank
Results

- Pointwise methods work very well, especially MART

<table>
<thead>
<tr>
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<th>Baselines</th>
<th>Pointwise</th>
<th>Pairwise</th>
<th>Listwise</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>sale</td>
<td>polarity</td>
<td>rating</td>
<td>MART</td>
</tr>
<tr>
<td>PHONE</td>
<td>p@1</td>
<td>0.006</td>
<td>0.006</td>
<td>0.006</td>
<td>0.106</td>
</tr>
<tr>
<td></td>
<td>p@5</td>
<td>0.041</td>
<td>0.018</td>
<td>0.029</td>
<td>0.282</td>
</tr>
<tr>
<td></td>
<td>NDCG@1</td>
<td>0.094</td>
<td>0.094</td>
<td>0.015</td>
<td>0.228</td>
</tr>
<tr>
<td></td>
<td>NDCG@5</td>
<td>0.170</td>
<td>0.093</td>
<td>0.099</td>
<td>0.256</td>
</tr>
<tr>
<td>CAMERA</td>
<td>p@1</td>
<td>0.000</td>
<td>0.000</td>
<td>0.004</td>
<td>0.606</td>
</tr>
<tr>
<td></td>
<td>p@5</td>
<td>0.238</td>
<td>0.004</td>
<td>0.018</td>
<td>0.688</td>
</tr>
<tr>
<td></td>
<td>NDCG@1</td>
<td>0.128</td>
<td>0.128</td>
<td>0.008</td>
<td>0.641</td>
</tr>
<tr>
<td></td>
<td>NDCG@5</td>
<td>0.254</td>
<td>0.094</td>
<td>0.061</td>
<td>0.495</td>
</tr>
<tr>
<td>LAPTOP</td>
<td>p@1</td>
<td>0.019</td>
<td>0.000</td>
<td>0.000</td>
<td>0.608</td>
</tr>
<tr>
<td></td>
<td>p@5</td>
<td>0.026</td>
<td>0.014</td>
<td>0.012</td>
<td>0.653</td>
</tr>
<tr>
<td></td>
<td>NDCG@1</td>
<td>0.239</td>
<td>0.002</td>
<td>0.002</td>
<td>0.695</td>
</tr>
<tr>
<td></td>
<td>NDCG@5</td>
<td>0.212</td>
<td>0.073</td>
<td>0.059</td>
<td>0.573</td>
</tr>
</tbody>
</table>
Product Recommendation Framework

• Candidate product generation
  – Manually generated rules
    • e.g. preferred price interval, preferred colors
  – Candidate product list pruning
    • At most 30 best-sale products

• Learning to Rank
Feature vector construction

• Given a user and a candidate product

Profiles

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Interests = Music

Learning to Rank
Feature vector construction

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</tr>
<tr>
<td>AGE</td>
<td>0.1</td>
<td>0.4 0.3 0.2</td>
</tr>
<tr>
<td>INTERESTS</td>
<td>Music</td>
<td>Travel</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.2  0.3 0.2</td>
</tr>
</tbody>
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Oct 4, 2012 Done! I have bought Galaxy II for my lovely son!
Purchase Intent Detection

Monitor tweets and discover purchase-intent tweets

"Need your recommendation for my new phone!"

Social contents

Purchase intent detection

Tweet streams → Keyword filtering → Classification based method

Table 2: List of purchase indicator keywords and their English translations.

<table>
<thead>
<tr>
<th>Chinese</th>
<th>English</th>
</tr>
</thead>
<tbody>
<tr>
<td>buy (买)</td>
<td>buy</td>
</tr>
<tr>
<td>recommend (推荐)</td>
<td>recommend</td>
</tr>
<tr>
<td>change (变)</td>
<td>change</td>
</tr>
<tr>
<td>which is better (哪个更好)</td>
<td>which is better</td>
</tr>
<tr>
<td>cheap (便宜)</td>
<td>cheap</td>
</tr>
<tr>
<td>cost (价格)</td>
<td>cost</td>
</tr>
<tr>
<td>auction (拍卖)</td>
<td>auction</td>
</tr>
<tr>
<td>on sale (廉价)</td>
<td>on sale</td>
</tr>
<tr>
<td>price (价格)</td>
<td>price</td>
</tr>
<tr>
<td>need (需)</td>
<td>need</td>
</tr>
<tr>
<td>shopping (购物)</td>
<td>shopping</td>
</tr>
</tbody>
</table>

Table 3: Performance comparison for purchase intent detection with SVM.

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Methods</th>
<th>Precision</th>
<th>Recall</th>
<th>F-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>Baseline+D</td>
<td>0.733</td>
<td>0.778</td>
<td>0.754</td>
</tr>
<tr>
<td></td>
<td>Ours</td>
<td>0.756</td>
<td>0.802</td>
<td>0.782</td>
</tr>
<tr>
<td></td>
<td>Ours+D</td>
<td>0.777</td>
<td>0.806</td>
<td>0.788</td>
</tr>
<tr>
<td>RBF</td>
<td>Baseline</td>
<td>0.812</td>
<td>0.582</td>
<td>0.678</td>
</tr>
<tr>
<td></td>
<td>Baseline+D</td>
<td>0.725</td>
<td>0.726</td>
<td>0.725</td>
</tr>
<tr>
<td></td>
<td>Ours</td>
<td>0.798</td>
<td>0.843</td>
<td>0.812</td>
</tr>
<tr>
<td></td>
<td>Ours+D</td>
<td>0.805</td>
<td>0.832</td>
<td>0.818</td>
</tr>
</tbody>
</table>
Product Demographic Learning

• The **product demographics**, sometimes called **the target audience**, of a product or service is a collection of the characteristics of the people who buy that product or service.
  – Modeled as distributions over attribute values
Demographic attributes

Table 1: List of demographic attributes.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>male, female</td>
</tr>
<tr>
<td>Age</td>
<td>1-11, 12-17, 18-30, 31-45, 46-59, 60+</td>
</tr>
<tr>
<td>Marital Status</td>
<td>single, engaged, loving secretly, married, relationship seeking, bereft of one’s spouse, separated, divorced, ambiguous, loving</td>
</tr>
<tr>
<td>Education</td>
<td>literature, natural science, engineering, social sciences, medical science, art, others</td>
</tr>
<tr>
<td>Career</td>
<td>internet technology, designing, media, service industry, manufacturing, medicine, scientific research, management, others</td>
</tr>
<tr>
<td>Interests</td>
<td>travel, photographing, music and movie, computer games, Internet surfing, other</td>
</tr>
</tbody>
</table>
Features

• Query dependent features
  – Demographic based features

• Query independent features
  – Sale
  – Rating
  – Opinion polarity score based on text
Samples of the learnt product demographics based on online reviews

Table 7: Samples of the learnt product demographics based on online reviews. Real numbers denote the learned weights for the corresponding attribute values.

<table>
<thead>
<tr>
<th>Samsung Galaxy S4 (White)</th>
<th>(SEX, [“male”, 0.271], [“female”, 0.729])</th>
</tr>
</thead>
<tbody>
<tr>
<td>Samsung Galaxy S4 (Blue)</td>
<td>(SEX, [“male”, 0.688], [“female”, 0.312])</td>
</tr>
<tr>
<td>Samsung Galaxy S4 (Black)</td>
<td>(SEX, [“male”, 0.852], [“female”, 0.148])</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Samsung Galaxy S4 (White)</th>
<th>(Age, [“&lt; 45”, 0.931], [“≥ 45”, 0.069])</th>
</tr>
</thead>
<tbody>
<tr>
<td>Samsung Galaxy S4 (Blue)</td>
<td>(Age, [“&lt; 45”, 0.755], [“≥ 45”, 0.245])</td>
</tr>
<tr>
<td>Samsung Galaxy S4 (Black)</td>
<td>(Age, [“&lt; 45”, 0.650], [“≥ 45”, 0.350])</td>
</tr>
</tbody>
</table>

Young females prefer white phones while young males like black phones more.
Samples of the learnt product demographic based on microblogs

Table 8: Samples of the learnt product demographic based on microblogs.

<table>
<thead>
<tr>
<th></th>
<th>Apple</th>
<th>Samsung</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$(SEX, { \text{“male”}, 0.593 }, { \text{“female”}, 0.407 })$</td>
<td>$(SEX, { \text{“male”}, 0.503 }, { \text{“female”}, 0.497 })$</td>
</tr>
<tr>
<td></td>
<td>$(\text{CAREER}, { \text{“IT”}, 0.28 }, { \text{“management”}, 0.219 }$</td>
<td>$(\text{CAREER}, { \text{“management”}, 0.252 }, { \text{“IT”}, 0.223 }$</td>
</tr>
<tr>
<td></td>
<td>${ \text{“media”}, 0.172 }, { \text{“industry”}, 0.139 }$</td>
<td>${ \text{“industry”}, 0.252 }, { \text{“media”}, 0.223 }$</td>
</tr>
<tr>
<td></td>
<td>$(\text{TAG}, { \text{“music&amp;movie”}, 0.316 }, { \text{“travel”}, 0.249 }$</td>
<td>$(\text{TAG}, { \text{“computer games”}, 0.281 }, { \text{“travel”}, 0.27 }$</td>
</tr>
<tr>
<td></td>
<td>${ \text{“Internet surfing”}, 0.163 }, { \text{“computer games”}, 0.161 })$</td>
<td>${ \text{“Internet surfing”}, 0.188 })$</td>
</tr>
</tbody>
</table>

1) Samsung has a more balanced sex distribution;
2) Apple products are more preferred by the consumers in the IT field.