Social Fashion Media Mining for Fine-grained Outfits’ Recommendation

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Agenda

- Project Motivation
- Semantic Fashion Knowledge Extraction from Social Media
- Outfit2Vec and PartialOutfit2Vec Recommendation Models
- Evaluation
- Conclusions
Project Motivation

1. Better Fashion Personalisation for online shopping

I don’t like Heels

I like pink and yellow

Casual

I like it to be Elegant as well

I like Cardigans

Better ways to automatically understand customers’ intentions and preferences and turn them into smart recommendations ??
Project Motivation

1. Better Fashion Personalisation for online shopping

Customer’s Social Media Behavior => Intentions for new purchases from online shops
Project Motivation

1. Better Fashion Personalisation for online shopping

1. Analysis of the customer’s previous images and text to extract Fashion info

2. Analysis of the customer’s interactions with digital fashion influencers outfit images and text to extract Fashion preferences

3. Analysis of the customer’s previous purchase history (some info about preferred brands and budget preferences)
Semantic Fashion Knowledge Extraction from Social Media

#lbd #mididress #blazerdress #doublebreasted #workchic #businesschic #officelook #elegantwomen #timelesselegance #dressitoimpress #streetstylechic #streetchic #fashioninsider #fashioninfluencers

hello, may I ask where your boots is from please? Thank you 😊

Nice total black 👍 😊 🌸

So chic
Semantic Fashion Knowledge Extraction from Social Media

<table>
<thead>
<tr>
<th>Fashion Vocabulary</th>
<th>Related Word</th>
</tr>
</thead>
<tbody>
<tr>
<td>brands</td>
<td>hunter:29.57%, lole:25.82%, rusty:25.21%, weekend:19.40%</td>
</tr>
<tr>
<td>hashtags</td>
<td>#liketkit, #ltkunder100, #wiw, #fallfashion, #fall, #whatiwore, #ootd, #ootd_magazine_whatiwore</td>
</tr>
<tr>
<td>item_category</td>
<td>jumpers_and_cardigans:30.95%, shoes:26.45%, all_accessories:22.37%, trouser_and_shorts:20.23%</td>
</tr>
<tr>
<td>item_sub_category</td>
<td>scarf:49.72%, sweater:21.17%, cardigan:14.79%, boot:14.32%</td>
</tr>
<tr>
<td>materials</td>
<td>leather:34.96%, denim:29.08%, cashmere:19.61%, lace:16.35%</td>
</tr>
<tr>
<td>patterns</td>
<td>striped:26.79%, checked:26.13%, herringbone:24.80%, print:22.29%</td>
</tr>
<tr>
<td>styles</td>
<td>sporty / casual / easy / practical - style:34.60%, trendy / creative / unique / fashion-forward - style:25.30%, classic /</td>
</tr>
</tbody>
</table>

Fine-Grained Fashion Outfits’ Recommendation

1. Generating Fine-Grained Fashion Recommendations

Fine-Grained Clothing Information is what really helps in understanding the customer’s real needs
Outfit2Vec and PartialOutfit2Vec Recommendation Models

A complex scenario: outfit sequence consisting of multiple items where each item has attributes
Outfit2Vec and PartialOutfit2Vec Recommendation Models

- Existing Neural Recommendation Models based on the idea of Word2Vec and focusing on one type of inputs: Prod2Vec, Item2Vec, MetaProd2Vec

- Need for a methodology to generate representative vectors of such hierarchically composed items such as outfits to be provided to a neural embeddings model
Outfit2Vec and PartialOutfit2Vec Recommendation Models

Finding a representation of each outfit such that similar outfits based on their vectors’ similarity can be recommended to the user.

As each outfit is composed of multiple clothing items and each item has different attributes, a strategy of projecting these details into vectors should be decided:

- Mapping Items into Clothing Entities
- Projecting the entities into outfit vectors
Outfit2Vec and PartialOutfit2Vec Recommendation Models

Mapping Items into Clothing Entities

Pattern material subcategory category (structured words)
**Pattern-material-subcategory-category**
(structured entities)

Solid-Leather-Handbag-Bags = One word in the model’s vocabulary

Solid-Leather-Handbag-Bags = Structured Entity
Solid Leather Handbag Bags = Structured Words
Outfit2Vec and PartialOutfit2Vec Recommendation Models

Rule-based approach for consistency

(1) Add Jacket or Coat Entity if Exists
(2) If Upper Body and Lower Body Exists:
   a. Add Upper Body Entity
   b. Add Lower Body Entity
(3) If Upper Body doesn’t Exist and a Dress Exists: Add Dress Entity
(4) Add Tights and Socks Entity if Exists
(5) Add Shoes Entity if Exists
(6) Add Bags Entity if Exists
(7) Add Accessories Entity if Exists

Upper body entities consist of the following categories: (1) Blouses and Tunics, (2) Tops and Shirts, (3) Jumpers and Cardigans
Lower body categories include: (1) Skirts, (2) Jeans, (3) Trousers and Shorts
Outfit2Vec and PartialOutfit2Vec Recommendation Models

Outfit Sequence:

- Striped_Wool_Sweater_SweatersAndCardigans
- Solid_Leather_HandBag_Bags
- Solid_Viscose_PleatedSkirt_Skirts
- Solid_Leather_Sandal_Shoes

Paragraph Vector (PV-DM) and Paragraph Vector (PV-DBOW)
Outfit2Vec and PartialOutfit2Vec Recommendation Models

Outfit Sequence:
- Striped_Wool_Sweater_SweatersAndCardigans
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Outfit 1
Outfit 2
Outfit 3
...

Predict Next Outfit

Whole outfits Prediction
Outfit2Vec and PartialOutfit2Vec Recommendation Models

Outfit Sequence:

- Striped_Wool_Sweater_SweatersAndCardigans
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Item 1 Item 2 Item 3 ???

Predict Next Item

Partial outfits Prediction
Outfit2Vec and PartialOutfit2Vec Recommendation Models

Evaluation Metrics

- Normalised Discounted Cumulative Gain (NDCG)
- Mean Average Precision (MAP)
- Mean Reciprocal Rank (MRR)

Position of Retrieved Outfit
- Binary Metric Multiclass output for each item
- Relevant Item = 0.7 of the details of the ground truth entity/sequence

Rank position of first relevant Outfit
Outfit2Vec and PartialOutfit2Vec Recommendation Models

<table>
<thead>
<tr>
<th>Model</th>
<th>NDCG@30</th>
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<th>MAP@30</th>
<th>MAP@40</th>
<th>MRR@30</th>
<th>MRR@40</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outfit2Vec(PV-DM)-SE</td>
<td>0.22</td>
<td>0.33</td>
<td>0.37</td>
<td>0.41</td>
<td>0.06</td>
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Whole Outfits Recommendation:

Defining Structured Entities for the PV-DM has resulted in +19% for the NDCG evaluation

Both Structured Words and Structured Entities have improved in MRR and MAP when compared to the random sequences
Outfit2Vec and PartialOutfit2Vec Recommendation Models

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Whole Outfits Recommendation:

Defining Structured Entities for the PV-DBOW has resulted in +25% for the NDCG evaluation

Both Structured Words and Structured Entities have improved in MRR and MAP when compared to the random sequences
Outfit2Vec and PartialOutfit2Vec Recommendation Models

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<tr>
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<th>MAP@40</th>
<th>MRR@30</th>
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<td>0.05</td>
</tr>
</tbody>
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**Partial Outfits Recommendation:**

Structured words has improved results (Shorter length for prediction)

Both Structured Words and Structured Entities have improved when compared to the random sequences
MultiClass Style Classification
Conclusions

- Methodology for learning representations of hierarchically-composed complex structures to learn their embeddings as unique instances within a taxonomy.
- Outfit2Vec and PartialOutfit2Vec for learning clothing embeddings
- Whole- and Partial outfits prediction experiments where our approaches: Structured Entities and Structured Words have shown improvements in evaluation metrics
Thank You