



Social Fashion Media Mining for Fine-grained Outfits' Recommendation











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



Better ways to automatically understand customers' intentions and preferences and turn them into smart recommendations ??

Project Motivation

1. Better Fashion Personalisation for online shopping

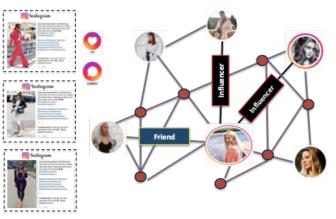


Customer's Social Media Behavior => Intentions for new purchases from online shops

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
#dresstoimpress #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

The states the	Fashion Vocabulary	Related Word
to a to a	brands	hunter:29.57%, lole:25.82%, rusty:25.21%, weekend:19.40%
	hashtags	#liketkit, #ltkunder100, #wiw, #fallfashion, #fall, #whatiwore, #ootd, #ootdmagazinewhatiwore
		jumpers_and_cardigans:30.95%, shoes:26.45%, all_accessories:22.37%, trouser_and_shorts:20.23%
it and the second se	item_sub_category	scarf:49.72%, sweater:21.17%, cardigan:14.79%, boot:14.32%
	materials	leather:34.96%, denim:29.08%, cashmere:19.61%, lace:16.35%
		striped:26.79%, checked:26.13%, herringbone:24.80%, print:22.29%
	styles	sporty / casual / easy/ practical - style:34.60%, trendy / creative / unique/ fashion-forward -style:25.30%, classic /

1] Kim Hammar, Shatha Jaradat, Nima Dokoohaki, Mihhail Matskin. Deep Text Mining of Instagram Data Without Strong Supervision. To appear in proceedings of 2018 IEEE/WIC/ACM International Conference on Web Intelligence., Santiago Chile, 2018.

Fine-Grained Fashion Outfits' Recommendation

1. Generating Fine-Grained Fashion Recommendations

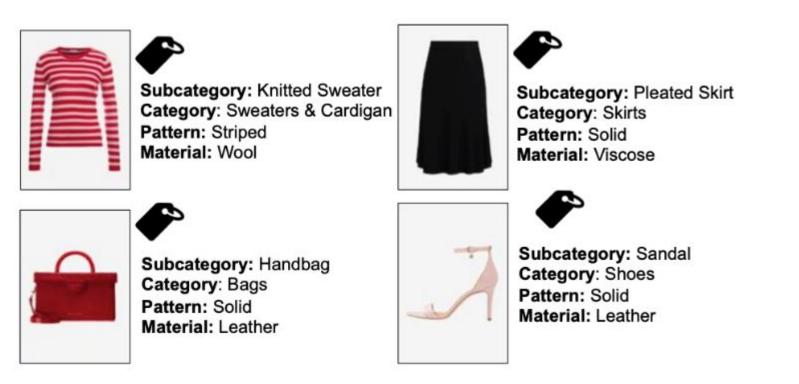


Multi-class classification:					
[1] Tops and Tshirts [2] Jackets					
[3] Jeans	[4] Shoes				

The subcategories level as well:					
[1] Long-sleeve Top	[2] Vest				
[3] Skinny-Fit	[4] Sandals				

 Multi-attributes classification: <u>Material & Patterns</u>: Denim, Leather, Wool, Lace, Checked, Print
 Style and brands information

Fine-Grained Clothing Information is what really helps in understanding the customer's real needs



A complex scenario: outfit sequence consisting of multiple items where each item has attributes

- 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

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

Mapping Items into Clothing Entities Pattern material subcategory category (structured words) **Pattern-material-subcategory-category** (structured entities)



Subcategory: Handbag Category: Bags Pattern: Solid Material: Leather Solid-Leather-Handbag-Bags = One word in the model's vocabulary

Solid-Leather-Handbag-Bags = Structured Entity Solid Leather Handbag Bags = Structured Words

Projecting the entities into outfit vectors

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

Outfit Sequence: Striped_Wool_Sweater_SweatersAndCardigans Solid_Leather_HandBag_Bags Solid_Viscose_PleatedSkirt_Skirts

Solid_Leather_Sandal_Shoes

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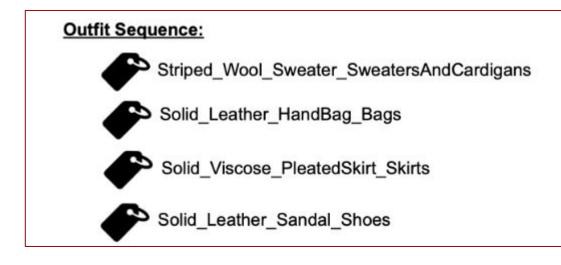
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marl_leather_hat_allAccessories

Paragraph Vector (PV-DM) and Paragraph Vector (PV-DBOW)



Outfit 1 Outfit 2 Outfit 3

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Predict Next Outfit

Whole outfits Prediction

Outfit Sequence:

Striped_Wool_Sweater_SweatersAndCardigans



Solid_Leather_HandBag_Bags



Solid_Viscose_PleatedSkirt_Skirts

Solid_Leather_Sandal_Shoes

Item 1 Item 2 Item 3 ???

Predict Next Item

Partial outfits Prediction

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

+1	9%
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Model	NDCG@30	NDCG@40	MAP@30	MAP@40	MRR@30	MRR@40
Outfit2Vec(PV-DM)-SE	0.22	0.33	0.37	0.41	0.06	0.06
Outfit2Vec(PV-DM)-SW	0.08	0.09	0.39	0.44	0.06	0.05
Outfit2Vec(PV-DBOW)-SE	0.30	0.38	0.37	0.41	0.07	0.07
Outfit2Vec(PV-DBOW)-SW	0.08	0.10	0.21	0.23	0.04	0.04
PV-DBOW-Random	0.08	0.09	0.13	0.14	0.03	0.03
PV-DM-Random	0.07	0.07	0.23	0.23	0.04	0.03

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

Model	NDCG@30	NDCG@40	MAP@30	MAP@40	MRR@30	MRR@40
Outfit2Vec(PV-DM)-SE	0.22	0.33	0.37	0.41	0.06	0.06
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Outfit2Vec(PV-DBOW)-SE	0.30	0.38	0.37	0.41	0.07	0.07
Outfit2Vec(PV-DBOW)-SW	0.08	0.10	0.21	0.23	0.04	0.04
PV-DBOW-Random	0.08	0.09	0.13	0.14	0.03	0.03
PV-DM-Random	0.07	0.07	0.23	0.23	0.04	0.03

Whole Outfits Recommendation:

+25%

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

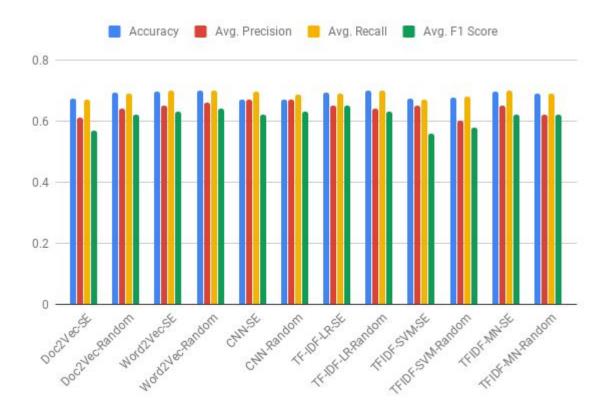
Model	NDCG@30	NDCG@40	MAP@30	MAP@40	MRR@30	MRR@40
PartialOutfit2Vec(PV-DM)-SE	0.43	0.60	0.26	0.34	0.19	0.26
PartialOutfit2Vec(PV-DM)-SW	0.77	0.86	0.65	0.67	0.59	0.58
PartialOutfit2Vec(PV-DBOW)-SE	0.54	0.67	0.34	0.38	0.28	0.31
PartialOutfit2Vec(PV-DBOW)-SW	0.77	0.79	0.82	0.81	0.74	0.75
Word2Vec-SkipGram	0.07	0.08	0.19	0.29	0.05	0.05

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 hierarchicallycomposed 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