Mind the Gap

Exploring Shopping Preferences Across Fashion Retail Channels

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Motivation

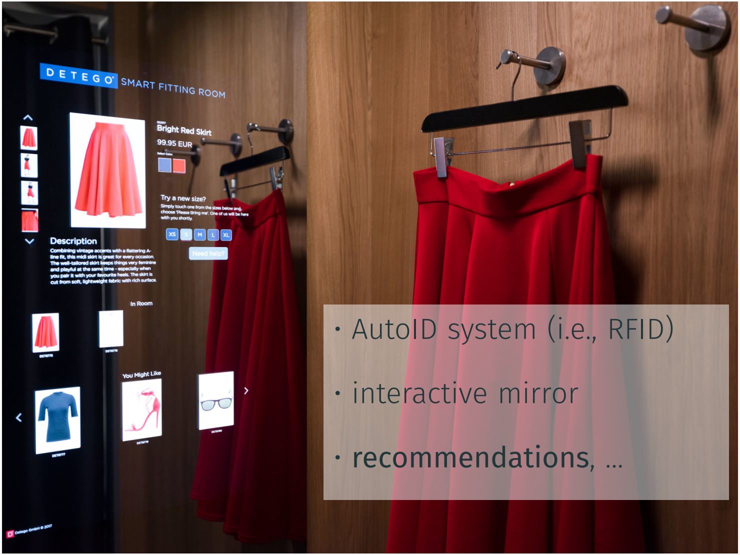
Line between physical and virtual world gets blurry

- especially in the fashion retail industry
- customers use and combine multiple channels
- enabled by new technologies (e.g., RFID)

→ Increasing number of data sources for retailer

Multi-channel Example

Smart Fitting Rooms



- AutoID system (i.e., RFID)
- interactive mirror
- **recommendations, ...**

Problem

Multi-channel recommender system

- customer preferences may change with channel
- leverage and combine multiple data streams

Hence, we need to **learn more about user preferences** in the form of shopping patterns (i.e., online vs. brick-and-mortar).

Further, we need to investigate and evaluate the **impact of these preferences on recommender systems**.

Datasets

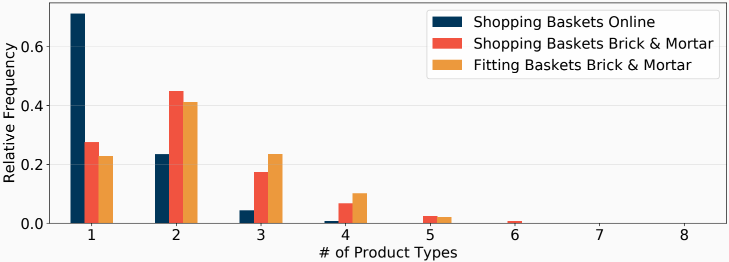
Data[1] of a large international fashion retailer

- online and brick-and mortar shopping baskets
- baskets of products in smart fitting rooms
- additional product metadata (e.g., product categories)

Dataset	# Baskets	# Products
Online Shop Sales	1,119,570	14,585
Brick-and-Mortar Sales	2,080,072	17,626
Brick-and-Mortar Fittingroom	32,279	3,790

[1] https://github.com/detegoDS/mind_the_gap_dataset

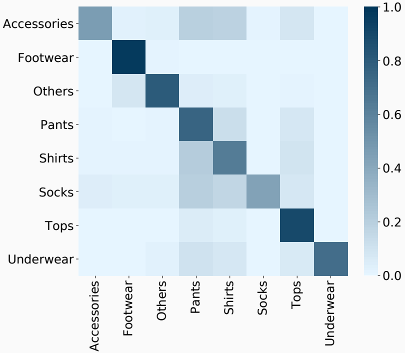
Empirical Analysis | Basket Anatomy



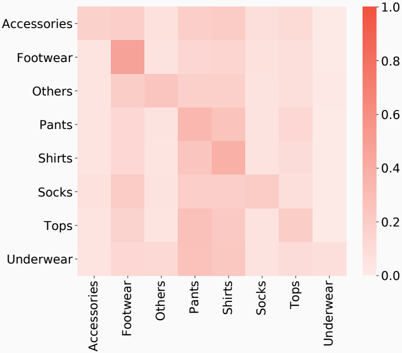
(a) Number of Product Types per Basket

→ Online shopping is focused while offline is more diverse

Empirical Analysis | Product Co-Purchases



(b) Online Sales

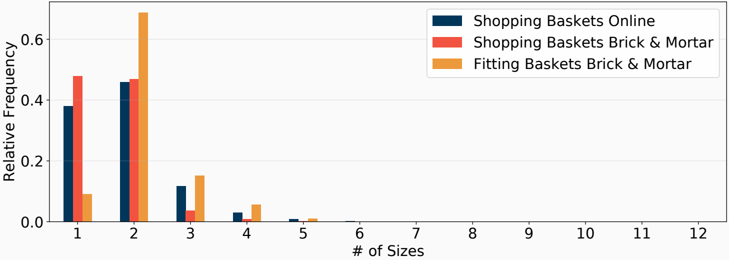


(c) Brick-and-Mortar Sales

→ Shop online for a single product type and offline for outfits

We find that 36% of online shopping baskets contain a product multiple times (13% for brick-and-mortar baskets).

Implication for shopping baskets:



(d) Number of Sizes

→ No fitting online, buy the product in multiple sizes

Impact on Recommender Systems

Multiple recommendation algorithms (rand, pop, embed)

Evaluation metrics

- accuracy metrics (Recall and NDCG)
- beyond-accuracy metrics (Coverage, Diversity, Novelty)

Data & models

- shopping baskets with overlapping products
  (336,256 online and 823,753 brick-and-mortar baskets)
- individual and combined models

Impact on Recommender Systems

Online recommendations are easier due to a stronger focus

- not the case for popularity-based recommendations
- prod2vec on online data outperforms brick-and-mortar

Model	Training Set	Test Set	*NDCG*	*Recall*	*Novelty*	*Diversity*	*Coverage*
POP	Brick & Mortar	Brick & Mortar	0.0316	0.0461	7.7969	0.7356	0.0010
POP	Online	Online	0.0197	0.0319	8.3355	0.7111	0.0010
EMBED	Brick & Mortar	Brick & Mortar	0.0966	0.1264	10.8430	0.5297	0.5967
EMBED	Online	Online	0.1919	0.2601	11.6272	0.3735	0.6917

Impact on Recommender Systems

Transferring and combining recommender models

- transfer decreases accuracy, but improves novelty
- combination leads to mixed effects on accuracy
- beyond-accuracy improve for the most part

Model	Training Set	Test Set	*NDCG*	*Recall*	*Novelty*	*Diversity*	*Coverage*
POP	Online	Brick & Mortar	0.0128	0.0213	11.7956	0.7111	0.0010
POP	Brick & Mortar	Online	0.0066	0.0077	13.0900	0.7356	0.0010
EMBED	Online	Brick & Mortar	0.0528	0.0695	13.4118	0.4305	0.6842
EMBED	Brick & Mortar	Online	0.0759	0.0981	13.2781	0.5249	0.5589
EMBED	Combined	Brick & Mortar	0.0969	0.1267	10.9778	0.4932	0.7861
EMBED	Combined	Online	0.1574	0.2066	12.3362	0.4119	0.8123

Conclusion

Contributions

- substantial differences in shopping behavior
    - brick-and-mortar more diverse shopping
    - online focused on specific categories
- combining multiple data sources is challenging
    - accuracy vs. beyond-accuracy
    - recommendation context (online vs. brick-and-mortar)
- real-world dataset[2]

Future Work

- generalization on different domains and settings

[2] *https://github.com/detegoDS/mind_the_gap_dataset*