What Matters for Shoppers: Investigating Key Attributes for Online Product Comparison

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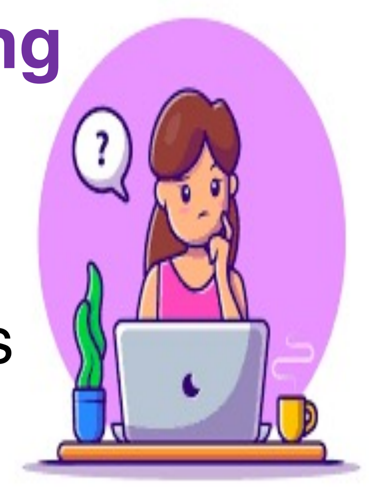
Motivation

Information Overload while Shopping



Objective
- ➢ Product details/catalog
- ➢ Search filters

Subjective
- ➢ Customer Reviews
- ➢ Feature ratings

Identifying key product attributes improves the overall search & shopping experience significantly:

- ❖ Guide sellers to highlight specific product details
- ❖ Guide buyers about key aspects to compare products

ReBARC (Review Based Attribute Ranker for Product Comparison)

Popularity based Attribute Ranking

- Get review sentences with useful terms [7] or attributes
- Append product title to sentence sample
- Compute embeddings for sentences + attributes (SentenceBERT [3])
- Rank the top 3 attributes similar to each review sentence, via MMR [6]

Opinion based Attribute Re-Ranking

- Assume: sentiment of review sentence = sentiment of attribute mention in it
- Find sentiment score of each attribute in popularity based ranked list using RoBERTa [2] fine-tuned on SST-2 [4]
- Re-rank attributes based on sentiment score to get final ranked list

Problem & Data

Amazon Product Reviews Data [1]

Products
- ~10K products from 10 categories

Reviews
- Customer Reviews (~116K per product category)

Attributes
- Catalog attributes + feature ratings
- ~64 per product

We propose an approach, ReBARC:

- ❖ Domain-agnostic & unsupervised
- ❖ Ranks objective & subjective product info based on frequency + sentiment in reviews
- ❖ Avoids direct use of noisy review data
  - maps review attribute mentions to catalog data (more reliable + structured)

Experiments and Results

Product Category (#Products, #Attributes, #Reviews)	Human imp. attrs.	Human imp. num. attrs.	Human imp. cat. attrs.	Sample key attributes frequently detected by ReBARC per category
Home (2319, 61, 150K)	0.66	0.78	0.55	*color, assembly, easyToClean*
Electronics (3267, 84, 339K)	0.71	0.82	0.56	*price, display, color, resolution*
Tools (1218,76,291K)	0.73	0.82	0.55	*durability, easy to install rating*
Beauty (546, 48, 66K)	0.77	0.82	0.71	*brand, skinType, valueForMoney*
Appliances (1104, 78, 91K)	0.81	0.84	0.72	*batteries, price, brand, rating*
Avg (all 10 categories)	0.71	0.77	0.61	N/A

Product Category	MAP@5				MAP@3				NDCG@5				NDCG@3			
	R	S	Q	C	R	S	Q	C	R	S	Q	C	R	S	Q	C
Home	**0.51**	0.38	0.34	0.42	**0.32**	0.24	0.19	0.26	**0.57**	0.36	0.12	0.45	**0.43**	0.25	0.08	0.36
Electronics	**0.5**	0.35	0.36	0.4	**0.4**	0.2	0.24	0.26	**0.48**	0.27	0.14	0.39	**0.45**	0.13	0.05	0.34
Tools	**0.5**	0.36	0.35	0.39	**0.3**	0.21	0.18	0.21	**0.55**	0.32	0.18	0.44	**0.44**	0.19	0.1	0.34
Pets	**0.52**	0.37	0.34	0.41	**0.42**	0.33	0.25	0.31	**0.6**	0.36	0.17	0.5	**0.48**	0.34	0.1	0.37
Beauty	**0.6**	0.32	0.32	0.43	**0.35**	0.14	0.15	0.22	**0.65**	0.13	0.12	0.5	**0.52**	0.1	0.05	0.41
Grocery	**0.6**	0.33	0.35	0.46	**0.5**	0.22	0.23	0.37	**0.68**	0.11	0.18	0.51	**0.6**	0.1	0.13	0.47
Appliances	**0.57**	0.37	0.35	0.41	**0.48**	0.28	0.21	0.33	**0.7**	0.28	0.19	0.57	**0.64**	0.17	0.1	0.5

Baselines:

1. **S**: Common online product search filters
2. **Q**: Online search query auto-completion logs
3. **C**: unsupervised aspect extraction [5]

ReBARC significantly outperforms strong baselines in finding key attributes via human evaluation

Conclusions

- ReBARC: an unsupervised approach to identify and rank key product attributes across multiple product categories
- We also studied the correlation between attributes of interest to customers based on reviews, and those available to them for search on shopping websites

References

[1] Ni et al .2019. Justifying recommendations using distantly labeled reviews and fine-grained aspects
[2] Liu et al. 2019. A robustly optimized BERT pretraining approach.
[3] Riemers et al. 2019. Sentence BERT: sentence embeddings using Siamese BERT networks.
[4] Socher et al. 2013. Recursive deep models for semantic compositionality over a sentiment treebank.
[5] Tulkens et al. 2020. Embarrassingly simple unsupervised aspect extraction.
[6] Carbonell et al. 1998. The use of MMR, diversity based re-ranking for reordering documents and producing summaries.
[7] Campos et al. 2020. A Yake keyword extraction from single documents using multiple local features