

Label generation

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Motivation

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Topic modeling

Brand-Topic Model built on the Poisson Factorisation model with adversarial learning

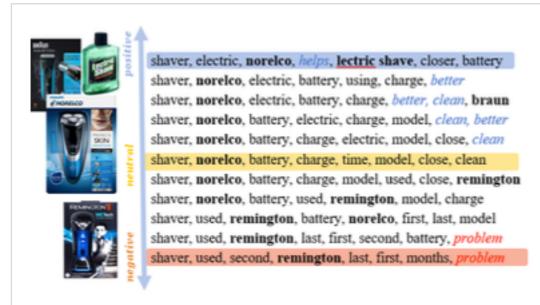


Figure 1: Example topic results generated from proposed Brand-Topic Model. We observe a transition of topics with varying topic polarity scores. Besides the change of sentiment-related words (e.g., 'problem' in negative topics and 'better' in positive topics), we could also see a change of their associated brands. Users are more positive about BRAUN, negative about REMINGTON, and have mixed opinions on NORELCO.

Topic modeling parameters

- Train/Test split: 10% reviews (7,826 reviews) as the test set and the remaining (70,436 reviews) as the training set
- Batch size: 1,024

- Maximum training steps: 50,000
- Topic number (K): 30
- Temperature in the Gumbel-Softmax equation: 1

Nr. of topics

30

Label

Single or multi-word manually generated labels

Label selection

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Label quality evaluation

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Assessors

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Domain

Domain (paper): Polarity-bearing topic modeling

Domain (corpus): Online store reviews

Problem statement

Proposing the Brand-Topic Model (BTM), which aims to detect brand- associated polarity-bearing topics from product reviews.

BTM is able to automatically infer real-valued brand-associated sentiment scores and generate fine-grained sentiment-topics in which we can observe continuous changes of words under a certain topic while its associated sentiment gradually varies from negative to positive.

Corpus

Origin: Amazon

Nr. of documents: 78,322 (113,730 in the oversampled dataset)

Details:

• Reviews in the Beauty category from the Amazon review corpus

• Final dataset contains a total of 78,322 reviews from 45 brands

Dataset	Amazon-Beauty Reviews
Documents per classes	
Neg / Neu / Pos	9,545 / 5,578 / 63,199
Brands	45
Total #Documents	78,322
Avg. Document Length	9.7
Vocabulary size	~ 5000

Table 1: Dataset statistics of reviews within the Amazon dataset under the *Beauty* category.

Document

A single amazon review belonging to the Beauty category.

Each review is accompanied with the rating score (between 1 and 5), reviewer name and the product meta-data such as product ID, description, brand and image.

Pre-processing

We use the product meta-data to relate a product with its associated brand.

Reviews with the rating score of 1 and 2 are grouped as negative reviews; those with the score of 3 are neutral reviews; and the remaining are positive reviews.

Documents are represented as the bag-of-words

Tokens, i.e., n-grams ($n = \{1, 2, 3\}$), occurred less than twice are filtered.

Oversampled dataset

Since the dataset is highly imbalanced, we balance data in each mini-batch by oversampling.

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@inproceedings{zhao_2021_adversarial_learning_of_poisson_factorisation_model_fo
r_gauging_brand_sentiment_in_user_reviews,
    title = "Adversarial Learning of {P}oisson Factorisation Model for Gauging
Brand Sentiment in User Reviews",
   author = "Zhao, Runcong and
     Gui, Lin and
     Pergola, Gabriele and
     He, Yulan",
    booktitle = "Proceedings of the 16th Conference of the European Chapter of
the Association for Computational Linguistics: Main Volume",
   month = apr,
   year = "2021",
   address = "Online",
   publisher = "Association for Computational Linguistics",
   url = "https://aclanthology.org/2021.eacl-main.199",
   doi = "10.18653/v1/2021.eacl-main.199",
   pages = "2341--2351",
   abstract = "In this paper, we propose the Brand-Topic Model (BTM) which
aims to detect brand-associated polarity-bearing topics from product reviews.
Different from existing models for sentiment-topic extraction which assume
topics are grouped under discrete sentiment categories such as {`}positive{'},
{`}negative{'} and {`}neural{'}, BTM is able to automatically infer real-valued
brand-associated sentiment scores and generate fine-grained sentiment-topics in
which we can observe continuous changes of words under a certain topic (e.g.,
{`}shaver{'} or {`}cream{'}) while its associated sentiment gradually varies
from negative to positive. BTM is built on the Poisson factorisation model with
the incorporation of adversarial learning. It has been evaluated on a dataset
constructed from Amazon reviews. Experimental results show that BTM outperforms
a number of competitive baselines in brand ranking, achieving a better balance
of topic coherence and unique-ness, and extracting better-separated polarity-
bearing topics.",
}
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#Thesis/Papers/Initial