goldberg_2022_sourcing_product_innovation_intelligence_from_online_reviews

Year

2022

Author(s)

David M. Goldberg and Alan S. Abrahams

Title

Sourcing product innovation intelligence from online reviews

Venue

Decision Support Systems

Topic labeling

Manual

Focus

Secondary

Type of contribution

Established approach

Underlying technique

Manual labeling

Topic labeling parameters

Nr or inspected words: 15

Label generation

We manually labeled each topic based on its contents.
Most topics identified different types of products, but we identified topic #2 as denoting negative product experiences, which we used to predict irritators, and topic #4 as denoting positive product experiences, which we used to predict compliments.
None of the topics seemed to relate to feature requests.

Table 6
10-topic analysis output from LDA [5].

Topic	Top terms
#1: Pans and cookware	pan, set, pans, stick, use, it, non, cooking, cook, cookware, great, heat, well, clean, stainless
#2: Negative product experience	one, product, amazon, back, it, unit, get, first, reviews, new, could, time, buy, made, replacement
#3: Water filters	water, air, kettle, it, filter, unit, room, use, filters, smell, much, really, dust, clean, fan
#4: Positive product experience	it, great, easy, use, love, product, one, works, well, recommend, bought, price, opener, clean, gift
#5: Purchasing narrative	one, years, it, bought, needed, old, used, new, last, year great, use, another, model, still
#6: Blenders/juicers	blender, ice, it, use, make, cream, clean, juicer, machine, great, easy, juice, blade, food, get
#7: Slow/rice cookers, mixers	rice, mixer, cooker, it, pot, use, time, one, cooking, bowl, cook, slow, great, love, used
#8: Coffee makers	coffee, cup, maker, water, it, machine, hot, pot, use, carafe grinder, one, great, brew, makes
#9: Popcorn and waffle makers	popcorn, easy, it, use, pop, great, waffle, clean, cooking, one, time, cook, make, oil, waffles
#10: Toasters	toaster, it, oven, toast, lid, top, one, use, well, unit, makes, get, time, bread, nice

Case study topics:

Table 10
Aspect mining analysis of coffee maker reviews.

Topic	Key terms	Consolidated sentiment score
1: Coffee maker	Machine, reservoir, clean, noise, setup	+0.79
2: Coffee/tea	Tea, coffee, espresso, bean, selection	+0.90
3: Product functionality	Cup, make, oz., pot, brewing	+0.82
4: Time	Time, month, morning, day, work	+0.66
5: Product size	Mini, thing, plastic, bigger, size	+0.53

Motivation

Negative product experiences topic used to predict irritators, and positive product experiences topic used to predict compliments.

In Table 7, we show the performance of each technique at the top 200 reviews (see LDA):

Table 7
Performance of each technique within the top 200-ranked reviews.

	Number (percentage) of true instances in top 200-ranked reviews		
Technique	Compliments	Feature requests	Irritators
Unigrams	171 (85.5%)	62 (31.0%)	**148 (74.0%)**
Bigrams	**173 (86.5%)**	87 (43.5%)	140 (70.0%)
Trigrams	**173 (86.5%)**	**103 (51.5%)**	135 (67.5%)
LDA	116 (58.0%)	–	67 (33.5%)
AFINN	95 (47.5%)	27 (13.5%)	77 (38.5%)
Harvard GI	85 (42.5%)	31 (15.5%)	63 (31.5%)
Star ratings	102 (51.0%)	8 (4.0%)	97 (48.5%)

Topic modeling

LDA

Topic modeling parameters

Nr of iterations: 1500

Nr of topics: 2 to 25

Nr. of topics

10

Case study: 5

Label

Single or multi word label referring to a product, negative product experiences (one topic) or positive product experiences (one topic)

Label selection

\

Label quality evaluation

\

Assessors

\

Domain

Paper: Text mining

Dataset: Online reviews (Amazon)

Problem statement

In this study, we use text mining tools to propose a method for rapid prioritization of online reviews, differentiating the reviews pertaining to innovation opportunities that are most useful for firms.

We draw from the innovation and entrepreneurship literature and provide an empirical basis for the widely accepted attribute mapping framework, which delineates between desirable product attributes that firms may want to capitalize upon and undesirable attributes that they may need to remedy.

Based on a large sample of reviews in the countertop appliances industry, we demonstrate the performance of our technique.

We validate the usefulness of our technique by asking senior managers at a large manufacturing firm to rate a selection of online reviews, and we show that the selected attribute types are more useful than alternative reviews.

Corpus

Origin: Amazon.com

Nr. of documents: 733,411

Details:

- In collaboration with a large Fortune 1000-listed manufacturer of countertop appliances earning over $500 million in annual revenue, we chose the Amazon product categories pertaining to that firm's key product offerings
- Each review is tagged for the three target classes: irritators, compliments, and feature requests.
- For case study: "We chose a line of coffee makers by a competitor of the collaborating countertop appliance manufacturer […]. We filtered the reviews pertaining to those

products"

Document

An Amazon review textual content, together with the product that each review referred to, its date, its title, and its star rating on a scale of 1 to 5, inclusive and tagged for the three target classes: irritators, compliments, and feature requests.

Pre-processing

```
@article{goldberg_2022_sourcing_product_innovation_intelligence_from_online_rev
iews,
  abstract = {In recent years, online reviews have offered a rich new medium
for consumers to express their opinions and feedback. Product designers
frequently aim to consider consumer preferences in their work, but many firms
are unsure of how best to harness this online feedback given that textual data
is both unstructured and voluminous. In this study, we use text mining tools to
propose a method for rapid prioritization of online reviews, differentiating
the reviews pertaining to innovation opportunities that are most useful for
firms. We draw from the innovation and entrepreneurship literature and provide
an empirical basis for the widely accepted attribute mapping framework, which
delineates between desirable product attributes that firms may want to
capitalize upon and undesirable attributes that they may need to remedy. Based
on a large sample of reviews in the countertop appliances industry, we
demonstrate the performance of our technique, which offers statistically
significant improvements relative to existing methods. We validate the
usefulness of our technique by asking senior managers at a large manufacturing
firm to rate a selection of online reviews, and we show that the selected
attribute types are more useful than alternative reviews. Our results offer
insight in how firms may use online reviews to harness vital consumer
feedback.},
  author = {David M. Goldberg and Alan S. Abrahams},
  date-added = {2023-03-24 17:35:38 +0100},
  date-modified = {2023-03-24 17:35:38 +0100},
  doi = {https://doi.org/10.1016/j.dss.2022.113751},
```

```
  issn = {0167-9236},
  journal = {Decision Support Systems},
  keywords = {Online reviews, Text mining, Data mining, Innovation, Business intelligence},
  pages = {113751},
  title = {Sourcing product innovation intelligence from online reviews},
  url = {https://www.sciencedirect.com/science/article/pii/S0167923622000227},
  volume = {157},
  year = {2022}}
```

#Thesis/Papers/Initial