Assessing and predicting review helpfulness

EURO29

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Joint work with Ashwin Ittoo
HEC Liège, Belgium

Outline

Problem statement

Roll over image to zoom in

Amazon Echo (2nd generation) - Smart speaker with Alexa - Heather Grey Fabric

by Amazon

11,829 customer reviews | 1000+ answered questions

Amazon's Choice for "echo heather gray fabric"

Price: £89.99 & **FREE Delivery** in the UK. Delivery Details

Buy 2 and Save £25. Add 2 Amazon Echo devices to your cart and automatically receive £25 off your order. Terms and Conditions

In stock.

This item does not ship to **Belgium**. Learn more

Dispatched from and sold by Amazon EU Sarl. Gift-wrap available.

Note: This item is eligible for **click and collect.** Details

1 new from £89.99

Colour Name: **Heather Grey Fabric**

Style Name: **Amazon Echo**

Amazon Echo | Amazon Echo + Philips Hue Color Kit (E27) | Amazon Echo + Philips Hue Color Kit (B22) | Amazon Echo + Philips Hue White Kit (E27)

- Amazon Echo connects to Alexa-a cloud-based voice service-to play music, make calls, set alarms and timers, ask questions, check your calendar, weather, traffic and sports scores, manage to-do and shopping lists, control compatible smart home devices, and more.
- Just ask for a song, artist or genre from Amazon Music, Spotify, TuneIn and more. With multi-room music, you can play music on Echo devices in different rooms, available for Amazon Music, TuneIn and Spotify; Bluetooth not supported. Echo can also play audiobooks, radio stations, news briefings and more.
- Call or message anyone hands-free who also has an Echo device or the Alexa App. Also, quickly connect to other Echo devices in your home using just your voice.
- New speaker with Dolby processing that fills the room with immersive, 360° omnidirectional audio, and delivers crisp vocals, deep bass, and clear highs at louder volumes.
- With seven microphones, beam-forming technology and noise cancellation, Echo hears you from any direction-even while music is playing.
- Just ask Alexa to control your compatible smart lights, switches, TVs, thermostats and more
- Alexa is always getting smarter and adding new features and skills. Just ask Alexa to request an Uber, order a pizza, get train times, and more.

Problem statement

Customer Review

★★★★☆ **it went through fine and works quite well**

By Mike Joe on 8 January 2018

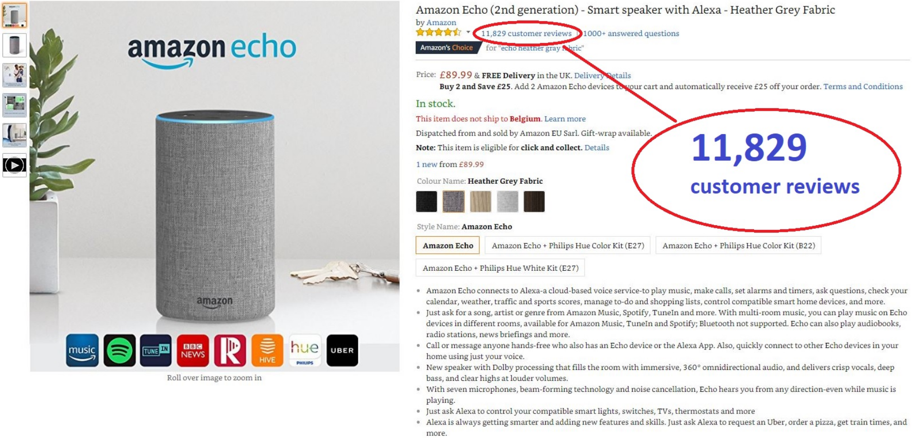
Colour: Heather Grey Fabric | Style: Amazon Echo | **Verified Purchase**

I had a bit of a problem setting it up as I had two delivered a day apart and one was a present and had to be de-registered. Unfortunately I de-registered the wrong one as Amazon gave them identifications and I didn't know which was which. Anyway after I had sorted that, it went through fine and works quite well. The only problem I can foresee with this kind of kit which is developing rapidly is how future-proof it is and for how long updates will be provided as new features get added. It would be good if Amazon could give some idea on their development path.

18 people found this helpful

Helpful | Not Helpful | Comment | Report abuse | Permalink

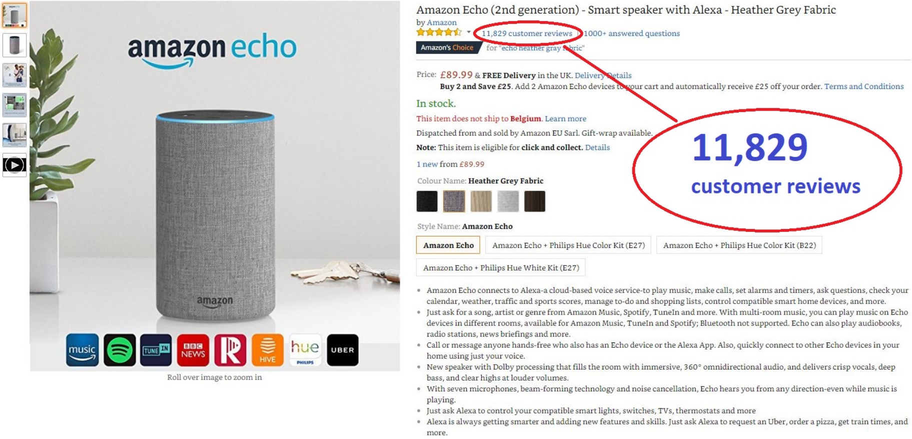
Problem statement



LIÈGE université

Problem statement

Predict review helpfulness with review, product and reviewer-related features.



Outline

Literature review

- Vast literature on the topic of review helpfulness prediction
- but highly fragmented and heterogeneous
- Contradictory and conflicting findings

↪ literature review to synthesize and critically analyze the extant research.

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$\hookrightarrow$ literature review to synthesize and critically analyze the extant research.

	NS	S	Positive	Negative	Moderated
Product					
Rating	[30, 43, 42]	[40]	[20, 1, 11, 5, 18, 27, 6, 17, 22, 31, 45, 28, 21]	[19, 46]	[17] by product type
					[31, 28] by product type, ▶ for E.*
					[45] by length & readability
Rating squared	[19, 17]		[27, 46, 4, 22]	[5, 45]	[45] by length & readability
					[28] by product type (negative for E.*, positive for Se.*)
Neutral			[28]	[20, 25, 46, 13]	[28] by product type, ▶ for E.*
Extremity	[30, 21]	[23, 25]	[8]	[39, 5, 43, 4]	[43, 4] by product type, ▶ for E.*
					[23] by product type, ▶ for Se.*
					[4] by price, ▶ for low-priced products
Product type	[11, 25, 17]		[39]	[43, 6, 4, 31, 28]	[4] S for E.*
Nb reviews	[19, 25]		[20, 13]	[4, 31]	
Price	[1, 19, 25, 13]			[43, 4]	

LIÈGE université

	NS	S	Positive	Negative	Moderated
Review					
Length	[30, 40, 19, 43, 25, 42, 13]	[25, 45]	[39, 20, 11, 36, 18, 27, 6, 25, 46, 4, 17, 22, 28, 21]	[35, 8]	[11] by product type & rating, S for E.* & $1-2^{\star}$
					[4] by product type & price, ▶ for Se.* & higher-priced products
					[6, 31] by product type, ▶ for Se.*
					[35] by review type (positive effect for comparatives reviews, negative effect for suggestive reviews)
					[18, 4] threshold nb words
Readability	[39, 30, 19, 23]	[40, 45]	[1, 11, 27, 22, 13]	[1, 46, 22]	[1] by reviewer experience, ▶ for less experienced rev.
					[11] by product type & rating, S for Se.* & $1-2^{\star}$
Age	[30, 25, 42, 31]	[39, 23, 29]	[36, 19, 31]	[8]	[23] by product type, ▶ for Se.*
					[29] by reviews source, ▶ on `Amazon.com` than on `Yelp.com`

	NS	S	Positive	Negative	Moderated
Review					
Sentiment	[30, 11, 19, 36, 5, 23, 43, 42, 21]	[40, 46]	[39, 1, 43, 4, 13]	[39, 1, 11, 36, 13]	[39] by product type, ▶ for Se.*
					[43] by product type, ▶ for E.*
					[11] by product type & rating, S for Se.*, $1-3^\star$ & for E.*, $1-2^\star$
					[1] by reviewer experience, ▶ for less experiences rev.
					[36] by polarity, ▶ for neutral reviews
					[4] by price, S for higher-priced products
Total people voting	[35, 5, 17, 28]	[39]	[6, 4]	[11, 22]	[11] by product type & rating, S for E.* & $1-3^\star$

	NS	S	Positive	Negative	Moderated
Reviewer					
Experience	[19, 18, 27, 42, 13]	[29]	[1, 11]		[11] by product type, S for Se.*
					[29] by reviews source, ▶ on `Yelp.com` than on `Amazon.com`
Disclosure	[20, 1, 27, 4, 13]		[20, 27, 6, 13]	[39]	[13] by product type, S for Se.*
					[20] by length, ▶ for longer reviews
Cumulative helpfulness	[25]	[29]	[18, 13]	[13]	[13] by product [29] by reviews source, ▶ for `Yelp.com` than for `Amazon.com`

Contradictory & conflicting findings

Factors contributing to contradiction & confusion:

- different data sources (`Amazon.com`, `Yelp.com`, `TripAdvisor`, etc)
- various pre-processing applied to collected reviews
- huge variety of features (190 listed features) and several proxies for measuring same variables
- different operationalizations for review helpfulness
- different methodologies

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Predicting and assessing review helpfulness with review, product and reviewer-related features

$\hookrightarrow$ still an open problem

Our proposal:

- predict review helpfulness based on product, review & reviewer-related features
- propose a new method based on lasso & tobit regression
- assess its performance against baselines (such as random forest, SVM, tobit/linear regression)

Outline

Features

- 190 different features in the current literature
- Select features
    - most often used
    - and/or identified as important in review helpfulness prediction

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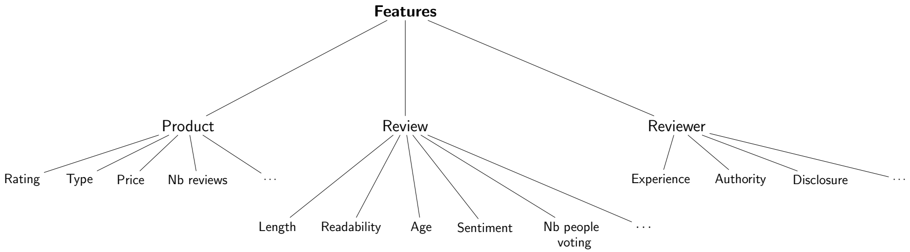
Features

Features classified into three categories according to our taxonomy



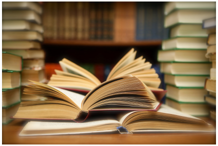
Features

- Product
  - rating(^{2})
  - average rating
  - extremity ((absolute) difference between individual rating and average rating)
  - product type

    Search goods

    Experience goods

  - nb reviews per product

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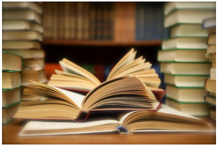

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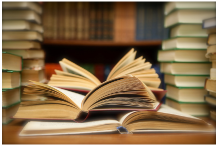

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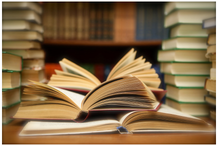

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Features

- Product
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  - ➤ average rating
  - ➤ extremity ((absolute) difference between individual rating and average rating)
  - ➤ product type (experience or search goods)
  - ➤ nb reviews per product

  - ★ median rating
  - ★ extremity computed based on median ((absolute) difference between individual rating and median rating)
  - ★ neutral (star rating of 3 or not)

Features

- Review
  - length (words count, characters count, sentences count)
  - review age (elapsed days since the posting date)
  - readability (ARI, CLI, FOG, FK, SMOG, AGL)
  - polarity
  - sentiment (with 3 different lexicons)
  - total people voting

  - ★ emotion (anger, sadness, joy, disgust, fear, surprise, anticipation, trust)
    Paul Ekman
  - ★ tf-idf of words & of their parts-of-speech (POS) tags

$$tf - idf_{t,d} = tf_{t,d} \times idf_t = tf_{t,d} \times \log\left(\frac{N}{df_t}\right)$$

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Features

- Reviewer
  - experience (nb reviews written by a reviewer)
  - cumulative helpfulness (all helpful votes of a reviewer to total votes of a reviewer)
  - real name disclosed

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Outline

1. Part I: Literature review
   - Problem statement
   - Literature review

2. Part II: Predicting & assessing review helpfulness
   - Features
   - Review helpfulness operationalization
   - Approach
   - Case study

3. Conclusion

Review helpfulness operationalization

- If numerical variable: helpfulness ratio (HR)

$$HR = \frac{\#\text{ helpful votes}}{\#\text{total votes}}$$

- If categorical variable:

$$= \begin{cases} 1 & \text{if} \quad HR \geq 0.6 \\ 0 & \text{if} \quad HR < 0.6 \end{cases}$$

Outline

Approach in current literature

- 17 different methods listed in current literature
- Predominant method: Tobit regression (only for feature analysis)
- Best performing method: Random forest

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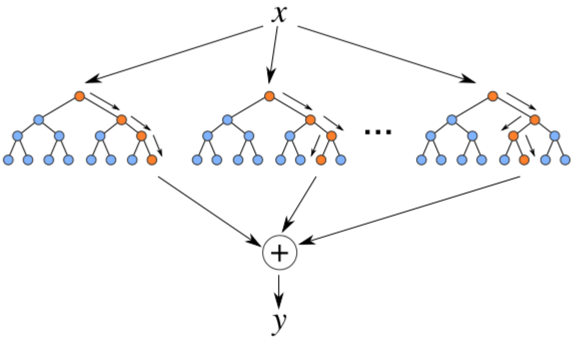
Approach

1. Baselines with existing features:
   - Random forest
   - Support Vector Machine (SVM)
   - Tobit regression
   - Linear regression

Approach

1. Baseline with existing features:

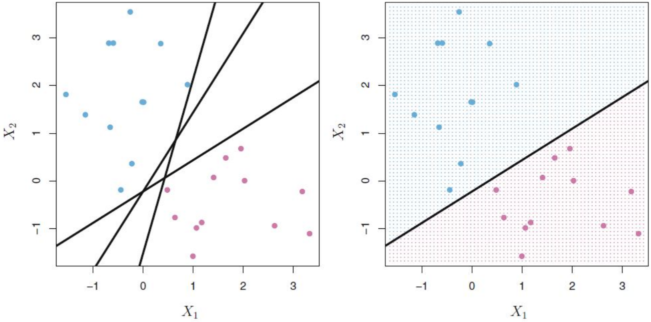
    - Random forest



Approach

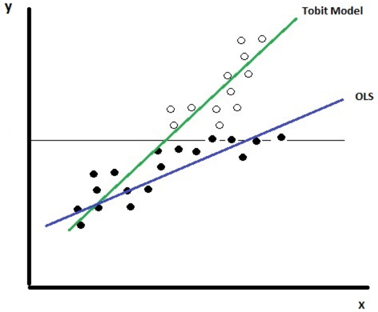
1. Baseline with existing features:

   - Support Vector Machine (SVM)



Approach

1. Baselines with existing features:
   - Tobit regression



   - Linear regression

Approach

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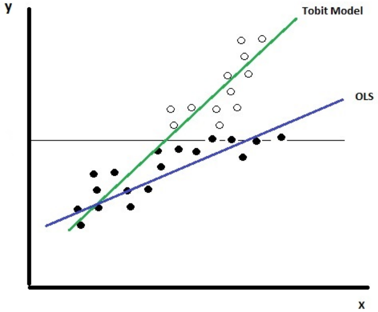


   - Linear regression

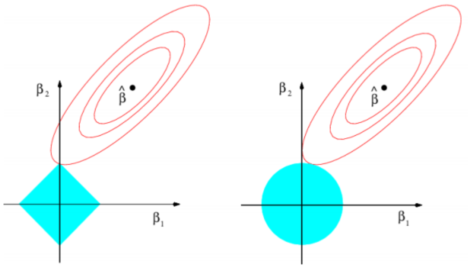
Approach

2. New approach with existing features:
   - Lasso

$$\min_{\beta} \|y - X\beta\|^2 + \lambda \sum_{j=1}^{d} |\beta_j| \text{ L1 penalty}$$

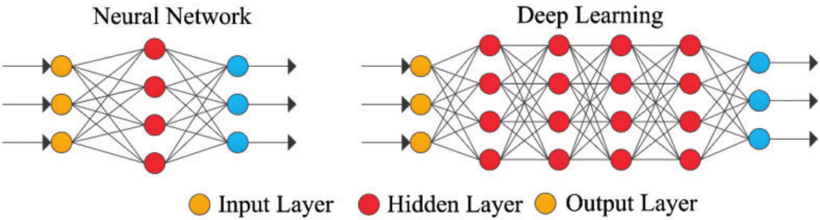
   - Ridge

$$\min_{\beta} \|y - X\beta\|^2 + \lambda \sum_{j=1}^{d} \beta_j^2 \text{ L2 penalty}$$



Approach

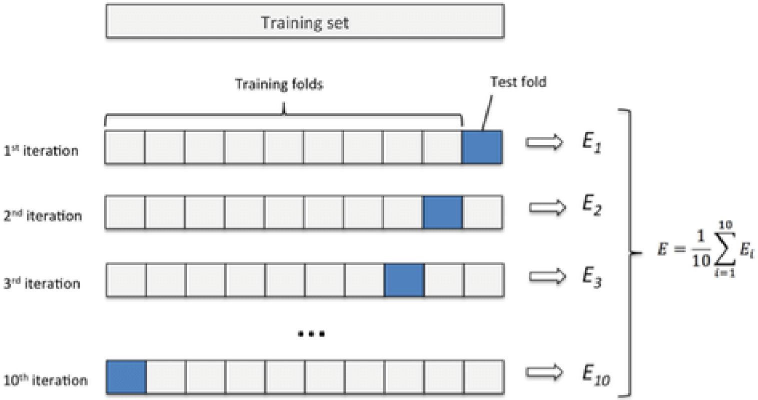
2. New approach with existing features:
    - Lasso & tobit
    - Deep neural networks



Approach

1. Baseline with existing features:
    - Random forest
    - Support Vector Machine (SVM)
    - Tobit regression
    - Linear regression
2. New approach with existing features:
    - Lasso
    - Ridge
    - Lasso & tobit
    - Deep neural networks
3. Baseline with existing & new features
4. New approach with existing & new features

10-fold cross-validation



Outline

Case study

Dataset* 83.68 million reviews collected on Amazon.com


```
{
  "reviewerID": "A2SUAM1J3GNN3B",
  "asin": "0000013714",
  "reviewerName": "J. McDonald",
  "helpful": [2, 3],
  "reviewText": "I bought this for my husband who plays the
piano.  He is having a wonderful time playing these old hymns.
The music  is at times hard to read because we think the book
was published for singing from more than playing from.  Great
purchase though!",
  "overall": 5.0,
  "summary": "Heavenly Highway Hymns",
  "unixReviewTime": 1252800000,
  "reviewTime": "09 13, 2009"
}
```


* R. He, J. McAuley. Modeling the visual evolution of fashion trends with one-class collaborative filtering. WWW, 2016

J. McAuley, C. Targett, J. Shi, A. van den Hengel. Image-based recommendations on styles and substitutes. SIGIR, 2015

Dataset

For one product:

37,126 reviews

but only 13,133 received a vote

↪ Analysis performed on 35% of the initial dataset

POS tags & tf-idf

Matrix $13,133 \times 20$

	nns	vbg	vbp	vbn	vbz	vbd	jjr	jjs	nnp	prp	pos
1	0.08	0.22	0.27	0	0	0	0	0	0	0	0
2	0.12	0	0.2	0.2	0	0	0	0	0	0	0
3	0	0	0.27	0.27	0.35	0	0	0	0	0	0
4	0.12	0	0	0.	0.00	0.41	0	0	0	0	0
5	0.08	0.03	0.06	0.09	0.25	0.06	0.15	0.15	0	0	0

	rbr	wdt	nnps	wrb	wp1	rbs	prp1	pdt	sym
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0

$\hookrightarrow$ sparsity

Words & tf-idf

Matrix $13,133 \times 4,795$

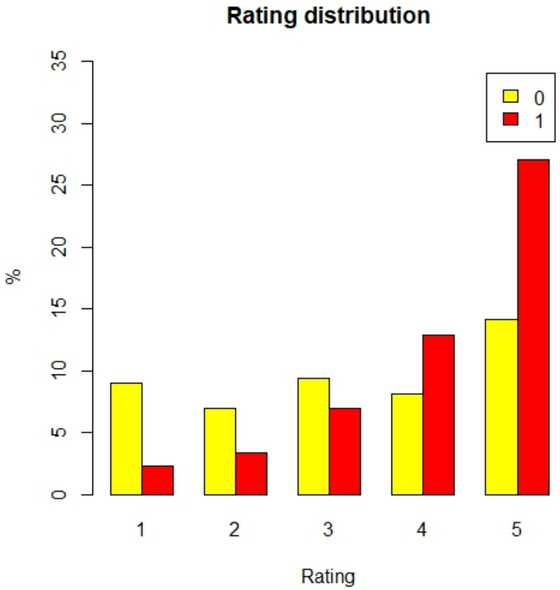
	appeal	big	boring	detective	english	expectations	guy	love
1	0.61	0.38	0.47	0.49	0.56	0.63	0.41	0.20
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0	0	0	0	0.05	0	0	0

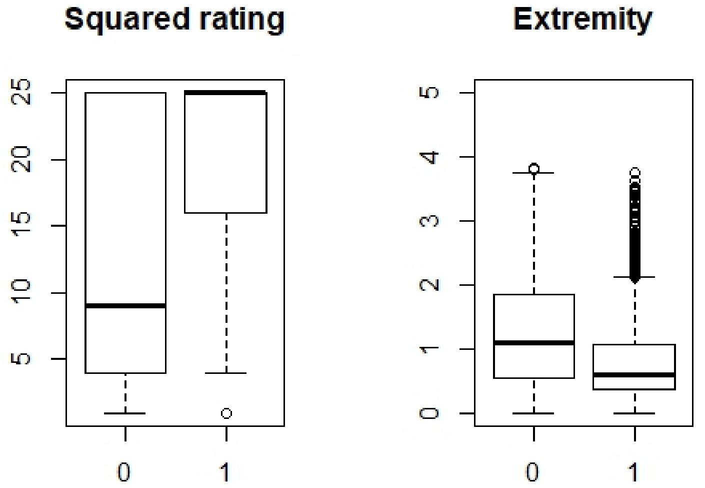
$\hookrightarrow$ high-dimensionality & sparsity

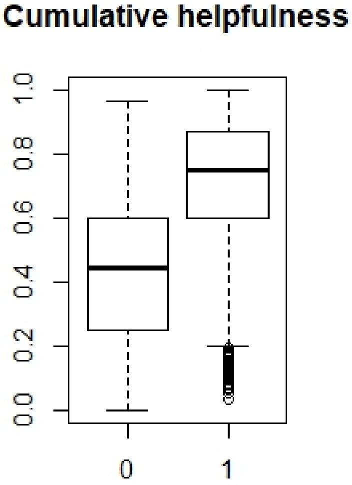
Info on dataset

52.5% helpful reviews & 47.5% of non-helpful reviews

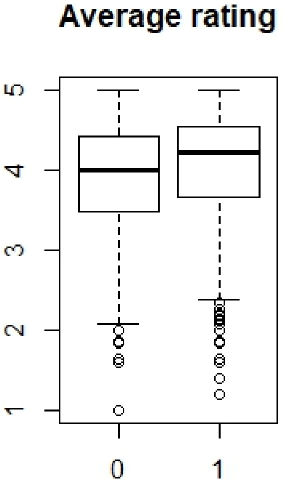
$\hookrightarrow$ hopefully no problem of imbalanced dataset


Rating distribution
0
1
%
35
30
25
20
15
10
5
0
1
2
3
4
5
Rating

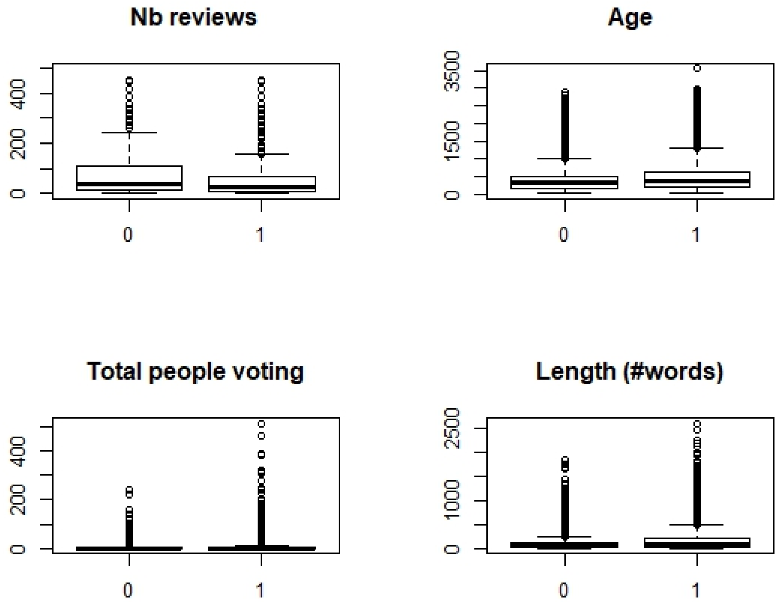

Squared rating
25
20
15
10
5
0
1
Extremity
5
4
3
2
1
0
0
1

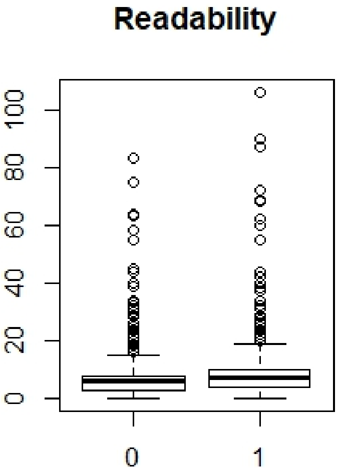


Cumulative helpfulness
0.0
0.2
0.4
0.6
0.8
1.0
0
1

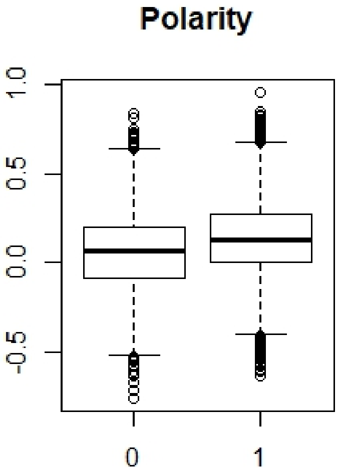


Average rating
1
2
3
4
5
0
1

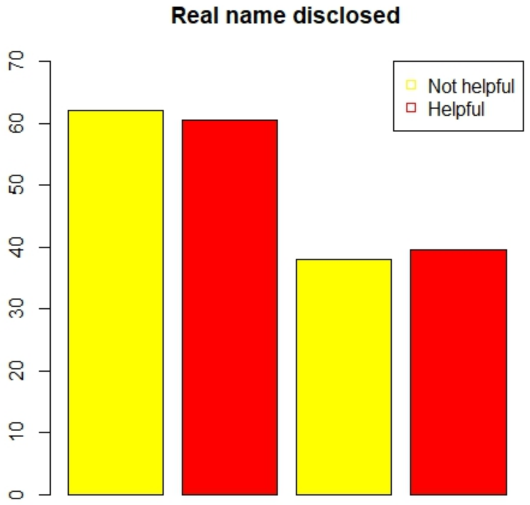

Nb reviews
0
200
400
0
1
Age
0
1500
3500
0
1
Total people voting
0
200
400
0
1
Length (#words)
0
1000
2500
0
1



Readability
0
20
40
60
80
100
0
1



Polarity
-0.5
0.0
0.5
1.0
0
1


Real name disclosed
70
60
50
40
30
20
10
0
Not helpful
Helpful

Conclusion

Predict review helpfulness with review, product and reviewer-related features.

- propose a novel regression method based on lasso (or ridge) and tobit
- assess its performance for review helpfulness prediction
- compare this new method with baselines
  - Random forest
  - SVM
  - Tobit regression
  - Regression
- assess existing & new features (POS tags, tf-idf, median rating...)

Thank you!

If you have any question:

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