Assessing and predicting review helpfulness
EURO29

A-S. Hoffait

HEC Liège - Belgium

Anne-Sophie Hoffait
HEC Liège, Belgium
ashoffait@uliege.be

Joint work with Ashwin Ittoo
HEC Liège, Belgium
Part I: Literature review
- Problem statement
- Literature review

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

Conclusion
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
Problem statement

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

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

Colour Name: Heather Grey Fabric

Style Name: Amazon Echo

- 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, noise-canceling technology and audio 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

Rating: ★★★★★ 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
Problem statement

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

11,829 customer reviews
100+ answered questions
Amazon’s Choice
for “echo heather grey 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 (£27) | Amazon Echo + Philips Hue Color Kit (£27)
Amazon Echo + Philips Hue White Kit (£27)

- 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

Predict review helpfulness with review, product and reviewer-related features.
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
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.
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.
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.
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.
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.
<table>
<thead>
<tr>
<th>Product</th>
<th>NS</th>
<th>S</th>
<th>Positive</th>
<th>Negative</th>
<th>Moderated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating</td>
<td>[30, 43, 42]</td>
<td>[20, 1, 11, 5, 18, 27, 6, 17, 22, 31, 45, 28, 21]</td>
<td>[19, 46]</td>
<td>[17] by product type</td>
<td></td>
</tr>
<tr>
<td>Rating squared</td>
<td>[19, 17]</td>
<td>[27, 46, 4, 5, 45]</td>
<td>[5, 45]</td>
<td>[28] by product type, ▶ for E.*</td>
<td></td>
</tr>
<tr>
<td>Neutral</td>
<td>[28]</td>
<td>[20, 25, 46, 13]</td>
<td>[28] by product type, ▶ for E.*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extremity</td>
<td>[30, 21]</td>
<td>[23, 25]</td>
<td>[8]</td>
<td>[39, 5, 43, 4]</td>
<td>[43, 4] by product type, ▶ for E.*</td>
</tr>
<tr>
<td>Product type</td>
<td>[11, 25, 17]</td>
<td>[39]</td>
<td>[43, 6, 4, 31, 28]</td>
<td>[4] S for E.*</td>
<td></td>
</tr>
<tr>
<td>Nb reviews</td>
<td>[19, 25]</td>
<td>[20, 13]</td>
<td>[4, 31]</td>
<td>[43, 4]</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>[1, 19, 25, 13]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Review</td>
<td>NS</td>
<td>S</td>
<td>Positive</td>
<td>Negative</td>
<td>Moderated</td>
</tr>
<tr>
<td>--------</td>
<td>----</td>
<td>---</td>
<td>---------</td>
<td>----------</td>
<td>-----------</td>
</tr>
<tr>
<td></td>
<td>19, 43, 39, 20, 11, 35, 8</td>
<td>6, 25, 46, 4, 17, 22, 28, 21</td>
<td>[4] by product type &amp; price, ▶ for Se. &amp; higher-priced products</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>25, 42, 19, 43, 19, 11, 35, 8</td>
<td>6, 25, 46, 4, 17, 22, 28, 21</td>
<td>[6, 31] by product type, ▶ for Se. *</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>19, 43, 19, 11, 35, 8</td>
<td>[35] by review type (positive effect for comparatives reviews, negative effect for suggestive reviews)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>6, 25, 46, 4, 17, 22, 28, 21</td>
<td>[18, 4] threshold nb words</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>19, 23, 19, 11, 35, 8</td>
<td>[1] by reviewer experience, ▶ for less experienced rev.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>19, 23, 19, 11, 35, 8</td>
<td>[11] by product type &amp; rating, S for Se. * &amp; 1 − 2*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>36, 18, 27, 19, 23, 19, 11, 35, 8</td>
<td>[23] by product type, ▶ for Se. *</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>6, 25, 46, 4, 17, 22, 28, 21</td>
<td>[29] by reviews source, ▶ on Amazon.com than on Yelp.com</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Review</td>
<td>NS</td>
<td>S</td>
<td>Positive</td>
<td>Negative</td>
<td>Moderated</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>----</td>
<td>-----</td>
<td>----------</td>
<td>----------</td>
<td>----------------------------</td>
</tr>
<tr>
<td><strong>Sentiment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[30, 11]</td>
<td>[40, 46]</td>
<td>[39, 1, 43, 4, 13]</td>
<td>[39, 1, 11, 36, 13]</td>
<td>[39] by product type, ▶ for Se.*</td>
<td></td>
</tr>
<tr>
<td>[19, 36]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[5, 23]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[43, 42]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[21]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[43] by product type, ▶ for E.*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1] by reviewer experience, ▶ for less experiences rev.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[36] by polarity, ▶ for neutral reviews</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total people voting</strong></td>
<td></td>
<td></td>
<td>[39]</td>
<td>[6, 4]</td>
<td>[11, 22]</td>
</tr>
<tr>
<td>[35, 5]</td>
<td></td>
<td></td>
<td>[39]</td>
<td>[6, 4]</td>
<td>[11, 22]</td>
</tr>
<tr>
<td>[17, 28]</td>
<td></td>
<td></td>
<td>[39]</td>
<td>[6, 4]</td>
<td>[11, 22]</td>
</tr>
<tr>
<td>[4] by price, S for higher-priced products</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[11] by product type &amp; rating, S for E.* &amp; 1 – 3*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NS</td>
<td>S</td>
<td>Positive</td>
<td>Negative</td>
<td>Moderated</td>
</tr>
<tr>
<td>-------------------</td>
<td>----</td>
<td>----</td>
<td>----------</td>
<td>----------</td>
<td>----------------------------------------</td>
</tr>
<tr>
<td><strong>Reviewer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[19, 18, 27, 42, 13]</td>
<td>[29]</td>
<td>[1, 11]</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Disclosure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[29] by reviews source, ▶ on Yelp.com than on Amazon.com</td>
</tr>
<tr>
<td></td>
<td>[20, 1, 27, 4, 13]</td>
<td>[20, 27, 6, 39, 13]</td>
<td>[20, 27, 6, 39, 13]</td>
<td>[13] by product type, S for Se.*</td>
<td></td>
</tr>
<tr>
<td><strong>Cumulative helpfulness</strong></td>
<td>[25]</td>
<td>[29]</td>
<td>[18, 13]</td>
<td>[13]</td>
<td>[20] by length, ▶ for longer reviews</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[29] by reviews source, ▶ for Yelp.com than for Amazon.com</td>
</tr>
</tbody>
</table>
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
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
Predicting and assessing review helpfulness with review, product and reviewer-related features

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

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
Features

- 190 different features in the current literature

- Select features
  - most often used
  - and/or identified as important in review helpfulness prediction
Features

- 190 different features in the current literature

- Select features
  - most often used
  - and/or identified as important in review helpfulness prediction
Features

• 190 different features in the current literature

• Select features
  ➢ most often used
  ➢ and/or identified as important in review helpfulness prediction
Features

• 190 different features in the current literature

• Select features
  ➤ most often used
  ➤ and/or identified as important in review helpfulness prediction
Features

Features classified into three categories according to our taxonomy

- **Product**
  - Rating
  - Type
  - Price
  - Nb reviews
  - Length
  - Readability
  - Age
  - Sentiment
  - Nb people voting

- **Review**
  - Experience
  - Authority
  - Disclosure
  - Nb people voting

- **Reviewer**
  - Experience
  - Authority
  - Disclosure
  - Nb people voting
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
Features

- **Product**
  - rating\(^2\)
  - average rating
  - extremity ((absolute) difference between individual rating and average rating)
  - product type
  - nb reviews per product
Features

- Product
  - rating
  - average rating
  - extremity ((absolute) difference between individual rating and average rating)
  - product type
    - Search goods
    - Experience goods
  - nb reviews per product
Features

- Product
  - rating
  - average rating
  - extremity \( ((\text{absolute}) \text{ difference between individual rating and average rating}) \)
  - product type
    - Search goods
    - Experience goods
  - nb reviews per product
Features

• Product

➤ rating
➤ 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

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

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

\[
\text{tf} - \text{idf}_{t,d} = \text{tf}_{t,d} \times \text{idf}_t = \text{tf}_{t,d} \times \log \left( \frac{N}{df_t} \right)
\]
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
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
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:

\[
= \begin{cases} 
1 & \text{if } HR \geq 0.6 \\
0 & \text{if } HR < 0.6 
\end{cases}
\]
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
Approach in current literature

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

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

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

1. Baselines with existing features:
   - Tobit regression
   - 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

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

Diagram showing the 10-fold cross-validation process with a training set and 10 iterations, each involving a training fold and a test fold.
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
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

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 × 20**

<table>
<thead>
<tr>
<th></th>
<th>nns</th>
<th>vbg</th>
<th>vbp</th>
<th>vbn</th>
<th>vbz</th>
<th>vbd</th>
<th>jjr</th>
<th>jjs</th>
<th>nnp</th>
<th>prp</th>
<th>pos</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.08</td>
<td>0.22</td>
<td>0.27</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0.12</td>
<td>0</td>
<td>0.2</td>
<td>0.2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0.27</td>
<td>0.27</td>
<td>0.35</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0.12</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>0.41</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0.08</td>
<td>0.03</td>
<td>0.06</td>
<td>0.09</td>
<td>0.25</td>
<td>0.06</td>
<td>0.15</td>
<td>0.15</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>rbr</th>
<th>wdt</th>
<th>nnps</th>
<th>wrb</th>
<th>wp1</th>
<th>rbs</th>
<th>prp1</th>
<th>pdt</th>
<th>sym</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

→ sparsity
Words & tf-idf

Matrix 13, 133 × 4, 795

<table>
<thead>
<tr>
<th></th>
<th>appeal</th>
<th>big</th>
<th>boring</th>
<th>detective</th>
<th>english</th>
<th>expectations</th>
<th>guy</th>
<th>love</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.61</td>
<td>0.38</td>
<td>0.47</td>
<td>0.49</td>
<td>0.56</td>
<td>0.63</td>
<td>0.41</td>
<td>0.20</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

→ high-dimensionality & sparsity
Info on dataset

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

→ hopefully no problem of imbalanced dataset
Real name disclosed

![Bar chart showing the comparison between Not helpful and Helpful categories. The chart indicates a higher percentage for the Helpful category.]
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...)

A-S. Hoffait
HEC Liège
Thank you!

If you have any question:

ashoffait@uliege.be


