Who Are the Top Reviewers on Amazon

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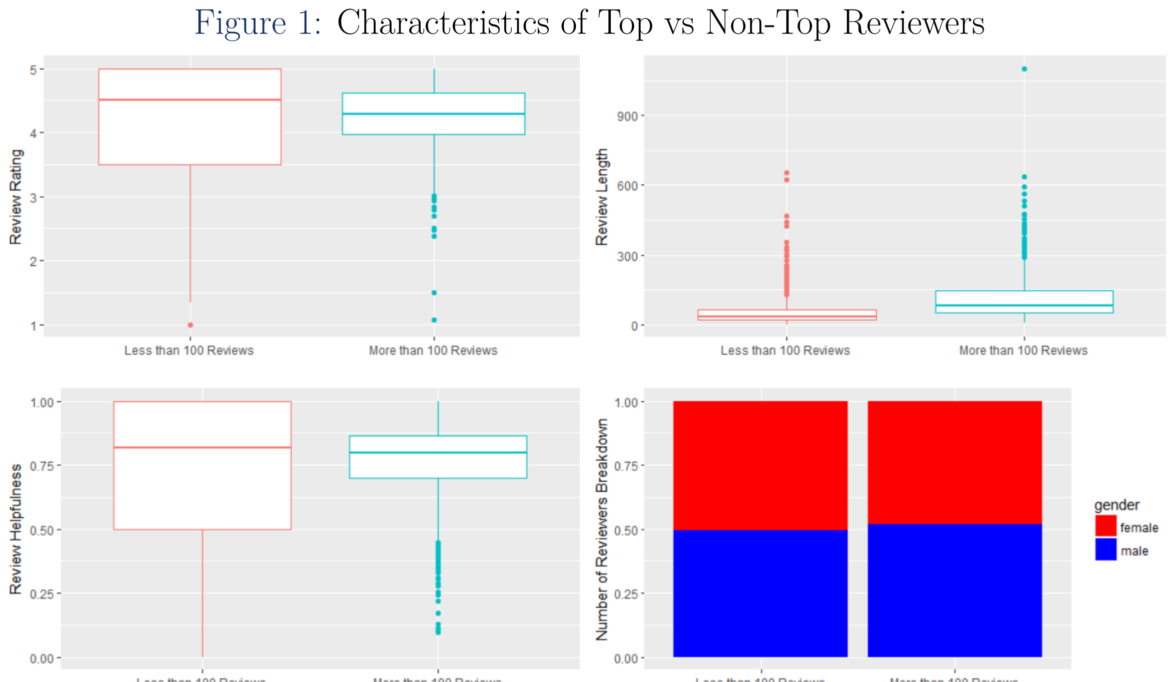
Introduction

Recent studies found that consumers rely on Amazon reviews before making purchasing decisions in both online and offline context [3]. Amazon has become one of the biggest information source consumers trust and consequently, Amazon can derive a lot of profits from the reviews and feedback it provides to consumers. In this study, we will focus on examining the reviewers on Amazon and discuss what makes a top reviewer. Using reviewer level characteristics, we try to predict and identify those with potential to be high value review contributors. **First, we predict which reviewer will write more than 100 reviews using his or her first 1, 3 or 10 reviews.** Using our prediction model, Amazon will be able to target and incentivize their top reviewers from early on. **Second, using the LDA model, we categorize reviewers based on the product categories they have reviewed.** We want to discover the different types of successful reviewers, and discuss whether they demonstrate different reviewing behavior on Amazon. We found there are four groups of reviewers with distinct interests and reviewing behavior on Amazon.

Data

For each reviewer, we have numerical data on the following attributes of reviews he or she wrote: average review score, average length of review(in words), average rating deviation from product mean, average helpfulness in percentage, average review sequence. We also derive text attributes from the reviews, such as proportion of reviews with verbs, nouns, adj and swear words. Figure 1 plots the numerical attributes distribution for 2 groups of reviewers and it demonstrates that there are some differences in the rating behavior between reviewers with more than 100 reviews and reviewers with less than 100 reviews. These differences will help our algorithm in prediction.

Figure 1: Characteristics of Top vs Non-Top Reviewers



In the first part of predicting on who will write more than 100 reviews, we will use a random sample of reviewers: 1000 reviewers with more than 100 reviews and 1000 without. In the second part of exploring various reviewer types, we select reviewers with more than 500 reviews, which gives us around 2200 reviewers. The full data comes from a project by Poppy Zhang and Vishal Singh.

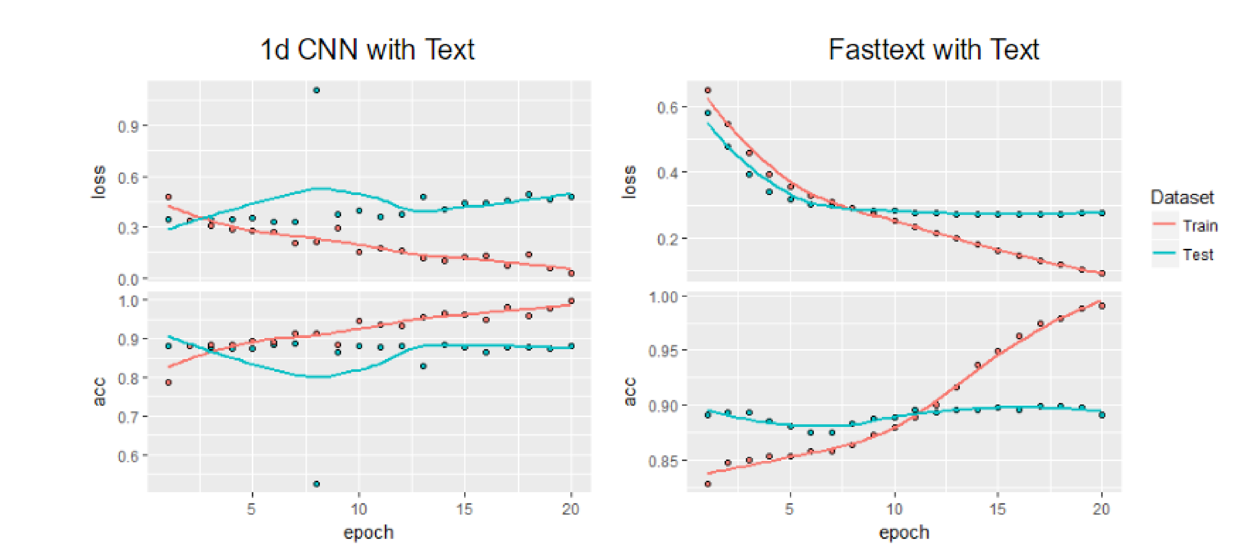
Method and Result: Predict Who Will be the Top Reviewers

For the prediction, we tried different combination of prediction methods and data. Table 1 summarizes the accuracy for different combinations of methods and data we used. We alternate between using first 1, 3 and 10 reviews in prediction. We first tried several MLP with numerical data and then we tried to incorporate textual attributes derived from the reviews, such as weighted number of preps and verbs. In the end, we tried to feed the full review text that a reviewer has written into the text-classification model. Intuitively, more reviews we use in modelling, more accurate is our result. The classification model we used is 1-d CNN and Fasttext by Facebook[2]. Here in figure 2 we report the results we got from simple MLP models using the numerical attributes. The best prediction we can achieve without using any text information is 80%.

Figure 2: MLP with Numerical Attributes

In the following figure, we report our results for text classification model using the review text one reviewers have written. This gives us a prediction accuracy as high as 90%.

Figure 3: Text Classification Models with 10 Review Text



To summarize, we report the accuracy for our models in the table below. This tells us that first, by using the numerical attributes we gathered, such as average rating, the platform managers can do a decent job at predicting who will keep writing; second, review text is embedded with information that can be very helpful to predict the number of reviews a reviewer will write the future.

Model	Numerical Data	Numerical and Textual	Review Text
MLP	1st Reviews: 61%	1st Reviews: 80%	
MLP	3 Reviews: 71%	3 Reviews: 81%	
MLP	10 Reviews: 78%	10 Reviews: 83%	
LTSM		10 Reviews: 84%	
1-d CNN			10 Reviews: 87%
Fasttext			10 Reviews: 90%

Table 1: Prediction Accuracy for Methods and Data

Method and Result: Categorize the Top Reviewers

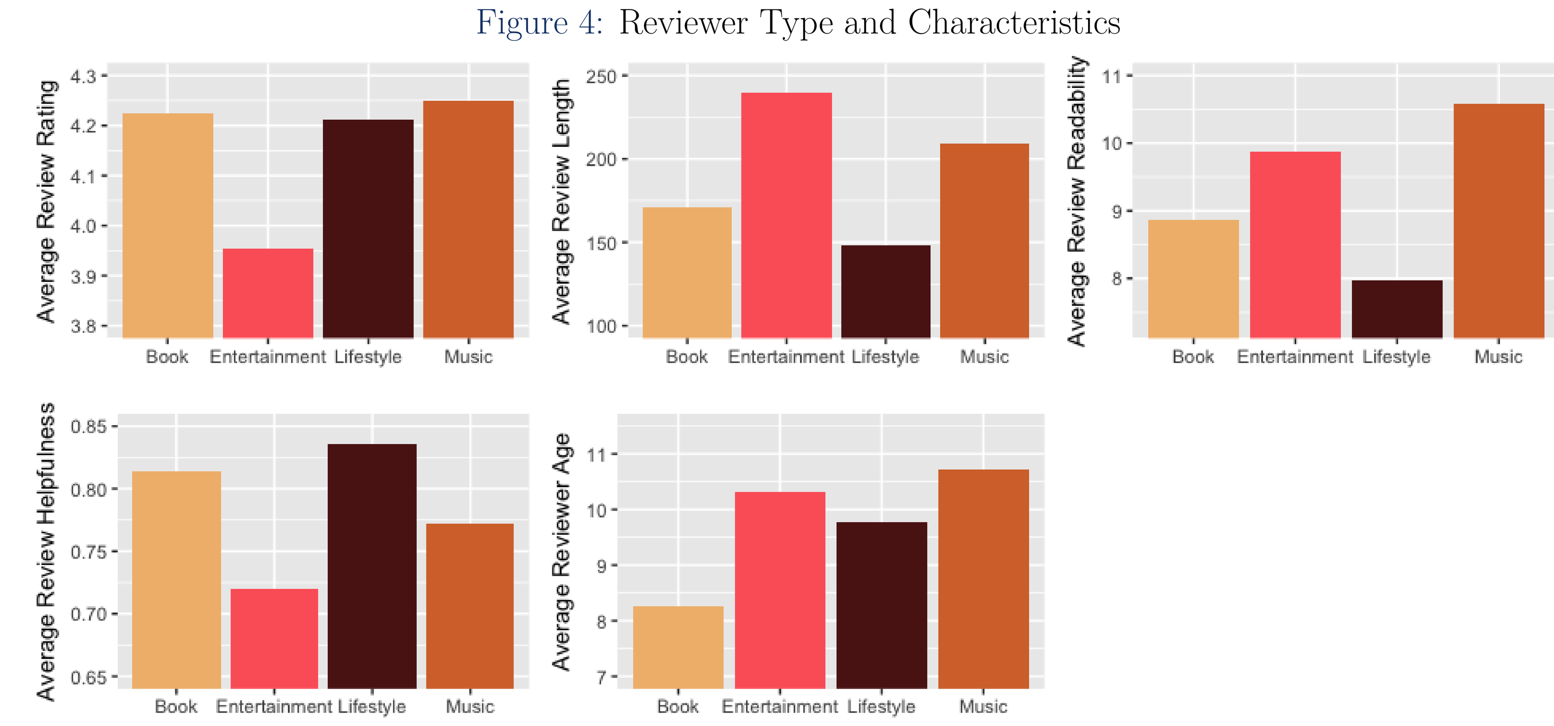
In this section, we examine 2200 reviewers who have written more than 500 reviews and see how they differ from each other in terms of the product categories they review in. We use LDA [1] algorithm and treat each reviewer as a document and the product category as the word. The number of the reviews a reviewer post in specific product category serves as the word frequency in our example. We selected 4 topics, which translate to 4 reviewer groups in our case, as our optimal strategy. We are reporting the leading category for each group in the following table.

Book	**Entertainment**	**LifeStyle**	**Music**
Books	Movies and TV	Electronics	CDs and Vinyl
Kindle Store	Video Games	Health and Personal Care	Digital Music
Arts	Amazon Instant Video	Grocery and Gourmet Food	Musical Instruments

Table 2: Leading Categories for Reviewer Types

To understand how they differ from each other on other attributes, we summarized the average star rating, review length, helpfulness, readability(higher means less readable), and reviewer age(how long has been active). The results are plotted in the figure below. We can see that entertainment oriented reviewers give lower ratings and are less helpful compared to others. Even though their reviews are on average longer than others', their reviews are not as helpful as others. The music-loving reviewers has the longest history and write the most sophisticated reviews. The lifestyle reviewers give shorter but more helpful reviews. This is probably related to the fact that lifestyle related products are mostly utilitarian products so reviewers need to be concise and direct in their reviews.

Figure 4: Reviewer Type and Characteristics



Main Findings

1. Using our model, we can predict who will become top reviewers with 90% accuracy. Platform managers can use our model to target and motivate reviewers to constantly contribute to the community.
2. There are different types of reviewers with distinct interests in different product categories.

References

[1] David M Blei, Andrew Y Ng, and Michael I Jordan. "Latent dirichlet allocation". In: *Journal of machine Learning research* 3.Jan (2003), pp. 993–1022.

[2] Armand Joulin et al. "Bag of Tricks for Efficient Text Classification". In: *arXiv preprint arXiv:1607.01759* (2016).

[3] Susan M Mudambi and David Schuff. "What makes a helpful review? A study of customer reviews on Amazon. com". In: (2010).