Trojan Horses in Amazon's Castle:

Understanding the Incentivized Online Reviews

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Trojan Horses in Amazon's Castle: Understanding the Incentivized Online Reviews

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Animater—During the past the years, sames non-monaging of the deferred discounted or free products to selected reviewers of e-commerce platforms in exchange for their reviews. Such incommerce platforms in exchange for their reviews.

explicit keywords) and normal reviews can accurately detect Amazon products and users.

The importance of online reviews has also prompted major along with their associated products and reviewers. e-commerce sites (e.g., Amazon) to implement certain policies The second contribution of this paper is the characterization to ensure that the provided user reviews and ratings are legitimate and unbiased to maintain the trust of online shoppers. Our analysis demonstrates the effect of Amazon ban on the In response to these policies, seller's strategies for boosting prevalence of EIRs as well as the difference between the their product rating have further evolved. In particular, in features of EIRs and normal reviews. We also examine the the past few years, some sellers have increasingly offered temporal pattern of EIR, and non-EIR reviews that a product discounted or free products to selected online shoppers in receives and a reviewer produces to address two questions: (i) exchange for their (presumably positive) reviews. We refer how the arrival pattern of EIRs for a specific product affects

Abstract-During the past few years, sellers have increasingly to these reviews as incentivized reviews. Major e-commerce commerce platforms in exchange for their reviews, both store-tized and offer two-positive reviews an improve the radius of a product which in turn ways where were 'opinion about the product. Despite their importance, the prosting, characteristics, and the influence of incentificial reviews in a major examenter higher have not been yellowed by all qualitatives and the influence of the reviews and the influence of the review and the r This paper examines the problem of detecting and characters other reviewers for the following reasons: (i) They might ting inemitized reviews in two primary categories of Amazon
oner reviewers for the rotationing reasons; (i) They migni products. We describe a new method to identify Explicitly
enders, the describe a review see the products are
locatived Reviews (EIR) and then onlier a few datasets
provided for free or with a considerable discount, (ii) Their
to capture an extensive collection of EIRs along with their eciated products and reviewers. We show that the key features the full price, and (iii) They do not often consider the longassociated products and reviewers. We show that the sey features in the run price, and (m), they are not constituted of EIRs and normal reviews exhibit different characteristics term usage of the product (e.g., product return or customer usage). Furthermore, we illustrate how the prevalence of EIRs has evolved and been affected by Amazon ban, Our examination of service) in their reviews. The presence of such incentivized evered and been affected by Amazon ban. Our examination of the temporal pattern of submitted reviews for sample products reveals promotional campaigns by the corresponding sellers to our knowledge, the prevalence of incentivized reviews, their and their effectiveness in attracting other users. Finally, we demonstrate that a classifier that is trained by EIRs (without commence site have not been systematically and quantitatively commence site have not been systematically and quantitativel commerce site have not been systematically and quantitatively other EIRs as well as implicitly incentivized reviews. Overall, studied. Although Amazon has officially banned submission of this analysis shed an insightful light on the impact of EIRs on studied. Although Amazon has officially banned submission of study such reviews to be able to determine whether Amazon's new policy solved the issue or just forced reviewers to go

As the popularity of online shopping has rapidly grown To tackle this important problem, this paper focuses or during the past decade, the shoppers have increasingly relied capturing and characterizing several aspects of incentivized on the online reviews and rating provided by other users reviews in the Amazon.com environment. We leverage the to make more informed purchases. In response to shoppers' hierarchical organization of Amazon products into cate behavior, product sellers have deployed various strategies to gories/subcategories and collect all the information for topattract more positive reviews for their products as this could 20 best-seller products in all subcategories of two major directly affect their popularity among users and thus their categories. The first contribution of this paper is a method shility to sell more products online. Several prior studies have—to identify explicitly incentivized reviews (FIRs) on Amazon examined different aspects of online reviews including fake or We identify a number of textual patterns that indicate explicspam [8], [12], [9], [15], [11], [2] and also biased and paid itly incentivized reviews (EIRs). We carefully fine-tune and reviews [19], [20], [21], [16], [5] in different online shopping capture these textual patterns using a regular expression. We then use these patterns to identify a large number of EIRs

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Galaxy Note 4 Screen
Protector,

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Protector,

★★☆☆☆ 225 \$6.99 **√Prime**



Galaxy Note 4 Screen
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Galaxy Note 4 Screen Protector,AMCHOICE(TM) 2.5d Rounded Edges 0.3mm Thin Premium...

\$6.99 **Prime**



Galaxy Note 4 Screen
Protector,AMCHOICE(TM
) 2.5d Rounded Edges
0.3mm Thin Premium...

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Galaxy Note 4 Screen
Protector, AMCHOICE (TM
) 2.5d Rounded Edges
0.3mm Thin Premium...

全全全全全 1,117

\$9.99 **/Prime**



Galaxy Note 4 Screen
Protector, AMCHOICE (TM
) 2.5d Rounded Edges
0.3mm Thin Premium...

★★★☆☆ 225

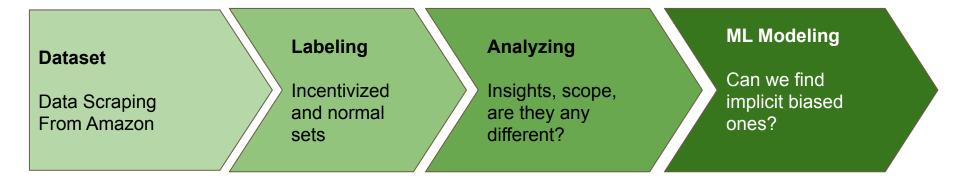
\$9.99 **/Prime**

Incentivized Reviews

- Incentivized review?
 - Seller's strategy to attract more positive reviews and gain reputation
- Why are they important to be studied?
 - They are different from normal reviews and can improve the sentiment of the product.
 They are different as by getting a free or discounted product:
 - i. Customers feel obligated to post positive reviews,
 - ii. paid a fraction of retailer price, their expectations are lower
 - iii. As it becomes a business for some users, they prefer to post positive reviews to attract more sellers and get more free/discounted offers.
 - iv. Not going through the return process, dealing with customer service, short-term

Process

• Here the process to study IRs



1. Dataset Characteristics

- Scraping product reviews from Amazon.com
 - Focusing on Top 20 products per category

Example:

https://www.amazon.com/gp/bestsellers/grocery/

	Product-centric (DS1)	EIRs (DS2)	Normal	User-centric (DS3)
Reviews	3,797,575	100,086	100,086	217,000
Users	2,654,048	39,886	98,809	2,627
Products	8,383	1,850	1,641	184,124

Amazon Best Sellers

Our most popular products based on sales. Updated hourly.

- Any Department
- Grocery & Gourmet Food
- Snack Foods

Cookies

Animal

Biscotti

Biscuits Butter

Chocolate

Chocolate Chip

Assortments & Samplers

Fortune

Fruit

Ginger Snaps Ladyfingers

Merinaues

Nut

Oatmeal

Peanut Butter Pizzelles

Sandwich

Shortbread Snickerdoodles

Sugar

Wafers

Best Sellers in Biscuit Snack Cookies



Nature Valley Biscuits, Almond Butter.... 全全全全 201 \$2.50 prime pantry



2.

Godiya Chocolatier Assorted Chocolate... **全全全全** 131 \$16.00 yprime



Belvita Breakfast Biscuits, Cranberry...



Belvita Breakfast Biscuits, Chocolate ********* 108 \$2.98 prime pantry



1. Dataset Characteristics

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 - Focusing on Top 20 products per category

Example:

https://www.amazon.com/gp/bestsellers/grocery/

	Products	EIRs	Normal	Reviewers	
	(DS1)	(DS2)	Reviews	(DS3)	
Reviews	3,797,575	100,086	100,086	217,000	
Reviewers	2,654,048	39,886	98,809	2,627	
Products	8,383	1,850	1,641	184,124	

TABLE II. ATTRIBUTES CRAWLED FOR DATASET ENTITIES

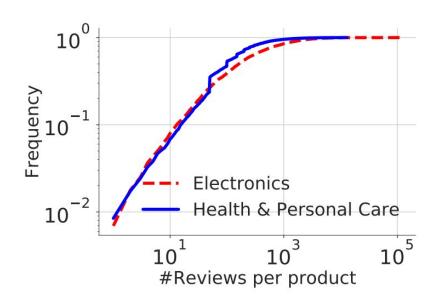
Reviews
id
user_id
Product_i
isVerified
Date
rate
likes
title
text

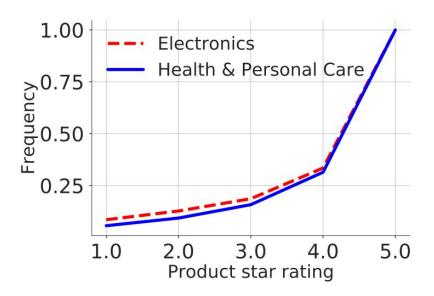
ImageURL

	Products
	id
	Seller_id
_	Price
	Category
	URL
	Rate
	Cmnt_number
_	Title

id rank Helpful Following Lists MoreInfo Name Location	Users
Helpful Following Lists MoreInfo Name	id
Following Lists MoreInfo Name	rank
Lists MoreInfo Name	Helpful
MoreInfo Name	Following
Name	Lists
1000 ID	MoreInfo
Location	Name
	Location

Two Categories

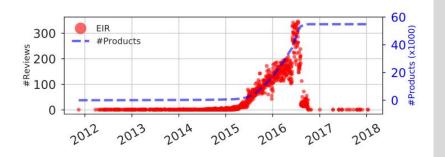


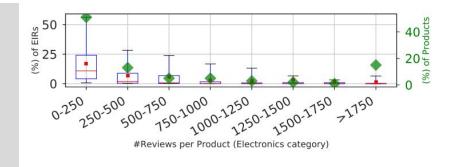


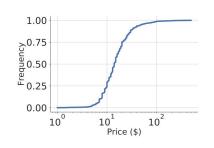
- Absence of labeled data
- Required reliable way to label them manually
- Large dataset
 - Required to be done automatically
- After extensive manual inspection, we used the following Regex:

```
\label{eq:cont_receive} \begin{split} '(sent|receive|provide) [^{\.}!?]* \\ (discount|free|in-trade|in-exchange) [^{\.}!?]* \\ (unbiased|honest) [^{\.}!?]* \\ (review|opinion|feedback|experience) ' \end{split}
```

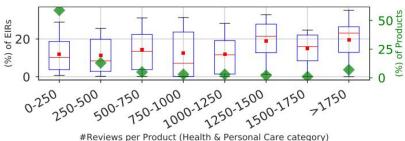
3. Characteristics of IRs



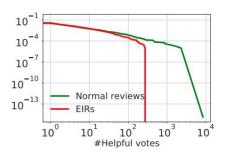


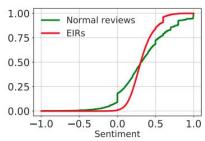


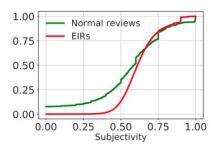


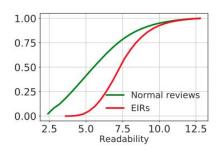


3. Characteristics of IRs

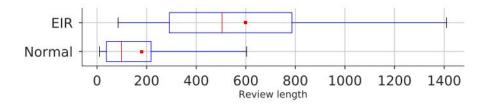




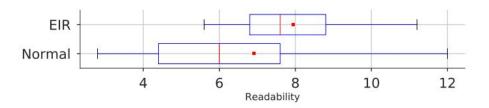




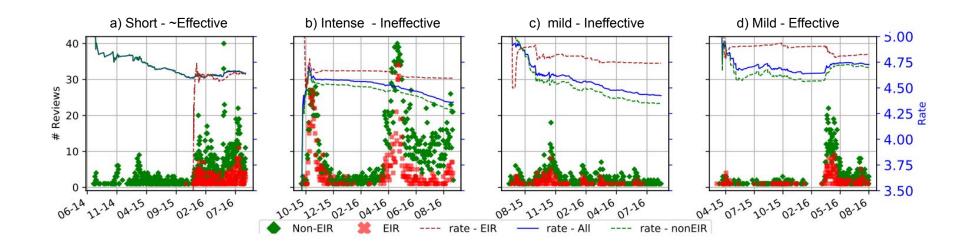
3. Characteristics of IRs

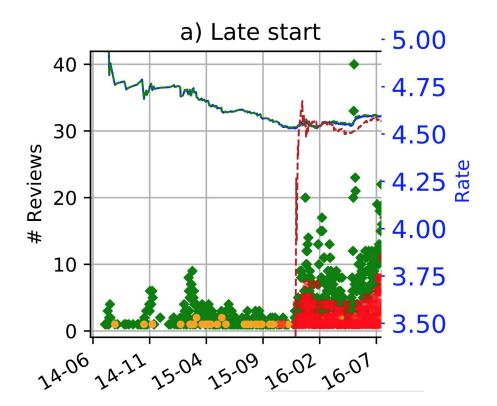




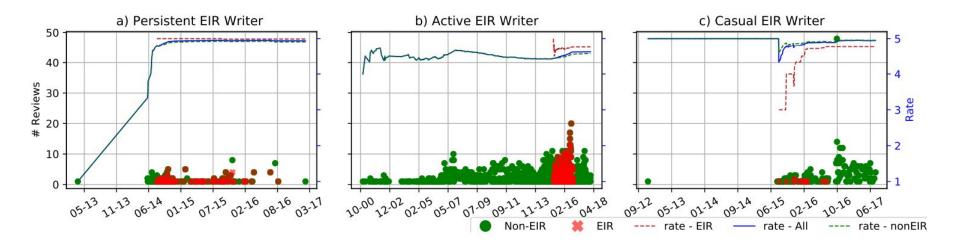


4. Temporal patterns (products)





4. Temporal patterns (Users)



- Given the different characteristics of normal and EIRs
 - Modeling and detection should be possible

Text Length	Rate	Text Sentiment	
Title Sentiment	Helpfulness	Title Subjectivity	
Text Subjectivity	Readability	Title Length	

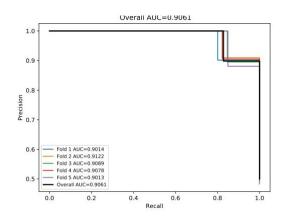
- We trained an accurate MLPC, using the above attributes
- Then, applied it to an evaluation set
 - Reviews that are not Incentivized nor Normal and submitted in 2016
 - Out of 78K reviews, our model labeled 5,891 (7.57%) of them as Incentivized
 - 54% of them, have Explicit signal (different than ours)
 - "I had opportunity to get it for my review"
 - "received with a promotion rate

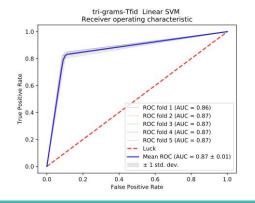
- Given the different characteristics of normal and EIRs
 - Modeling and detection should be possible

Text Length	Rate	Text Sentiment
Title Sentiment	Helpfulness	Title Subjectivity
Text Subjectivity	Readability	Title Length

- Removed the signature part of the review ("received free product in exchange ...") for text-based modeling
- We trained an accurate MLPC, using the above attributes

- Then, applied it to an evaluation set
 - Reviews that are not Incentivized nor Normal and submitted in 2016
 - Out of 78K reviews, our model labeled 5,891 (7.57%)
 of them as Incentivized
 - 54% of them, have Explicit signal (different than ours)
 - "I had opportunity to get it for my review"
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	Acc.	Rec.	Prec.	F1-score	P-R AUC	AUC
Basic	0.84	0.81	0.78	0.81	0.86	0.81
Text	0.88	0.89	0.89	0.89	0.91	0.89
Basic+Text	0.92	0.89	0.86	0.89	0.93	0.89
C-Elect.	0.8	0.8	0.79	0.8	0.85	0.8
C-Health	0.87	0.86	0.84	0.86	0.9	0.86

Conclusion

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- 1. Incentivized Reviews
- 2. Explicit Incentivized Reviews
- 3. Behavior Deviation of EIRs
- 4. Modeling and Predicting

The End

Comments and questions....