The Value of Online Customer Reviews

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ABSTRACT

We study the effect of the volume of consumer reviews on the purchase likelihood (conversion rate) of users browsing a product page. We propose using the exponential learning curve model to study how conversion rates change with the number of reviews. We call the difference in conversion rate between having no reviews and an infinite number *the value of reviews*. We find that, on average, the conversion rate of a product can increase by as much as 270% as it accumulates reviews, amongst the users that choose to display them. We also find diminishing marginal value as a product accumulates reviews, with the first five reviews driving the bulk of the aforementioned increase. To address the problem of simultaneity of increase of reviews and conversion rate, we use customer sessions in which reviews were *not* displayed as a control for trends that would have happened regardless of the increase in the review volume. Using our framework, we further find that high priced items have a higher value for reviews than lower priced items. High priced items can see their conversion rate increase by as much as 380% as they accumulate reviews compared to 190% for low priced items.We infer that the existence of reviews provides valuable signals to the customers, increasing their propensity to purchase. We also infer that users usually don't pay attention to the entire set of reviews, especially if there are a lot of them, but instead they focus on the first few available. Our approach can be extended and applied in a variety of settings to gain further insights.

Keywords

Marketing, Online Reviews, Word of Mouth

1. INTRODUCTION

Electronic Word of Mouth (eWOM) in the form of online customer reviews, is omnipresent and part of many customers' purchase journey. Reviews are being collected, aggregated and displayed to consumers in an easy-to-digest format in all types of settings: all of the top-10 U.S. online retailers (as well as most of the biggest retailers in the rest of the world) collect and display user reviews for their products. The same is true for all the major digital stores. Furthermore, companies like Yelp, Facebook, Google, IMDb and Rotten Tomatoes provide platforms for users to submit reviews that are, in-turn, aggregated and displayed to other users. User reviews are also being used to build trust between customers in decentralized marketplaces like eBay, Airbnb and Uber.

For online shoppers, reviews are not just an option anymore but an expectation. A recent survey[1] found that 30% of shoppers under the age of 45 consult reviews for every purchase they make, while 86% say that reviews are essential in making purchase decisions. In fact, after price, reviews are the factor with the most impact on purchases. An extensive literature has also showcased the economic importance of positive reviews for restaurants [14, 1], books [2], movies [6], mobile apps [8], and consumer goods [15].

In this work we aim to gain insights on a slightly more fundamental question. We ask, *should retailers seek reviews for their products?* Can the existence of reviews (without any assumptions on their valence or other characteristics) increase the likelihood of purchase? Our analysis suggests positive answers. We further explore the value of reviews for the three largest product categories of the studied retailer: electronics, apparel and home living. Within categories, we explore the value of reviews for high- and low-priced items.

2. THE EFFECT OF REVIEW VOLUME ON PURCHASE

Prior research on review volume has produced mixed results. Volume is believed to exert positive effects by increasing review credibility and/or signaling product popularity. Volume has been shown to have a positive effect on box office sales [7, 13] and sales rank of electronic products [5, 11]. Moreover, it influences other outcomes such as consumer attention [9, 13], product evaluation [4], product popularity [18] and purchase intention [17]. However, [10] finds that volume does not impact the sales of cell phones, and [3] shows that volume has no significant impact on box office performance. There is no evidence for a negative effect.

In order to understand the effect of volume on purchase we propose the following assumptions:

[1]http://www.powerreviews.com/blog/survey-confirms-the-value-of-reviews

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- **Assumption 1**: Each product has an inherent conversion rate, in the absence of any reviews.
- **Assumption 2**: Each product has an upper bound on its conversion rate that is less than 1.
- **Assumption 3**: As a product accumulates more reviews, their marginal value decreases.

Consider a product (or service). When the product is first introduced it will not have any reviews, and there will be an initial probability of purchase, which we will call the *intercept*. Over time the product will attract reviews. The accumulating reviews should cause the probability of purchase to increase and approach an *asymptote*. This asymptote can theoretically be 1, i.e., given an infinite number of reviews every product view can lead to purchase, but in reality we expect it to be much lower. The exact location of the asymptote will depend on other factors, such as the price, product category, quality, and the level of marketing support. We furthermore assume that as a product accumulates reviews, the value of each additional review will decrease, i.e., the marginal value of the 5th review will be higher than that of the 50th review. If these assumptions are accepted then one possible function for the value of reviews is the *exponential learning curve* [16, equation 13.9 and §13.5]:

$$\pi(x) = \gamma_0 - \gamma_1 e^{-\gamma_2 x}, \quad x \geq 0, \gamma_2 > 0, \tag{1}$$

where $0 \leq \pi(x) \leq 1$ is the probability that a product with x reviews is purchased. Parameter γ_0 specifies the asymptote because $\lim_{x\to\infty} \pi(x) = \gamma_0$. The intercept is $\pi(0) = \gamma_0 - \gamma_1$, and so γ_1 gives the distance between the intercept and the asymptote. Thus, γ_1 gives the **value of reviews**, since it is the difference between the conversion rate with no reviews and when there are infinite reviews. We do not constraint $\gamma_1 \geq 0$, and $\gamma_1 < 0$ would indicate that the conversion rate decreases as reviews are added. The other parameter, γ_2, characterizes the steepness of the function, where large values indicate $\pi(x)$ approaches γ_0 quickly and smaller values indicate a more gradual approach. This model has been used extensively for modeling learning curves and memory [12].

3. METHODS

We have data for the entire year 2015 from an online retailer that sells high-end specialty gifts. The data record every visit to the site for each user id, including the date and time, what products were viewed, whether the user viewed reviews and whether the user purchased the product. We also know the number of reviews that the user was exposed to, where the number increases over the year. Thus, we can study the conversion rate as a function of the number of reviews.

Our dataset consists of around 15.5 million page views for 1800 unique products, from 7.8 million users over the course of one year (January 4, 2015 – January 2, 2016). For each product, we track the number of its page views and sales as it accumulates reviews. Hence, for each product and number of reviews, n, we calculate the product's conversion rate while it had n reviews. We then average the conversion rate over all products for each n, to calculate the average conversion rate as a function of the number of reviews. When we want to study the value of reviews for products of a specific category or characteristic (e.g., price) we repeat the above approach but restrict our attention to the relevant products. We then estimate the parameters of Equation 1 by using the curve fit function of the scipy module for Python[2].

Our approach has a built-in control group, since we are tracking the conversion rate of a fixed set of products while they accumulate more reviews. Since we are comparing the conversion rate of the products to their past selves, many effects due to the products' characteristics are controlled for within our model. What our model doesn't inherently control for are temporal trends related to exogenous time related variables. To address this issue we use a control set of observations. Observations regarding page views in which the user *did not display reviews*. We use these sessions as a control for time and other exogenous trends. We adjust our exponential function to incorporate these distinction between page views where the user did and did not display the reviews.

$$\begin{aligned} \pi(x) &= (\gamma_0 + \gamma_1 \mathrm{disp}) - (\gamma_2 + \gamma_3 \mathrm{disp}) e^{-(\gamma_4 + \gamma_5 \mathrm{disp})x}, \\ & x \geq 0, \gamma_2 > 0 \end{aligned} \tag{2}$$

where disp is a binary indicator of whether a display of reviews happened. By fitting Equation 1 on our data, we isolate the effect of the display of reviews while controlling for all other exogenous trends. To further remove any noise from our data, we focus only on products whose first page view was observed after March 1, 2015. This is to ensure that our data cover the beginning of a product's life cycle, and we don't use data for products that have been on the market already for some time in the beginning of 2015.

4. RESULTS

Overall, the conversion rate of a product increases by 270% as it accumulates reviews. This increase is calculated as the difference between the asymptote (γ_1) and the intercept (γ_0), divided by the intercept. Moreover, over the bulk of that effect happens within the first 10 reviews the product receives. Figure 1 displays the fitted curve. Note that this effect is isolated for when the display of reviews happened, i.e., when disp equals 1 in Equation 1.

Figure 2 compares the value of reviews for high- and low-priced items. Products were categorized into high and low price depending whether their price was above or below the median price amongst the studied products. The median price was $79.99. We notice that low-priced items have consistently higher conversion rates than the high-priced products. The value of reviews is around 190% for low-priced items but much higher, at 380% for high-priced items. It seems that users gain confidence in their purchase when they see other users have bought a high-priced item. For low-priced items, the monetary risk is lower and perhaps that's why the value of reviews is lower.

Finally, we also explored the value of reviews for high- and low-quality products. We approximate a product's quality by observing all the reviews it accumulated over its (observed in our date) lifetime. Products with a lifetime average below 3.5 were classified as low quality and products with a lifetime average above 3.5 stars were classified as high quality. We notice that high-quality products have consistently higher conversion rate than lower-quality products. But, perhaps surprisingly, low-quality products have a higher value for reviews, at 324% compared to high-quality

[2] Python Documentation, http://bit.ly/1XDwA76

products, at 135%. This could be because of the lower baseline for low-quality products as well as that social signals are more important and valuable when the product in question is of lower quality.

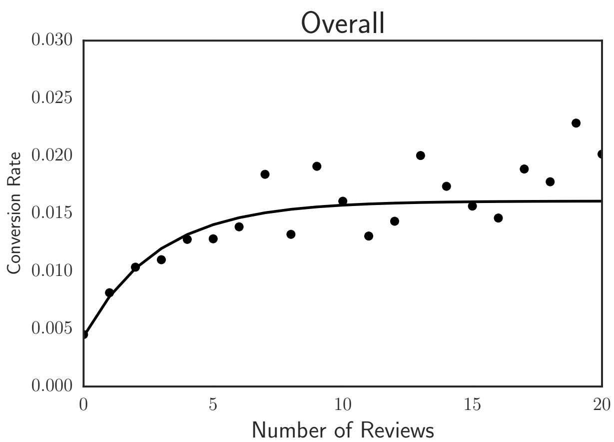

Figure 1: Effect of Number of Displayed Reviews on the Conversion Rate

5. CONCLUSION AND FUTURE WORK

Our work provides strong evidence for a positive value of reviews, i.e., causal effect of the existence of reviews towards the purchase likelihood of a browsing customer. This is with no assumptions on the characteristics of the reviews. Practitioners should take this to mean that it's beneficial for their platform to solicit reviews, even if they have no control over the reviews they will get (e.g., their valence).

We explore the value of reviews for various product characteristics such as price and category, but our results are still confined under the specific retailer we study. The exact value may change depending the specific characteristics of the retailer. We believe our approach, and model, can help guide future studies for other settings and retailers.

Many interesting directions are available for future work, and our dataset can be utilized to help explore them. First,

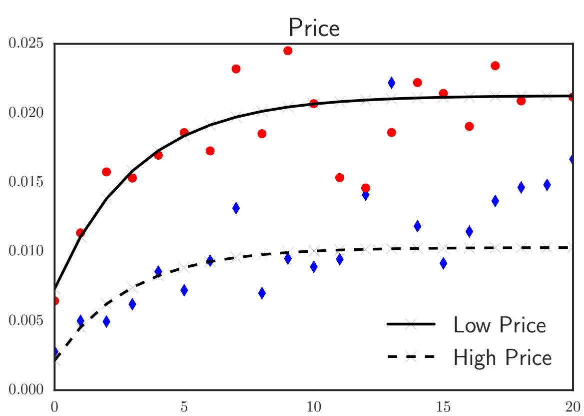

Figure 2: Effect of Number of Displayed Reviews on Various Price

better understanding of the value of reviews for various types of products as well as users can be important. Are reviews more important for returning or new users? How about users that have submitted a review themselves? Insights here, can help a retailer identify products and users for whom the value of reviews is high and act accordingly, e.g., by more prominent displays.

Moreover, the effect of valence can be better studied and understood. What is the value of higher ratings versus lower ratings? Studying the interaction between volume and valence can also help with understanding the way that customers interpret consumer reviews. For example, all else being equal, is it better for a product to have a 4.5 star average rating based on 5 reviews or a 4 star average based on 50 reviews?

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Table 1: Learning Curve Parameter Estimates

Category	$\hat{\gamma_0}$	$\hat{\gamma_1}$	$\hat{\gamma_2}$	$\hat{\gamma_3}$	$\hat{\gamma_4}$	$\hat{\gamma_5}$
Overall	0.07 (0.008)	-0.053 (0.008)	0.042 (0.008)	-0.03 (0.015)	0.078 (0.04)	0.27 (0.7)
High Price	0.073 (0.0025)	-0.063 (0.0064)	0.06 (0.01)	-0.05 (0.014)	0.046 ($3.6 \cdot 10^6$)	0.3 ($3.6 \cdot 10^6$)
Low Price	0.059 (0.002)	-0.037 (0.0038)	-0.0028 (0.011)	0.017 (0.014)	13.1 ($3.2 \cdot 10^5$)	-12.79 ($3.2 \cdot 10^5$)
High Rated	0.051 (0.002)	-0.03 (0.006)	-0.001 (0.01)	0.013 (0.014)	13.58 ($3.6 \cdot 10^6$)	-13.37 ($3.6 \cdot 10^6$)
Low Rated	0.036 (0.006)	-0.013 (0.16)	-0.03 (0.014)	0.047 (0.15)	0.33 (0.35)	-0.29 (0.64)

Values in parentheses are standard errors.

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