Intelligence of Crowd: Could Voting Predicts Product Sales?

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1. INTRODUCTION

The value creation process in Web 2.0 provides new challenging "open business models" based on customer participation [Wirtz, Schilke and Ullrich, 2010]. People are no longer simply consumers of a company's products or a target of its value proposition. They are major partners of companies and sometimes co-creators of value [Vargo and Lusch, 2004]. Businesses can thus be built through incorporating customer interactions as a core value-generation strategy and innovation processes. Over the past decade, many business models of crowdsourcing communities have received intensive attention from scholars and practitioners. It is defined as the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined network of people in the form of an open call [Howe, 2006]. Many crowdsourcing systems not only generate creative content but also contain a rich community of collaboration and evaluation in which creators and adopters of creative content interact among themselves and with artifacts (e.g., creative content) through overlapping relationships such as affiliation, communication, affinity, and purchasing.

In new product development, demand forecasting is critical for firms to make optimal decisions and resource allocation. Accurate forecasting before product release has been a challenging task because of the lack of the product's prior sales history and the difficulty to identify potential consumers [Foutz and Jank, 2010; Moe and Fader, 2002]. In the Web 2.0 environment, consumers frequently generate product prerelease buzz and many companies collect responses in brand communities to maximize new product success [Xiong and Bharadwaj, 2014]. Although research has examined post-release product reviews, there is little empirical research on the intelligence of a crowd to reveal the value of a new product before release.

2. RESEARCH CONTEXT AND QUESTIONS

Threadless.com, a crowdsourcing platform and ecommerce website for creative t-shirts, produces t-shirts designed and voted by its community users. Rather than reviewing existing products, the Threadless voting system is designed to evaluate the quality of future products: voting scores are not published during the voting period. Therefore we can consider the voting activities representing the intelligence of the crowd and study its contribution on new products evaluation. This study focuses on the following two questions related to crowd intelligence:

1. Does community voting reveal the value of potential products accurately?
2. Which voting statistics better predict the success of a product when released?

3. DATA DESCRIPTION

Our data includes detailed voting information of submitted designs and sales of accepted and printed designs from 2007 to 2010. Based on the voting records, we construct average scores, standard deviations, the total numbers of votes, the numbers for each voted score (from 0 to 5) and the numbers of comments. Sales information includes the quantity sold and revenue for different time periods.

We categorize consumers into three groups: voted community users who were registered and voted on the design before its production, non-voted community users who were registered but did not vote on the design, and guest users who only purchased from Threadless without registration. We choose quantity sold in the first 30 days as it counts for the majority of early sales for most of the sample (1,395 products in total). It is not surprising to find that only a tiny amount of sales quantity comes from voted community users (about 2%). Non-voted community users account for 42% and guest users account for 56%. Controlling for the product prices and years, we conduct a series of regression analysis of first 30-day sales quantity to examine the prediction power of different sets of voting indices on sales made by the three consumer groups.

4. EMPIRICAL ANALYSIS

We first investigate the effect of word-of-mouth (WoM) represented by the comments made to each design. We found that the number of comments had a positive impact only on purchases made by voting users. As a large amount of the comments are focused on praise and encouragement, the positive WoM circulates among voters and helps increase their purchase. Similarly, we examine the effect of aggregate score measures including the average vote scores and score dispersion (i.e. standard deviations of vote scores). Average scores have a positive impact on all consumer groups while score dispersion has a positive impact only on community users (both voted and non-voted). Not surprisingly, both impacts are largest among voted users.

Given the findings above, we further study the impact of score dispersion by exploring detailed score distribution using the percentages of 0-score, 1-score, 2-score, 4-score and 5-score while taking 3-score as the baseline. The table below shows the estimation results by consumer groups (dependent variable is the natural log of first 30-day sales quantity). Overall only 0-score percentage and 5-score percentage have significant effects. This shows that the score dispersion takes effect through the extreme ratings and the middle ratings contains little useful information for sales prediction. 5-score percentage has a positive impact on all consumer types and the impact is largest for voted users. Interestingly, 0-score percentage is found to have a positive impact on voted community users but a negative impact on non- community users. The impact

on non-voted community users is insignificant. The differential impacts of extreme scores on different consumer groups reveal the information contents and effectiveness of crowd intelligence. As the score dispersion (either standard deviations or score percentages) is unobserved to consumers, we need to explore the mechanism underlying the functionality of score dispersion.

Variable	Voting users	Non voting users	Guest users	All
Avg price	-0.097***(.006)	-0.098***(.008)	-0.084***(.008)	-0.090***(.008)
Num colors	0.022 (.016)	-0.012 (.017)	-0.027 (.017)	-0.018 (.016)
Vote count	0.0008***(.0000)	0.0005***(.0000)	0.0001*** (.0000)	0.0003***(.0000)
Zero-score %	0.029** (.012)	-0.002 (.013)	-0.029** (.013)	-0.017 (.013)
One-score %	0.013 (.017)	-0.015 (.018)	-0.033* (.018)	-0.025 (.017)
Two-score %	0.018 (.019)	0.028 (.020)	0.023 (.020)	0.025 (.020)
Four-score %	-0.013 (.016)	0.006 (.018)	-0.011 (.017)	-0.005 (.017)
Five-score %	0.059*** (.010)	0.028*** (.010)	0.018* (.010)	0.023** (.010)
Constant	0.41(.95)	5.49 (1.05)	7.13 (1.04)	7.13 (1.01)
Adjusted R^2	0.62	0.39	0.31	0.34

Note: Standard errors in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.10$

5. DISCUSSION

In general, the number of comments, average scores and score dispersion all predict product sales. However, they have different prediction power for different user groups as indicated by explained variation (i.e. R-square). Sales among voting users are the easiest to predict while sales among non-voting users is more difficult. Sales among guest users are the hardest to predict. Although the number of comments and vote scores are positively correlated, the number of comments predicts sales beyond what is predicted just by scores. When combining score dispersion with WoM, the impact pattern of score percentages remains the same while the number of comments becomes significantly negative for non-voting community users and guest users. Since the detailed distribution of votes is not observable for all users and the comments are displayed with the designs all the time, an important next step is to study the content of comments to see what it reveals about how consumers react to the intelligence of a crowd.

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