Fake Negative Review on Taobao

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1 Introduction

Online review is crucial for Taobao (`https://www.taobao.com/`) from the perspectives of both buyers and sellers. In addition to giving ratings based on a predetermined scale, reviewers are often requested and encouraged to upload relevant photos and provide detailed comments on their experience. Objective reviews can help consumers get more information about the searched products so as to alleviate asymmetric information. For sellers, online reviews are relevant and non-trivial for customer relationship management. Positive feedback is one determinant for ranking sellers on Taobao's organic search pages for keywords. In addition, reviews will influence consumers' attitudes as well as conversion rates.

Lack of regulations and weak enforcement of laws lead to distortions in markets outcomes [5]. Many sellers created fake sales record to gain popularity and attract customers. Fake online reviews have aroused much attention and became an increasingly severe problem in China. For example, on March 15th 2016, which was the Day for Protecting Consumers' Rights in China, China Central Television (CCTV) uncovered that more than one million people were involvd in producing fake online review [9]. As cheap as 1000 RMB (160 USD), one seller can purchase more than 200 fake records with "all-star" ratings and reviews teeming with compliments. According to the public report, without buying fake positive reviews, honest sellers could not compete with cheaters.

Obviously, such "professional services" are intolerable for Taobao. More than

300 algorithms have been developed to detect fraudulent transactions and delete fake reviews. In addition, the punishment for sellers to generate fake reviews has been increasingly heavy [3]. However, this underground industry persists and develops its anti-detection tricks. For example, given that the logistic history is used to decide fake reviews, some cheaters sent empty packages to escape punishment.

One possible reason for fake reviews on Taobao is its rule for online reviews. After submitting their reviews, customers have fifteen days to communicate or negotiate with sellers. In order to get higher ratings, sellers usually promise customers with monetary rewards in exchange for improving their ratings. While both Amazon and Taobao strictly prohibit promising a refund in exchange of posting positive reviews [9, 1], this problem is serious and pervasive on Taobao during this period of negotiations. As a consequence, on the five-point Likert scale, the average ratings for most keywords are higher than 4.5 and many ratings for flagship stores are close to perfection.

Fake reviews increase consumer uncertainty. Suspicious of online reviews, Experienced buyers may conjecture that part of positive reviews are fake. Another source of uncertainty arises from information cascade. Consumers also know that online reviews are susceptible to social opinions.

In order to manipulate reviews and gain market shares, some sellers posted false negative reviews for their competitors. Given that past reviews are one of the determinants for organic keyword searches on Taobao, fake reviews from competitors will possibly negatively affect the ranking on the result page. The higher one good is located on the result page, the more clicks the shop will collect for a given period of time. Negative reviews also will take effect when consumers make decisions between several options. Negative reviews decrease the utility for risk-averse consumers by reducing the mean and increasing the variance for the competitors' products. What's more, the distribution of reviews will influence the sequential review generation due to conformity or asymmetric information. Such theoretical predictions are consistent with observations in the industry. There are many examples of deliberately negative reviews on Taobao, some of which were manipulated by organized teams [8].

1.1 Literature Review

User-generated contents have been continuously gaining credibility and are regarded an essential component of the consumer decision-making process. Online reviews have non-negligible economic values (Wu et al., 2015) [10] and interact with management responses (Proserpio & Zervas, 2017) [7]. Wu et al. (2015) [10] finds that consumers learned the distribution of quality and costs summarized by the mean and variance across consumer population. Different from this project, Wu et al (2015) [10] focuses on experiential services in the restaurant, which are much more heterogeneous than keyword searches for products on Taobao. Proserpio & Zervas (2017) [7] is one of the few studies that pay attention to negative reviews, which demonstrates the relationship between management responses and online reputations. The authors found that hotels received fewer but longer negative reviews when hotels began to response. Proserpio & Zervas (2017) [7] implies that response from the seller side could be used to deal with false negative reviews from competitors. This study is consistent with the high satisfaction rates on Taobao given that mutual evaluations are mandatory.

There has been growing concern for posting deceptive opinion spam. Computer scientists have focused on detection techniques (Mukherjee et al., 2012 [4]; Ott et al., 2012[6]) especially in the domain of false positive reviews. Zhao et al. (2013) [11] models how consumers learn online reviews especially in the domain of experiential products. Their model predicts that when consumers are uncertain about online reviews, the effects of higher means and more popularity on sales will be reduced. Taking into consideration the sequential and temporal dynamics of online opinion (Godes & Silva, 2012 [2]), fake negative reviews will influence long-turn revenues when subsequent consumers evaluate the products and services.

This paper aims at building analytic models to explore the effects of false negative reviews on consumer decision making. The rest of the paper is organized in several parts. In §2, I present the model on fake negative reviews covering organic search ranking ,consumer choice decision and sequential dynamics of reviews. I conclude the proposal in §3 with possible future directions.

2 Model Construction

2.1 Modelling Organic Search Ranking

When consumers browse the shopping website for some products with keywords, the result ranking is defined as $R = (R_1, R_2, ..., R_n)$. To simplify the model, I assume that for each product j, the ranking algorithm considers total sales (N_j), the mean ratings (μ_j) and other covariates (X):

$$r_j = \beta_1 N_j + \beta_2 \mu_j + \alpha X \quad \forall R_i, R_j \in R, R_i \succ R_j \Longleftrightarrow r_i > r_j \tag{1}$$

Given that different positions have different click-through rates, the click-through rates CT_j are a parsimonious function of R_j such that for a parsimonious function ϕ

$$CT_j = \phi(R_j) \text{ where } R_+ \xrightarrow{\phi} R_+ \tag{2}$$

For all individuals targeting at one specific keyword, the probability of clicking on the j^{th} recommended good is CT_j. Consequently, the expected number of products to browse is $\sum_j CT_j$.

Given that the number of consumers are M_t in total at period t, the expected attentions collected by the product at the j^{th} highest position is $M_t \times CT_j$. The ranking algorithm bridges previous online reviews with subsequent consumers' choice set.

2.2 Modelling Consumer Choice Decisions

My model is built on and adapted from Wu et al. (2015) [10]. For the browsing session of the user i, the user has a choice set S_i. For each good $j \in S_i$, there are multiple attributes, represented by a vector variable A_{ij} that will influence consumers' choice utility. In this setting, A_{ij} includes the quality Q_{ij} and the cost C_{ij}. These attributes are individual-specific with a prior expectation $E(A_{ij})$ and a prior uncertainty $Var(A_{ij})$. For each product j in the choice set S_i, the user reads K_j reviews and altogether $K = \sum_{j \in S_i} K_j$ reviews. The information set I_k is based on all the K reviews. Conditioned on I_k, the expectation is updated as $E[A_{ij}|I_k]$ and the uncertainty $Var[A_{ij}|I_k]$.

The expected utility function for individual i to choose product j is specified with Multinomial Logit Model. More specifically,

$$E[U_{ij}|I_k] = \alpha_{ij} + w_i^Q E[Q_{ij}|I_K] + \gamma_i^Q E[Q_{ij}^2|I_K] + w_i^C E[C_{ij}|I_K] + \epsilon_{ij} \tag{3}$$

where α_{ij} measures the user's intrinsic preference for the restaurant; w_i^Q and w_i^C represent the utility weights of quality and cost; Q_{ij} is the parameter of the risk preference for quality.

The probability that individual i chooses product j is

$$\theta_{ij} = \frac{exp(\tilde{U}_{ij}(I_k))}{1 + \sum_{j' \in S_i} exp(\tilde{U}_{ij'}(I_k))} \tag{4}$$

where $exp(\tilde{U}_{ij}(I_k))$ is the deterministic part in Equation 3.

The reviewer's consumption experience of the attribute, A_{ij}, is assumed as

$$A_{ij} = A_j + \xi_{kj} \tag{5}$$

where A_j is the mean consumption experience across all consumers and ξ_{kj} is a stochastic component with a variance $\sigma_{\xi,j}^2$.

Assume that for an attribute A, reviewer k reports L evaluations, $R_{kj} =$

$(R_{kj}^1, R_{kj}^2, R_{kj}^3, \ldots, R_{kj}^L)$ such that the relationship between the review evaluation and A_{kj} is

$$R_{kj} = A_{kj} e_L + \epsilon_{kj} \tag{6}$$

where e_L is a vector with every element being 1.

Wu et al. (2015) [10] proposes the differentiated learning model where a user learns about an individual-specific consumption experience, A_{ij}, based on her perceived taste correlations with the reviewers [10]. More specifically, one consumer may put more weights on some reviews than other reviews because she may consider the reviewer's evaluations to have less noise reflecting the true consumption experiences. This model assumes that the random error ϵ_{ij} follows a normal distribution

$$\epsilon_{ij} \sim N(0, \lambda_k^{-1} \Omega \sigma_{\xi,j}^2) \tag{7}$$

where λ_k captures the accuracy with higher λ_k indicating higher accurate.

To identify λ_k, the authors use two objective variables that relate to where the review is posted. While review positions are proper proxies for accuracy, this identification ignores the effects of consumers' subjective judgment of review authenticity. In addition, the scalar λ_k is identical for all individuals. Define the variable pos_k as an indicator of review k to be positive. Then the accuracy λ_k can be modelled as

$$\lambda_k = exp(\rho_1^{pos_k} Z_k \alpha^K) \tag{8}$$

where α captures the "review page" effects (which page the review is displayed); Z captures the "review order" effects (the order of the review on a page); ρ_1 represents consumers' subjective evaluation of positive review credibility. The larger ρ_1 indicates the higher confidence for consumers to believe in the positive reviews. Even though this model focuses on positive reviews, it can be extended to include the subjective negative reviews with ρ_2.

In addition to lowering attractiveness and ranking, fake negative reviews have indirect effects of firms' long-term profits on dynamic opinion generation.

2.3 Sequential Dynamics of Fake Reviews

Studies on online review from the past literature treat the browsing history as exogenous. However, the keyword search result on Taobao is partially determined by past reviews. To capture the dynamics of online reviews, this model assumes that post hoc ratings are decided by individual utilities and the distribution of past reviews. Assume that the proportion of position and negative reviews are, respectively, ψ_1 and ψ_2. Thus, the rating for individual i on product j after reading K reviews is

$$R_{ij} = \pi_1\psi_1 + \pi_2\psi_2 + \pi_3 E[U_{ij}|I_k] \tag{9}$$

where π_1, π_2 and π_3 respectively represent the weights for positive reviews, negative reviews and personally shopping experiences.

For the ranking algorithm on Taobao, the overall rating for product i is determined by

$$R_i = \sum_i R_{ij} \tag{10}$$

Up to now, this dynamic model combines the following three possible channels for fake online reviews to take effects: a) Organic Search Ranking; b) Consumer Choice Decision; c) Sequential Dynamics of Reviews.

3 Future Direction

This model is innovative in studying user-generated contents in that it describes consumers' behavior and decision-making when fake reviews are pervasive. Subjective assessment of the proportion of fake reviews is included as a source of credibility issue. In particular, this model focuses on fake negative reviews, which have been ignored in the extant literature. In order to estimate the effects of fake negative reviews on market shares and long-term revenue, this dynamic model manages to include the three existing mechanisms. While this model assumes that when one firm makes fake reviews, other firms do not change their behavior, it is possible for other firms to retaliate from the perspective of game-theoretical modeling. This model also assumes that consumers are not aware of fake negative reviews. However, if large proportion of sellers calumniate each other, this model can be extended so that consumers take the possibility of fake negative reviews into consideration. Furthermore, this model accounts for the development of oligopolies and scrutinizes the market design on Taobao.

Many simplifications in this model are worth further exploration. For example, there are many other ways for firms to impose negative effects on their competitors. Spiritually similar to fake negative reviews, some firms deliberately dampened their competitors' conversion rate by frequent fake visits without any purchases. The ranking algorithm regards low conversion rates as an indicator of inferior quality or attractiveness so Taobao would put its relative position away from top on the result page. In addition, the ranking results are not purely decided by the algorithm. Consumers on Taobao can choose the criterion for ranking goods, which implies that the weights for different attributes may vary across user groups.

One major challenge for model identification is to distinguish fake negative reviews from real negative reviews. When posting fake nega1tive reviews, it is natural for the competitor to disguise his true (immoral) purpose. There are two strategies to deal with this identification problem. If IP addresses associated with transactions were available, we can identify whether the negative reviewers were exactly the competitors. However, this strategy did not work when fake negative reviews had been "outsourced" to some "professional teams". Another strategy is to conduct field experiments so that endogenous variable can be controlled.

References

[1] Amazon. *About Customer Reviews.* URL: https://www.amazon.com/gp/help/customer/display.html?nodeId=201145120.

[2] David Godes and José C. Silva. "Sequential and Temporal Dynamics of Online Opinion". In: *Marketing Science* 31.3 (2012), pp. 448–473. ISSN: 0732-2399. DOI: 10.1287/mksc.1110.0653. URL: http://pubsonline.informs.org/doi/abs/10.1287/mksc.1110.0653.

[3] maijia.com. *Punishment for Fake Transactions.* URL: http://www.maijia.com/software/tutorial/1014737.

[4] Arjun Mukherjee, Bing Liu, and Natalie Glance. "Spotting fake reviewer groups in consumer reviews". In: *Proceedings of the 21st international conference on World Wide Web - WWW '12.* 2012, p. 191. ISBN: 9781450312295. DOI: 10.1145/2187836.2187863. URL: http://dl.acm.org/citation.cfm?doid=2187836.2187863.

[5] Laxman Narasimhan, Kannan Srinivasan, and K. Sudhir. "Editorial —Marketing Science in Emerging Markets". In: *Marketing Science* 34.4 (2015), pp. 473–479. ISSN: 0732-2399. DOI: 10.1287/mksc.2015.0934. URL: http://pubsonline.informs.org/doi/10.1287/mksc.2015.0934.

[6] Myle Ott, Claire Cardie, and Jeff Hancock. "Estimating the prevalence of deception in online review communities". In: *Proceedings of the 21st international conference on World Wide Web - WWW '12.* 2012, pp. 201–210. ISBN: 9781450312295. DOI: 10.1145/2187836.2187864. arXiv: 1204.2804v1. URL: http://dl.acm.org/citation.cfm?doid=2187836.2187864.

[7] Davide Proserpio and Georgios Zervas. "Online Reputation Management: Estimating the Impact of Management Responses on Consumer Reviews". In: *Marketing Science* November (2017). ISSN: 1556-5068. DOI: 10.2139/ssrn.2521190. URL: http://www.ssrn.com/abstract=2521190.

[8] sina.com. *Malign Reviews from Competitors.* URL: http://tech.sina.com.cn/i/2013-07-29/09098584137.shtml.

[9] Taobao. *Fake Transactions.* URL: https://daxue.taobao.com/markets/daxue/jy_tdtw.

[10] Chunhua Wu et al. "The Economic Value of Online Reviews." In: *Marketing Science* 34.5 (2015), pp. 739–754. ISSN: 07322399. DOI: 10.1287/mksc.2015.0926. arXiv: /dx.doi.org/10.1287/mksc.2015.0926 [http:]. URL: http://search.ebscohost.com/login.aspx?direct=true%7B%5C&%7Ddb=bth%7B%5C&%7DAN=109946278%7B%5C&%7Dsite=ehost-live.

[11] Yi Zhao et al. "Modeling Consumer Learning from Online Product Reviews". In: *Marketing Science* 32.1 (2013), pp. 153–169. ISSN: 0732-2399. DOI: 10.1287/mksc.1120.0755. URL: http://pubsonline.informs.org/doi/abs/10.1287/mksc.1120.0755.