Analysis Of Fraud On A
Chinese Business Review Website

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ABSTRACT

Recently, local business-review websites have gained popularity, but the problem of fraud has become more and more severe. We did research based on the biggest Chinese local business-review website: Dazhongdianping. We collected 792,364 reviews of every registered restaurant on the Dazhongdianping website in Hangzhou, and our findings include:

1. Compared with US businesses Luca and Zervas (2016) who give both unfavorable reviews to their competitors and favorable reviews to their own business, Chinese businesses focus only on the latter, perhaps because of the differences in business ethics between the two countries.

2. Review frauds have a close relationship with the user's social network. Users with many followers and higher interaction scores are always more powerful than other users, and they also have reasonable incentives to commit fraud. We found that these users are more likely to post fake reviews.

3. Finer restaurants are less likely to commit review fraud.

Keywords: Fraud; eWOM; Visiting Intention; Review Fraud; Social Network

INTRODUCTION

$\mathcal{W}$ith the rapid development of local business-review websites, more and more consumers began to search for a business review before making an actual visit. Famous review websites include Trip Adviser, Yelp, Angie's List, and Epinons. Also, a lot of shopping websites developed review functions in order to provide more information to consumers. When customers finish shopping on these websites, they can write reviews regarding their shopping experiences (Anderson & Magruder, 2012). However, although the number of reviews on those websites keeps increasing, we may question the authenticity of the reviews: Can we really trust every review on these websites?

Luca and Zervas (2016) stated that nearly 16% of the Yelp reviews are filtered by the website, and the main reason for posting a fake review is weak reputation (posting good reviews for the restaurant itself) and severe competition between restaurants (posting unfavorable reviews about competitors). Yelp has been fighting fraud since 2010, and in 2012, Yelp started a Consumer Alerts program to fight against fraud stings. When a business attempts to purchase reviews or takes any action to force people to write reviews, a warning message will pop up to inform users that this business has been committing fraud. If the business stops its offending actions, the warning message will be removed after 3 months.

Similar to Yelp, Amazon.com - the biggest internet shopping website in the US - has also been caught committing such fraud. Before 2016, Amazon.com used to have a specific type of review called incentivized reviews. It was initially set up to promote new products or new brands. If customers were unwilling to leave reviews for these newcomers of products/brands, Amazon.com allowed the business to distribute coupons to their customers in order to inspire the customers to write reviews. However, these reviews gradually turned to "bribe reviews," in that people who received coupons or discounts clearly give higher grades and use more favorable words in their reviews. After finding out this problem, Amazon.com immediately abolished this policy. Currently on Amazon.com only books are still allowed to have incentivized reviews.

Fake reviews also exist in restaurant review websites. Different from other review websites, some restaurant-review websites have developed well-established booking systems for the convenience of users. The booking function is definitely user-friendly and is effective in improving a user's dining experience. However, it also encourages business to leave fake reviews. Anderson and Magruder (2012) used a combined dataset of Yelp's registered restaurants and their reservation situation on a booking application and found out that an increase of half a star in a business's star ratings could bring 19% more sales. This finding suggests that businesses may have strong incentives to increase their star ratings by all means. Consistent with our common experiences on such websites, star ratings manipulation clearly exists in almost every review website.

Facing so many authenticity problems, local business-review sites have claimed to develop various filtering algorithms. When applying these filtering algorithms to the reviews, it can automatically judge the authenticity of the review. If fraudulent reviews are caught, then the website will filter them immediately. However, a determined user can still find those filtered reviews by clicking several links. Most companies keep the algorithm system confidential to prevent other businesses from finding the loopholes (Anderson & Magruder, 2012). Also, previous skeptical reviews (if any) will also be filtered as the algorithms develop.

Given the rapid improvement of filtering algorithms, fake review posters are getting smarter as well. Professional fake reviews can almost pretend to be real. The posters attach photos to them and write very detailed information (because of least length requirements by the business), and sometimes those fake ones seem to be even better than a legitimate review. These phenomena made us wonder what might be the reasons for businesses to commit fraud; hence, we carried out research on the biggest Chinese business-review website: Dazhongdianping.

LITERATURE REVIEW

Online review websites have long been considered to be effective platforms to provide useful shopping information. Generally, customers would like to share their experience after an especially pleasant consumption or a particularly disappointing one (Öğüt & Taş, 2012). If we focus on the contents of online reviews, positive reviews always include "information on core functionalities, technical aspects and aesthetics to be more helpful", and they contain more topics than negative ones as well. Negative reviews, most of the time, focus on service failure, and they tend to focus on a small number of topics (Ahmad & Laroche, 2017; Mankad, Goh, & Gavirneni, 2016). However, if customers are eager to gain useful information from the reviews, they need to pay attention to the review's trustworthiness as well. "Quality, credibility, usefulness and adoption for information, needs for information, and attitude towards information are the key factors of eWOM in social media that influence consumers' purchase intentions", according to Erkan and Evans (2016). Whether a review is trustworthy definitely affects a user's adoption for information and attitude towards information and will certainly affect their purchase intentions as well. Reimer and Benkenstein (2016b) carried out research on review valence (whether the review is positive or negative). Their findings suggest that trustworthiness influences the purchase intention in the same direction with the valence - trustworthy positive reviews increase purchase intentions, but trustworthy negative reviews decrease consuming intentions. Untrustworthy reviews can be rather tricky, in that they cause a "boomerang effect". When the review is considered untrue, its effect goes opposite to its valence (positive reviews reduce purchase intentions and negative reviews vice versa). Because of their great influence on a customer's purchase intention, the reviews can also be used to forecast product sales (Fan, Che, & Chen, 2017).

As the effects of online reviews gradually emerge, several studies have concentrated on how eWOM influences business sales and revenue. Luca (2011) did research about Yelp.com and found that a one-star increase for a restaurant can bring in 5 to 9 percent more revenue. Consistent with other previous studies that low-reputation restaurants were more influenced by the website, Luca also found that the revenue-increase effect does not affect chain restaurants. Similarly, Anderson and Magruder (2012) studied Yelp.com and another restaurant reservation application. Their findings indicate an extra half-star rating will cause the restaurant to be sold out 19% more frequently; and low-reputation restaurants (ones that are not externally accredited) will be sold out 27% more frequently.

Online reviews affect people's purchase incentives, business sales, and sometimes the product return rate on an online shopping mall (Minnema, Bijmolt, Gensler, & Wiesel, 2016). Having clear awareness of the benefit of positive reviews, businesses devote their efforts to counter unjust negative reviews. Ho (2017) studied how hotels deal with

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negative reviews and unsatisfied customers. By diligently posting comments that contain denials of the problems and apologies for actual problems, hotels can increase rapport with their customers and manage customer relationships more effectively. Similarly, Sparks, So, and Bradley (2016) and Mei and Blodgett (2016) also discussed how a business should react to negative reviews and arrived at the findings.

However, review manipulation does not always happen for a good purpose. More and more business owners learn about the benefits from online reviews and think about how to manipulate the reviews in an improper way. Kaghazgaran, Caverlee, and Alfifi (2017) carried out research based on a professional fraudulent review company. They compared the legitimate reviews with fraudulent ones, and finally found out that there are more five-star length reviews. However, even though these reviews are professionally made up, they still differ from legitimate ones, in that these reviews seemed to have been done very quickly. We can call this "the burst of reviews".

There are also researchers focusing on business reputation and manipulation of reviews. Hu, Liu, and Sambamurthy (2011) found out that when a product/vendor has comparatively lower quality and average ratings, it is more likely to manipulate its online reviews. In other words, a weaker reputation may increase the tendency of review manipulation. Similarly, Luca and Zervas (2016) found that Yelp businesses with weaker reputations have committed more review fraud, but chain restaurants with well-established reputations tend to have less intention to commit fraud.

Anderson and Magruder (2012) also focused on review manipulation and further studied the relationship of star ratings to being sold out. Their research suggested that star ratings increase is clearly beneficial to business revenue. With a half-star increase, a business can see a 19% increase in selling out. Other researches are also focusing on the economic benefits of review manipulation. Luca (2016) studied Yelp star ratings and business revenues. His research revealed that when a restaurant has a one-star increase in its star ratings, its revenue can have a 5-9 percent increase. Also, he stated that chain restaurants seldom benefit from the star rating increase and therefore have no significant increase in revenue. These findings are in line with other studies, in that a star ratings increase can boost sales, and businesses have a strong incentive to manage or even manipulate their reviews.

As fraud gradually became common on those review websites, regulations and new functions to restrict unethical behaviors were launched by both websites and the government. Hunt (2015) studied the fake reviews, their influence, and the related regulation in Australia. According to this research, the Australian government revised consumer laws to prevent fake reviews from happening.

Although review fraud stings were exposed several times in China, and review manipulation in some cases has become an open secret for users and business owners, there is little research on review fraud and its intentions for the Chinese market. Most studies focused on improvement of the filtering algorithms (Li, Chen, Liu, Wei, & Shao, 2015; Li, Chen, Mukherjee, Liu, & Shao, 2015; Zhang, Zhang, Liu, Ma, & Feng, 2013).

Luca and Zervas (2016) have done research based on Yelp. They analyzed 316,415 reviews in the Boston metropolitan area. Their research first analyzed the characteristics of filtered reviews in detail and found out that nearly 16% of the reviews were filtered and tended to be extreme (very favorable or very unfavorable). They break down the variables to reputations and location in order to see if review fraud was related to a restaurant's reputation or to competition. Based on their data from Yelp, the fake ratings are extreme. Therefore, these fake reviews might have been posted by businesses (who would like to increase their star ratings) or competitors (who may leave intentionally unfavorable reviews for their competitors). After analyzing the business panel data, Luca and Zervas (2016) found out the incentives behind review fraud as follows:

First, they found that reputation is closely related to review fraud. When a restaurant has a weaker reputation, it is more likely to commit review fraud; Chain restaurants had committed less review fraud, because of their business characteristics. A chain restaurant's' reputation is established already, so Yelp reviews do not affect their business as much.

Second, Luca and Zervas (2016) found that competition could cause review fraud. In China, when a restaurant receives malicious comments, it would be natural to relate it to malicious customers who expect to get a refund. However, according to Luca and Zervas (2016), when a restaurant has competitors around it, they may receive malicious fake

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reviews from their competitors. They found that when a restaurant has more competitors around it, it gets more intentionally made unfavorable reviews. This finding aroused our interest and made us wonder if it is the same situation in China. If not, what would be the incentive for a Chinese business to commit review fraud?

DATA

The Dazhong Dianping website (hereinafter referred to as "Dianping") was established in April 2003. It is China's leading local life information and trading platform, and it is also the world's first independent third-party consumer review site. Dianping not only provides business information, customer's reviews and customer's preferences to all the users, but also provides various services, such as customer's group-buying coupons, restaurant reservations, delivery information, and electronic membership cards, as well as other O2O (Online To Offline) trading services. In China, Dianping was the first to develop local life mobile applications. It has now grown into a mobile Internet company; its mobile application is an essential tool for local Chinese.

By the 1st quarter of 2015, Dianping had covered more than 2,500 cities in China and nearly 100 popular tourist countries and regions in the United States, Japan, and France. The number of businesses on Dianping exceeded 14 million, and the active users are more than 200 million.

However, recently review frauds were caught in websites including Amazon.com, Taobao, Yelp, and Dianping. In order to prevent the fake reviews from affecting people's choices, these websites have been developing complicated and scientific algorithms to filter the fake reviews. According to our dataset, nearly 23.11% of the total reviews are filtered by the algorithm. Also, since 2011, Dianping has launched a campaign called "Zero Tolerance" to prevent fraud. Businesses and users that have committed fraud (such as posting fake reviews, buying fake reviews, or posting negative reviews on purpose) has been punished. When customers opened the link of the business, they could see a yellow banner saying, "This business is proved to have committed fraud", The business links were removed from Dianping, and their previous reviews were all deleted. The business would go through a 1-3 months' continuous inspection by Dianping; if it hadn't done anything illegal, its business website would be found on Dianping again.

Since the start of "Zero Tolerance", Dianping has exposed fraudulent businesses and users several times. Many of the fraudulent businesses were from the hairdressing and beauty industry. This industry has the characteristics of high price, high value added, and long intervals between services (a person may go to a hair salon only twice a year and will carefully evaluate the salon before visiting). Also, these businesses are strongly affected by reputations. Based on such characteristics, severe frauds happened frequently in the hairdressing and beauty industries.

In addition, users who posted fake reviews are also exposed by the website several times. These users have typical and strong incentives to post fake reviews. They are always influential and powerful accounts, gained popularity during early years of diligently posting helpful and productive reviews, and began to receive commissions from businesses and to post fake reviews for them. These users' accounts always have an enormous number of followers and high interaction scores (calculated by the Dianping site, based on an accounts comprehensive interaction, such as leaving comments on other reviews or receiving comments themselves). These accounts always post reviews that seem like real experiences—with many pictures, usually a "4 star" comment (because a "5 star" may seem too fake), they may even mention an insignificant disadvantage of their so-called experience to make the review look more real. After finding these users posting fake reviews, the Dianping site deleted their interaction scores and blocked their previous reviews.

After conducting its "Zero Tolerance" Campaign, Dianping improved its image and gained more active accounts in China. However, in March 15 (the World Consumer Rights Day), 2016, Dianping was revealed to have committed fraud again. Several businesses had been caught paying users money or giving them coupons in order to get better reviews. Similarly, these frauds have been found in the United State in Yelp as well. Since 2013, Yelp has been making great efforts to examine the reviews and figure out unreliable ones. Research on these business stings and fake reviews had been done that enabled them to figure out the incentives and motives of fake reviews.

Luca and Zervas (2016) analyzed the characteristics of filtered reviews in the Boston metropolitan area and found that filtered reviews had a close relationship with a restaurant's reputation and competition. When a restaurant has a weak

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reputation or faces more severe competition, it is likely to have more filtered reviews. Also, whether a restaurant is a chain store or not can also influence its filtered reviews. Chain restaurants, whose reputation is less affected by the reviews, have comparatively fewer filtered reviews.

In order to study the Chinese review website, we collected all the reviews of restaurants in Hangzhou. The data includes 792,364 reviews in total; 183,115 reviews were caught by the algorithms, and 609,249 reviews were legitimate.

We first calculated the published and filtered reviews counts by quarter (see Figures 1 and 2). According to the quarterly statistics, in 2010-2015, the filtered review counts had been increasing as the legitimate review counts increased. In addition, the total reviews increased rapidly during this time. In the 4th quarter of 2015, review amounts came to a peak. However, since the end of 2015, the review counts (both published reviews and filtered reviews) have been decreasing; the decreasing trend lasted until the 1st quarter of 2017.

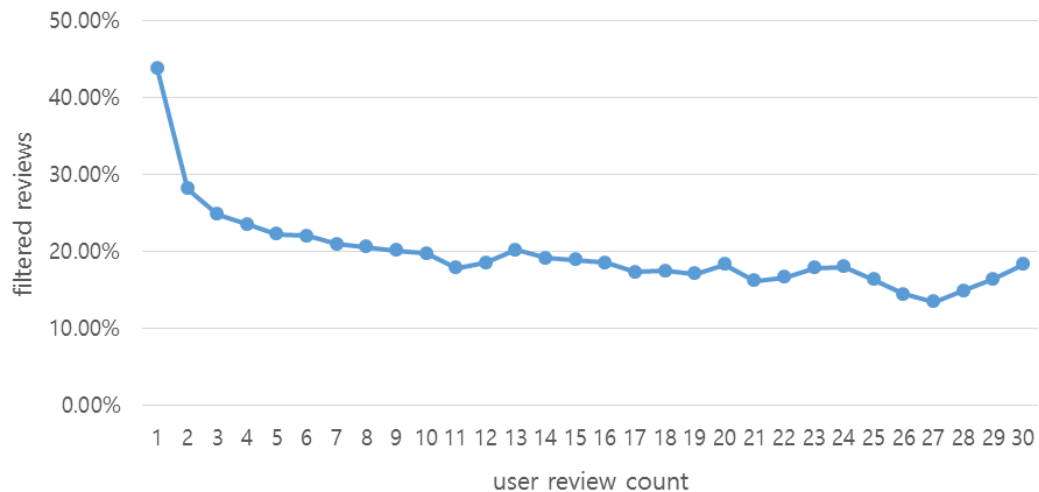**Figure 1.** Published and filtered review counts by quarter
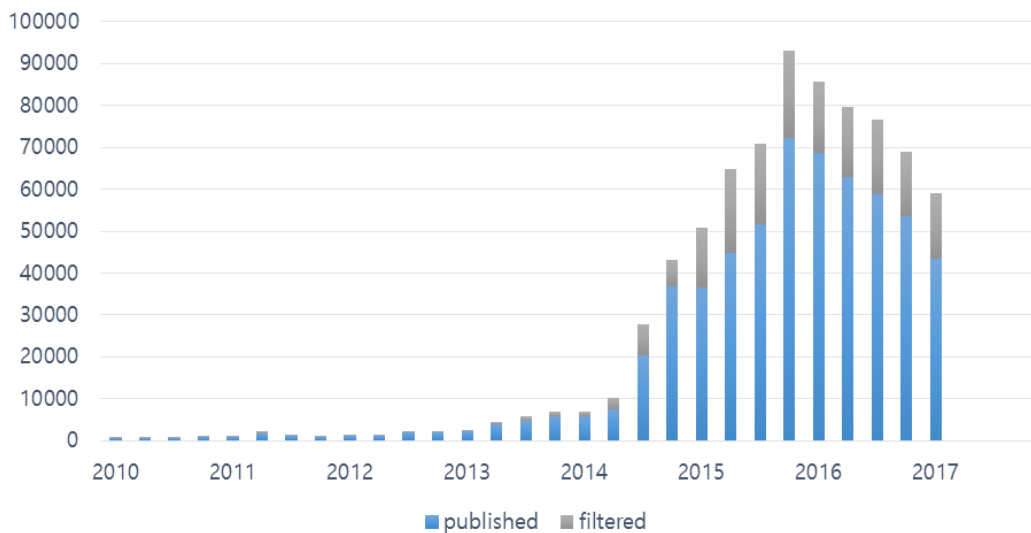
Figure 2. Percentage of filtered reviews by quarters

Figure 2 indicates the percentage of filtered reviews by quarter. From it, we can see a clearly increasing trend from 2010 to 2017, though the percentage varies from quarter to quarter.

Figure 3. Users review count and filtered review percentage

In Figure 3, we calculated the user's review count and the filtered review percentages. We could clearly find out from this chart that. as the user's total review increases, the percentage of filtered reviews decreases. The decrease is quite obvious when the user's review counts increase from 1 to 5. Especially, when review counts increased from 1 to 3, the filtered reviews declined by almost 20%.

HYPOTHESES

We collected 792,364 reviews in total (including legitimate and filtered reviews). For each review, we collected the variables as in Table 1.

Table 1. Definition of variables

Variable	Definition
Ratings by users	Every user can leave reviews for restaurants. The review must have a final rating that represents this user's overall experience in the restaurant.
Review length	Character count for a certain review.
Users' review count	A user's total number of reviews.
Profile picture	If the user has a profile picture or not
Average spending	Average spending in a restaurant (calculated by the average spending of every reviewer). This variable represents the price level of a restaurant.
Comment pictures	A user can choose to post photos of food, the interior, or even the menu of the restaurant together with their reviews. Dianping calculates the total number of photos and mark the number on user's profile.
Likes	Similar with Facebook "Likes," one can put restaurants in the "Likes" folder so that they could browse these restaurants later.
Visits	This function was initially made for users to tag their locations on the Dianping website and interact with other users.
Following	"Following" shows this user is following other users.
Follower	"Follower" shows how many other users are following this user.
Interaction	Interaction is an abstract concept, calculated by liking other's reviews, writing comments under other's reviewers or receiving reviews from other.

We have the following hypotheses:

H1: Review fraud causes the filtered reviews to go to extremes. There will be more 1-star and 5-star reviews caught by the filtered algorithm.

Star ratings and filtered probability: Hu et al. (2011) studied books, DVDs, and videos products on Amazon.com and found that review manipulation exists and is quite obvious at the start of a product launching. These reviews were mostly favorable reviews, done by vendors, publishers, or authors. Our data included restaurants only and may be somehow different from the data for book and CD reviews. However, we could also infer that review manipulation exists, so that 4-star and 5-star reviews would be more frequent than moderate reviews.

Luca (2016) stated that review fraud is also related to competition. So we could infer that reviews tend to go to extremes (with more 1-star and 5-star reviews), and that 5-star reviews will be much more frequent than other reviews.

H2: Shorter reviews tend to be more likely to be filtered than longer reviews.

Review length and filtered probability: Our assumption is that filtered reviews are always insincere reviews done by anonymous users. These reviews are probably shorter than legitimate reviews.

H3: If a user has uploaded more pictures with the reviews, the reviews are less likely to be filtered.

Comment pictures and filtered probability. Corresponding with the hypothesis above, we expect comment pictures to have a negative relationship with filtered probability.

H4: When a user has done more reviews in total, those reviews will be less filtered.

Review count and filtered probability. We believe that review count also has a negative relationship with filtered probability.

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H5: Average spending has a positive relationship with review fraud.

Average spending and filtered probability: Unlike websites that have only an ambiguous price level of the business, Dianping lets every customer post their average cost for certain restaurants and finally calculates an average price for other customer's reference. This special information from Dianping allows us to study the relationship between fraud and restaurant price.

There is evidence showing that restaurant sales can be largely affected by word of mouth. Anderson and Magruder (2012) studied 328 restaurants with reservation service. Their research found out that half a star increase of a restaurant would cause a restaurant to sell out 19% more frequently.

Supreme restaurants with higher than average prices may need to boost their sales by attracting newcomers and may have more incentives to commit review fraud and post fake favorable reviews for their businesses. However, once the newcomers are successfully attracted, all they need to do is to keep them as existing customers. So, we infer that average spending has a positive relationship with review fraud.

H6a: Visits have a negative relationship with review fraud.

H6b: Likes have a negative relationship with review fraud.

Visits, likes, and review fraud: "Visits" represents a user's actual visit to a restaurant, or when a user come to a place nearby and accidently searches on this restaurant, the user may also finish one "visit". The "Visits" function in Dianping doesn't have to be an actual visit but rather a social network function between website users.

"Likes" happens a lot when a customer browses the website and finds out interesting places to visit, but may not yet have had a chance to dine in the restaurant. Therefore, pushing likes to a restaurant is similar to marking this restaurant for a future visit.

These above two variables do not always accompany real experience in a certain restaurant, so we infer that the "visits" and "likes" variables will have a negative relationship with review fraud.

H7: Profile pictures have a negative relationship with review fraud.

Profile pictures and review fraud: Dianping allows users to upload their own profile pictures or use pictures from other social network websites. We infer that profile pictures will have a negative relationship with review fraud; in other words, if a user does not have profile pictures, those reviews are more likely to be filtered.

H8a: When a user has more followings, his reviews are less likely to be filtered.

H8b: When a user has more followers, his reviews are less likely to be filtered.

H8c: When a user has more interaction with others, his reviews are less likely to be filtered.

Following, follower, interaction, and review fraud:

Following, follower, and interaction are interactive variables between users. Therefore, we infer that if a user has more following/followers, or if the user interacts more with other users (i.e., giving "likes" to others' reviews, leaving comments under others' reviews, or responding to others' comments), this user's review will be more authentic.

H9a: If a review gives out high scores on taste to a restaurant, the filtered probability will increase.

H9b: If a review gives out high scores on environment to a restaurant, the filtered probability will increase.

H9c: If a review gives out high scores of service to a restaurant, the filtered probability will increase.

Taste, environment, service scores, and reviews: The Dianping website allows users to comment about a restaurant's taste, environment, and service in order to provide detailed information to customers. However, these three ratings are not as obvious as the total ratings of a restaurant. In other words, when choosing a restaurant, a user generally notices the total ratings first, then the taste, environment, and service score.

A wiser fake review may give extremely high scores on taste, environment, and service because these fake scores are less likely to be caught by website algorithms.

Based on the observations above, we infer that taste/environment/service will have a negative relationship with the filtering probability.

MODEL

In order to analyze the characteristics of the reviews, we formed a linear probability model as below: where *i* represents the restaurant *i*, and *j* represents the jth review of the restaurant *i*; and b_i is a constant term, $\beta_1 - \beta_{14}$ are the coefficients of variables.

$$
\begin{aligned}
\text{filtered}_{ij} = b_i &+ \beta_1 \text{rating}_{ij} + \beta_2 \log_{\text{reviewlength}_{ij}} + \beta_3 \log_{\text{commentpictures}_{ij}} + \beta_4 \log_{\text{reviewcount}_{ij}} \\
&+ \beta_5 \log_{\text{averagespending}_{ij}} + \beta_6 \log_{\text{likes}_{ij}} + \beta_7 \log_{\text{visits}_{ij}} + \beta_8 * \text{profilepictures}_{ij} + \beta_9 \log_{\text{following}_{ij}} \\
&+ \beta_{10} \log_{\text{follower}_{ij}} + \beta_{11} \log_{\text{interaction}_{ij}} + \beta_{12} \log_{\text{taste}_{ij}} + \beta_{13} \log_{\text{environment}_{ij}} + \beta_{14} \log_{\text{service}_{ij}}
\end{aligned}
$$

FINDINGS AND ANALYSIS

From table 2, we can summarize these findings as follows.

On the Dianping website, when we use 3 stars (the middle star ratings) as the standard, the filtered reviews are tilted to the left. There tends to be fewer 1-star and 2-star filtered reviews, but more 4-star and 5-star reviews. This indicates that most restaurants post fake reviews to promote their business, instead of posting malicious reviews of their competitors. One interesting finding is that 4-star reviews seem to be the concentrated area of fake reviews. This may show that even though these fake contents are made up, those reviewers are quite smart and tried to disguise their reviews as real ones.

Compared with the findings by Luca and Zervas (2016), Chinese review fraud concentrated mostly on positive valence, whereas American review fraud concentrated on both negative and positive valence. Perhaps the significant difference between the two countries can be attributed to the ethics and values of business owners. Baglione and Zimmener (2007) carried out a comparative study of Chinese and American business owners. They found that US business owners tend to relate ethics to both short- and lon- term rewards, but Chinese business owners believe in only the long-term rewards. This finding is consistent with our analysis results, in that US business commit both frauds to boost their own business (positive valence fake reviews) and downgrade their competitor (negative valence fake review); both behaviors can have both short-term and long-term effects. On certain websites for the hotel business, 50 vicious fake reviews done by competitors were enough to lower another business's rank. The higher rank would then bring much more exposure on the website and definitely more revenue (Lappas, Sabnis, & Valkanas, 2016). Therefore, US business owners committed fraud both for themselves and against their competitors. Unfair vicious reviews can affect a competitor's business instantly, and favorable fake reviews can bring them a long-term good reputation. Chinese businesses, on the contrary, believe in only long-term rewards and post merely favorable fake reviews.

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Table 2. Results from anlaysis

Hypothesis	Variable	Coefficient (Standard error)	Conclusion
H1	star rating1	-1.267 (0.117)	not supported
	star rating2	-0.656 (0.071)	
	star rating4	0.528 (0.034)	
	star rating5	0.316 (0.041)	
H2	log review length	-0.22348 (0.01)	supported
H3	log comment pictures	0.122 (0.007)	not supported
H4	log review count	-0.558 (0.009)	supported
H5	log average spending	-0.186 (0.011)	not supported
H6b	log likes	-0.131 (0.005)	supported
H6a	log visits	0.112 (0.005)	not supported
H7	profile picture	0.002 (0.014)	not significant
H8a	log following	-0.072 (0.008)	supported
H8b	log follower	0.074 (0.01)	not supported
H8c	Log interaction	0.158 (0.008)	not supported
H9a	log taste	1.222 (0.051)	supported
H9b	log environment	0.71 (0.046)	supported
H9c	log service	0.112 (0.042)	supported

R square: 0.223

Longer reviews are less likely to be filtered. Consistent with our assumption about reviews, longer reviews always come up with more details and more seemingly real experiences, and these reviews are naturally less likely to be filtered.

When users have more pictures uploaded with their reviews, their reviews are more likely to be filtered.

Reviews by a user with more review counts are less likely to be filtered. This finding fits our previous expectation for filtered reviews: fake reviews tend to be done by a "one-time" anonymous account with few reviews.

If a restaurant is more expensive (in Table 1, it refers to higher average spending), its reviews are less likely to be filtered.

Previous studies of the hospitality industry proved that in a local market, online word of mouth can bring market transparency and thus affect a business's behaviors (Neirotti, Raguseo, & Paolucci, 2016). Premium restaurants with higher spending have more visibility on review websites, which results in more transparency than for cheaper restaurants. That is, customers know more about what services or products are offered in such restaurants, how much

the prices are, and when and where they can be served. The market transparency effect may be why there is comparatively less review fraud by expensive restaurants, in that their potential customers are more sensitive and well aware of the restaurants. Fraudulent behaviors as such would hurt the restaurant's reputation much more than the short-term sales increase would ever make up for.

When a user has more "likes", their reviews are less filtered; however, when a user has more "visits", their reviews are more filtered, perhaps because of the different features of these two functions. On Dianping, a user who puts a restaurant in his "likes" folder can could look it up conveniently. Also, if a restaurant launched new dishes, users could also get the information immediately from their "likes" folder. Therefore, although the "likes" folder doesn't mean a real visit to the restaurants, it can show the user's strong intention to visit. This is why we conclude that "likes" are closely related to visiting intention and further influenced the authenticity of reviews. Concerning the "likes" folder and further visiting intention, we will explain more in Section 7: Likes and actual visiting intention.

However, the "visits" folder in Dianping doesn't represents real visits. Like the Facebook "visits" tag, it simply means that the user has come nearby and may not have really visited the restaurant.

Users with more followers did more fake reviews, whereas users who follow more people don't. Previous research studied the incentives and determinants of consumer engagement in electronic word of mouth (Chu & Kim, 2011; Reimer & Benkenstein, 2016a) and found that helping incentives and donation incentives are part of the reasons to engage in electronic word of mouth and can strengthen a reviewer's altruistic motivation. Also, SNS users who focus on the information content of the eWOM tend to be more information-seeking. They desire to obtain useful information from knowledgeable contacts when searching for an item, and such information can increase a user's SNS engagement as well.

There are also several studies focused on SNS community opinion leaders and expertise reviews. Wu and Yang (2010) indicate that online community opinion leaders can be divided into three classes: the top class is the chief opinion leader, nest is the opinion leader inside a community, and the third class is the opinion leader in one topic. In terms of our dataset, users with many followers can be considered to be the second class of opinion leaders. They are usually influential figures who have excellent knowledge in a forum, and "they probably also have relatively rich social ties about a particular topic" (Wu & Yang, 2010).

Reviews by website expert users, or, in other words, website opinion leaders, have both better visibility (according to the Dianping website, these reviews tend to be ranked higher than others and thus have much more exposure than general reviews) and more influence. Also, a positive review by a website expert user is more influential than a review by a peer reviewer; it increases others' buying intention, according to Plotkina and Munzel (2016), who also compared different products and got the same results: an expert's positive reviews strengthen consumer's purchase intention.

Given the previous studies, it is reasonable for us to speculate that powerful users intend to cooperate with businesses and post unreal reviews for them. In order to confirm our speculations, we searched the historical fraudulent issues on Dianping forum, and the results are consistent with our speculation above. On September 24th, 2015, the Dianping website launched a new function and posted the news on its forum. According to the news, Dianping's new function was called "VIP cancellation". It concentrates on VIP users and calculates their fraudulent behaviors for three months. As soon as they are caught posting improper reviews, their VIP identities will be canceled directly by the website. The improper reviews refer to a business's related person's reviews (such as the business owner's relatives or employees' reviews), monetary incentivized reviews (e.g., a business offers a discount or free gift to those VIP users in exchange for their reviews), and other reviews that obviously show economic incentives. According to this news, 397 VIPs were cancelled by the website.

Other evidence comes from the Chinese biggest online shopping mall: Taobao. If we type "Dianping, favorable reviews" in Taobao, there are numerous links saying that they can help the business manipulate negative valence reviews and do positive VIP reviews instead. According to the website sales data, these services are quite popular. Based on such evidence, we conclude that powerful users who have many followers post more fake reviews than peer reviewers do.

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If a user interacts more with other users, such as leaving comments under other reviews, or gives "likes" to other reviews, these users' reviews seem more likely to be fake.

Taste, environment, and service scores given by reviews are observed to have a positive relationship with filtered reviews, which means that when these three categories' scores increase, the filtered probabilities increase as well.

LIKES AND ACTUAL VISIT INTENTION

In the previous analysis we offered a glimpse of what could be related to review fraud. From the results above, we found out that if a user has more "Likes", his reviews are less filtered, but when a user has more "Visits", his reviews are more filtered. These findings are not consistent with our common-sense concept of fraud, in that people tend to believe that "Visits" are more related to actual visits and that those reviews are definitely more reliable. However, our research shows completely opposite results.

Can we infer that "visits" don't have to mean actual visits, but if a user keeps more restaurant in the "Likes" folder, this user might have a strong intention to visit the restaurant and finally make the visit?

The above assumption aroused our interest in the user's actual visits. As we know, there are millions of reviews on such websites, and it would be almost impossible for a single user to tell whether a review was based on real experience at the restaurant or was just a made-up review from a random account. From our previous findings, we assumed that "likes" are more related to a user's actual visit. In order to confirm this finding, we collected subdata in Shanghai.

At the end of 2013, Dazhongdianping launched its online reservation service. By offering the reservation service, Dianping provided users with much convenience when they dine out. This service is widely used at the peak time of dining out (usually between 7 and 11 pm). People are able to choose the date and time they want, how many people are going, and whether they prefer a private room or not. Simply by clicking several buttons, the reservation could be made successfully. Although the online reservation service still has several problems, for instance, the cost of no-shows and dissemination of the service. Also, if the business already has their own online reservation system, the new online reservation system may have problems merging with the existing offline system as well.

Despite the current problems of online reservations, it still provided convenience to users for booking a table. The reservation service is especially popular in large cities, such as Beijing, Shanghai and Shenzhen. Based on the popularity of the reservation service, we collected 20 restaurants' reviews in Shanghai, 8552 reviews in total. Those restaurants all have a reservation service, and their accumulated times of reservation are shown on the webpage.

We first collected all the published reviews and the reviewers' profiles. For every review, we have variables consistent with Table 1. On the basis of those variables, we collected the restaurants; accumulated reservation times, and then we divided the total reservation times by their total operation periods (in months) to get their average reservations per month. After that we divided each user's "likes" by his "review count" and got the percentage, hereinafter referred to as "Likes Percentage". Based on "Likes Percentage", we separated all the reviews into two groups: one group with a greater "Likes Percentage"; the other group is the opposite. Here for the convenience of readers, we name the two groups as "More-likes" and "Less-likes" groups. By doing a *t*-test, we got the results below:

Table 3. Comparison of "More-likes" and "Less-likes"

	Mean	Std. Err.	Partial SS	MS	Prob>F
More-likes	107.421	1.563641	27836.862	27836.862	0.0063
Less-likes	102.8698	0.7273178			

From Table 3, we could clearly tell that the two group's means and variances are significantly different. The More-likes group obviously has more reservation than less likes group.

As we all know, business review sites are basically used by customers who would like to do some research when choosing a restaurant. Based on this most common usage of the websites, it is reasonable for us to say that the

reservation difference is affected by "Likes". Although the online reservation may have a cancellation or no-show problem, it still represents a strong visiting intention of the users. From this perspective, we confirmed our previous findings of "Likes": "Likes" actually lead to user's visiting intention; and with more actual visits, the authenticity of reviews increased.

CONCLUSION

Business review sites provide people with mass information but also require them to have the ability to analyze the authenticity of the information. Given a perfect filtering algorithm, WOM can be extremely helpful to users. However, currently the algorithm still needs to be improved, and it is necessary to help website users keep clear of these fake reviews.

Our research studied the incentives of business review fraud and found that Chinese businesses focus on favorable review fraud more than on unfavorable review fraud, whereas US business owners may commit both favorable review fraud (to themselves) or carry on unfavorable reviews (to their competitors), Chinese business owners have more motivation to improve their own star ratings, probably because of the intentions of the website users. Chinese users are more affected by these positive kinds of reviews and have more trust in the website. This is why business can gain more by posting favorable reviews for themselves. As Anderson and Magruder (2012) revealed, when a restaurant has half a star more than before, its sell-out rate takes a significant jump. Chinese business owners also obviously benefited from the favorable review fraud. Those direct benefits include an increase in reservations and in customers attracted by the high star ratings of the restaurant. Indirect benefits can also happen in an unobservable way, such as more potential customers in the future and a good reputation among website users. US businesses, in the other hand, commit both favorable fraud and unfavorable fraud because of competition and reputation problems (Luca & Zervas, 2016).

Another finding of ours is that finer restaurants do less review fraud. This finding aroused our thinking on how reputation and profits drive a restaurant to commit fraud. Basically, if a restaurant wants to achieve higher profits than before, it may consider attracting more newcomers, keeping the existing customers, and lowering its costs, while gaining more revenue. A higher star rating is the easiest way for restaurants to attract newcomers; however, it may not be as effective for keeping the existing customers or gaining more revenue. Finer restaurants, unlike general restaurants, focus more on their brand image and reputation. These restaurants tend to devote more effort on how to retain regular customers than on attracting newcomers. Finer restaurants always have an established image and reputation. Committing review fraud, on the one hand, can hurt their brand image and further affect the sales in the long term; on the other hand, good reviews may not be as effective when attracting newcomers to a finer restaurant.

We have also carried out research on fraud and user's activeness. A review website is not only a place to share product information, but also a social network between people. Websites developed various functions, such as writing comments to other users, following other users, liking a restaurant (for possible visit), and tagging a restaurant when visiting. These functions largely improve user's activeness, attracting more users as well as improving the authenticity of reviews. With all the benefits of a social network, the functions provided can also cause fraud problems to some extent. According to our research, a user's activeness can be reflected by several parameters, such as likes, visits, following, followers, and interaction. These functions differ from one another, and they affect the reliability of reviews in various ways. Among the social network functions, "likes" and "following" affect the reviews' authenticity in a positive way. "Likes" indicates the visiting intention of a user, but "following" indicates the user's interest in other users. This finding can help a business improve its customer management. Rather than diligently improving star ratings or posting fake reviews for themselves, restaurant need to pay more attention to customers who "Like" them and try to increase the number of "likes".

For web users of those review websites, our findings can be helpful with the awareness of review fraud. With the generalization of such review websites, website users became much more aware of fraud than before. Although a wise consumer can understand the existence of review manipulation, they can only partially correct for the manipulation based on the overall manipulation level (Hu et al. 2011). There is still far more fraudulence that needs to arouse consumers' realization. Despite the general star ratings provided by the websites, more important information is provided to users: taste, environment, and service. Such detailed information is where Dazhongdianping differs from other websites—it gives out numerical information to web users that is not always shown on other websites. The three

scores about taste, environment and service may not be as reliable as they seem to be. Accordance to our findings, taste, environment, and service parameters were negatively related to the filtered probability, indicating that fake reviewers not only commit fraud on the general star ratings but also give incredibly high scores to a restaurant's taste, environment, and service. Our studies revealed where the fraud happens on such business websites and can effective alert users to the review fraud.

Another aspect of fraud awareness arises from our findings on fraud and social networks. Users tend to believe in those so-called "VIP" users who have more followers. Those VIP users seem quite professional when making reviews, and their reviews can easily arouse interest and get others' trust. However, can we always trust their review? Our research finds that a "VIP" user with a large number of follower may post more fake reviews than expected. Therefore, we broke the common sense of users review evaluations, to give them another perspective to inspect those VIP's reviews. These findings may help web users greatly improve their awareness of fraud and may indirectly help them to make wiser choices.

AUTHOR'S NOTE

This work was revised from the Master's thesis of Wei Li.

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