Characterizing Social Marketing Behavior of E-commerce Celebrities and Predicting Their Value

Xiang Li, Yuchun Guo, Ye Sheng, Yishuai Chen
School of Electronic and Information Engineering
Beijing Jiaotong University
Beijing, China
{18120100, ychguo, 16120116, yschen}@bjtu.edu.cn

***Abstract*—With the rapid development of online social networks, marketing through online social platforms attracts a lot of attention. Recently, a special social marketing method is prevailing, i.e., e-commerce celebrities(ECs). ECs run their social network accounts to attract followers and then sell products to them directly. While the sales of ECs have dominated the e-commerce marketing in China, there is, however, a lack of accurate measurement and model about it. In this paper, we first conduct a large-scale cross-platform measurement on two of the biggest online social network platforms and e-commerce platforms in China, i.e., Sina Weibo and Taobao. We then characterize the typical behavioral patterns of ECs and build a machine learning model to quantitatively represent the relationship between the social network behavior and their product sale volumes. Experimental results show that we can accurately predict an EC's sale volume based on the 41 social network behavior features (F1 score can reach 0.83). Furthermore, we obtain the top-10 most important features that affect the sales. Our measurement and modeling results provide beneficial insights in understanding and optimizing social marketing for ECs.**

***Index Terms*—social media, e-commerce celebrity, behavior analysis, prediction, machine learning**

I. Introduction

Various aspects of consumer behavior [1]–[3] have witnessed great changes due to the rapid development of social network and e-commerce, and the consumption habit has changed from offline to online [4]. Naturally, there are e-commerce celebrities (ECs) who use e-commerce platforms for business activities, and online social platforms for marketing activities.

There is, however, a lack of accurate measurement and model of ECs, in particular, the relationship between the social network behavior and e-commerce performance, i.e., sale volumes. Existing work usually studied it as a business case [5] and conducted qualitative analysis [6], lacking an accurate quantitative analysis.

The measurement and modeling are valuable. For instance, brokerage companies want such a model to guide and cultivate their ECs to achieve sustained success. In particular, after finding the key features that affect sales, ECs can optimize their actions accordingly to improve their social marketing behavior.

The challenge of building an accurate model is that we have to make cross-platform measurements. Specifically, EC's social network behavior is on one online social network platform, while the sales behavior on another e-commerce platform. Since user data between two independent platforms is generally not shared, it is difficult to link the data in two platforms and find the relationship between ECs' social network behavior and business performance. So, combining with CBNData[1] reports and some online shop evaluation bloggers, we choose some representative ECs and then obtain the data through the crawler for data linking.

We then characterize the typical behavioral patterns of ECs on the two platforms and build a model to quantitatively represent the relationship between the social network behavior and the sale volumes. Our contributions are as follows.

- We extract 41 features from ECs' marketing and non-marketing behaviors on the social platform and find the top-10 features which have the greatest impact on the sales. For instance, we find that "Buyer Shows", which is an interesting interaction with the followers, is of greater significance than the number of followers.
- We build a suite of machine learning models to predict the sales on Taobao. Experimental results show that we can accurately predict a EC's sale volume based on the 41 social network behavioral features (F1 score can reach 0.83).

To the best of our knowledge, this work presents the first measurement and modeling study of ECs, in particular, the relationship between behaviors on social platforms and sales on e-commerce platforms. Our measurement and modeling results provide beneficial insights in understanding and optimizing social marketing for ECs.

The rest of this paper is organized as follows. After an overview of the related work in Section II, we briefly describe the dataset used in our analysis in Section III. Then we analyze the behavior of ECs and construct features in

This work was supported in part by the National Science Foundation of China under Grant No.61572071 and No.61872031.

Yuchun Guo is the corresponding author.

[1] https://www.cbndata.com/report

Section IV. And with these features we predict the sales level on Taobao in Section V. At last, we draw a conclusion in Section VI.

II. Related Work

Evans [7] proposed a core marketing theory that social media effectively connects enterprises and consumers. Previous studies have shown that in social media marketing activities, marketers can post or repost promotional messages, provide suggestions, and make personal comments through social media accounts to gain recognition, thereby affecting followers' interests [5], [8]–[10]. Some papers explored the relationship between brands and social media marketing. Surveys such as that conducted by Ashley and Tuten [11] have shown that different levels of consumer engagement in social media channels depend on consumer needs, motives, goals, and consumer interpersonal relationships with brands. Sweet, Taylor, Austin and Xuan [12] used machine learning techniques for brand-influencer matching to help different brands find the right influencer to balance advertising spending and return.

Word-of-mouth marketing is a classic marketing strategy. The rapidly growing consumers on social networks have transformed traditional company-driven advertising into a consumer-driven world [13]. Previous works on word-of-mouth marketing helped marketers estimate the tangible impact of word-of-mouth on brand equity and sales [9]. According to [14], users who act as both marketers and consumers have a strong marketing effect on word-of-mouth marketing. Similarly, we also carefully analyzed the word-of-mouth marketing behavior of ECs and extracted the corresponding features.

Much of the current literature pays particular attention to extracting multiple features from social media for downstream tasks. Reza, Angel, and Noël [15] presented a large-scale measurement-based characterization of cross-posting activity for professional users across Facebook, Twitter, and Google+. Similarly, feature engineering techniques were presented to help influencer marketing specialists to better represent their data for recommendations, outline influencer detection and brand recognition [16]. Classification methods are often used to distinguish users. For example, k-means was used to divide users on YouTube into five classes with 9 features in [17]. In addition, researchers in [18] used the behavior, geography, and social network size of different users on Twitter to divide users into three classes.

However, only a few features were used in these researches, and the long-term returns of the business could not be fully predicted. As a comparison, we analyze the behavior of ECs different from ordinary users and extract features of marketing and nonmarketing behaviors to predict their sales level on Taobao.

III. Measurements

In this section, we introduce ECs' social media data set and its related sales data and then analyze the basic statistics of these data.

As the largest online social network platform in China, the active e-commerce microblogs on Weibo are representative. In addition, Taobao is the largest e-commerce platform in China. So, we choose ECs who conduct marketing activities on Weibo and sales activities on Taobao as our research object. The data is highly representative.

Combining with the CBNData data report, some online shop evaluation bloggers and online shopping rights protection sites, we finally selected 108 eligible ECs as shown in Appendix A. Although the selected data cannot cover all ECs, there is high representativeness and reference value. Then we crawl their basic personal information, microblogs on Weibo and sales on Taobao. We finally obtain 449,489 EC microblog data on Weibo from 2010 to 2018, sale data on Taobao in April 2018, and the basic information data of 46,470 Weibo users liked and reposted by ECs.

TABLE I shows the statistics of microblogs, sales, followers of ECs, and followers of original authors reposted or liked by ECs. The data set includes ECs of different sizes and the large standard deviation of the data indicates that the data has a high degree of discrimination and meets the expected requirements.

TABLE I
The Statistics of E-commerce Celebrities

	Microblogs	Sales (¥)	Followers $/_{EC}$	Followers $/_{original\ authors}$
Mean	4162	43118	160623	421804
Std	2791	76131	1614619	3299073
Min	353	143	11725	0
25%	2173	4170	518297	302
50%	4034	10801	1004896	999
75%	5509	33722	2107624	8735
Max	13758	326284	6738735	210023472

IV. Behavior Analysis

Existing researches only used limited features to analyze the behavior of ECs [12], [15]–[17], [19], [20]. These features do not highlight the behavioral difference between ECs and general users. In this section, we divide the social behavior of ECs into marketing behaviors and nonmarketing behaviors, and build several behavioral features.

A. Marketing Behavior

ECs carry on the marketing with the microblogs. They use original or reposted microblogs to arouse followers' interest in products, thus turning followers into consumers. TABLE II gives examples of marketing microblogs. After reading these microblogs, we find that there are three kinds of marketing behaviors: new product behavior, lottery behavior and word-of-mouth behavior. TABLE III gives the statistics of these behaviors.

TABLE II
SAMPLES OF MICROBLOGS

Content	Translation
12.12 我来啦！ 这个月很多高级的东东, 我的女王殿下们。 转抽 3 个 BB 送， 喜欢哪款大声告诉我， 都是高级货抽中了好划算啊 ...	12.12 here I come! There are many awesome goods this month, my queen. I will pick 3 babies from those who repost this microblog for a gift, and tell me aloud which one you like best. It's a good deal because it is a premium product...
留言送出一整套 look！ 这次新品里我超愛的一個 牛仔背心很酷, 很街頭俏皮的短裙 也可以混搭的很有型, 穿上那一刻覺得自己 ... 又帥了!	I will choose one person from the those who comment this microblog ant send out a set of the clothes! A cowboy vest I love in this new products is cool, and the street-playful skirts can also be matched. The moment I put on the clothes, I felt... handsome again!

TABLE III
THE STATISTICS OF DIFFERENT BEHAVIOR

	New product	Repost -ing lottery	Comment -ing lottery	Giving-a -like lottery	Buyer show
Mean	7.72%	3.47%	1.71%	1.37%	76.36%
Std	5.42%	3.07%	2.38%	1.55%	17.41%
Min	0.31%	0.00%	0.00%	0.00%	28.57%
25%	4.57%	1.47%	0.18%	0.19%	63.62%
50%	6.65%	2.59%	0.81%	0.78%	80.21%
75%	10.49%	4.78%	2.26%	2.26%	90.60%
Max	36.04%	16.65%	12.54%	6.03%	98.21%

1) New Product Behavior: New product behavior refers to the promotional activities carried out before the release of new products. Before launching a new product, ECs will promote their products through microblogs to attract followers. We find that new product behavior is cyclical, with a period of about 28 days, which may be determined by the supply chain capabilities. We construct four features and calculate their Pearson correlation coefficient with sales level on Taobao as shown in TABLE IV. It can be seen that the average number of reposted microblogs per month has a strong correlation, which indicates that the release of new products contributes to sales.

2) Lottery Behabior: There are three kinds of lottery behaviors: reposting lottery, giving-a-like lottery and commenting lottery, i.e., prize draws according to the corresponding behavior. Examples are given in TABLE II. ECs use the lottery activities to attract users to read, comment, giving likes and repost microblogs for secondary diffusion. Accordingly, we construct three features from the lottery behavior as shown in TABLE V, from which we can see that reposting lottery has the highest correlation with sales. At the same time, from TABLE III, we find that ECs prefer reposting lottery. One possible explanation is that reposting will make reposters' followers reach these microblogs and achieve better advertising results.

TABLE IV
FEATURES OF NEW PRODUCT BEHAVIOR

Features	Pearson correlation coefficient
#New product posts/$_{month}$	0.268
#Reposts/$_{new\ product\ blog}$	0.301
#Comments/$_{new\ product\ blog}$	0.092
#Likes/$_{new\ product\ blog}$	0.187

3) Word-of-mouth Behavior: As a major part of online consumer interactions [21], word-of-mouth marketing is a kind of preferential reposting and giving-a-like behavior. ECs usually repost and give likes to the "Buyer Show" microblogs to interact with the followers. "Buyer Shows" refer to the feedback microblogs posted by consumers. ECs will select the high-quality "Buyer Shows" for word-of-mouth marketing to expand the number of followers and further increase the stickiness of existing followers.

As shown in TABLE I, most of the original authors have a small number of followers, but a few authors have even more than 100 million followers. Through observation, we find that the authors with a large number of followers are opinion leaders(OLs) in some fields. ECs sometimes give likes to or repost OLs' microblogs to enhance their influence. Based on the different identities of the reposted or liked followers, we find that ECs tend to repost or give likes to those with a smaller number of followers than themselves. This tendency is quite different from that of ordinary users. ECs tend to spread the "Buyer Show" microblogs for secondary advertising, which is a classic word-of-mouth marketing strategy. Therefore, we can infer that users with a small number of followers may bring ECs more commercial benefits.

As shown in TABLE III, the proportion of "Buyer Show" is much larger than others, which shows that word-of-mouth marketing is the main marketing method for ECs. Because it is a simple and, in particular, free way to interact with consumers that can satisfy the vanity of consumers to increase their stickiness. Most importantly, it is an effective way to attract strangers.

TABLE V
FEATURES OF LOTTERY BEHAVIOR

Features	Pearson correlation coefficients
#Reposting lottery/$_{month}$	0.416
#Commenting lottery/$_{month}$	0.045
#Giving-a-like lottery/$_{month}$	0.012

We summarize five attributes from ordinary users who have been reposted or liked by ECs, respectively:

- #Followers: The number of followers
- #Follows: The number of follows
- #Posts: The number of posts
- #Interaction: The number that a user is liked or reposted by an EC
- #Overlap: The number of ECs who have interacted with the user

We divide these attributes into different levels and the details are shown in TABLE VI. It can be seen from the Pearson correlation coefficient that the higher the level of interaction, the greater its contribution to the sales, which shows that effective interaction between ECs and followers is very valuable.

TABLE VI
LEVELS OF ATTRIBUTES OF USERS WHO HAVE BEEN REPOSTED OR LIKED BY ECS

Level	Number(n)	Pearson correlation coefficient
Followers-lv1	$[0, 10^4)$	0.116
Followers-lv2	$[10^4, 10^5)$	0.346
Followers-lv3	$[10^5, 5 \times 10^5)$	0.358
Followers-lv4	$[5 \times 10^5, 10^6)$	0.172
Followers-lv5	$[10^6, +\infty)$	0.187
Follows-lv1	$[0, 10^2)$	0.174
Follows-lv2	$[10^2, 5 \times 10^2)$	0.172
Follows-lv3	$[5 \times 10^2, 10^3)$	0.294
Follows-lv4	$[10^3, +\infty)$	0.185
Posts-lv1	$[0, 10^2)$	0.152
Posts-lv2	$[10^2, 10^3)$	0.188
Posts-lv3	$[10^3, 5 \times 10^3)$	0.136
Posts-lv4	$[5 \times 10^3, +\infty)$	0.159
Interaction-lv1	1	0.198
Interaction-lv2	2	0.036
Interaction-lv3	3	0.020
Interaction-lv4	4	0.322
Interaction-lv5	$[5, +\infty)$	0.304
Overlap-lv1	1	-0.125
Overlap-lv2	$[1, 10)$	0.276
Overlap-lv3	$[10, 30)$	0.013
Overlap-lv4	$[30, 50)$	-0.025
Overlap-lv5	$[50, +\infty)$	-0.085

And we also construct some other features for each EC as shown in TABLE VII. The first three features reflect the ability of microblogs to spread, that is, the propaganda function that ordinary users can bring to ECs. The latter two features reflect the tendency of ECs to repost and like.

B. Nonmarketing Behavior

1) Daily Behavior: According to the idea of building features of marketing behaviors, we construct four features from the daily behavior, i.e., personal behaviors similar to normal users.

2) Personal Information: We select the number of followers and follows as the personal information features.

TABLE VII
FEATURES OF MARKETING BEHAVIOR

Features	Pearson correlation coefficient
$\#\text{Reposts}/_{marketing\ blog}$	0.121
$\#\text{Comments}/_{marketing\ blog}$	0.308
$\#\text{Likes}/_{marketing\ blog}$	0.184
$\#\text{Reposts}/_{month}$	0.442
$\#\text{Giving likes}/_{month}$	0.294

Features of nonmarketing behaviors are shown in TABLE VIII. It can be seen that the number of followers has the highest correlation with the sales, but subsequent experiments show that effective interaction with followers is more important.

TABLE VIII
FEATURES OF NONMARKETING BEHAVIOR

Features	Pearson correlation coefficient
$\#\text{Daily posts}/_{month}$	0.212
$\#\text{Reposts}/_{daily\ blog}$	0.228
$\#\text{Comments}/_{daily\ blog}$	-0.026
$\#\text{Likes}/_{daily\ blog}$	0.304
$\#\text{Followers}/_{EC}$	0.507
$\#\text{Follows}/_{EC}$	0.118

V. PREDICTION

In this section, we first introduce the experimental settings and then use three classifiers to predict the sales level on Taobao.

A. Experimental Setup

Firstly, we define the sales level. We use k-means to analyze the distribution of ECs. As shown in Fig. 1, we can divide the distribution of EC sales into three levels according to the SSE curve, and the dividing conditions are shown in TABLE IX. The e-commerce performance are divided into "high sales", "medium sales" and "low sales" according to the sales volume. So, predicting sales through social data turns to a three-class classification problem. Then, different features are sent to the classifiers to predict the sales level. The data includes 31 "low sales", 59 "medium sales" and 18 "high sales". The ratio of training set to test set is set to 6:4.

TABLE IX
THE CLASSIFICATION OF E-COMMERCE CELEBRITIES

Types	Partition Conditions
High	$sales > (mean + \frac{1}{2}std)$
Medium	$(mean - \frac{1}{2}std) < sales \leq (mean + \frac{1}{2}std)$
Low	$sales \leq (mean - \frac{1}{2}std)$

B. Classifiers and Performance

We use Random Forest, Logistic Regression and k-Nearest Neighbor to predict the sales. The experiment in this paper is carried out by Scikit-Learn[2], which is divided into the following five comparative experiments.

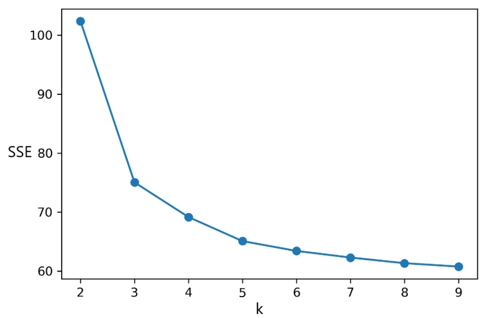

Fig. 1. The influence of k on SSE(within-cluster sum of squared errors)

- Full-time Nonmarketing Behavior Model(FNBM)
  We use daily behavior features and basic personal information features to train classification model, and explore the impact of nonmarketing behavior features on the sales level.
- Full-time Marketing Behavior Model (FMBM)
  We use marketing behavior features to train classification model, and explore the impact of marketing behavior features on the sales level.
- Full-time Full-feature Model (FFM)
  In this model, all types of features are used to predict the sales level.
- Full-feature Model in the past three years (FM3)
  All features corresponding to the data from the past three years are fed into the model.
- Full-feature Model in the last year (FM1)
  All features corresponding to the data from the past year are fed into the model.

As shown in TABLE X, there is no significant difference between strong and weak classifiers when only using nonmarketing or marketing behavior features. The performance of the full-feature model is much better than that of only using marketing or nonmarketing behavior features, and the F1 score of the full-time data can reach 0.77. It shows that the marketing behavior features, daily behavior features, and personal information features complement each other. The full-feature model of the past-three year and the last year are better than full-time, and the model using the data in the last year has the best result of 0.83, which indicates that the sales is time-sensitive, and using newer data can achieve better prediction performance than accumulated data.

[2]https://scikit-learn.org/

TABLE X
The Macro-F1 Score of Different Models

	FNBM	FMBN	FFM	FM3	FM1
LR	0.53	0.59	0.64	0.65	0.68
kNN	0.61	0.61	0.69	0.74	0.78
RF	0.61	0.60	0.77	0.81	**0.83**

C. Discussion

By RF, we rank the top-10 most important features as shown in TABLE XI. The sum of the importance of these 10 features accounts for about 50%.

From the table, we can find that high interaction levels have the strongest impact on sales. A possible explanation for this result may be that high interaction means more “Buyer Shows”, in other words, more consumption. In word-of-mouth behavior, the repost-based approach has the greatest impact on sales because reposting makes the microblogs' content visible to reposters' followers, thereby increasing the reach of the blog. From Overlap-lv3 and Followers-lv2 we can infer that users with medium overlap and followers scale are more likely to generate mutually beneficial business practices with ECs. After screening the data, we find that most of the users with high overlap and followers are OLs or content-based media accounts. It is normal for them to have a high overlap and followers, so reposting or giving likes to their microblogs contributes little to the sales. Not surprisingly, posting more new product microblogs contributes to sales, as new products always increase users' willingsness to purchase.

For the nonmarketing behavior, the fourth feature, #Likes/$_{daily\ blos}$, shows that followers' behaviors of giving likes to daily microblogs have a lot to do with whether they buy the products. This may be explained by the fact that the giving-a-like interaction is simpler, without any pop-ups and page jumps, which makes it a favor for followers to support ECs. It is worth noting that the Pearson correlation between #Followers/$_{EC}$ and the sales level in TABLE VIII is the highest of all the features. But #Followers/$_{EC}$ is only ranked third because of the cheating component of “Zombie” accounts in the followers. Therefore, the ability to use social platforms to interact with active followers is critical to EC success.

VI. Conclusion

In this paper, we present the first cross-platform measurement of the relationship between behaviors on the social network platform and sales level on the e-commerce platform. First, we extract multiple features from Weibo to predict the sales level on Taobao. Specifically, the Weibo data is characterized into 41 features, including marketing features and nonmarketing features. Then k-means is used to divide the sales into three levels. Finally, the RF is used to extract the top-10 features, and discussions on these features can help ECs optimize their marketing strategies.

TABLE XI

THE TOP-10 IMPORTANT FEATURES

Rank	Features	Importance
1	Interaction-lv5	6.43%
2	#Reposts/$_{marketing\ blog}$	6.29%
3	#Followers/$_{EC}$	5.87%
4	#Likes/$_{daily\ blos}$	5.81%
5	Interaction-lv4	4.65%
6	Overlap-lv3	4.39%
7	Followers-lv2	4.21%
8	#New product posts/$_{month}$	3.97%
9	#Comments/$_{marketing\ blog}$	3.72%
10	#Reposting lottery/$_{month}$	3.51%

The most important limitation is the size of our data. In addition, ECs now execute marketing strategies through various platforms, so there are potential features we have not extracted. Future work needs to scale up the data and present measurements from multiple types of platforms.

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APPENDIX A

TABLE XII

THE LIST OF ECS

ALU_U	DALU 大璐	Z_ 子晴
腻总 ninitalk	Lin 张林超	DDshadow
阿花花酱	朴瑟 seul	AM___FASHION
delicious 大金	白涩涩的茉莉	十元诗苑
MALInv	D-nana	蔡珍妮
时髦人绵羊 er	Tikilee	DoraPE
茶茶ヾ	孙嘉一 Zoe	yeswomen 小宜
Dreamy_ 梦梦	超级蓝大大	唐颖 Connie
ZY 喜哥	FAIRY_WANG	陈小末
滕雨佳 Amiu	阿希哥 VCRUAN	FEERIQUE 梵莉可
大兔子 PINZIKO	王火锅是火锅王	狼宝-LangBoom
FengFan_x	大喜庆	王幼宣幼乖
林珊珊 _Sunny	fishdo	大小姐 77
魏妮妮 Yanni	卢洁云	Hera 是你的苗哥
大旭呀大旭	我是 miss 阮阮	美美 de 夏夏啊
Isabella 陈子仙	管阿姨	小饭噶
呛口小辣椒	JIN_ 阿金	龟酱 turtle
心蓝 grace	小刘小粒赵大喜	Lisa 兔牙
韩雨嘉 Yoga	凶猛熊猫 87911	小怡吖小怡
LOVE-小银子	郝静 sevi	许雯 May
雪梨 Cherie	MINI 猪七七	狠赵狠蛇蛇
杨泡泡 _quan	于 momo 小饺子	MOSSMOSSMOSS
花花 ONGAHONG	杨小卷 _NatureQ	张大奕 eve
Mr 九九 _s	花花-Yumi	余人三日
13c13c	NanaStore 微博	加比 Gaby
造型师邹邹	onlyanna	oopsLUNA
金蘑菇菇	张思佳-SISI	_aaayuko
Saya 一	李雨桐 Luyee	张予曦
13_macy	SecretChan 陳嫣	林糊糊
张雨乔 Babijisa	A-bowlife	seina 施依娜
林小宅-	张智研	Alice 赵静
SHIWEILIANG	刘钰懿-Shirleylau	张佐佐 997
ashui-AS	UVN 许微娜	卖皮草的 CC
长胖了的 AVIVA	Ciny 心霓儿	VIMAS-小维
南表妹	赵若语 _Crystal	周小熊大人
周扬青	左岸潇	左娇娇 Rosemary