Social Media Influencers' Advertisement in Social Networks and Effect on Cloth Shop in China

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December 2, 2022

1 Introduction

The social media influencers (abbreviated as SMI) have a rising commercial effect in China [1]. The social media influencers share their lives on social media and have a tremendous number of followers who admire their elegant lifestyle and personalities. Served as an "expert" in the specific field, for example fashion, food, cosmetics, these social media influencers would share products they used in the field. Different from the advertisements of celebrities on television, social media influencers have a sense of intimacy to common people and their comments about one product present a feeling of authenticity. Their followers will easily become the potential purchasers of their recommended products. Another advantage is the low cost and spreadability of social media. Because of these advantages of working with social media influencers, cooperating with the social media influencers to facilitate sales becomes a popular choice among companies and retailers in China. In this project, I am going to build a dynamic model to simulate the market of a product and investigate the influence of social media influencers on one product. By building this model, I could answer the questions that social media influencers work, by how much the social media influencer contributes to the sales and how different social media influencers perform in my model.

2 Background

E-commerce has become a popular trend and is changing people's lifestyle in China. It breaks the territory restrictions and offers bargains by providing people with various choices of the product. In 2021, the Chinese e-commerce sales reached about 2.64 trillion dollars and boosts up by 12 percent compared to last year [2].
The social media influencers, who regularly post their professional suggestions on social media in the form of pictures or videos, own a reputation in one specific field. Attracted by the content of these enthusiastic social media influencers' posts, people start to follow them. After entrenching their reputation and owning a relatively large number of followers, the social media influencers will have a chance to influence the followers' decisions and add commercial advertisements on products. These social media influencers not only benefit the large companies, but also attract the small retailers. Before social media influencers became

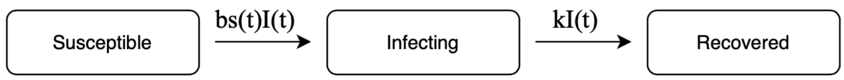
popular, the small retailers could only sell their products locally and promote interpersonally. The retailers cannot afford other kinds of high-cost advertisements, for example television advertisements. For these small-scale retailers, which include the in-season cloth stores, they are able to allow more people to know the existence of the brand and sell clothes online to people who are unable to physically present in the store.

3 SIR, SIS Models and Previous Researches

3.1 SIR Model in Epidemiology

The SIS model is a variation of the SIR model, which is derived for epidemiology to calculate the effect of infectious diseases. The SIR model is a mathematical model by William Ogilvy Kermack and A. G. McKendrick in 1927 [3]. In the context of the SIR model in epidemiology, S, I, and R represent the susceptible, infected, and recovered group respectively. The SIR model depicts the dynamic connection between S, I, and R using different change rates from one group moving into another group. In the SIR model, it describes the disease that once the person is infected, he or she will never be infected again in the future. People in a susceptible group might be infected by people in an infectious group and are able to infect other people in a specific time period. After that time period when they are unable to infect other susceptible people, these people in the infectious group will move to the recovered group.

Figure 1: SIR Model



The SIR model contains two parameters in total. In the model, b represents the average number of people each infected person contacts and infects if the person is able to be infected per unit time. Because per unit time, each infecting person will contact people proportionally based on the number of people in each group, namely S, I, and R, there will be $bs(t)$ number of people being contacted and infected by the infecting group. Thus, the rate of change from S to I will be $bs(t)I(t)$ per unit time. k is another parameter in the model, and it represents the average proportion of people who will lose the infect ability per unit time. Thus, the rate of change for I to R is $kI(t)$ per unit time. Based on these parameters, the differential equation for the SIR model is the following.

$$\begin{cases} \frac{dS}{dt} = -bs(t)I(t) \\ \frac{dI}{dt} = bs(t)I(t) - kI(t) \\ \frac{dR}{dt} = kI(t) \end{cases} \tag{1}$$

The SIR model makes sense in the case of epidemiology, but it does not make sense in the case of cloth products because it is highly likely for the customers to repurchase the product.

3.2 SIR Model in Market

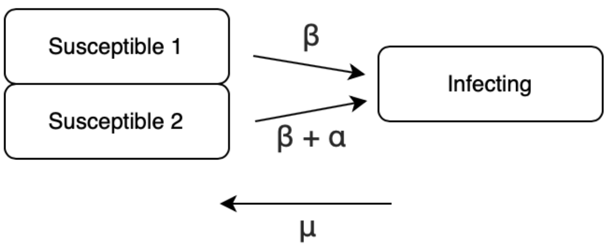
The previous research by Riktesh has investigated the blogging effect using SIR model. In specific, the Riktesh's research calculates the average number of customers who will purchase after reading the post [4]. In Riktesh's model, it also considers the situation that people who bought the product will infect other people to purchase. However, in the online sales, especially when the product only lasts for a short time, for example 15 days, such "infection" is negligible and hard to distinguish in real data. By removing the "infectious" property in my model, I change my model into SIS instead.

4 SIS Model in Cloth Market

In this project, I used the SIS model to simulate the dynamic market of a product in an online shop, which has one social influencer advertising it by having an advertisement in their blog. Similar to the SIR model, the SIS model also describes the dynamic change, but only depicts the change within a susceptible and infected group. The main difference is that in the setting of the SIS model, people who once had the disease could have the disease again, while they cannot in the SIR model. In the cloth market, it is possible for one person to repurchase the product if he or she likes this product, or the product is a necessity in their lives. Thus, it will be more suitable to use the SIS model to depict the market of a cloth product. Similar to the example in epidemiology that uses the status of the person's effectiveness to distinguish people into different groups, in my model, I used the desire to purchase the product to distinguish people into two groups.

I split the population N into two big groups, which are susceptible group S and infecting group I. People who have potential to purchase the product are considered to belong in the susceptible group, and people who have purchased the product and currently have no potential to repurchase the product are in the infecting group. I also divide the people in S into two groups exclusively to better examine the social media influencer's effects, according to whether or not the person is a fan of the social media influencer. In specific, people who are not fans of social media influencer are considered in S1, and people who are fans of social media influencer are considered in S2.

Figure 2: SIS Model in Cloth Market



This SIS model captures the change of people's purchasing motivation and purchase status. If one person never purchased the product before, he or she belongs

to the susceptible group S. For people in S1, they have potential to purchase the product, and the rate of those people changing into infecting group is β per unit time. For people in S2, they are fans of the social media influencer and rate for their transition is plus the social media influencer's effect $\alpha + \beta$ per unit time. Once you purchase the product, you make a transition from susceptible group S into infecting group I. You will stay in infecting group I until you generate a motivation to purchase the product again. And at that time, you will go back to the susceptible group S. The rate of infecting people going back to susceptible group is μ per unit time. The diagram of my model is presented in Figure 2.
Based on the rates of change described above, I derive the following differential equations to measure the dynamic change of each susceptible group and infecting group.

$$\begin{cases} \frac{dS_1}{dt} = -bS_1(t) + \mu s_1(t)I(t) \\ \frac{dS_2}{dt} = -(\alpha+\beta)S_2(t) + \mu s_2 I(t) \\ \frac{dI}{dt} = \beta S_1(t) + (\alpha+\beta)S_2(t) - \mu s_1(t)I(t) - \mu s_2(t)I(t) \end{cases} \tag{2}$$

In this model, we will assume that the total number of customers in the market is the same, namely, in the market for each product, the total number of customers remain the same though the number of S and I might change as time changes. We also assume that the people in S1 group will not see the social media influencer's post and not affected by the social media influencer. Another assumption is that when people in the infecting group regenerating the desire to repurchase the product, they will return to the S1 and S2 group proportionally based on the number of people in these two groups. For instance, if there are 1 person in S1 group, 2 people in S2 group, and 3 people going back from I to S, there will be 1 person return to S1 group and 2 people return to S2 group.

5 Dataset

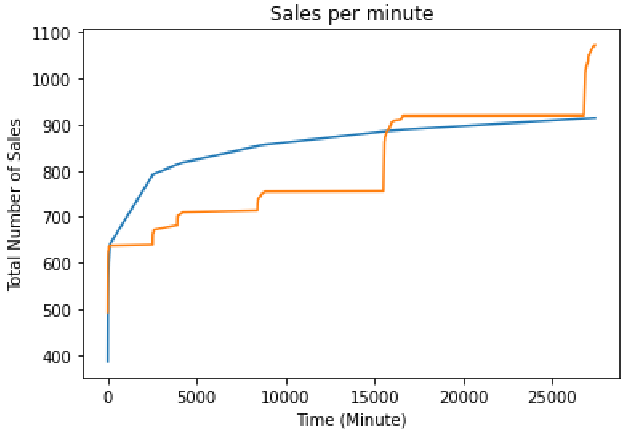
My dataset comes from a cloth store in China, and the dataset contains all the history orders of a coat. The dataset records the order time, payment time, and payment account. In total, there are 1073 orders for this product and the time duration is approximately 27404 minutes. Here is an overview of the dataset.

Figure 3: Overview of Dataset

	Order_no	Order_status	Order_time	Payment_time	Shipping_time	Size	Product_no	Product_id	SKU_id	Minute
0	819699396876564	待发货	2022-11-13 20:44:00	11/13/2022 20:45	NaN	桃木褐36号	1	5730170770	85770385839	27404.0
1	819699012788048	已发货	2022-11-13 20:43:00	11/13/2022 20:43	11/15/2022 19:06	狐狸灰36号	1	5730170770	85770539838	27403.0
2	819698748969658	已关闭	2022-11-13 20:03:00	NaN	NaN	桃木褐34号	1	5730170770	85770385837	27363.0
3	819698079600420	已发货	2022-11-13 18:54:00	11/13/2022 18:55	11/14/2022 13:07	狐狸灰36号	1	5730170770	85770539838	27294.0
4	819698112155428	已发货	2022-11-13 18:47:00	11/13/2022 18:48	11/14/2022 13:07	桃木褐34号	1	5730170770	85770385837	27287.0

For this product, almost half of the product is purchased when the product launches on the website, and in the remaining time the sale increases at a decreasing rate. Here is a graph of the sale trend.
The orange line represents the original sale trend, and the blue line represents the smoothed sale trend by fitting the data into logarithm function.
The original sale trend has some surges because of manually increasing in stock. There is only a limited number of products for the coat. When customers receive the product, and if the product does not fit or they dislike the product, they

Figure 4: Cumulative Sale Trend per Minute



will ask for a return. After noticing the return, the shop will increase the stock for the product, and thus result in a surge in sales. These surges are unnatural if we consider the stock will automatically decrease whenever there is a return. Thus, I used the smoothened trend, which is represented by the blue line, as the line that I will simulate in the model simulation part.

6 Parameter Simulation

Because all the parameters in the model are arbitrary, I instead use the model simulation to find the parameters. In specific, I wanted to find β, α, μ, S_1 at time 0 and S_2 at time 0. The best set of parameters should fit the smoothed cumulative purchases of the real data. So, I used the cumulative number of purchases as the parameters' key performance indicator because these cumulative number of purchases are my main focus on exanimating the effect of social media influencers.

In this simulation, I used python to solve the differential equations per unit time, and calculated the cumulative number of purchases. In specific, for per unit time, I timed the rate of change for each susceptible group by the corresponding rate of change. By summing all these values, I could retrieve the simulated cumulative number of purchases. Then, I compared the trend of the simulated cumulative purchase and the smoothed cumulative purchase.

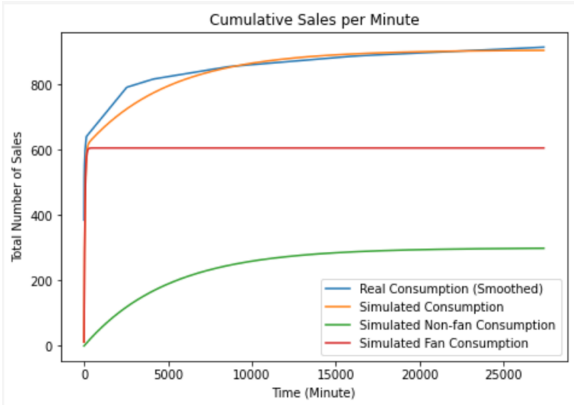
From this simulation, I obtained the best result and is shown in the Table 1. The simulated trend is also shown below in Figure 5, with an mean absolute error of 328.2.

The simulation suggests several implications of the market of the product. First, it suggests that the cumulative sales are increasing in a decreasing rate, not only for the non-fan population, S1, but also for the fan population, S2. Second, the fan population will finish almost all of their purchases in the first 200 minutes, while the non-fan population continues to purchase overtime. Third, the social media influencer's attraction is 100 times of the attraction other than the social media influencer's attraction.

Table 1: Parameters

Parameter	Value
α	0.02
β	0.0002
μ	0.0000001
S_1	300
S_2	600

Figure 5: Cumulative Sale Trend per Minute

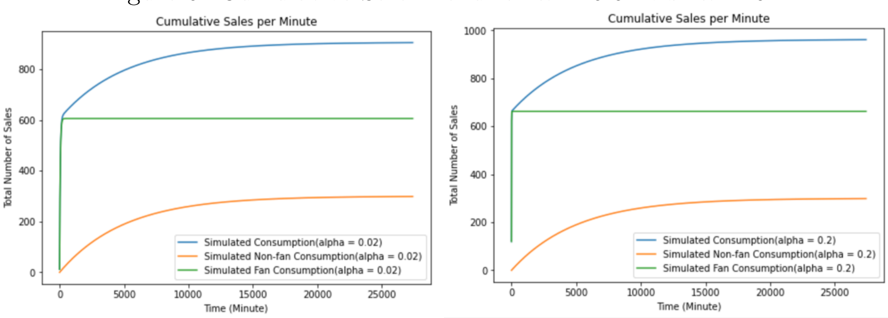


7 Change of Variables

In this model, there are two parameters related to the social media influencer, which are the number of people in the S2 and the social media influencer's attraction rate α. Thus, I investigated how change of these two factors influence the cumulative purchase trend.

7.1 Ceteris Paribus, More Attraction to Fans

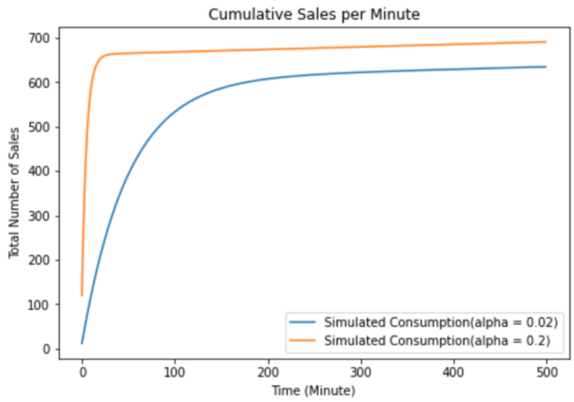
Figure 6: Cumulative Sale Trend for $\alpha = 0.02$ v.s. $\alpha = 0.2$



If we increase α by ten times, which is from 0.02 to 0.2, this indicates the situation that if we are using a social media influencer who has the same amount of fans but be more attractive when persuading the fans to purchase, for exam-

ple, more attractive words to describe the product, better quality of pictures of product.
From the graphs, the total sale only increased by about 50. The starting points for the number of consumptions at time 0 is about 100 higher for the $\alpha = 0.2$, but the overall trends of the two graphs look the same. However, if we zoom in the cumulative purchases during the first 500 minutes, the number of consumptions for $\alpha = 0.2$ still has a steeper trend and quicker to converge. It makes sense because per unit time, there will be more proportion of people in the S2 group going to the infecting group if α is bigger.

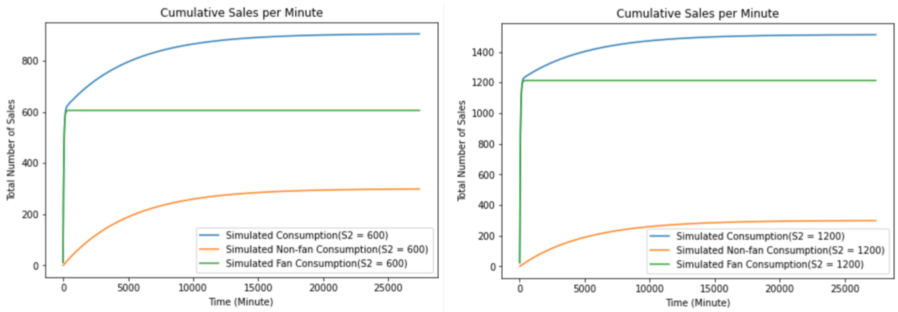
Figure 7: Zoom in Cumulative Sale Trend for $\alpha = 0.02$ v.s. $\alpha = 0.2$



7.2 Ceteris Paribus, More Population of Fans

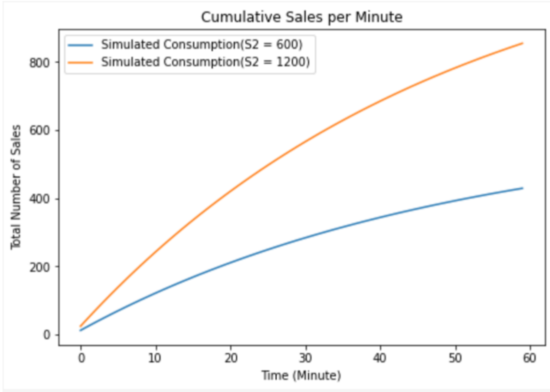
If we increase S2 by twice, which is from 600 to 1200, this indicates the situation that the social media influencer is having the same post, pictures, and attraction to the fans but with more number of fans.

Figure 8: Cumulative Sale Trend for $S_2(0) = 600$ v.s. $S_2(0) = 1200$



The graphs suggest that the total sale will boost by about 600. The overall trends of the two graphs look similar, but if we zoom in, the fan population with 1200 people has a faster growth rate. This can be explained because given the same fraction of people will go to the infecting group per unit time, if there are more people in the group then more of them will purchase the product per unit time.

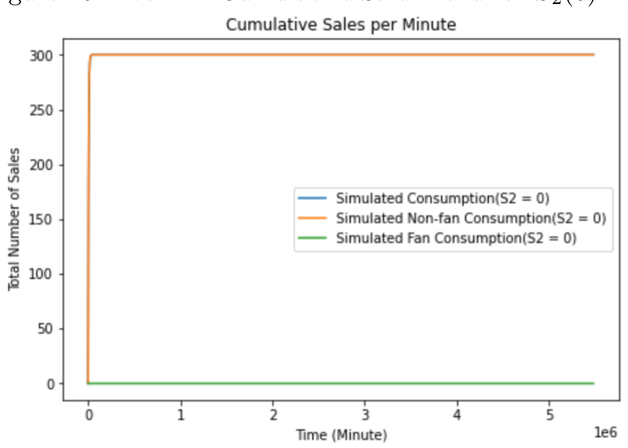
Figure 9: Zoom in Cumulative Sale Trend for $S_2(0) = 600$ v.s. $S_2(0) = 1200$



7.3 Ceteris Paribus, Not Using Social Media Influencer

If we decrease S2 to zero when we do not use any social media influencer, which is from 600 to 0, the total sales will not increase over time and remains at about 300.

Figure 10: Zoom in Cumulative Sale Trend for $S_2(0) = 0$



7.4 Conclusion

Even though this model is only applicable to the specific product, the coat that was released last month, we could still conclude several essential implications in the cloth market from this model and my question.
If we compare the results of 7.1 and 7.2, the graph suggests that if the store wants to have more cumulative purchases overall, it will be more efficient to

increase the population of fan, which is S2, compared to α. Because from the 7.1, when we increase the α by 10 times, the cumulative sale has only increased by about 50. However, if we increase the S2, the cumulative sale will increase at least by the change of S2.
From result 7.3, we could conclude that working with the social media influencer will contribute to the number of purchases of the product. Because if we do not use any social media influencer, as time increases, the total number of purchases will remain around 300 and increase very slowly over time. With the help of social media influencers, it will increase the sale to around 900. So the social media influencer will increase the sales by 600.

8 Improvements

In this model, there are some deficiencies. We would only know how the social media influencer will affect the product's sale when we have such a dataset that records the sales per unit time and simulates the parameters. Thus, in the future, I propose the following improvements to make model more predictive:

1. Find the meaningful key performance indicator to estimate α, β, and μ. Because the parametersα, β, and μ are arbitrary and not connected to real life. This can be solved if in the future we can estimate parameters for example μ using the repurchasing rate.

2. Try to approximate the population in S1, S2 before the model. For example, if we can try to use previous dataset to find the average S1 and S2 if we are using the same cloth shop and social media influencer.

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