Big Data Analysis of Weather Condition and Air Quality on Cosmetics Marketing

Zebin Wang* · Tong Wu** · Xinshuang Zhao*** · Shuchun Cheng**** · Genghui Dai***** · Weihui Dai*****

Abstract

Demands of cosmetics are affected not only by the well-known elements such as brand, price, and customer's consumption capacity, but also by some latent factors, for example, weather and air environment. Due to complexity and dynamic changes of the above factors, their influences can hardly be estimated in an accurate way by the traditional approaches such as survey and questionnaires.

Through modeling and statistical analysis of big data, this article studied the impacts of weather condition and air quality on customer flow and sales of the cosmetics distributors in China, and found several hidden influencing factors. It provided a big-data based method for the analysis of unconventional factors on cosmetics marketing in the changing weather condition and air environment.

Keywords : Cosmetics Marketing, Big Data, Mathematical Modeling, Statistical Analysis

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1. Introduction

In the past, most of the Chinese women were using cosmetics with merely some simple functions, since the average income of Chinese people was rather low then. Nonetheless, in the recent years, some high-end brands of cosmetics are increasingly popular among Chinese women. The country of China is the second biggest economic entity after the United States of America in the year of 2017. The flourish of economy and the increase of population enable China to become an enormous market of high-end cosmetics.

In this article, we use the data provided by a shop of a certain brand that is owned by the company of ROHTO in Japan in order to prove the reliability of our research. ROHTO entered the market of China in 2010 and got lots of data in the process of communicating and trading with their customers. The shop that we collected data in detail is located in the city of Shanghai. We manage to bridge the gap between the marketing data collected by the company and weather factors in Shanghai that will influence the customer flows. As a result, some marketing strategies may be developed and applied so as to raise the familiarity and recognition of the brand among Chinese customers.

According to the definition shown in Wikipedia, big data is a term to describe data sets that are so large or complex that traditional data processing procedures are inadequate or even unable to deal with them. In 2008, big data was mentioned in *Nature* [Frankel and Reid, 2008], and the terminology of 'Big Data' was popular all over the world since then [Guo, 2014].

Figure 1 shows that there are four words used by researchers to define the characteristics of big data. The four words are known as Volume, Variety, Velocity and Veracity. The data sets have been extracted from authentic events but still with some unreliable parts. The volume and the variety of the data forces researchers to use some elaborate procedures to cope with them. The velocity of the generation of the data sets requires researchers to provide the result of data analysis within 3 seconds. Otherwise, the results are obsolete and useless. Data Mining (DM) and mathematics modeling are modern methods of analyzing huge amounts of data, which have already been equipped in many specific aspects such as Traditional Chinese Medicine (TCM) and epidemiology [Brockmann and Helbing, 2013; Zhao et al., 2014].



⟨Figure 1⟩ The Four V's of Big Data

In the traditional concepts of businessmen, there are several fundamental components of a successful marketing strategy.

At first, the shops shall be carefully located in prosperous downtown areas so as to attract as many customers as possible. Second, the salespersons need to be carefully elected and trained to ensure their service quality. Finally, companies shall learn to collect and analyze data to predict the requirements of the customers in the near future.

It is rather easy for us to find out that most of the cosmetics shops in China are located in modern shopping malls all around huge cities such as Beijing and Shanghai, some of which also have fancy decorations with plenty of promotion activities. Nevertheless, some companies unconcernedly ignore the importance of statistics analysis and some hidden rules beneath the data are completely obscured. The article aims to find the ubiquitous connections between the weather condition and air quality in a certain place and the data of customer flows to provide a plausible way cosmetics marketing.

2. Impacts of Weather Condition and Air Quality

2.1 Characteristics of China's Cosmetics Customers

Chinese women seem to have an unstoppable passion of buying and using skin-care cosmetics to make them increasingly elegant. The potential of their demand of cosmetics can hardly be estimated since they may earn much more money than expected in the following decades and even the most exquisite and expensive brands may be affordable for most of them at that time.

Usually, over seventy percent of the cosmetics are sold to customers who have already used cosmetics of this brand for a long period of time. In other words, customers are loyal to those brands that they have been trusting for years. This phenomenon contributes to the fact that the key for companies to get advantages in the competition is to reserve their frequent customers and develop new customers. As many regular customers may stop using cosmetics in a certain brand when they cannot find products that are capable of satisfying their requirements, companies shall find the potential of the cosmetics market in an efficient and accurate way.

Besides, customers of cosmetics are facing different kinds of skin problems in different seasons of a full year. For example, some people may be allergic to dust or pollen in spring. As a result, there may probably be itchy red bumps on their faces that are caused by allergy. Lipsticks, lotions and hand creams usually occupy a higher percentage of the total business volume of a cosmetics company in winter since the air moisture is statistically lower than that in summer. A lot of customers find their skin too dry to stay in a healthy condition and they want to buy some make-ups to compensate the negative effects caused by weather condition.

2.2 Influencing Variables of Weather Condition and Air Quality

The condition of people's skin is controlled by several factors, some of which can hardly be controlled. The quality of people's skin deteriorates when people are getting older or exposed towards the sun directly [Young et al., 2016]. Besides, weather condition and mental condition may also contribute to the difference of skin quality.

AQI (Air Quality Index) is an index used to measure the condition of air in China. The range of the index is from 0 to 500. The higher the AQI is, the worse the air condition will be. The AQI can be checked and copied from some national statistics websites of China. Ultrafine particles with a diameter of 2.5µm or less are called $PM_{2.5}$, which may penetrate into people's lungs and cause diseases such as chronic bronchitis or lung cancer. $PM_{2.5}$ is one of the most important components that are used to calculate the index of AQI.

In 2017, researchers in Bahrain found out that rapid urbanization and industrialization negatively impacted the air quality there [Jassim and Coskuner, 2017]. As researchers have proved some severe hazards of PM_{2.5} over people's respiratory systems [Yang et al., 2017], the potential relationship between PM_{2.5} and customers' demands of cosmetics remains unknown.

Since PM_{25} is an important component in calculating the AQI and we did not find any accurate records of the level of PM_{25} from 2011/01/01 to 2011/06/30 in Shanghai, we use AQI index to represent the air condition so as to simplify the problem.

Theoretically, the average air humidity will affect the moisture of customers' skin. Nevertheless, the relationship between humidity and the total sales volume of cosmetics has not been carefully examined.

In conclusion, we are attempting to depict the profile of the hidden relationship of cosmetics market and weather variables including but not limited to those that have been mentioned above.

Modeling and Statistical Analysis of Weather Condition and Air Quality

3.1 The Relationship Between Humidity and Customer Flow

In statistics, the Pearson correlation coefficient is used to measure the linear correlation of two vectors[9]. The value is between +1 and -1, as +1 means complete positive linear correlation, -1 means complete negative linear correlation and 0 means no linear correlation. Habitually, we use the alphabet 'R' to denote the Pearson correlation coefficient. The absolute value of the correlation coefficient is used to measure the level of linear correlation. The phenomenon that the correlation coefficient is lower than 0.1 and higher than -0.1 indicates that there is nearly no linear correlation between two variable vectors. In this article, we use the data of the number of customers buying different kinds of cosmetics and the weather nearly everyday in the first half of the year of 2011.



<Figure 2> Air Humidity and Customer Numbers I



<Figure 2> and <Figure 3> both show the relationship between air humidity and cosmetics market in the first half of 2011, but they have a crucial difference, as the X-axis variable in <Figure 2> is the number of customers who buy all kinds of cosmetics in the following 15 days, and the X-axis variable in <Figure 3> is the number of customers who buy special-care cosmetics that are designed to cope with skin dehy-drate in the following 15 days.

After some statistics calculation, the Pearson correlation coefficient of the data shown in \langle Figure 2 \rangle is R = 0.0752, the absolute value of the correlation coefficient is lower than 0.1, which indicates that there is nearly no linear connection between the two variables.

In \langle Figure 3 \rangle , the numbers of customers who buy special-care cosmetics are weakly connected with the air humidity at that time. The Pearson correlation coefficient is R = -0.2011,which shows a weak negative correlation between the two variables. If we use a one-degree polynomial (i.e. linear function) to fit the data spots, the equation of the line is shown in Equation 1.

$$f(x) = -0.3882x + 74.18\tag{1}$$

This phenomenon may tell us that customers are likely to buy more special-care cosmetics to cope with dry weather, which proves the assumption mentioned above that dryer weather might contribute to the increase of the sales volume of special-care cosmetics. However, the connection between air humidity and the sales volume of all kinds of cosmetics remains unknown.

3.2 The Relationship Between AQI and Customer Flow

At first, we downloaded the AQI reports from relative websites, and we want to find connections between AQI and customer numbers.

We tried to use the data of AQI and the number of customers directly and we created a plot with unprocessed data. Nonetheless, the data was almost chaotic and we could not find any connection between the two vectors of data. The unprocessed data is shown in <Figure 4>.



(Figure 4) The Unprocessed Data of AQI and the Number of Customers

The data shown in \langle Figure 4 \rangle has a correlation coefficient R = -0.0441, which shows that there is nearly no linear correlation between the AQI and customer number.

When we were examining the data once again, we found that the number of customers who entered the shop between 2011/4/16 and 2011/4/22 was extremely high. After checking the promotion plan of the cosmetics company in our research, we found that this company held a promotion activity at exactly the same time, which lasted for an entire week. Besides, The AQI index was extremely high in a short period of time and even reached 500 from 2011/5/2 to 2011/5/3. Those abnormal data points that can be noticed clearly in <Figure 5> may induce the phenomenon that the results drawn from <Figure 4> is not convincing.



(Figure 5) Some Abnormal Data Sets of AQI and Customer Number

It is straightforward to see from the plot that both the highest peaks of customer number and AQI in <Figure 5> shall be considered to be abnormal data that are not reliable in calculating the Pearson correlation coefficient. Besides, there might be a delay between the deterioration of air quality and customers' demands of buying and using cosmetics.

In order to show the correlation between air quality and the number of customers and guarantee the accuracy of our research, some data points are removed from the plot shown in <Figure 4>. There are still 150 data points that are used and shown in <Figure 6>. In <Figure 6>, we use the numbers of customers 15 days later as the X-axis variable.



Figure 6> The Plot of AQI and Customer Number 15 Days Later

After the calculation of Pearson correlation coefficient, we find that the correlation coefficient between AQI and the number of customers is R = 0.2190, which indicates that AQI and the number of customers have a positive correlation, though the correlation is rather weak. The linear fitting function in Figure 6 is shown in Equation 2.

$$f(x) = 0.3754x + 61.59 \tag{2}$$

The result shows that there are more people coming to the cosmetics shop a few days after the deterioration of air quality. Some of the abnormal data points need to be removed so as to find an appropriate approach towards the core of this issue.

4. Hidden Influencing Factors through Big Data Analysis

4.1 Dimension Reduction Process

Dimension Reduction Process is a process of reducing the dimension of the data sets so as to simplify the issue to be researched. The unprocessed data may compose of over 20 factors that are linearly independent. The process of dimension reduction may refine the data sets and find some intrinsic characteristics in huge amount of big data. The process of factor analysis through dimension reduction can be separated into four steps.

The first step is to collect unprocessed data sets and normalize them via Z-score Normalization (i.e. to set the average of the statistics as 0 and set the variance as 1) in order to eliminate the difference of the order of magnitude between different data sets.

The second step is to judge whether the data sets are suitable enough to be processed through the process of dimension reduction. In this step, we use the Kaiser-Meyer-Olk in Measure of Sampling Adequacy and Bartlett's Test of Sphericity. Habitually, the data sets are suitable for dimension reduction when the KMO Measure is bigger than 0.75 and the significance level (usually abbreviated as Sig.) of Bartlett's Test of Sphericity is lower than 0.005.

The third step is to construct the factors and rotate them to explain them in an appropriate way.

The forth and the final step is to calculate the score of the factor variables and ultimately get the factors from the original data sets. The process of dimension reduction has been used in a variety of aspects such as medical science, as researchers use fast dimension reduction to analyze cancer molecular classification [Wu et al., 2015]. Some pieces of statistics software such as SPSS (Statistical Product and Service Solutions) already have several built-in functions of reducing the dimension of data sets, which may significantly raise the efficiency of big data analysis. We use SPSS to cope with the data sets that are related to weather condition and cosmetics market.

4.2 Rotated Component Matrix

In this article, we use 18 linearly independent sets of data to represent the weather condition in Shanghai between 2011/1/1 and 2011/6/30. The 18 variables are shown in <Table 1>. All the temperatures mentioned in this article are recorded by degrees centigrade.

<Table 1> Declaration of Variables

Name	Type	Unit
Max Temperature	Number	Degree (Centigrade)
Mean Temperature	Number	Degree (Centigrade)
Min Temperature	Number	Degree (Centigrade)
Max Dew Point	Number	Degree (Centigrade)
Mean Dew Point	Number	Degree (Centigrade)
Min Dew Point	Number	Degree (Centigrade)
Max Humidity	Number	Relative Humidity
Mean Humidity	Number	Relative Humidity
Min Humidity	Number	Relative Humidity
Max Air Pressure	Number	hPa
Mean Air Pressure	Number	hPa
Min Air Pressure	Number	hPa
Max Visibility	Number	Kilometer
Mean Visibility	Number	Kilometer
Min Visibility	Number	Kilometer
Max Wind Speed	Number	km/h
Average Wind Speed	Number	km/h
AQI	Number	-

At first, we need to normalize the variables that are shown above in the software of SPSS. The results of the KMO Measure and Bartlett's Test are shown in <Table 2>.

<Table 2> KMO and Bartlett's Test

Kaiser-Meyer-Olkin	Measure of Sampling	.769
Adequacy.		
Bartletts Test of	Approx. Chi-Square	7107.766
Sphericity	df	153
	Sig.	.000

The results of the tests show that the variables used in this case are suitable for dimension reduction, as the KMO Measure of the data sets is 0.769 and the significance level of Bartlett's test is smaller than 0.001.

We may use the scree plot of the factors that are generated by our data sets as shown in <Table 1> to choose appropriate factors. The bigger the eigenvalues shown in the scree plot are, the higher the importance of the factors will be. In this case, we omit the factors with eigenvalues that are smaller than 1 to reduce the total dimension of the data sets from 18 to 4.



<Figure 7> The Scree Plot of the Variables

In other words, 4 linearly independent factors are enough to describe the unity of the entire data sets.

In \langle Table 3 \rangle , we rotate the component matrix by Varimax method with Kaizer Normalization and omit the coefficients that are smaller than 0.300 to emphasize the characteristics of all the four factors. The factors are denoted f₁, f₂, f₃ and f₄ from the left of the table to the right hand side.

<table< th=""><th>3></th><th>Rotated</th><th>Component</th><th>Matrixa</th></table<>	3>	Rotated	Component	Matrixa
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	Component				
	1	2	3	4	
Zscore(MaxTemp)	.962				
Zscore(MeanTemp)	.985				
Zscore(MinTemp)	.977				
Zscore(MaxDewPoint)	.955				
Zscore(MeanDewPoint)	.943	.310			
Zscore(MinDewPoint)	.878	.406			
Zscore(MaxHumidity)		.877			
Zscore(MeanHumidity)		.950			
Zscore(MinHumidity)		.899			
Zscore(MaxPressure)	972				
Zscore(MeanPressure)	967				
Zscore(MinPressure)	955				
Zscore(MaxVisibility)		.367	.835		
Zscore(MeanVisibility)			.972		
Zscore(MaxWindSpeed)			.897	.899	
Zscore(MeanWindSpeed)				.882	
Zscore(AQI)		417		334	

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 5 iterations.

The Rotated component matrix indicates that f_1 is mainly related to temperature and air pressure, f_2 is mainly related to humidity and weakly related to dew point, max visibility and AQI, f_3 is mainly related to Visibility and f_4 is mainly related to wind speed and weakly related to AQI.

4.3 Multiple Linear Regression

By using the four factors generated above, we may use multiple linear regressions to find some intrinsic connections between weather and cosmetics market. The scores of the factors are used to find linear connections between a dependent variable and the factors via linear regression. In SPSS, the scores can be calculated and saved as variables automatically by executing its built-in programs.

The numbers of the customers who enter the shop in the following 15 days between 2011/1/1 and 2011/6/30 are served as dependent variables. In order to prevent inaccuracy, we adjusted customer numbers of the shop from 2011/4/16 and 2011/4/22 to minimize the effects caused by a promotion activity of the cosmetics company as mentioned above.

At first, we use all the four factors to con-

struct a multiple linear regression in SPSS and check the significance level of our procedure. The results are shown in <Table 4>.

The significance level (abbr. Sig.) on the right hand side of <Table 4> represents the reliability of using this factor to generate a linear regression over the dependent variable. When the significance levelof a certain factor is over 0.020, we shall remove this factor and use the rest of the factors to finish the process of regression.

The significance levels of f_2 , f_3 and f_4 in our case are 0.089, 0.086 and 0.592, so we are going to remove all those factors and execute the program of linear regression once again. The results are shown in <Table 5>.

We may construct a regression model with the equation as shown in Equation 3 to find the hidden linear connection between weather and customer numbers.

<Table 4> The Coefficients I

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	sig
		В	Std. Error	Beta		
1	(Constant)	282.045	6.795		41.511	.000
	REGR factor score 1 for analysis 1	48.412	6.814	.471	7.105	.000
	REGR factor score 2 for analysis 1	11.671	6.814	.114	1.713	.089
	REGR factor score 3 for analysis 1	-11.766	6.814	114	-1.727	.086
	REGR factor score 4 for analysis 1	3.657	6.814	.036	.537	.592

^aDependent Variable: Customer Number.

<table< th=""><th>5></th><th>The</th><th>Coefficients</th><th>$\$</th></table<>	5>	The	Coefficients	$\ $
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Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	sig
		В	Std. Error	Beta		
1	(Constant)	282.045	6.857		41.134	.000
	REGR factor score 1 for analysis 1	48.412	6.876	.471	7.040	.000

^aDependent Variable: Customer Number.

⟨Table 5⟩ The Coefficients III

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	sig
		В	Std. Error	Beta		
1	(Constant)	149.477	2.739		54.574	.000
	REGR factor score 3 for analysis 1	-6.504	2.747	177	-2.368	.019

^aDependent Variable: Purchase Number.

$$y = 48.412f_1 + 282.045 \tag{3}$$

The significance level is smaller than 0.001 in this case, which indicates that the result is significant and reliable.

By the same procedure, we found out that the number of the customers who buy cosmetics from the shop in the following 15 days is linearly related to the factor f_3 , which can be shown in $\langle Table 6 \rangle$.

In this case, the linear connection is shown in Equation 4.

$$y = -6.504f_3 + 149.477 \tag{4}$$

The significance level of the third factor in this case is 0.019, which is rather high but still tolerable. It is possible for us to use other data sets such as the numbers of customers who buy a specific kind of cosmetics as the dependent variable and find multiple linear connections between weather and cosmetics market through the same method.

5. Summary and Discussion

In conclusion, linear fitting and factor analysis are both effective methods of analyzing data sets and seeking for hidden correlations between variables. By drawing linear fitting lines and calculating Pearson correlation coefficients, we found that air humidity and the customer numbers of buying special-care cosmetics have a weak negative linear correlation in the first half of the year of 2011, as customers were more likely to buy special-care cosmetics when they found the weather was too dry. Besides, daily AQI index shall positively affect the number of customers who enter the shop 15 days later. The cosmetics shop may increase the storage and intensify their promotion activities when the index of AQI is rising rapidly or the air humidity has been remaining in a low position for a long period of time. Besides, even strong correlations between variables may be undermined by some abnormal values in the data sets. In this situation, the abnormal values may be changed or omitted during statistics analysis so as to strengthen the correlation.

The data sets in <Table 1> may describe a mathematics model used to predict the tendency of cosmetics market. As we may see in the beginning, the dimension of the model is high and we need to find a proper method to simplify it. Dimension Reduction Process is a well-known procedure discovered for analyzing data with multiple dimensions. We may use the idea of

factor analysis to simplify the model mentioned in <Table 1>. After the method of Multiple Linear Regression, we may generate and examine the connection between marketing data collected by companies and factors that have been refined from daily weather reports. We are glad to see that this process of dimension reduction remains effective when the dimensions of variables in the data sets are higher than we have researched in this article. The prediction of the tendency of cosmetics market via statistical analysis of big data may improve the working efficiency of cosmetics manufacturers and distributors. With some necessary adjustments, the idea of lowering the dimensions of variables can be adapted into other specific aspects such as economics and medical science.

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