https://doi.org/10.5392/IJoC.2017.13.4.080

The Conformity Effect in Online Product Rating: The Pattern Recognition Approach

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ABSTRACT

Since the advent of the Internet, and the development of smart devices, people have begun to spend more time in online platforms; this phenomenon has created a large number of online Words of Mouth (WOM) daily. Under these changes, one of the important aspects to consider is the conformity effect in online WOM; that is, whether an individual's own opinion would be influenced by the majority opinion of other people. This study, therefore, investigates whether there is the conformity effect in online product ratings for Amazon.com using the method called Markov Chain analysis. Markov Chain analysis considers the stochastic process that satisfies the Markov property, and we assume that the generation of online product ratings follows the process. Under the assumption that people are usually independent when they express their opinion in online platforms, we analyze the interdependency among rating sequences, and we find weak evidence that there exists the conformity effect in online product rating. This suggests that people who leave online product ratings consider others' opinions.

***Key words**: Word-of-mouth, Conformity Effect, Markov Chain, Sequential Pattern.*

1. INTRODUCTION

Since the advent of the Internet, people are gradually overcoming the limit of physical space. These days, people could interact with others wherever and whenever: ubiquitous circumstance in real life. This new way of interaction could be related to the concept of 'public sphere', proposed by Jurgen Habermas [1]. He defined public sphere as the space where people discuss pending issues, exchange the information on the area which constitutes the human society. Public sphere appears along with the advent of human being and have been left trace on the course of history as form of Guild, Party and etc. Form of communication and interaction which occurs on public sphere among people is face to face basically, however, with the advent of the online media such as online newspaper, social network services, the breakthrough had occurred in the aspects of communication and information delivery.

With the advancement of the online media, people now can communicate and interact with each other with their own devices such as personal computer, smart phone, etc. without any of physical limitations. Such expansion of online communication also enables people to discuss their opinion on products and services such as online word-of-mouth (online WOM) which became one of the most effective marketing tools nowadays [2]. In particular, Amazon.com become one of the most prolific platform for gathering customers' state of mind on the products and services.

Particularly, the representative types of communication on online WOM in these days are ratings and comments on each product. Customers could state one's view about product on the website of online shopping malls such as Amazon.com and these sites also provide rating systems where people can score the quality of products based on their own assessments and experiences on products. Other customers can refer the scores from the sites when they have interest on products or services.

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Manuscript received Aug. 10, 2017; revised Oct. 12, 2017; accepted Oct. 13, 2017

Not only the online shopping malls, but also online databases such as IMDb, Rotten Tomatoes and News website such as New York Times and Huffington Post have also built similar systems. Comments and ratings are treated as material for capturing people's mind and opinion on products or contents in their systems.

Under this expansion of the online platforms that promote online WOM, one of important aspects to consider is the conformity effect [3], that is, whether individual's own opinion would be influenced by the majority opinion of other people. Previous study argued that people could be hindered to bring one's mind up their own opinion on a certain topic under offline environment due to the conformity effect [4]. Even some studies conducted supposing that there would be kinds of conformity effects in online platform. For example, company exploits fake reviews on its own products for the purpose of promotion and increase of sales [5]. However, in an online situation where anonymity is guaranteed, which means one's independence would be secured, it is still in question whether people may act differently in comparison to an offline situation.

This study, therefore, investigates whether there is also the conformity effect in online WOM, that is, whether people state one's own opinion independently with others in online platform. Specifically, we examine whether people act as individual or a crowd of majority in online platform, considering the characteristic of online WOM such as anonymity. In order to do so, we use the method called Markov Chain analysis which is a management scientific tool. Markov Chain analysis considers the stochastic process that satisfies the Markov property[1][6] if one can make predictions for the future of the process based on its present state just as well as one could know the process' full history, hence independently from such history [7], [8]. More specifically, we first hypothesize that each rating is independent itself, not influenced by prior rating. In other words, no informational cascades occur when decision makers choose to ignore their own private information in favor of imitating others who faced the same decision earlier on [7]. Then, we assume that people do not tend to rate products following the average ratings, although sequences have gone to latter period. Lastly, we test whether there is a significant evidence on conformity effects in online platform by analyzing pattern of ratings on products on Amazon.com.

2. LITERATURE REVIEW AND HYPOTHESES

2.1 Online WOM and Conformity Effect

Word-of-mouth (WOM) is defined as interpersonal communication on specific products, brands, or services in case that customers perceive information as non-commercial [2], [9], [10]. WOM became one of a major academic topic in marketing, economics and other management literature, it has been extensively examined in different fields. Particularly, in marketing, research on the characteristics of WOM have been extensively studied [11]-[14]. They suggested that WOM 1) occurs in informal conversation, 2) is usually non-commercial and 3) is act of telling and exchange of information. In addition, most of researchers chorused that 4) WOM is usually post-purchase behavior.

Later, advancement of the Internet caused the advent of new type of WOM, that is, online WOM. In online situation, people have become to interact with each other more frequently and freely, and do not need to talk face-to-face to exchange information. It means that WOM is generated more often in online than offline situation. This makes its own new names and applications including viral marketing, Internet WOM, e-mail marketing, WOM marketing, or e-WOM [2]. These all new terminologies refer to different concept, but differences are not quite noteworthy.

As online platforms for commerce and communication became prevalent, online WOM also became a powerful tool for capturing customers' needs and responses on products of companies. Above-mentioned concepts, viral marketing, e-WOM are all have designed for this purpose. For example, some companies open a space such as online forum for current and potential customers, then expect that they could get some useful implications for research and development of products [13]. Sometimes, they use cyber agora of which they do not make for gathering responses of their products released on market. Furthermore, recent studies on online WOM are not restricted on commercial-related fields. For example, Godes, and Mayzlin [15] has applied this concept onto content industry domain for quantifying online WOM to make itself more objective index for management application.

Several studies have suggested positive relationships between customers' online product evaluation and sales of products. Chevalier and Mayzlin [16] showed that positive appraisals on specific product increase sales in book industry and Dellarocas et al. [17] also proved this notion in movie industry. Meanwhile, Liu [18] who also studied movie industry asserted that the total amount of customers' online WOM has greater impact than whether they are positive or negative. Interestingly, anonymity could also affect the degrees of the impact of online reviews on product sales [18].

Particularly, most of researchers have argued that the impact of online reviews and ratings vary with time. For example, the most common idea is that the impact of online WOM become weakened gradually [19], [20]. They discussed that online WOM could cause or be related with herding effect or informational cascades [21] that are typical type of conformity effect which describes the phenomenon that individual's own opinion would be influenced by those of majority group [3]. The informational cascades are said to occur when decision makers choose to ignore their own private information in favor of imitating others who faced the same decision earlier on. It usually arises when others' actions are observable, in the case that individual's decision made in a sequence [9]. This phenomenon would be well matched in online situations, especially leaving responses on products or services. Each commentator is allowed to see other opinions, and there are possibilities to overturn one's own idea or opinion in response to prior ones. However, the conformity effect or the information cascade in online WOM has not been well explored in the previous literature.

[1] Markov property refers to the memoryless property of a stochastic process (Markov, 1954).

2.2 Markov chain analysis and hypothesis development

In order to test whether there is the conformity effect in online WOM, we apply Markov chain analysis. The Markov chain is mathematical application that contains transition process among all the states in system. It is classified as discrete and continuous Markov chain by characteristic of set of times, and also divided into finite and infinite Markov chain by time limitation [6]. Generally, Markov chain means discrete-time finite Markov chain and in broad sense, it refers to Markov process. The premise of Markov chain is memoryless also called memoryless property or Markov property described as 'future state (*n+1* step state) is only influenced by current state (*n* step state). Namely, a Markov chain is a sequence of random variables with memoryless property (X_1, X_2, X_3 ...), given the present state, the future and past states are independent [22]. A Markov chain is formally defined as probability below.

$$Pr(X_{n+1} = x | X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) \\ = Pr(X_{n+1} = x | X_n = x_n)$$

There are some variations with different properties related features with this study are stationary Markov chains and Markov chain of order m.

Stationary Markov chains also called, Time-homogeneous Markov chains are processes that all the transition probabilities are same over times. For all n, the theorem below holds.

$$Pr(X_{n+1} = x | X_n = y) = Pr(X_n = x | X_{n-1} = y)$$

Markov chain of order m is the variation of expanded memoryless, the future state depends on the past m states. It is described as below probabilities.

$$Pr(X_n = x_n \, | X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_1 = x_1) \\ = Pr(X_n = x_n | X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2,\dots,} X_{n-,} \\ = x_{n-m})$$

Sequential process by time, Markov chain has briskly applied in several different fields mainly in Finance. In marketing area, research by Styan and Smith [23] has regarded as first footstep of application. They conducted the research analyzing the flow of brand loyalty exchange of each household with 26 weeks panel data on detergent purchases. This proposed the potential and possibility as marketing tool of Markov chain.

In recent, advanced application of Markov chain such as Next-purchase-to-buy model (NPTB model) proposed by Knott et al. [24] has handed baton from Styan and Smith [23] work of application Markov chain in marketing. NPTB model is also focused only former purchase memory excluding other restrictions. Meanwhile, in Finance, Markov chain is applied for estimating bond value and assessing stock prices. Besides, it has also applied in design area such as for smartphone UX [25], and would be used in any fields where states could be clearly defined.

Markov chain and contingency table generated from Markov chain are used for analysis sequential pattern on ratings on each product. Setting whole sample data as type of state for Markov chain, then contingency table had drawn for analysis.

Chronological aligning process divides data into two type rating group, prior rating and posterior. Two rating group consist contingency table as row and column then, Chi-squared test are conducted afterward. According to Styan and Smith [23], with contingency table and chi-squared test, it could be proved that the contingency table has Markov property or not. Accordingly, the null and alternative hypotheses are defined as below.

H0. Online WOM sequences are independent (A zero order Markov chain)

H1. Online WOM sequences are dependent on the immediately previous online WOM (A first order Markov chain).

Amazon.com usually provides the information of cumulative average at time, and 6 of posterior reviews and ratings. Further implementations are conducted with applied concept of Markov chain of m-order for investigating the impact of the information.

Pearson's chi-squared test is well-known statistical procedure evaluated by reference to the chi-squared distribution. This test is used to assess two types of comparison: tests of goodness of fit and tests of independence. In this study, we also focused on latter, test of independence. A test of independence assesses whether paired observations on two variables, expressed in a contingency table, are independent of each other [26]. Although its general usage for typical statistical analysis, Pearson's chi-squared test has a problem when it covers large amounts of samples. Complementing this, Cramer's V had proposed as post-hoc analysis index for tests of independence. Cramer's V is defined as

$$\boldsymbol{V} = \sqrt{\frac{\boldsymbol{\chi^2}}{\boldsymbol{N(k-1)}}}$$

where k being the number of rows or the number of columns, whichever is less [27]. If the value of V higher than 0.5, this backs rejection of the null hypothesis, even else lower than 0.3, relation between two variables is not significant, not be able to reject the null hypothesis.

We also test the analysis of variance to find out whether significant differences exist among 3 more groups of online WOM. In this study, we set sequential periods (1~5) as group variables and focused on the relationship with dependent variable that is one of the groups. The null and alternative hypotheses of analysis of variance are generally defined as

H0. The sequential groups of Online WOM are independent each other (Dependent variables are different with group variables)

H1. The sequential groups of Online WOM are dependent on previous groups of online WOM (Dependent variables are equivalent with group variables)

If 3 more groups are used in analysis, post-hoc analysis need to be conducted. In this research, applied 5 groups, Scheffe's test should follow examining the extent of differences between each group.

3. DATA AND DESCRIPTIVE ANALYSIS

Data used in this study consist of 1,048,572 entities including online reviews and ratings on 452,744 products published on Amazon.com. Each entity is composed of product ID, posted time of review and rating, rating information (1~5), cumulative rating average on each product, deviation between current rating and current cumulative rating average. Data had gathered from August 17th, 1996 to March 21st, 2006.

One of the interesting points is that there are only 2,072 products with more than 30 reviews (0.46% of all the products; Fig. 1). In concert with increasing of the Internet user and expanding of online platform, total numbers of posted ratings on each product shows increasing pattern (see. Fig. 2). However, regarding the reviews on 302,979 products that are posted since 2003, it could be concluded as very few products received attention from public.

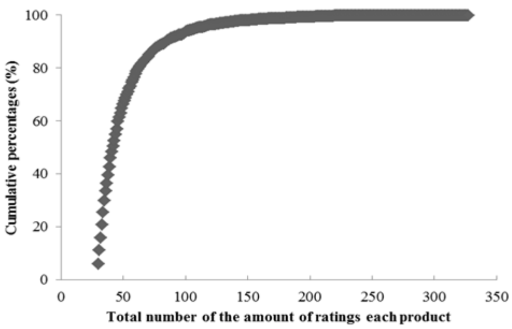

Fig. 1. Cumulative percentage by total amount of posted ratings on each product. Figure is made of data on products which have 30 over numbers of posted ratings. Only 0.46% of whole products are included

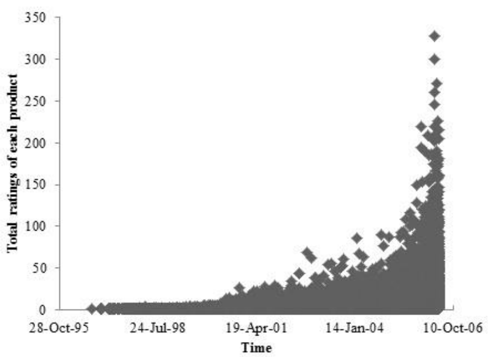

Fig. 2. During data gathering duration, each product captures different amount of total ratings. It usually increases by the time when it published. N=425,744

Among products with over 30 posted responses, few gathered 100 over reviews and ratings. Only 131 products (6.3% of 2,072 products gathered 30 over reviews) had captured 100 over responses. This could be interpreted that few products (maybe best seller or promotion products) could gather the large amount of public responses basically (see. Fig. 3).

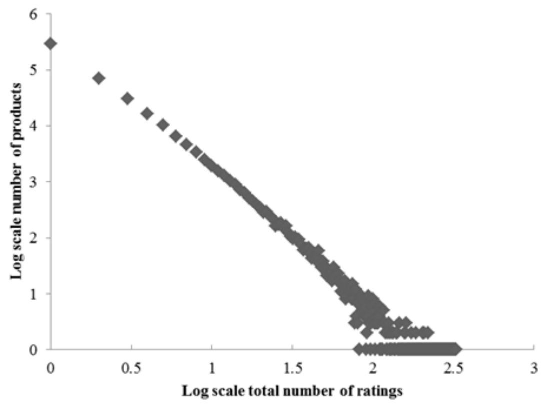

Fig 3. Log scale number of products by log scale total number of posted ratings. It shows that the number of product and total number of ratings on product are in power law relation. Few products dominate the responses of publics

Since this study examines the sequential pattern of online WOM, we use those samples with over 30 posted reviews. With data sampling procedure, around 30,000 entities are collected and used, 14,997 entities for Markov chain analysis and 16,503 for analysis of variance. Random sampling makes sampled data hold same composition in the manner of rating proportion.

4. RESULTS

4.1 Nature of online ratings on products

We first show the patterns of product ratings in Table 1 below. The highest rating, 5 shows more than 50 percentages of all the ratings. Next to rating 5, rating 4 and 3 take high percentage in sequence. Rating 1 and 2 take fewer portions of the total data. It shows that reviews are generally positive. This confirms the previous results of positive bias in product ratings in prior studies [16], [28].

Table 1. Proportion of Rating in Sample Data

Rating	1	2	3	4	5	Total
Count	944	1037	1830	3641	7545	**14997**
Proportion	6.29	6.91	12.20	24.28	50.31	**100.00**

Fig. 4 shows the relationship between ratings and time sequential orders of postings that are generated based on the posted time on each product. There are no outstanding characteristics, but the frequency of rating from 1 to 4 decreases from around 150th order. Apparently, order has no significant impact on rating.

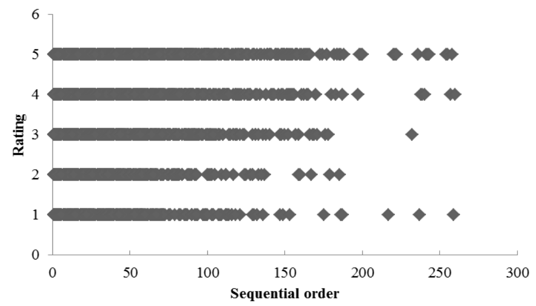

Fig. 4. During data gathering duration, each product captures different amount of total ratings. It usually increases by the time when it published. N=425,744

4.2 Markov chain analysis results for the occurrence sequential pattern

With Markov chain method, transition matrix (contingency table) had been estimated. With sampled data, the relationship between prior rating group and posterior rating group with all possible combinations have been examined. Markov matrix on whole sampled data and chi-squared coefficient (see. Table 2) show statistically significant results rejecting the null hypothesis, which suggests that independency between two rating groups is not significant, meaning (Pearson chi^2(16) = 778.56, P<0.001). However, Cramer's V coefficient (V = 0.1150) is lower than 0.3, thus, the dependency between two rating groups may not significant. Due to this contradictory result that does not strongly support the existence of conformity effect in online product reviews, we further analyze the data with controlled sample as below.

Table 2. Contingency Table between Prior and Posterior on Whole Sample Data, n=14717

Prior rating		Posterior rating 1	2	3	4	5	Total
1	Count	177	89	149	170	343	928
	% of transition	19.07	9.59	16.06	18.32	36.96	100.00
2	Count	100	127	175	264	352	1,018
	% of transition	9.82	12.48	17.19	25.93	34.58	100.00
3	Count	119	165	317	454	736	1,791
	% of transition	6.64	9.21	17.70	25.35	41.09	100.00
4	Count	187	265	460	987	1,661	3,560
	% of transition	5.25	7.44	12.92	27.72	46.66	100.00
5	Count	349	368	701	1,701	4,301	7,420
	% of transition	4.70	4.96	9.45	22.92	57.96	100.00
Total	Count	932	1,014	1,802	3,576	7,393	14,717
	% of transition	6.33	6.89	12.24	24.30	50.23	100.00

Pearson chi^2 (16) = 778.5560, Pr = 0.000
likelihood-ratio chi^2(16) = 691.5969, Pr = 0.000
Cramer's V =0.1150

Controlling the limitation of chi-squared coefficient related with the large sample size over 2,500 samples, we conducted re-sampling to downsize sample to the amount of 1,500 and retried the procedure described above. New chi-square result (see. Table 3) still shows that two groups are dependent but, V value is also still lower than 0.3 (Pearson chi^2(16) = 54.09, Pr = 0.000, Cramer's V = 0.0957), which does not strongly support the existence of conformity effect in online product reviews. However, in the analysis, there can be an issue of skewness of ratings, that is, the positive bias in online product ratings. Thus, we further analyze the data by regrouping the sample as below.

Table 3. Contingency Table between Prior and Posterior on Downsized Sample Data, n=1477

Prior rating		Posterior rating 1	2	3	4	5	Total
1	Count	12	10	16	14	30	82
	% of transition	14,63	12.20	19.51	17.07	36.59	100.00
2	Count	10	9	18	26	27	90
	% of transition	11.11	10.00	20.00	28.89	30.00	100.00
3	Count	7	15	28	49	87	186
	% of transition	6.64	9.21	17.70	25.35	41.09	100.00
4	Count	19	25	58	109	141	352
	% of transition	5.40	7.10	16.48	30.97	40.06	100.00
5	Count	40	45	86	196	400	767
	% of transition	4.70	4.96	9.45	22.92	57.96	100.00
Total	Count	88	104	206	394	685	1,477
	% of transition	5.96	7.04	13.95	26.68	46.38	100.00

Pearson chi^2 (16) = 54.0898, Pr = 0.000
likelihood-ratio chi^2 (16) = 50.7345, Pr = 0.000
Cramer's V =0.0957

4.2.1 Analysis on re-grouped rating

In order to overcome the skewness of the data towards rating 5, we follow the previous approach suggested by Jindal et al. [29]. We regroup the rating as 1) rating 1, 2: negative assessment, 2) rating 3, 4: neutral assessment, 3) rating 5: positive assessment. New Markov analysis on regrouped data, with sample number 500 conducted. Downsizing sample was done while securing power of chi-squared coefficient.

Regrouped data shows that slightly different result. P-value is surely larger than prior test. (Pearson chi^2(4) = 16.44, Pr = 0.002>0.001, likelihood-ratio chi^2(4) = 15.30, Pr = 0.004>0.001) Cramer's V is also very low so, it could not be said prior and posterior ratings are dependent (see. Table 4).

Table 4. Contingency Table between Prior and Posterior on Sample Data, n=489

Prior rating group		Posterior rating group 1	2	3	Total
1	Count	14	18	13	45
	% of transition	31.11	40.00	28.89	100.00
2	Count	30	78	80	188
	% of transition	15.96	41.49	42.55	100.00
3	Count	31	89	136	256
	% of transition	12.11	34.77	53.13	100.00
Total	Count	75	185	229	489
	% of transition	15.34	37.83	46.83	100.00

Pearson $chi^2 (4) = 16.4369$, Pr = 0.002
likelihood-ratio $chi^2 (4) = 15.3033$, Pr = 0.004
Cramer's V =0.1296

4.2.2 The impact of page information on reviewers

One thing to note is that Amazon.com shows the information about 6 recent comments in the viewing page. Therefore, one of limitations of above tests is that we only considered the rating just prior to the one we focus in the ratings' sequence. In other words, there is a possibility that the commentators' ratings are influenced by the shown 6 ratings. Therefore, we conducted revised form of Markov chain of order 6 with the data of average of 6 recent posterior ratings. It is divided into 3 different groups by the proportion of the number. It has been conducted with 1,000 sampled data.

It does not show different result compared to the previous results. While we find the highest Cramer's V value (Cramer's V = 0.1978), it is still below 0.3, which does not strongly support dependency between ratings. For whole samples (N=14997), Cramer's V coefficient goes higher to 0.2150 (see. Table 5), but it is still under the value of 0.3. Thus, after controlling the effects of most recent 6 ratings, we still cannot strongly support the existence of conformity effect in online product reviews.

Table 5. Contingency Table between Prior 6 Commentator's Average Rating and Posterior Rating on Sample Data, n=876

Prior rating		Posterior rating 1	2	3	4	5	Total
1	Count	14	10	16	19	23	82
	% of transition	17.07	12.20	19.51	23.17	28.05	100.00
2	Count	25	31	47	90	106	299
	% of transition	8.36	10.37	15.72	30.10	35.45	100.00
3	Count	13	24	54	132	272	495
	% of transition	2.63	4.85	10.91	26.67	54.95	100.00
Total	Count	52	65	117	241	401	876
	% of transition	5.94	7.42	13.36	27.51	45.78	100.00

Pearson $chi^2 (8) = 68.5705$, Pr = 0.000
likelihood-ratio $chi^2 (8) = 65.4158$, Pr = 0.000
Cramer's V =0.1978

4.2.3 One-way analysis of variance test

We further investigate whether the conformity effect exists in sequential flow and conducted the analysis of variance test as well. In other words, we analyzed the changes of sequential pattern over time. In order to do so, we classified reviewers' ratings by posted time sequential order, then divided them into five-time periods as groups and each group contains 30 samples. By examining the differences by group, we test whether conformity effect exist.

This test is restricted on products that have more than 100 customers' reviews. Naturally, the number of classified samples in the first period is highest among five groups and the fifth period group has the fewest samples. Controlling such characteristics, random sampling is conducted and, thus, each group has the same numbers of posted rating, 171. Variables used in the analysis of variances are deviation between current rating and the average of current cumulative rating based on the order of each period group. The former was used as dependent variables while the latter was independent group variable.

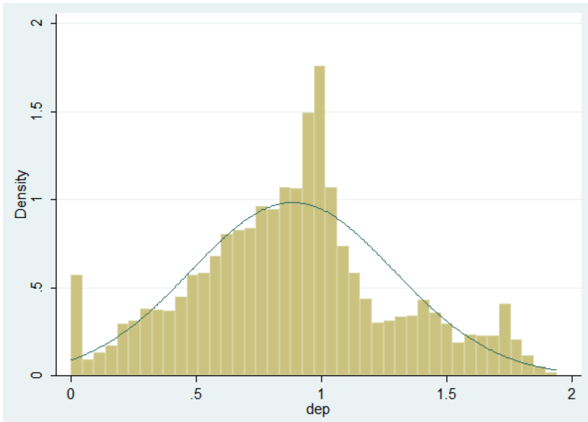

Fig. 5. Distribution of dependent variable, square root value of absolute value of deviation between current rating and cumulative rating average

Table 6. Levene's Test for Checking Homoscedasticity

Group	Sequential order	Summary of dependent variable Mean	Std. Dev	Frequency
1	51st - 80th	.93457548	.44463278	171
2	81st – 110th	.92319026	.35219564	171
3	111st – 140th	.9283119	.3920648	171
4	141st –170th	.91194663	.40745716	171
5	171st –200th	.90048323	.3881561	171
	Total	.9197015	.39728302	855

W0= 1.5838319, Pr>F = 0.17654, W10= 1.6178271, Pr>F=0.167688
W50= 1.2796014, Pr>F=0,27628982

We used the square root of the dependent variable for approximating normal distribution. Checking homoscedasticity, Levene's test is used within 5 order period groups. Fig 5 and Table 6 show that variables are satisfying basic assumptions for the analysis of variances.

Based on the result, we cannot reject the null hypothesis that there are significant differences between the dependent variable and previous period groups (see Table 7). The deviation between current rating and current cumulative average does not seems to be different. This can be an evidence that supports the conformity effect in online product ratings.

Table 7. Analysis of Variance

Source	SS	Df	MS	F	Prob > F
Between Groups	944	1037	.031507857	0.20	0.9390
Within Groups	6.29	6.91	.158428276		
Total	134.790066	854	.157833801		

5. DISCUSSION AND CONCLUSION

5.1 Discussion

This study is one of the earliest studies that apply pattern recognition method with Markov chain in analyzing online ratings data. It suggests that there is weak relationship between just prior and posterior ratings: People leave comments and ratings with the effect of others in online platform. Furthermore, in online platform, it seems that conformity effect that is frequently occurs in offline communication, does exist.

More specifically, we investigated two main hypotheses to understand the sequential characteristics of online ratings. First, in respect to the conformity effect, we examined sequential relationship between just prior rating and posterior rating. Specifically, the contingency table as which the Markov chain describes that groups of transition probabilities do not provide probabilistic evidence of conformity effect in online platform. However, chi-squared coefficients are statistically significant, although Cramer's V does not strongly support the conformity effect. It means that there can be weak dependency between prior rating and posterior rating.

We also checked the robustness of our results by regrouping ratings into three different stances of commentators and found consistent result. This modified test for the effect of recent six prior ratings does not raise satisfied result but, it draws relatively high Cramer's V value: It would reflect that prior commentators' average opinion is more similar with current rating rather than just one prior person's view.

We further conducted the analysis of variance and found that there is no significant differences in the deviation between current rating and the cumulated average for ordered period groups. This can be another evidence of the existence of conformity effect in online product ratings. In other words, the null hypothesis of dependency in ratings can be weakly supported by statistic measures.

Besides discussion on main hypothesis, some points have enough value to mention. First of all, in Amazon.com shopping page, people usually leave positive ratings rather to raise negative or critical points. More than 50% of ratings are point 5, negative ratings 1, 2 are just around 12%. It is also interesting that the portion of products that captured more than 30 reviews are just only 6%. In other words, not exactly 20%, but only small amounts of products could gain customers' response on online platform.

5.2 Implications

Online platform has become significant tools in daily life with the development smart devices as well as social network services. Correspondingly, effort to utilize prolific mine of customers' state of mind has also gathered great volume for managerial application. This study implies that companies that endeavor to capture customers' needs and wants from online platform could be more effective if they customize for different groups of customers since they usually behave following others' opinion. In other words, aggregate approach for online platform would not be effective as is the case for offline world.

5.3 Limitations and Avenues for Further Research

Although this research suggested some interesting findings, limitations are also clear. First of all, this study considered only online ratings, not including online reviews that contain more specific meanings for the ratings. Future research will have more profound finings with the analysis of the contents of those reviews. In other words, combining simple pattern recognition with the analysis of online review content can be another interesting approach. In addition, analysis of additional online platforms can strengthen the generalization of our results.

ACKNOWLEDGMENTS

This work has been prepared based on the master thesis of Hyung Jun Kim who graduated from Graduate School of Culture Technology, KAIST in 2014.2. and was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2015S1A3A2046742).

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