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A Bayesian Approach to Evaluate Online Rating Systems

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Abstract:

With the increasing number of people purchasing goods through an online medium, the choice available to buyers has hugely increased. Consumers often compare vendors, before selecting a particular seller. Generally, the rating of a buyer becomes a very crucial factor in the decision made by a purchaser. The concept of a "reputation system" is essential fall all e-commerce platforms to function effectively, while simultaneously satisfying both customers and sellers. This note introduces the concept of a reputation system and defines it, with respect to existing literature. We then provide three broad categories of reputation systems- contemporaneous or a simple rating system, a Beta-Binomial rating system and a Multinomial-rating system. We examine vendor performance across time to demonstrate the superiority of the Bayesian approach as opposed to a naïve method of discarding prior information. We conclude by briefly introducing a Dirichlet reputation system.

Keywords **—Bayesian, Binomial distribution, Dirichlet distribution, Beta distribution**

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I. INTRODUCTION

With a boom in the utilization of e-commerce platforms, reputation systems have become an integral part of assessing the performance and quality of goods and services in the supply chain. A reputation system enables users of these platforms to evaluate and compare vendors, thus incentivizing vendors to better their performance. The study in [1] states that this system of evaluating suppliers' performance is not only useful to consumers who can be selective about purchases but can also be used by the seller to improve his performance over time. He describes a reputation system functioning as a continuous cycle, where consumers procure services (depending on ratings), following which they provide feedback, and this process is repeated. The important point underlined in [1] is that a consumer is able to make a decision on whether or not to buy a product or service depending on past ratings. He then makes a decisionand is able to provide a rating reflecting his experience. This rating provided by the consumer is then aggregated with the previous ratings and serves as the new rating for that product. This cyclic rating system is an essential part of any e-commerce platform as it enables the users to exert their choice of different sellers for the same product. Simultaneously, a rating system also increases healthy competition among sellers to improve the quality of the goods and services they provide, so as look better than a rival seller. This competition in the long run will ensure an overall increase in quality of goods and services on the e-commerce platform.

[8] conducted a randomized field experiment to understand the importance and necessity of a reputation system in the setting of an e-commerce platform. Choosing the popular e-commerce website, eBay, they compared the sales of a highly reputed seller's profits, versus the same seller's

profits under a different name with very few ratings. The field experiment showed that most consumers preferred the reputed seller's goods over the new seller, thus, underlining the significance and impact that ratings have in e-procurement.

Lately, Bayesian methodologies are being introduced to reputation systems to make them more accurately reflect performance on e-commerce platforms. For example, [7] proposed a Bayesian reputation model, which combined a trustworthiness function with a credibility function, so as to cancel out the impact of unfair ratings. [2] showed a statistical filtering tool to combat the impact of unfair ratings in a Bayesian reputation system.

A generalized method of approaching a rating system would be to use a multinomial rating method. [4] developed a Dirichlet reputation system which could be used to effectively capture the impact of good or bad votes on products.

II. A GENERAL CATEGORY OF REPUTATION SYSTEMS

A. *Contemporaneous Rating System*

A Binomial reputation system includes positive and negative votes, indicating whether the consumer was satisfied or unhappy with the product/purchase. To demonstrate the most simple case of a binomial reputation system, we have shown below randomly generated data for a particular vendor's product for six given days (Table I.). Assuming that a total of ten votes were given for the product by different buyers on six different days, the proportion of positive or 'yes' votes is shown in the last column of Table I.

Fig 1. shows the point estimates of the proportion of positive votes for Day 1 through Day 6. This point estimate can serve as an indication of the performance. In the contemporaneous model, we only look at the current data and do not give importance to the past information. Therefore, we would conclude that the quality of the product as rated by buyers first decreases, then increases, and then decreases again as shown by the trend in the graph (Fig 1).

TABLE I
BINOMIAL RATING IN THE CONTEMPORANEOUS SYSTEM

Day	No. of positive votes (a)	No. of Negative votes (b)	a/(a+b)
1	6	4	0.6
2	2	8	0.2
3	5	5	0.5
4	6	4	0.6
5	9	1	0.9
6	7	3	0.7

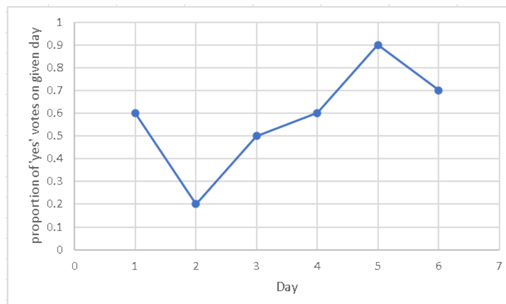

Fig 1. Daily proportion of 'yes' votes serving as point estimates of that particular days' performance

The contemporaneous model would seem to be a sufficient indicator of quality, but in certain extreme situations it may prove to misinform the vendor-performance. For example, consider a Vendor X's binomial ratings for 6 days, whose trend across time is shown in Fig 2.

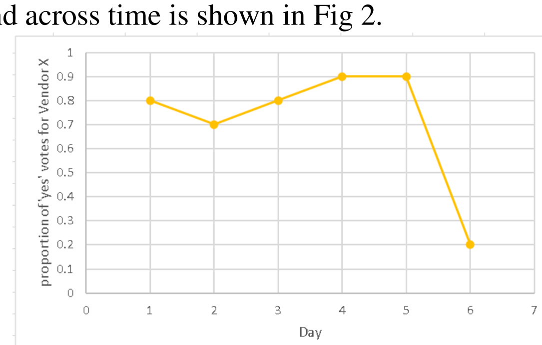

Fig 2. Vendor X's performance trend over 6 days

By analyzing the data on Day 6 to gauge performance, it would appear that the vendor is performing very poorly, and that most buyers had given his product a negative vote. However, if we look at the past data, it is clear that the vendor typically performs well and has a good reputation of receiving a high proportion of positive votes, suggesting that some unforeseen circumstance could have affected his performance on Day 6. This major drawback of the contemporaneous system calls for a model which will give importance to prior performance.

B. *Beta-Binomial Rating System*

A Binomial reputation system includes two reviews- either positive or negative. In the Beta-Binomial rating system, these reviews are continuously updated using a Bayesian model. Equation 1. shows the Beta distribution with parameters ‘a’ and ‘b’. The distribution of ‘Γ’ given by the Beta distribution and is denoted as Beta(a, b), and ‘Γ’ denotes the Gamma function.

If the prior distribution of ‘Γ’ is a Beta distribution - Beta(a, b), and the likelihood of observing data given the Beta distribution is Binomial distribution - Binomial(n; Γ), then the posterior will be a Beta distribution - Beta(a + k, b+n-k), where ‘n’ denotes the total number of votes, and ‘k’ is the number of yes votes. (Equation. 2.)

$$f(\theta;\alpha,\beta)=\frac{\Gamma(a,b)}{\Gamma(a)\Gamma(b)}\theta^{a-1}\theta^{b-1} \tag{1}$$

Equation 1. Prior distribution

$$f(\theta;\alpha+k,\beta+n-k)=\frac{\Gamma(a+k,b+n-k)}{\Gamma(a+k)\Gamma(b+n-k)}\theta^{a+k-1}\theta^{b+n-k-1} \tag{2}$$

Equation 2. Posterior distribution

We present below a simulation of the Beta-Binomial rating system (Table II), which contains randomly generated data to demonstrate how the Beta-Binomial rating system statistically updates the ‘reputation’. Consider each transaction to have a total of ten positive and negative votes (n=10).

TABLE II
BINOMIAL RATING IN THE CONTEMPORANEOUS SYSTEM

Day	**No. of positive votes**	**No. of Negative votes**	**Cumulative positive votes (a)**	**Cumulative negative votes (b)**	**a/(a+b)**
1	6	4	6	4	0.60
2	2	8	8	12	0.40
3	5	5	13	17	0.43
4	6	4	19	21	0.48
5	9	1	28	22	0.56
6	7	3	35	25	0.58

For example, the Table II. shows that in the first record (say, a particular product on Day 1), six positive votes and four negative votes were given. By using the cumulative of positive and negative votes, we obtain parameters for the Beta distribution. In contrast, the values of ‘a’ and ‘b’ in the contemporaneous model, were simply the number of daily positive and negative votes, respectively. Thus, by computing the cumulative positive and cumulative negative votes, we include prior information in the current data. Consequently, on each day we obtain different parameters for the Beta distribution, hence a different Beta distribution. As each day progresses, the prior Beta distribution is updated with the likelihood to obtain the posterior Beta distribution.

The last column of the table in Table II. shows a single value (point estimate) for the proportion of positive (‘yes’) votes on that day (mean for that corresponding distribution on a particular day).

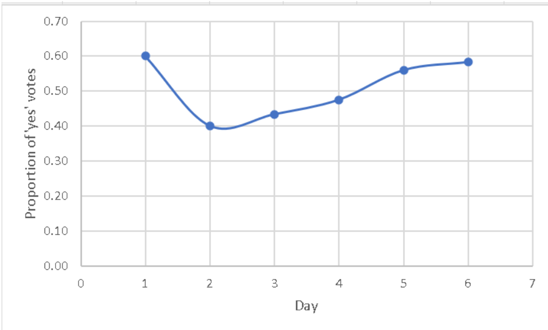

Fig. 3. Point Estimates for 'yes' votes

A different approach would be to obtain the entire distribution of the 'yes' vote proportion. This would result in more information about performance at every single point in time (here, day) because a distribution would be present, rather than a single point estimate of the proportion of 'yes' votes. Fig 4. Shows the various Beta distributions as the days progress. It is noticeable that on day 1, the variance is quite large as compared to the variance of day 6, implying that we become more sure as the days progress about the probability of good votes. Thus, by day 6, according to the graph, there is highest probability that fifty eight out of a hundred votes will be positive (deduced by comparing the graph to the point estimate of 'yes' votes on day 6).

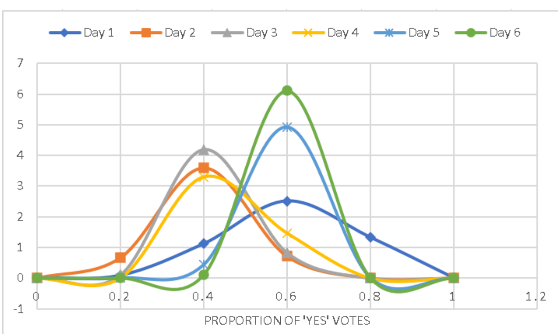

Fig. 4.- Bayesian updating of the binomial score in a reputation system

The importance of a distribution over a point estimate is significant. Consider the two figures, Fig 5. And Fig 6. Below. Fig 5. shows a vendor, say vendor X's performance (posterior Beta distribution) after a hundred days, whereas Fig 6. Shows another vendor, say vendor Y's performance after a hundred days. If we wish to compare the vendors to choose which vendor provides superior quality of goods, the mean indicates that vendor X is preferable (0.9>0.85). However, by looking at the entire posterior Beta distribution, Fig 5. Shows that there is 80% probability that more than seventy eight out of a hundred votes will be positive, while Fig. 8. Shows that there is 80% probability that eighty four out of a hundred votes will be positive. Thus, the posterior Beta distribution indicates that Vendor Y is more promising. This strengthens the argument that a single point estimate of the proportion of successes can be misleading.

This example is very useful, as it not only allows to compare, and contrast, two different vendors, from a consumer point of view, but it can also be used by a vendor to assess his own performance over time. (Fig 5. could hypothetically be a vendor's performance at the start of the year, while Fig 6. could be his performance at the end of the year. This would enable the vendor to gauge and understand his performance change, whether positive or negative, over time). By enabling a reputation system to show such outputs to the users of the platform, the quality of the overall platform should only improve.

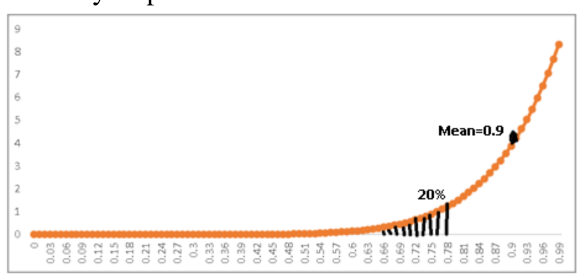

Fig. 5. Vendor X: 80% probability that 78/100 votes will be positive

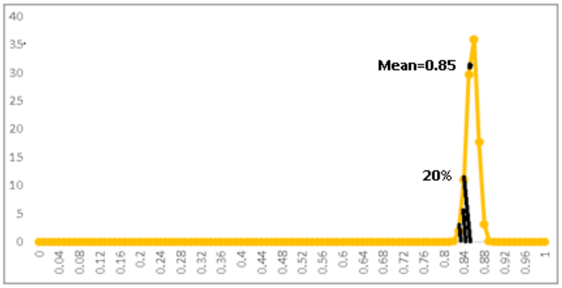

Fig.6. Vendor Y: 80% probability that 84/100 votes will be positive

C. Dirichlet Reputation Systems

Dirichlet or Multinomial reputation systems accommodate multiple levels of votes as opposed to Binomial reputation systems which involve only positive or negative votes. Thus, the categories of votes can be represented as $L = \{L_0, L_1, L_2 \ldots L_k\}$ with the probabilities $0 \leqslant p(L_i) \leqslant 1$ and $\Sigma_i p(L_i) = 1$. Similarto the Beta-Binomial conjugate priors, which yield a posterior Beta distribution, the Dirichlet-Multinomial conjugate yields a posterior Dirichlet distribution. Because of the provision for more than two levels of votes as in a Binomial case, this Multinomial approach serves as a generalization of the Beta-Binomial rating system.

III. CONCLUSION

To summarize, a reputation system is integral for the effective functioning of an e-commerce platform. Different e-commerce platforms choose to have different types of rating systems. We have discussed three broad categories of implementing a reputation system. Further, we have shown simple simulations of the contemporaneous rating system, as well as the Beta-Binomial rating system. We conclude that the Beta-Binomial System is superior to the contemporaneous system as it accounts for past behaviour, and that the Multinomial rating system is a generalized system, allowing for more variety in ratings. The findings of the study argue that introducing the idea of 'Bayesian updating" in a rating system could have a positive improvement in the rating systems functioning.

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