Reviewers Ranking as a Variable in Value Creation: Health Care Case

Ahmed Gomaa
University of Scranton

Satya Prattipati
University of Scranton

Users of healthcare services are providing online reviews of the services received from the healthcare providers. Positive patient reviews are likely to attract more patients and repeat visits. Health care providers are aware that a shift in the patient selection mechanism is taking place. One problem is the valuation of online reviews. This paper proposes a new algorithm that ranks each reviewer by weighting the type of feedback they provide for service providers to provide an economic valuation for the reviewers and their reviews. The algorithms calculate an Eigenvector and generate a weight for the reviews and the reviewers.

Keywords: Eigenvector, online reviewers, patient online booking, reputation economy, healthcare management

INTRODUCTION

Increasingly, more and more people are using Internet to select a service provider or a product. Online reviews have become a de-facto standard for all services providers. A majority of the consumers are expected to lookup a service provider or a product and find online reviews from prior users posted on sites like Facebook, google review, yelp, Amazon or even the providers web sites. Online reviews impact a purchase decision (Mudambi & Schuff, 2010); (Huang, Burtch, Hong, & Polma, 2016) and the absence of any online reviews will create a negative impression about the service provider or product.

This paper presents a new ranking algorithm for authors of health providers reviews to allow the economic valuation of the authors of the online reviews and their posted reviews. This research attempts to rank the reviewers of the healthcare providers, and their reviews, to assess the economic value of each reviewer. This paper models the value of the online reviewers of medical professionals by building on the **BiRank** ranking algorithm (He, Gao, Kan, & Wang, 2017)

The weighting is for the “Authority” or "contribution to," the online community, and “Hub” or "engagement with," the online community as well as the user’s interaction level with the reviews. The "Authority" variables are the summation of the A) number of reviews, and B) Stars rating left for the provider. The user’s interaction is the number of views and comments the reviews collected. Those variables help creating an "Authority Weight" for the reviewer. Another weight, the "Hub weight" is calculated based on the summation of A) the number of reactions and B) comments to other reviews. All variables are represented as a binary matrix to be able to calculate the corresponding Eigenvector and generate a weight for the reviews based on those variables. As shown in the demonstration results, the advantage of calculating the reviewer weight in this fashion is that it allows the reviewer weight to impact the reviews ranking even if that reviewer submitted review did not receive any positive feedback yet from the community. The algorithm weight the reviewer is based on her prior interactions. The algorithm variables are selected based on two datasets. First, the data available from Medicare.gov which provide information about groups, individual physicians, and other clinicians currently enrolled in Medicare. Second, is from Yelp dataset, which provides a subset of business, along with the stored attributes.

LITERATURE REVIEW

In recent years, researchers started to show growing interest in the relationship between online reviews and the selection of healthcare providers. Some of this research is in Table 1:

TABLE 1
RESEARCH SUMMARY

Author	Year	Title	Finding
Luca and Vats (HBR)	2013	Digitizing Doctor Demand: The Impact of Online Reviews on Doctor Choice	Established a relationship between online and the healthcare provider selection
Patel and, Brombach (MISQ)	2016	Patient Engagement: Digital self-scheduling set to explode in healthcare over the next five years	By the end of 2019, 64% of patients will book appointments digitally, delivering $3.2 billion in value and a competitive boost for health systems
Goh, Gao, and Agarwal (MISQ)	2016	The Creation of Social Value: Can an Online Health Community Reduce Rural-Urban Health Disparities?	Rural areas generate value from consuming the content created by urban areas, thus establishing the fact that a value is transferable from one area to another due to the reviews.
Xu, Armony, and Ghose, (Management Science – under review)	2017	The Interplay between Online Reviews and Physician Demand: An Empirical Investigation	Physician demand increase up to 7.24% from positive online reviews, the patient utility function increases up to 5.01% - thus establishing a monetary valuation of the online reviews
Lu and Rui (Management Science)	2017	Can We Trust Online Physician Ratings? Evidence from Cardiac Surgeons in Florida	Patients could trust the online ratings of physicians

Currently, there are several ranking algorithms that have proven to be effective. The common denominator across those algorithms is modeling the problem into a binary matrix of ones and zeros, and through an iterative process, the algorithm generates an eigenvector with the rank of the different components. PageRank developed by Google in 1998 (Page, Brin, Motwani, & Winograd, 1998), used it by modeling the web in a matrix of links, where one is an incoming link, and zero presents no link. The HITS algorithm (Kleinberg, 1999) presented both incoming links and outgoing links as matrixes and also used eigenvectors to rank the webpage. BiRank, developed in 2017, is an empirically superior algorithm (He, Gao, Kan, & Wang, 2017). It modeled as factors the time, current popularity of pages, and current influence of users. The algorithm is superior in predicting the level of popularity of a particular item with those three variables, time, item popularity, and user influence. In specific, BiRank algorithm has three hypotheses, 1) *Temporal Factor*. If an item has received many comments recently, it is more likely to be famous soon. More recent comments are a salient signal that more users focused on the item recently. 2) Item *Current Popularity*. If an item has already been widespread, it is likely to garner more views in the future. Popularity is partially affected by the existing visual interfaces of Web 2.0 systems: the more views an item has, the more likely it will be promoted to users.3) *User Social Influence*. If the users commenting on an item are more influential than uncommenting users, the item is more likely to receive more views in the future. It is important to note that BiRank is drastically different from PageRank and HITS. BiRank model users and their interactions and how that impact the popularity of the item, while the other two models model the webpage links. The fundamental difference lies within the information flow. As a result, PageRank and HITS will always rank popular websites like espn.com, CNN.com or FOXNews.com highly, while BiRank, given the influence of a celebrity like Michele Obama, her new page will be ranked high regardless of the website she decides to use too.

The BiRank algorithm includes the following variables/ equations.

$$w_{ij} = \delta^{a(t_0 - t_{ij})+b} \tag{1}$$

The Weight w from user i to object j is a function of the time it was provided. In other words, the older the comment is, the less valuable it is.

$$u_i^0 = \frac{\log(1+g_i)}{\sum_{k=1}^{|U|} \log(1+g_k)} \tag{2}$$

$$p_j^0 = \frac{\log v_j}{\sum_{k=1}^{|P|} \log v_k} \tag{3}$$

u stands for user i, and the user influence is a function of the g, which is the number of a friend that user has. The p stands for a post, page or object, and its value is a function of v which is the number of comments that page or object received.

FIGURE 1
BIRANK ALGORITHM

Algorithm 1: The Iterative BiRank Algorithm

Input: Weight matrix W, query vector $\mathbf{p}^0$, $\mathbf{u}^0$, and hyper-parameters α, β;

Output: Ranking vectors $\mathbf{p}, \mathbf{u}$;

Symmetrically normalize W: $S = D_u^{-\frac{1}{2}} W D_p^{-\frac{1}{2}}$;

Randomly initialize $\mathbf{p}$ and $\mathbf{u}$;

while *Stopping criteria is not met* **do**

$\quad \mathbf{p} \leftarrow \alpha S^T \mathbf{u} + (1-\alpha)\, \mathbf{p}^0$;

$\quad \mathbf{u} \leftarrow \beta S \mathbf{p} + (1-\beta)\, \mathbf{u}^0$;

end

return ***p** and **u***

(He, Gao, Kan, & Wang, 2017)

BiRank Algorithm in figure 1 presents how to calculate the rank of a particular page; the input is the weight matrix, which represents the comment and likes on a specific object, an initial random rank for the post or object *p* and an initial random rank for the user. The algorithm continues its iterations until *p* and *u* converges that is *p*, and *u* stop changing with further iterations. At this point, the algorithm finalizes the rank for the objects and the users.

ACCOUNTING FOR PATIENTS SPECIFIC CONDITIONS WITHIN THE BIRANK ALGORITHM

The paper applies "patients review" to the BiRank algorithm. First, the hypotheses are adjusted as follows:

H1. *Temporal Factor: If a review received many comments recently, the author of the review is more likely to be popular in the short term. More recent comments are a salient signal that more Patients focused on the recent reviews.*

H2. *User's Social Influence: If the users reviewing the physicians are more influential than others, the Physician is more likely to receive more views in the future. Interaction includes commenting, liking another comment, or commenting on another comment.*

H3. *Item Current Popularity: If a review is already viewed as helpful, it is likely to garner more patients to trust it in the future.*

It is important to note that the variables and the equations remain the same, but the semantics of the variables are different. For instance, in H1, the algorithm accounts for the time of ALL interactions, not only the comments. Furthermore, in H2, the user influence is not only by friends but also by the level of interaction and engagement with others within the community. Also, in H3, the object represents the health provider review itself as a step to evaluate the reviewer value.

ALGORITHM

We need to consider the effect of user influence on ranking physicians. We define a user influence matrix U whose elements indicate how many times a user has contributed or engaged with a review. This should contribute to the reputation score of the review.

As mentioned before, the p represents the post, in this paper context, the physician current popularity, and u represent the user social influence. In step 5, the customized algorithm represents u^0 with the equation u^o=$c^{\wedge 0}$ $xe^{\wedge 0}$

$$\mathbf{p} \leftarrow \alpha S^T \mathbf{u} + (1-\alpha)\mathbf{p}^0; \tag{4}$$

$$\mathbf{u} \leftarrow \beta S \mathbf{p} + (1-\beta)\mathbf{u}^0 \tag{5}$$

Here the initial value the user influence is not her friends as in BiRank, but instead the importance of the user contribution and engagement to the system. The new algorithm starts assuming that all users are fully contributing and fully engaged with a perfect score. The new algorithm multiplies the transpose of both vectors to get the initial U value

$c^{\wedge 0}$= 〚[1.1.1…..1]〛 ^T (6)

vector indicates the score of contribution given to the community, number of check-ins, and stars

$e^{\wedge 0}$= 〚[1.1.1…..1]〛 ^T (7)

vector indicates the number of engagements: (likes) and comments back

To get the U value, the customized algorithm uses the generated P in step 4 and plug in the values in equation 5.

The U score in step 5 is calculated based on the number of contributions, and Engagement, both presented as matrixes

C_ij, number of contributions: reviews, number of check-ins, and number of stars

E_ij number of engagements: (likes) and comments back

u^0 =C^T c+ E^T e (8)

WEIGHTS ON CONTRIBUTIONS AND ENGAGEMENT

The "Authority weight" represents Authors of online reviews contributions and is based on

A) number of reviews,
B) Stars rating left for the provider.

The “Hub weight” represents Authors of online reviews engagement and is calculated based on

A) the number of reactions and
B) comments to other reviews.

Both variables are creating the reviewer influence level

So far, the paper modeled the authors rank by using the amount of engagement and contribution to the community instead of using the number of friends as a point of reference. The resulting ranked authors of reviews lead to ranking reviews. The algorithm output will be ranked reviews, based on the reviewers’ level of engagement and contribution. The reviews are first classified into eight separate aspects according to Medicare classification, namely,

1. Getting timely care, appointments, and information.
2. Between-visit communication.
3. Attention to patient medication cost.
4. How well clinicians communicate.
5. Patients' rating of clinicians.
6. Health promotion and education.
7. Courteous and helpful office staff.
8. Clinicians are working together for patient care.

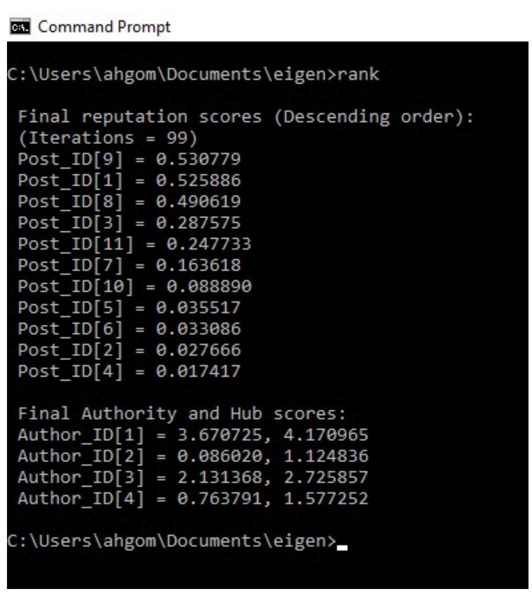
The paper ranks the reviewers based on the aspects they are reviewing a physician. Natural language processing allows for the classification of each review in one or more aspect, in addition to any other aspects presented in the Yelp reviews. In other words, for each identified aspect, related reviews are grouped and ranked based on the review popularity, reviewers influence and the temporal dimension.

IMPLEMENTATION DISCUSSION

For demonstration purposes, the implementation assumes the same time of review in one aspect. In the algorithm implementation, assume there are 4 reviewers addressing one identified aspect, which is attention to patient medication cost. All reviewers provided their reviews at the same time period. The four reviewers provided 11 reviews, and are interacting with each other's reviews. The Appendix presents the data used to generate the ranking of the reviews along with each reviewer rank as a hub and an authority to reflect the reviewer level of engagement and contribution to the community. The algorithm output shows that review 9, written by Author 3, is the most relevant review to the community, given the author of the review rank in terms of contribution and engagement. Author 1 is the most influential reviewer within the community, as she is the one the majority of the community interact with her posts. It is worth noting that post 1, written by Author 1 has a higher ranking than post 8 written by Author 3 due to the difference in the author authority and hub rank.

Accordingly, the algorithm allows for ranking reviews based on the reviewer influence, and the item popularity. The time of the review impacts the final ranking. Figure 2 shows the results of the algorithm. The results converge after 99 iterations. The levels of contributions, engagement and user interactions is presented in the Appendix.

FIGURE 2
RANKING RESULTS



ECONOMIC VALUE

Recent research suggests that there is an economic value from the online reviews of healthcare providers. The objective of exchanging the economic value with an online health community economy is to disseminate knowledge from the ecosystem point of view. In an attempt to formalize the ecosystem, it is essential to articulate the reviewers' economy variables in exchange. The reader of the reviews is trading their time and attention, in return, they are receiving the collective wisdom of the masses, and as a byproduct, the service providers are increasing their utility function, and the reviews readers book appointments with them more than the non-reviewed service providers. This paper uses the reviewer/patient engagement and contribution, and the health care provider reviews popularity to create a value function, where the patient generates value based on his effort (online reviews). According to the literature, the provider benefits from such engagement up to 7%, and the other system users benefit up to 5%. If a reservation system generates $250,000 per day, the benefits for the system to have a higher booking due to relevant reviews would be 7% daily or $17,500 per day. It might make sense to provide monetary compensation for the reviewers as a function of the value added they provide

$$ValueCreation_i^t = \frac{f(u_i^{(t)})}{\sum_{n \in all} f(u_n^{(t)})} \text{ x } income^t \tag{9}$$

The Value Creation is reviewer $\boldsymbol{i}$'s value creation in time $\boldsymbol{t}$. Income is the total income that may be distributed by the system to the community in time $\boldsymbol{t}$. $\boldsymbol{u}$ is the user influence score in time $\boldsymbol{t}$. $\boldsymbol{f}(.)$ is a reward function that controls the effect of change.

CONCLUSION

The paper presents a model to help incentivize online contributors in the form of reviews, where more compensation is delivered when more meaningful/sustainable contributions are provided. First, the paper identified an empirically tested superior ranking algorithm and modeled the patients' characteristics using the same methodology in the identified algorithm. The new algorithm defines the user influence as a result of the user contribution and engagement in addition to the importance of the reviews as viewed by the community. The algorithm implementation demonstrates the impact of the reviewer authority on the rank of the review. Second, the paper presents a value creation function based on the user influence, where each user is compensated based on her rank, which is derived from her engagement and contribution to the community, and the popularity of the physicians she is reviewing. To incentivize commentators, a financial model needs to pay the reviewer based on their impact. Future work includes automating the reviewers' compensation by presenting the knowledge created and disseminated in a blockchain ledger. Knowledge transactions may be recorded on a public ledger, similar to blockchain. The more usable the reviewer knowledge, the more transaction it generates. According to the paper model of value creation, it leads to more booking to the system in general, even if negative reviews exist. This is because the compensation is based on the quality and influence of the review, not the sentiment of the reviewers. An additional area of future research is to combine the temporal dimension with the spatial dimension of the patients using the build in mobile sensors to validate the physician popularity based on the number of signals detected in large medical buildings.

REFERENCES

Goh, J.M., Gao, G., & Agarwal, R. (2016). The Creation of Social Value: Can an Online Health Community Reduce Rural-Urban Health Disparities? *MIS Quarterly*, *40*(1), 247-263.

He, X., Gao, M., Kan, M-Y., & Wang, D. (2017). BiRank: Towards Ranking on Bipartite Graphs. *IEEE Transactions on Knowledge and Data Engineering*, *29*(1), 57 - 71.

Huang, N., Burtch, G., Hong, Y., & Polma, E. (2016). Effects of multiple psychological distances on consumer evaluation: A field study of online reviews. *Journal of Consumer Psychology*, *26*(4), 474–482.

Kleinberg, J.M. (1999). Hubs, authorities, and communities. *ACM Computing Surveys*, *31*(4), Article 5.

Lu, S.F., & Rui, A.H. (2017). Can We Trust Online Physician Ratings? Evidence from Cardiac Surgeons in Florida. *Management Science*, *64*(6), 2557–2573.

Mudambi, S.M., & Schuff, D. (2010). What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.com. *MIS Quarterly*, *34*(1), 185-200.

Page, L., Brin, S., Motwani, R., & Winograd, A.T. (1998). *The PageRank citation ranking: Bringing order to the web.* Stanford InfoLab.

Patel, D., & Brombach, M. (2016). *Insight Driven Health: Patient Engagement: Digital self-scheduling set to explode in healthcare over the next five years.* Accenture.

Xu, Y., Armony, M., & and Ghose, A. (2017). The Interplay between Online Reviews and Physician Demand: An Empirical Investigation. *Management Science - under review*.

APPENDIX

Engagement			
Author_ID	Post_ID	Linked_Post	Linked_author
1	1	9	3
1	3	10	4
1	3	11	4
2	4	6	2
2	5	7	3
2	6	8	3
3	7	3	1
3	8	4	2
3	9	5	2
4	10	1	1

Contribution	
Author_ID (Reviewer)	Post_ID (Review)
1	1
1	2
1	3
2	4
2	5
2	6
3	7
3	8
3	9
4	10
4	11

User interaction			
Author_ID (Reviewer)	Post_ID (Review)	Views	Comments
1	1	4	1
1	3	2	1
1	1	1	0
2	4	1	1
2	5	1	1
2	6	1	0
3	7	1	1
3	8	10	1
3	9	11	1
4	10	1	1
1	11	1	1