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Self-Regulating Social Platforms Leveraging Democratic Feedbacks for Rich Information

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Abstract. Sudden surge of user base and explosion of content at breath neck pace has created a void in maintaining the user experience as per the committed goals of social platform. The quality of user-generated content is a major motivation for new users to join the platform and for the existing users to contribute rich information. Quality ratio in platform varies taxonomically with the ever-growing user base that drives the platform. Classification of junk from useful resource is a critical task for a platform to thrive. Results are not much promising once the degradation starts. Solution to this acute problem can only be attained by understanding the granular differences that drives quality and motivation. Introduction of democratic feedback methods exposes credible content and brings users to the fore by building a self-governing social platform. Proposed differential weights for interactions strike right balance between volume and quality, without jeopardizing the basic factors such as authority and reputation that drives the platform growth.

Keywords: Social network services, tagging, Information analysis, User-generated content, Technology social factors

1. Introduction

The ever-growing user base in social platforms raises an important aspect to determine the value a user brings to the platform and areas where user's presence is more vital for the system. As the user participation in social platforms are increasing, there is an obvious increase in the content and an urgent need to maintain the quality of the content by removing spam posts, redundant entries, and obsolete items. This is humanly tedious and word-based detections are not accurate, which may give false results and can evade detections. This leads to unsatisfactory experience for users with the platform, thus reducing their interaction with the system. Democratic feedbacks are a way of validating characteristics such as user interests and content popularity with proofs evident from social interactions. The proposed method tackles the problem by linking the user reputation in the platform and introducing democratic feedback evaluation for quality moderation and visualization.[3]Moreover, the differential weights of contribution to a topic to encourage positive participation from the users.

Behavioral diversity is distinct among the users in content platforms, which reflects the same on the quality of user-generated content. The task of identifying quality content in these social platforms based on user contributions became daunting, attributing to the fact of noise in large content pools. User Generated Content (UGC) platforms have a rich variety of information sources. Apart from the content, there is diverse pool of semantics available, such as links between items, relationship between users, individual affinities towards various topics and explicit quality ratings from members of the communities. The proposed method attempts to deploy democratic feedback to identify high- quality content and blind spots in the system where interactions are necessary to foster quality equilibrium.

2. Background

Major factor that influences face value and profits of a social platform is the quality of content it stores. It's not so long ago that Facebook crossed 700M users and Twitter over 130M users. Large user bases in social platforms raises an important aspect to determine the value a user brings to the platform and areas where their presence is vital for the system. Social content platforms are logging every action that's been performed by the users to address the problem of expert location, critical resource identification, Spiking popularity of topics and other issues. There have been many research works in this area for improving quality of user-generated content in these platforms, unless the system is made self-governed with humans too involved at some level, no method can reach its full efficiency. Even the most advanced platforms such as Wikipedia, with rich semantics often face credibility issues [7]. If making users participate in the best interest of platform is one challenge, driving that positive participation and channeling this energy, where it needed most is a much bigger challenge in itself.

Quality in content platforms varies from excellent to junk and there had been extensive research in differentiating the junk data with relevant ones to maintain information reliability of the platform.[2][6] Automatic text processing and word tracking techniques mostly used in web pages have been introduced to get rid of common spam and junk but fails to adapt quickly[1] to the new variations of spam content.

Despite extensive research in this area, controlling the bottleneck problem is still a major issue. Considering the generic herd mentality of humans, which often leads to inequality in participation among certain topics, creating a democratic feedback system is very essential. One such system will introduce human factor [5] into the equation with technology intervening in between to remind them of system goals. Studying cause and effect from vast amounts data in various threads can reveal interesting patterns on how users go about a particular event or topic. This model can be reverse engineered by factoring right causes into the equation, thus leading towards a system capable of exposing unnoticed relations and affinities among users and diverse content. Overall effect will be improved as it's often proved that serendipitous actions will always squeeze more juice by keeping the element of surprise intact.

3. Methodology

3.1. Content Classification and Indexing

Considering a social platform with lots of activities, categorization makes sense. A topic index is created for classifying the content contributed by various users in the social platform into finite list of topics. Every time new content is contributed by the user, it is subsequently indexed to an appropriate topic in the topic index as suggested by the user. The relevance of the post to the topic and users interactions with it will determine the quality addition to that topic upon addition of the post. Further each topic is given an initial seed value for every new post to be tagged with. This is a function of the current quality ratio of the topic and the credibility of the user associated with the post.

3.2. User Share Evaluation

A contribution score for every user is computed based on the amount of content contributed by the user to the topic. This is determined based on the number of posts created by the user and interactions with the existing posts tagged to a topic. This generates a matrix to quantify the contribution by the user to a topic. So, higher interactions and posting will result in higher share ratio.

3.3. User Popularity Index

If the user is posting a good amount of quality content on the topic, and provided if the users are popular, then such users can often be considered as credible users with respect to that particular topic.[4] Popularity score listed in the popularity index indicates popularity and authority of the users with respect to the selected topic.[9] If the users are popular, then the content posted by the user is read by a large number of other users participating in the topic. So, the content posted by the popular user may have a huge impact on the topic quality.

The popularity scores for each user based on certain evaluation parameters. This may vary based on the platform and may include friends or followers associated with the user, activities and consistency of the user in the selected topic, reviews or feedback about the user, etc. The popularity index for each user can be evaluated as:

$$P = \alpha\frac{P_a}{P_A} + \beta\frac{P_r}{P_R} + \gamma\frac{P_h}{P_H} + \delta\frac{P_f}{P_F} \tag{1}$$

Where P_a represents a parameter associated with activities of the user in the selected topic, P_r represents a parameter associated with reach of 'friends' or 'followers', which indicates that the content posted by the user is reachable to how many other users associated with the social platform, P_h represents a parameter associated with authority of the user to drive people reactions which indicates how many other users are forwarding, acknowledging and circulating the content posted by the user to further users. Further, Pf represents a parameter associated with feedback associated with the user, as obtained from other users in form of reviews, rating, likes/dislikes, etc [10]. Corresponding values may be assigned to the above mentioned parameters for each user. Each of the parameters P_a, P_r, P_h, and P_f may have corresponding threshold values associated therewith, which are represented as P_A, P_R, P_H, and P_F respectively. The threshold values may be the highest expected value associated with the parameters and are platform specific. Each social platform may define different or similar threshold values for these parameters and is used to normalize the results.

The normalized values are summed up to obtain the popularity score P. Further, social platform coefficients, such as α, β, γ, and δ may be associated with the normalized values to vary the impact of the normalized values on the popularity. These values are also tailored according to the specification of the platform.

3.4. Topic Quality Assessment

A topic is a collection of posts and the related interactions with them. So the value is associated with every post and the summation of this defines value of the topic. For any individual posts, there are two parameters i.e., creation and interaction having a topic and user-specific value attached to them. The parameters of creations and interactions indicate whether the user has created the content or posted the content as an interaction to the content created by other users [9]. The initial content value is generated as a function of the current quality of the topic it's tagged with and the user who created it. This is further manipulated based on the interactions with the post. The post may be subjected to positive and negative interactions and there is platform specific norms fixed for each interaction which is summed to the initial value of the content [8]. The categorization as negative or positive may be based on various content assessment techniques -- likes, dislikes, votes, comments, sentiment analysis of responses, etc. Based on the weightage, the user contributed content may be assigned values. A weighted mean or average of these values is generated as the topic quality score.

A threshold topic quality score may be assigned to the topics in the topic index. If the topic quality score for a given topic is found to be lower than the threshold topic quality score, the topic quality is considered as bad or poor. Whereas, the topic quality is considered as good, when the topic quality score is above the threshold topic quality score. The low value will prompt user with higher reputation to add more value and thus can gain more reputation score.

Let C(α) is initial quality of the content contributed by a user and is a function of the popularity of the user in the topic and the topic contemporary quality. Once the initial quality of the content is computed, the topic quality assessment module computes the current quality of the content using following equation:

$$C(\alpha) - f\left(P_{Creator}, Q_{Topic}\right) \tag{2}$$

$$C = C(\alpha) + \sum I_{contetn} \tag{3}$$

Where I is the interactions associated with the content and comprises the democratic feedback gathered by the users in relation with the content and C is the current quality of the content and, denotes content quality that is assessed based on interactions regarding the content under consideration. The content quality may be computed based on the topic quality assessment parameters. The weighing technique involves defining weightage for each of the topic quality assessment parameters, and assigning a value to the content based on the corresponding weightage and the corresponding topic quality assessment parameter.

Once current quality of the content (C) is computed, a summation of the current quality of content with respect to each content represents overall quality of the content (V) associated with the topic, and is represented as:

$$V = \sum_{i \subset Subject} C_i \tag{4}$$

The obtained overall quality of the content (V) associated with the topic can be normalized using (5) to obtain topic quality (Q).

$$Q = \sum \frac{C_i}{C_i(\alpha)} \tag{5}$$

According to the above equation, the current quality of the content C is divided by the initial quality of the content C(α), to normalize the overall quality of the content. By doing so, the topic quality Q is obtained, which is not much influenced by the number of contents or posts. Thus, a topic having a large number of contents but not of much quality[12] may not have a high topic quality as compared to a topic having fewer posts but of good quality.

3.5. User Credibility Determination

As some users may be good at contributing noteworthy content in certain topics, whereas, other users may be good at contributing quality content in other topics. Thus credible users, that is, the users who are good at contributing the quality content in the topics under consideration or processing can be identified and encouraged [13] to contribute a greater volume of quality content in the topic, so as to improve the topic quality. The credibility scores can be computed for an individual topic, a group of topics, or all the topics collectively. The users with higher topic selective credibility scores are considered as credible users with respect to the selected topics, i.e. users who are capable [13] of contributing good quality content related to those topics. While, the users with high global credibility scores are considered as credible users who are capable of posting good quality content in all the topics in the topic index, taken together.

The credible users can be incentivized to encourage other users to contribute more quality content in the topic(s), so that the quality of the topic(s) can be improved. Even if the topic quality is good, the credible users can be identified and motivated to keep on contributing good quality content in the topic, so as to maintain the topic quality.

3.6. User Reputation Value

Each individual user may have a different contribution scores for each topic, depending upon the quantity of their contribution in the selected topic(s). The contribution score indicates the amount of content contributed by the users in the topic(s). The user value indicates value that the user contribution brings to the topic(s). In other words, the user value indicates the quality of their contribution in the topic(s).

The user value is computed based on the contribution score and the topic quality score corresponding to the selected topic(s). User value for a given user and a topic may be represented as an element O_{ij} in the matrix O as shown in (6).

$$O(m,n) = \sum_{i \subset m} \sum_{j \subset n} Z_{ij} . Q_i \tag{6}$$

Where, index 'm' represents the number of topic(s); index 'n' represents the number of users, and the O(m, n) represents the aggregated matrix of users contribution across the topic(s) calculated as a summation of amount of quality the users contribute to the topic(s).

The credibility scores for the users are based on the user value and the popularity score. The credibility score for a user (R) is computed by adding user value (O) and the popularity score (P) as represented in (7).

$$R = f(O, P) \quad (7)$$

Where, coefficient 'µ' is constant for a given social platform. Based on the kind of social platform, to vary the impact of popularity (P) of the user on the computation of the credibility, the value of 'µ' may vary.

Depending on the topic-selective credibility scores, one or more credible users with respect to topic can be identified and incentivized, to motivate the user to post more quality content in the topic [11]. The quality of the content in each and every topic in the social platform can be taken into consideration and quality enhancement actions can be taken to improve or maintain the quality of content in each topic, thereby raising the overall quality of content in the social platform.

A 'What if analysis' feature when provided on the website of the social platform the users can enter content and view the impact of the content on the credibility scores, thus creating a competitive environment to post high quality contents.

4. Implementation and Results

The dataset used for running the experiment is 'Just-Ask', a social Q&A platform used by TCS employees with a user base of about 100,000. The platform is highly social and rich in semantics, thus favoring our field experiment easily. Most of the networking features concerning authority and reputation gave out great deal of data in the light of current analysis. All in all the dataset had about 1Million interactions that include feedbacks, relations and deep interactions.

4.1. Initial Observation

The platform is active for over three years and one of the major concerns was to locate experts in various fields and analysis of the quality of interactions in the platform. The posts are tagged to topics but the quality in some topics is degrading and there was increasing migration of users from those topics, though they had many useful posts.

4.2. Implementation

Before testing the algorithm on the data collected from Just-Ask the initial and the refined data from administrator is captured to analyze the improvement. Finally we had three sets of data Default, which is the unedited dataset; Initial Refinement set containing the administrator monitored dataset; and finally the Algorithmic Refinement as a result of implementing our algorithm on initial data.

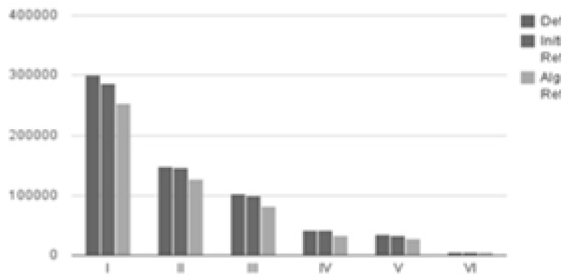

Figure. 1. Impact over range of Topics

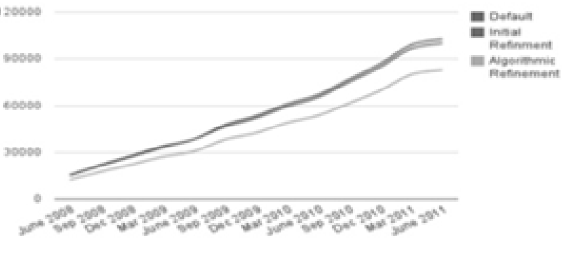

Figure. 2. Impact on timeline (Topic III)

5. Results

At the outset, total amount of interactions in the system got increased by a great deal with new feedback mechanism. Weighted interactions are a byproduct of the implementation and it did increase the user participation and assisted expert location. The data analysis of all three datasets plotted against the number of posts after filtering of the junk data is shown in Fig 1 and Fig 2. In our survey individual people were more satisfied than ever with the current quality on the platform. Democratic feedbacks are successful in controlling the bottleneck issue in trending areas, thus spreading the share of its attention to other areas too.

6. Conclusion

Users are naturally interested in content that does tend to deviate from their general interest graph. Democratic feedbacks can identify these affinities accurately, so that related selection of content can be used to improve positive participation. Results conclude an average decrease of 13.7% in irrelevant data when self-governing method is used, with about 37.5% of average participation in all sectors of the platform. Further, the differential weights of the future interactions can be pre-evaluated and a 'what-if' analysis on the platform can give a real-time updates on the effect of every posts to the topic and platform as a whole. Collaborative filtering in self-governing networks improves system efficiency by leaps and bounds. As motivation is such a turbulent and volatile factor, it needs to be continuously monitored and studied to understand user behavior on platform in order to be able to serve them better with right information.

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