Beyond Likes: Enhancing Social Media Engagement Metrics

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Abstract. Nowadays online social networks represent important platforms for communication and influence. Engagement metrics such as likes are crucial for measuring content popularity and user interaction. However, traditional like counts offer limited information since they do not take into account several factors that may increase or decrease the significance of each like. This paper proposes a novel method for weighting social media likes to derive a score that reflects the actual engagement of a post. Our approach considers multiple features including user influence, engagement history, geolocation, and temporal dynamics. Additionally, we sketched a validation process involving a representative sample of users who can help assess the weights associated with each like by trial and error. Overall we aim to provide a method to gain valuable insights to several actors, such as content creators, marketers, and researchers.

Keywords: Social Network · Like · Engagement Metrics

1 Introduction

In the last years, social networks diffusion [1, 8] has deeply changed the scenario about information sharing and public opinion. In fact social networking platforms became more and more diffuse, being almost every user subscribed to at least one of them. As a consequence they are often used as federated authentication systems on many websites [12]. Additionally, the high number of users in social network platforms has brought the need to adopt scalable, ad-hoc techniques, and protocols to manage the high demand effectively [11, 10].

Also due to the increasing need for privacy, anonymity [9, 7, 6] in social networks has become a challenging area of research. Anonymity can help users express themselves freely, possibly enabling the sharing of sensitive information without fear of retaliation. However, it also poses significant challenges, such as the difficulty in verifying user identities, which can lead to the proliferation of malicious behaviors, such as trolling, cyberbullying, and the spread of misinformation. Nowadays social networks can even create an interconnected ecosystem where IoT devices [14, 3] communicate and collaborate to enhance their functionalities. By integrating social networking principles, IoT networks can facilitate more intelligent and adaptive interactions between devices, similar to human social interactions.

Social media engagement metrics, such as the number of likes on a post, have become key indicators of content popularity and user interaction. However, these metrics often fail to capture the actual user engagement due to their simplistic nature. Indeed, traditional like counts do not consider various factors that influence the value of each like, such as the user's influence, the context of engagement, and the temporal dynamics of interactions.

In this paper, we present a method for assigning weights to likes on social network posts, taking into account user characteristics and engagement patterns. Our objective is to derive a comprehensive weighted score that more accurately reflects the significance of the likes received. To achieve this, we define a set of rules and corresponding mathematical formulas for calculating these weights. The motivation behind this work stems from the need to develop a more accurate method for evaluating social media engagement. Several studies have addressed the limitations of traditional user engagement metrics on social media such as likes. One key limitation is that likes alone do not capture the actual user engagement. For instance, some studies [23] revealed that while likes are easy to measure, they do not necessarily reflect meaningful engagement with content. On the other hand, other activities, such as comments or shares, were found to provide more insights into user engagement [17]. Additionally, the authors in [16] show how the likes generated artificially, often by bots or fake accounts, can be used to inflate engagement metrics. These likes obviously undermine the integrity of social media metrics. Some studies suggest that context and platform-specific behaviour significantly impact engagement metrics. For instance [20] examine propaganda on social media. While [22] examines how Facebook and Twitter influence political participation. The authors observed that a post on Facebook would have more influence on strong-tie networks. While a post on Twitter is more effective on weak-tie networks.

All these complexities highlight the need for comprehensive engagement metrics that consider user influence, interaction quality, and platform-specific behaviours to understand social media engagement better. Overall the proposed method provides a more accurate assessment of a post's impact. Therefore, this approach can help content creators and marketers gain deeper insights into their audience's behaviour and preferences, thus enabling more targeted and effective content strategies. Additionally, researchers can benefit from our approach to study information propagation in social media with greater accuracy.

The remainder of this paper is structured as follows. In Section 2 we present the related literature. Section 3 details the proposed approach for weighting social media likes. Section 4 describes the validation methodology. Finally, Section 5 offers concluding remarks and discusses potential avenues for future research.

2 Related Works

The importance of accurately measuring social media engagement has led to various studies proposing improvements over traditional metrics. In this section, we provide a review of the most significant contributions in the field.

Overall the scientific literature has highlighted the need for a framework to adjust the significance of likes based on several factors. For instance, [4] explored how user influence and network structure should be taken into account since they affect the diffusion of information on social networks.

The timing of user interactions plays a crucial role in determining their significance. [24] focused on the temporal aspects of likes, emphasizing that the value of a like can vary depending on when it was given relative to the post's publication time. [13] studied the dynamics of online social interactions and highlighted the importance of temporal patterns in understanding user engagement.

Additionally, it emerges from the literature the need to take into account the user's past engagement history, such as the frequency and type of previous interactions, suggesting that likes from users who rarely engage with content are more valuable. Several works in the literature are aimed at classifying people behaviour in given contexts [21]. For instance, [5] investigated how historical user behavior can predict future interactions. While [18, 19] are aimed at detecting potential criminals by examining social media profiles. Finally, the scientific literature has highlighted the impact of contextual relevance on engagement metrics. Indeed [2] analyzed the influence of topic relevance on user interactions in social media. While [15] studied the geographic aspects of social network interactions and their implications for engagement metrics.

3 The Proposed approach

In this section, we introduce a method for assigning different weights to likes on social network posts based on specific engagement patterns. Our goal is to derive a comprehensive weighted score that better reflects the significance of the likes received. To do so, we define a set of rules and corresponding mathematical formulas to calculate these weights.

3.1 Weighting Rules for Likes

User's Historical Engagement Likes from users who frequently engage with your posts are considered less significant. To represent this, we define the weight as inversely proportional to the number of past engagements from the same user.

$$P_{\text{frequency}} = \frac{\mu}{1+n}$$

where n is the number of previous engagements from the same user and μ is a normalization factor.

Account Verification Status Likes from verified accounts are given more weight. We introduce a multiplier α for verified accounts.

$$P_{\text{verification}} = \begin{cases} \alpha & \text{if the account is verified} \\ 1 & \text{if the account is not verified} \end{cases}$$

where α is a constant greater than 1.

Degree of Connection Likes from users with many mutual friends are less impactful. We use the number of mutual friends k to compute the weight.

$$P_{\text{connection}} = \frac{\delta}{1+k}$$

where k is the number of mutual friends and δ is a normalization factor.

User Influence Likes from more influential users (those with a larger follower base) carry more weight. We use the logarithm of the number of followers F to determine the weight.

$$P_{\text{influence}} = \log(1 + \frac{F}{M})$$

where F is the number of followers of the user and M is a normalization factor. This choice ensures that a user's impact grows with their follower number F, but at a decreased rate. This prevents users with high follower counts from disproportionately dominating the weight calculation, thus maintaining a fair and scalable influence metric.

Time of Like The time of a like may be valuable in determining its weight. We model this using an exponential decay function.

$$P_{\text{time}} = 1 - e^{-\frac{t}{\tau}}$$

where t is the time (measured in hours) elapsed since the post was published, and τ is a decay constant. The constant τ controls the rate at which the weight of a like increases over time.

- Small τ: Likes gain significant weight quickly after the post is published, meaning the initial reactions are more heavily discounted.
- Large τ: Likes take longer to obtain significant weight, so the decay effect is slower, making early likes relatively more valuable.

By adjusting τ, we can fine-tune how quickly the importance of a like increases over time after the post is made.

Geolocation of User Likes from users in significant geographical areas (such as your hometown) are given more weight.

$$P_{\text{geolocation}} = \begin{cases} \beta & \text{if the user is in a significant area} \\ 1 & \text{if the user is in a different area} \end{cases}$$

where β is a constant greater than 1.

Weighting likes based on the geolocation of the user can be significant in various contexts. In the following, we provide an example to illustrate its importance. Imagine a user running a local bakery in a specific city, say Milan.

The user posts updates on social media about new products or promotions. The geolocation of the user who likes these posts is obviously crucial. Indeed likes from users in Milan (or nearby areas) are more valuable because these users are potential customers who can visit the bakery. Their engagement is directly relevant to the business objectives and local market reach. Additionally, positive interactions from local users can enhance the visibility among the local audience, leading to higher sales. For example, if a like comes from someone in Milan, their friends or followers in the same area might also become aware of the bakery. In this scenario, we would assign a higher weight β to likes from users in Milan compared to those from other regions. This focus ensures that the engagement metric aligns with potential users' business goals of attracting local customers. We observe that this weight may not always be significant. In this case, its value would always be 1.

Content Quality of User's Profile Likes from users whose posts receive high engagement are considered more valuable. We use the average number of likes L on their posts for this weight.

$$P_{\text{quality}} = \log(1 + \frac{L}{N})$$

where L is the user's average likes per post, and N is a normalization factor.

Contextual Relevance of User's Engagement Likes from users who frequently engage with content similar to yours are more significant. This is based on the number of interactions H with posts sharing similar hashtags or topics. This similarity can be computed via NLP techniques such as semantic similarity.

$$P_{\text{context}} = 1 - \frac{m}{1 + H}$$

where H is the number of interactions with similar content, and m is a normalization factor.

External Interactions by the User Likes from users who also comment or share your post have more weight.

$$P_{\text{external}} = 1 + \gamma(C + S)$$

where C is the number of comments and S is the number of shares by the user, and γ is a weighting factor.

3.2 Comprehensive Weight Calculation

To compute the overall weight P_{total} for a like, we combine the individual weights from the rules defined above:

$$P_{\text{total}} = P_{\text{frequency}} \times P_{\text{verification}} \times P_{\text{connection}} \times P_{\text{influence}} \times P_{\text{time}} \times P_{\text{geolocation}} \times P_{\text{quality}} \times P_{\text{context}} \times P_{\text{external}}$$

3.3 Example Application

Consider a scenario where a user A gives a like to a post p from a user B. In the following, we list the information necessary to compute the P_{total} associated with this like.

- A has liked 5 of the B's posts previously ($n = 5$). No other types of engagements between A and B have occurred in the past, otherwise, their numbers would have been added together to n.
- A is not verified ($\alpha = 1$).
- There are 10 mutual friends ($k = 10$) between A and B.
- A has 5000 followers ($F = 5000$).
- A gave the like 3 hours after the post was created ($t = 3$ hours).
- A is in the same city as B ($\beta = 1.5$).
- A's posts receive an average of 100 likes each ($L = 100$).
- A has interacted with similar content 5 times ($H = 5$).
- A has both commented and shared the post ($C = 1, S = 1$).

By replacing these values in our formulas, we obtain the following.
Assuming $\mu = 1$,

$$P_{\text{frequency}} = \frac{1}{1+5} = \frac{1}{6} \approx 0.167$$

$$P_{\text{verification}} = 1$$

Assuming $\delta = 1$,

$$P_{\text{connection}} = \frac{1}{1+10} = \frac{1}{11} \approx 0.091$$

Assuming $M = 1$,

$$P_{\text{influence}} = \log(1 + 5000) \approx 8.517$$

Assuming $\tau = 5$ hours,

$$P_{\text{time}} = 1 - e^{-3/5} \approx 0.451$$

$$P_{\text{geolocation}} = 1.5$$

Assuming the normalizing factor $N = 10$,

$$P_{\text{quality}} = \log(1 + \frac{100}{10}) = \log(11) \approx 2.398$$

Assuming $m = 5$,

$$P_{\text{context}} = 1 - \frac{5}{1+5} = 1 - \frac{5}{6} \approx 0.167$$

Assuming the weighting factor $\gamma = 0.5$,

$$P_{\text{external}} = 1 + 0.5(1+1) = 2$$

Therefore, the overall weight P_{total} is calculated as:

$$P_{\text{total}} \approx 0.167 \times 1 \times 0.091 \times 8.517 \times 0.451 \times 1.5 \times 2.398 \times 0.167 \times 2 \approx 0.236$$

Thus, the total weight for this like is approximately 0.236, indicating a lower value compared to an unweighted like. Through this concrete example, we showed how the "significance" of each like can be dynamically adjusted based on the criteria defined in the previous section.

4 Validation

In this section, we sketch a methodology to validate the effectiveness of the proposed approach for weighting social media likes. The validation process aims to determine whether the computed weighted likes accurately reflect user engagement by comparing the results with a ground truth derived from user interactions. The validation methodology involves the following steps.

Sample Selection To ensure an unbiased evaluation, we select a sample of users from diverse backgrounds and with varying levels of social media activity. The sample group should be designed to be representative of the general user population.

Data Collection We consider a set of social media profile. For each of them, we collect all the posts they have recently published (e.g., in the last month or year). For each post, we extract the raw like counts and the user profiles behind each like. Then, for each profile, we extract the information useful for computing the weights of each like (e.g., frequency of likes, account verification status, etc.).

The procedure we describe in the following is the same for each social media profile. Thus, for the sake of clarity, in the following, we will consider a single social media profile.

Weighted Like Calculation Using the proposed weighting formula from Section 3, we calculate the weighted like score for each post of the considered social media profile. We then rank the posts based on the sum of the weighted likes.

User-Like Simulation The users in the sample are asked to interact with the posts by liking them as they normally would. These interactions are recorded to generate new post rankings based on actual user engagement.

Comparison and Adjustment The rankings derived from the sum of the weighted likes can be compared with the rankings based on actual user interactions. The degree of alignment between these two sets of rankings can be assessed using rank correlation metrics such as Spearman's rank correlation coefficient. This coefficient measures the strength of association between two ranked variables. Therefore it can be used to assess how well the relationship between two variables can be described using a monotonic function. If discrepancies are found between the weighted and actual rankings, we can employ a trial-and-error process to adjust our formula, by considering different normalizing factors. This iterative adjustment continues until the rankings show a satisfactory level of correlation, indicating that our weights accurately reflect user engagement.

5 Conclusion

By analysing social media engagement metrics we can understand user interactions and content popularity in the digital platforms. However traditional metrics, such as simple like counts, do not take into account the actual impact of a post on social media. This paper introduced a comprehensive approach for weighting likes based on engagement patterns. Specifically, our proposed method considers factors such as user influence, past engagement, geolocation, and the timing of likes to calculate a weighted score that more accurately reflects the significance of each like. Additionally, we sketch a validation mechanism for our proposal. This approach involves comparing the weighted scores of likes on a post with actual user interactions collected from a representative sample. Then based on the correlation value between the weighted rankings and the actual engagement patterns, we can iteratively adjust the weights to better reflect user engagements.

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