Profiling Online Social Network Platforms: Twitter vs. Instagram

Veruska Ayora
Federal University of ABC, Brazil
veruska.ayora@ufabc.edu.br

Flávio Horita
Federal University of ABC, Brazil
flavio.horita@ufabc.edu.br

Carlos Kamienski
Federal University of ABC, Brazil
carlos.kamienski@ufabc.edu.br

Abstract

Online Social Networks (OSN) have been increasingly used as sources of information for different applications, ranging from business, politics, and public services. However, there is a lack of information on OSN platforms' behavior that may impact big data processing and real-time services. In this paper, two of the most widely used social networks, Instagram and Twitter, are investigated to broaden the understanding of how each platform's message characteristics influence data completeness and latency. We performed a series of experiments to emulate data posting and collection automatically. Our results increase the level of transparency of the platforms' internal behavior, showing that both can deliver data with reasonably low latencies and high completeness, but Twitter can be up to eight times faster when it comes to multimedia messages.

1. Introduction

The increasing use of Online Social Networks (OSN) in different areas reveals a critical and mostly unexplored question regarding the performance provided by their underlying platforms. With the rapid growth and proliferation of OSN platforms, a vast amount of user-generated content becomes a valuable information source for applications in different areas. Also, data is widely accessible since it can be collected through web-crawlers or public APIs. These two characteristics, i.e., massive and open data, represent the primary motivation for most OSN research [41].

User-generated messages on OSN platforms, such as Instagram[1] and Twitter[2], have emerged as powerful, real-time means of information sharing on the Internet. By the online communication of billions of individual users, these platforms have involuntarily created a global participatory sensing network that can be harnessed as an observatory of social events. Data collected from OSN provides social, economic, and cultural information that can be utilized by governments, policymakers, authorities, and businesses to understand market trends and behavioral patterns [38].

Several studies have also demonstrated the potential of OSN in defining people's sentiments about events, incidents, products, and services [41]. The potential of Twitter as a platform for improving awareness over variables of interest and thus supporting a more informed decision-making process has been highlighted in the literature for different areas, such as earthquake detection [46], influenza virus epidemics [1][6], disasters [14][25], elections [21], mobility [10], organizational issues [43], or crimes [33].

Existing social media methods are mostly focused on event detection [20][52], content analysis [27], and rumor analysis [13], which can describe specific phenomena often retrieve data to transform it into services. The challenge now is to investigate how the behavior of such platforms can influence data completeness and latency. This additional understanding is necessary as OSN platforms were not originally designed to support real-time services, even though they belong to private providers and data audition is not allowed [7].

In this context, the main goal of this paper is to examine the influence of message characteristics of OSN platforms (in particular, photo, video, hashtags) on data completeness and latency. We shed some light on the currently unexplored and poorly understood OSN platform behaviors, increasing the level of transparency of their internal working. Particularly, we seek to answer the following research questions:

RQ1: Are there messages shown to the Twitter and Instagram users, but not readily shown to other users? If so, what proportion of posted messages can be reliably retrieved?

RQ2: Does any message characteristic (e.g., photo, video, hashtag) affect the decision to make them available to other users?

RQ3: After a user posts a message, how long does it take for Twitter and Instagram to make it available to other users?

[1] https://www.instagram.com/about/us
[2] https://about.twitter.com/

Here, we analyze two social networks, namely, the microblogging platform Twitter and the photo- and video-sharing platform Instagram, as they have millions of users worldwide and allow data to be collected by automated processes. We utilized two key metrics to understand OSN platform characteristics, i.e., completeness, measured as the message return rate, and latency, measured as the time it takes for a message to be available to other users. We are aware that OSN data distribution policies and algorithms may change according to different criteria. Still, we believe there are solid reasons to understand and track them over time, by taking snapshots of their most significant behaviors as perceived by their users.

Hence, the main contributions of this paper are threefold. Firstly, we introduce a methodology for evaluating OSN platforms based on heterogeneous data quality and its impact on the users. Secondly, we examine two of the most widely used OSNs, Twitter, and Instagram to broaden the understanding of the similarities and differences in data quality across platforms. For example, our results reveal that the Twitter platform reposts up to 18% of the tweets shown in the user timeline. On the other hand, this behavior has not been observed on Instagram. Thirdly, we help developers by summarizing relevant OSN technical limitations when designing scenarios for different applications.

In the remainder of this paper, Section 2 presents related works, and Section 3 explains the proposed research methods. Experimental results are presented in Section 4. Section 5 discusses the lessons learned, and finally, Section 6 draws some conclusions and presents future work.

2. Background & Related Work

Recently, due to the broad adoption of mobile platforms, OSN represents an increasingly up-to-date digital reflection of society. It supports people in interacting with places around the city, with other people, and businesses, while talking about topics of common interest, such as sentiments, political beliefs, social interactions, human mobility, presence in specific events, likes [47].

OSN behaves as "human as sensors," recording human activities and preferences [22]. This data becomes a crucial asset since it can be transformed into valuable knowledge, helping the decision-making process [37]. Furthermore, enabled by OSN, these human sensors provide 24 per 7 real-time data streams at virtually no cost [16][46][1][6][33]. Also, [15] have argued that OSN updates shared by the citizens can serve as a complementary or a supplementary source of information that could shed light on why and how the events and patterns measured by physical sensors emerge.

The potential of this approach has also been confirmed by [3], which mentions the power of OSN during emergencies: *"In July 2013, a Boeing 777 aircraft crashed on landing at the San Francisco International Airport, after a transpacific flight from Seoul, South Korea. An observer waiting to board another flight snapped a photograph of the accident with her mobile phone and uploaded it to Twitter less than 1 min after the impact. Within 30 min, there had been more than 44,000 tweets about the accident, including photos and videos taken by survivors as they escaped from the wreckage (International Air Transport Association, 2014)."*

Despite all the attention to OSN, using data without clearly understanding what it comprises might be very problematic [17]. The more we understand a system's inner workings, the more justifiable it can be governed and held accountable [4]. Transparency provides additional reliability and validity for algorithms in charge of decisions that affect society. Also, it makes it possible for users to evaluate the correctness of OSN outputs and identify incorrect data [44].

However, even though transparency mechanisms ideally can empower users to question and critique the system, Ananny & Crawford [4] have highlighted some technical limitations of the difficulties in getting to know how algorithms operate. They suggested that imposing transparency is not as simple as it seems, as system developers themselves are often unable to explain how a complex system works or which parts are essential for its operation [9].

Transparency becomes even more relevant, as many OSN platforms are owned by commercial corporations that profit over data and interaction [30]. Eslami et al. [18] showed that the majority of Facebook users have a lack of awareness or understanding about their News Feed being structured by an algorithm. When users miss an important post from a friend, they usually blame themselves, ignoring that the OSN has an algorithm making decisions that could be misleading or hiding important content from them. On the other hand, even if users are aware of such complex algorithms, they have no way of knowing how it works, which may prevent them from being sure about the results of their actions [18].

2.1. Social Networks Platforms

From the literature review, it is possible to understand how to integrate OSN platforms as data distributors for various services that can be provided for the needs of a variety of smart applications. For instance, Anthopoulos & Fitsilis [5] explore the need of custom social networks for smart cities, considering that OSN platforms are the ideal implementations within the smart city ecosystem.

OSN platforms and their applications have revolutionized the Internet, radically changing the communication methods while enabling dynamic interactions between users [48]. However, OSN platforms differ significantly in their conventions and characteristics [24]. For instance, Twitter is primarily a text-based medium that, until recently, only allowed tweets up to 140 characters, which meant individuals needed to condense their ideas into simple messages. In contrast, Instagram is a visual-first medium that emphasizes pictures and videos over written text [23].

Twitter is nowadays a popular microblogging service that allows its users to send short messages of up to 280 characters[3], called tweets, as well as images and videos. Monthly, almost 500 million[4] messages are created and redistributed by millions of active users, around 330 million[5] users worldwide. Like Instagram, Twitter is hashtag-driven [19] and has been associated with the proliferation and dissemination of news and events [45]. Twitter holds a prominent position among OSN as it offers: i) real-time update; ii) flexibility, as a user can track someone else's post without being friends; iii) ability to harvest vast amounts of data through its APIs, and; iv) potentiality for the predictions of future situations [28].

With 1 billion monthly active users [11] [34], Instagram focuses on sharing photos and short videos that motivate the interaction between users through private conversations, public comments, and the like concept to show approval. Most photos have tags and captions with high-level descriptions [51]. Instagram is often used for self-expression and self-documentation through the showcasing of everyday life [2].

Due to growing concerns about privacy and data security, OSN platforms face frequent changes to their security policies and data restrictions through APIs. The latest changes on Instagram included restrictions on data permissions, updating platform policies, and regularly evaluating an app's access to user permissions [31][40]. Thus, this study focuses on data captured by web-crawlers and not by public APIs, as our previous study focused on the Twitter Streaming API performance [7]. Instagram is currently changing its privacy policy due to recent data leaks, and the European General Data Protection Regulation (GDPR) may require changes in the future.

[3]https://blog.twitter.com/official/en_us/topics/product/2017/tuíteing madeeasier.html
[4]https://www.internetlivestats.com/twitter-statistics/
[5]https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users

2.2. Social Networks Methods

Existing studies on OSN are mostly focused on content analysis [5][8][12][35][39][47]. However, there are a few studies that investigate the data completeness collected through public APIs. For instance, Morstatter et al. [36] analyzed the completeness of samples collected by the Twitter Streaming API, using a feed that allows access to all public tweets. Their study concluded that query parameters impact the coverage of API results. In the same manner, Joseph, Landwehr, Carley [29] established five simultaneous connections for tracking similar keywords simultaneously and analyzing whether the data returned by each connection was the same. Their results revealed an average of more than 96% overlap and concluded by the impossibility of collecting 100% of the data with multiple connections.

Driscoll & Walker [17] discussed how platform bias could influence data completeness, comparing two sources retrieved from Twitter, namely the public Streaming API and the commercial firehose streaming connection provided by Gnip PowerTrack. While the Streaming API excels at longitudinal data collection, it is a poor choice for massive, short-term events. Firehose offers an extensive collection of tweets sent within short periods, but the companies do not disclose data collection and processing procedures.

Another approach focused on examining the arrival data rate returned by the Twitter Streaming API. Perera et al. [42] found a pattern in Barack Obama's tweets that can be modeled as a Poisson distribution, while retweets follow a geometric distribution. Sakaki et al. [46] identified that inter-arrival times during natural disasters such as earthquakes and typhoons, fit well into an exponential distribution with $\lambda = 0.34$.

Other studies also examined the current technological issues of OSN. For example, Stieglitz et al. [49] presented a three-layers social media analytics framework determining the main components and analytical approaches to gain deeper insights. On an extension of their previous work, Stieglitz et al. [50] further highlighted the need for suitable data storage and scalable and flexible software architecture to deal with the high volume of data gathered from OSN. On the other hand, Hammerl et al. [26] introduced a series of critical factors and key performance indicators to OSN usage's success. The authors mentioned the indicator "Reduction of response time" as part of the critical success factor "Team".

The differences in our study in comparison to the previously mentioned papers are manifold. Firstly, it does not aim to compare extracted data through APIs but using web-crawlers. Our purpose is to mimic user behavior and compare Twitter and Instagram, where the latter does not provide an API like the former. Secondly, to understand data completeness and latency, we automatically simulated all the steps of a legitimate user's post, producing a synthetic workload. Furthermore, most studies are related to evaluations and classification of OSN content and user behavior. Unlike them, our paper seeks to evaluate the OSN data perceived by its users, such as completeness and latency of posts.

3. Research Design and Methods

Even though each platform has different interface features, they support similar core functions for users to interact with one another. These core functions (e.g., to attach a photo, or to send a simple text message) enable us to compare data completeness and latency across platforms. The following subsections describe our 4-step methodology to achieve this purpose.

3.1. Step 1: Environment Configuration

This step aims at simulating how users interact with each other on the Twitter and Instagram platforms. We set up a test environment, as shown in Figure 1. On the left side, user A sends messages from her account to Twitter and Instagram. On the right side, user B, who follows user A, checks the update messages on her timeline. Two computers were used to establish simultaneous connections, having the same configuration: 1.8 GHz Intel Core i5, 8GB 1600MHz DDR3.

Instagram is geared towards mobile devices with Android and iOS. Posting photos on a laptop is possible, but it requires simulating a mobile user in a web browser. For doing so, we used Google Chrome that provides a shortcut to access the mobile version. This approach does not work for posting videos though. In this case, we used Gramblr[6], a free smartphone app and web service with a desktop client, where the primary interactions are with the web service. While Gramblr is now discontinued after the submission of this work, other similar tools should be used for the same purpose.

Although OSN platforms allow different settings for the visualization of the timeline, we configured Twitter for showing messages in chronological order. Instagram does not offer such an option, but we observed that it returned the results in a chronological order for new posts (a strict chronological order is not enforced since it automatically reposts old messages sometimes).

[6] https://gramblr.com

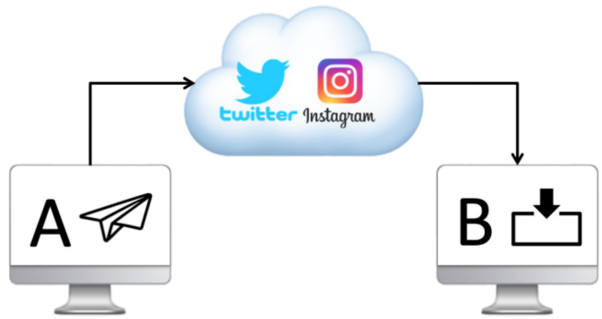

Figure 1. Environment Configuration

Our experiments were performed between March 13 and May 6, 2019, with ten replications to avoid bias in the samples. It is essential to notice that the experiments took a long time to complete and had to be repeated often since the platforms have different mechanisms to avoid automated robots. Users were blocked many times, and the procedure to unblock them frequently took many days.

3.2. Step 2: Experimental Design

This step defines the test scenarios for each platform, considering that the evaluation process was repeated several times with different parameters to test the robustness of the experiment. Our process involves three test scenarios, depicted in Table 1, aiming at evaluating whether messages with hashtags, video, or image can interfere in the metrics under analysis. In all scenarios, each experiment was repeated 10 times. For each replication, 50 messages were published. The estimated execution time for each scenario was about 10 hours to post 500 messages per platform.

- **Scenario 1**: Image & Specific Hashtag - the messages are composed of a 3.1 MB image, the specific hashtag #aksurevlorrainearoya, the replication number, and the post number. These posts are sent from the timeline of user A, while user B waits until they are available on her timeline.

- **Scenario 2**: Image & Generic Hashtag - the messages are composed of a 3.1 MB image and 6 most common generic hashtags, namely #beautiful #cute #instagood (from worldwide), #tbt #love and #brasil (from Brazil). Also, the replication number, and the post number. These posts are sent from the timeline of user A, while user B waits until they are available on her timeline.
- **Scenario 3**: Video - messages are composed of a 14.1 MB video, the replication number, and the post number. These posts are sent from the timeline

of user A, while user B waits until they are available on her timeline.

Table 1. Configuration of the Experiments

Scenario	Media	Hashtag	Msgs	Replications
1	Image 3 MB	Specific	50	10
2	Image 3 MB	Generic	50	10
3	Video 14 MB	--	50	10

3.3. Step 3: Posting and Capturing Messages

This step required the development of two algorithms for different purposes. The first algorithm simulates message submissions step by step as if a user in front of a computer performs them. We used Python 3 and PyAutoGUI[7] for controlling the mouse programmatically. Selenium WebDriverAPI[8] allows the web browsing automation, automating web applications by driving a browser natively like a user either locally or on a remote machine, using the Selenium Server. Also, Selenium WebDriverWait[9] and ExpectedCondition allow the program to wait for a particular condition to occur (i.e., finding an element from the next page) before proceeding further in the code.

Figure 2 shows the algorithm used for posting messages. The content of each message varies for the three scenarios, as presented in Table 1. We used the Poisson distribution for the message arrival rate, meaning that the time between posting two consecutive messages is given by an Exponential distribution with λ = 0.34 seconds, according to the literature [42].

```
Log in with user A
T = exponential random variable with ⌊=0.34
set seed = n, n>0
T= get variate from T
sleep t
choose media (image or video) by user clicks
write hashtag (specific or generic)
post message
repeat steps 4, 5, 6, 7 and 8 for all
messages
```

Figure 2. Algorithm for automated message posting

The message capture algorithm is developed in Python 3 to record the exact moment the message sent by user A and becomes available to be viewed by user B (Figure 3). The application monitors the HTML webpage over the user B timeline to check if a new post is available. The Selenium WebDriverWait and ExpectedCondition are also used here to refresh the page and establish the conditions for recording messages.

```
Log in with user B
L = last post at User B timeline
L'= Last post saved
L'=L
refresh page
Read L
If L' ↑ L
      Save L and time
      Repeat steps 4, 5, 6 and 7
else
     Repeat steps 5, 6 and
```

Figure 3. Algorithm for automated message capture

3.4. Step 4: Data Analysis

This last step identifies how the collected data can be evaluated and measured. Using Venn diagrams, the set theory allows us to understand five possibilities for creating the captured dataset (Figure 4). We considered the U, P, and C sets:

- Set U: the universe set of messages posted by all users of the OSN platform.
- Set P: the set of messages posted by user A in our experiments.
- Set C: the set of messages captured by user B, including not only those posted by user A.

The scenarios analyzed include the following possibilities for data completeness. In Figure 4(a) we have $P \cap C = \{x \in U \mid x \in P \; and \; x \in C\}$, that is, how many tweets are captured (C) from the set of posted ones (P), and how many belong only to the set U posted by other Twitter users. In Figure 4(b), we have $P \cap C = \{\}$, where samples were unable to capture any tweet posted by the experiment.

In Figure 4(c), C is a proper subset of P ($C \subsetneq P$), i.e., samples returned only tweets posted by the experiment, but in a smaller number. In Figure 4(d), we have the opposite situation, i.e., P is a proper subset of C, which means that all posted tweets were captured, but many more tweets from other users were also captured. Finally, Figure 4 (e) shows that $C = P$ ($P \subseteq C$ and $C \subseteq P$), which means that samples returned all and only the tweets posted by the experiment.

[7] https://pyautogui.readthedocs.io/en/latest/
[8] https://docs.seleniumhq.org/projects/webdriver/
[9] https://selenium-python.readthedocs.io/waits.html

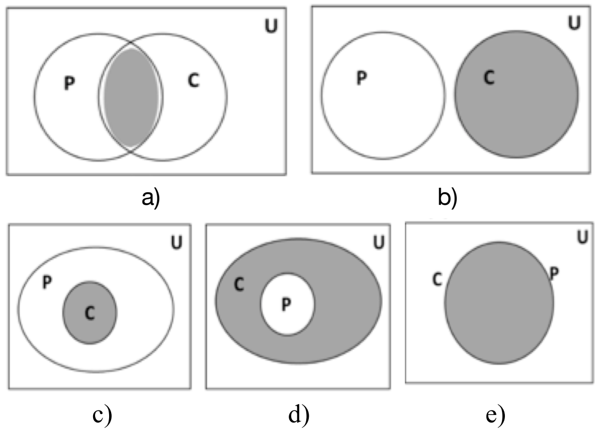

Figure 4. Venn diagram for the evaluation of collected data

3.5. Metrics

We used the following metrics to analyze the results of the experiments:

- Twitter completeness: calculated as the number of messages captured from user B timeline divided by the number of messages posted by user A.
- Twitter latency: calculated as the difference between the timestamp of a message captured by user B and the timestamp of the same message posted by user A.
- Instagram completeness: calculated as the number of messages captured from user B timeline divided by the number of messages posted by user A.
- Instagram latency: calculated as the difference between the timestamp of a message captured by user B and the timestamp of the same message posted by user A.

The values of the metrics presented in the results are the mean of the 10 replications. We computed asymptotic confidence intervals at the level of 95% that are shown as error bars whenever they are meaningful.

4. Results

By performing experiments with Instagram and Twitter, we can compare how these platforms respond to their users and, consequently, perform better for different configurations. Based on the data collected in these experiments, we revisit the research questions formulated in Section 1.

RQ1: Are there messages shown to the Twitter and Instagram users, but not readily accessible by automated applications? If so, what proportion of posted messages can be reliably retrieved?

Figure 5 shows that the average completeness for scenario 1 is 100% and 97% for Twitter and Instagram, respectively. On the other hand, scenario 2 (generic hashtags: #beautiful #cute #instagood #tbt #love #brasil and 3 MB image) reveals that Twitter also achieved average completeness of 100%, but for Instagram, this figure was much lower, amounting 61%. Finally, scenario 3 (no hashtag and 14 MB video) shows that Twitter amounted again 100% and Instagram a lower percentage of 73%.

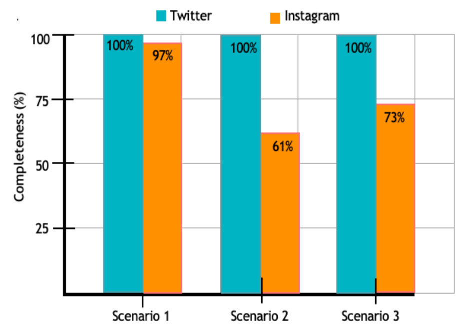

Figure 5. Data completeness for Twitter and Instagram

According to the possible scenarios presented in Figure 4, the data captured from the Twitter platform presented the characteristics of Figure 4(d), in which P is a proper subset of C. This means that all tweets posted by user A are shown in the timeline of user B, but tweets from other users (set U) are visualized as well. On the other hand, for Instagram the captured posts behave as shown by Figure 4(a), where the set C of messages visualized by user B was less than the set P of messages posted by user A. Also, other messages appeared in the timeline of user B that belong to the U set (i.e., posted by other users).

Some findings were found observing the captured data. We observed in Twitter datasets that some tweets were reposted by the platform itself, even though the profile is configured to display messages in chronological order in the timeline. The experiments show that about 18% of previously viewed tweets appear on their timeline again, without being reposted by user A. Of that percentage, 67% had videos (scenario 3), and 33% had images (scenarios 1 and 2). Besides, we observed that the platform policies could repost a single message up to 8 times. The interval between the first reposting and the last one ranged from 3 minutes to 18 hours within the experiments. This behavior was not observed for Instagram.

RQ2: Does any message characteristic (e.g., photo, video, hashtag) affect the decision to make them available to other users?

Figure 5 shows that for Twitter, user B can visualize 100% of messages from user A, regardless of the hashtag type (specific or generic) or media type (image or video). However, for Instagram, the completeness involved in the messages with six top hashtags (scenario 2) presented the lowest completeness of 61%, meaning that 39% of the messages with this characteristic are not visualized by user B. Also, it is possible to verify (scenario 3) that the posts involving videos are less likely to be visualized (73%), compared to (scenario 1) images and specific hashtag (97%).

RQ3: After a user posts a message, how long does it take for Twitter and Instagram to make it available to other users?

Figure 6 shows the latency for both platforms, i.e., how many seconds have elapsed from user A posting an image up to the point it is available in the timeline of user B. For scenario 1, the latency for Twitter is about 3 seconds (varying between 2.89 and 3.12 seconds). In contrast, for Instagram, it is about 25.616 seconds (varying between 21.95 and 29.29 seconds), considering a confidence level of 95%. We can notice that posts with images travel eight times faster through the Twitter platform than through the Instagram platform for this case.

For scenario 2, Twitter achieves higher performance once again, with an average of 6.89 seconds, varying between 6.18 and 7.62 seconds. On the other hand, it is 25.73 seconds for Instagram, varying between 18.503 and 32.950 seconds. In scenario 2, messages with generic hashtags travel through the Twitter platform about four times faster than through Instagram.

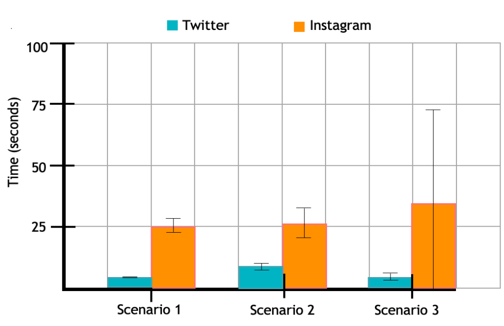

Figure 6. Latency for Twitter and Instagram

The results show that when it comes to posts with videos (scenario 3), Instagram can take up to 71.45 seconds to make it available for user B timeline, with an average of 33.15 seconds. On the other hand, posts with videos on the Twitter platform take 4.79 seconds on average (varying between 4.19 and 5.39 seconds). Thus, the same message with video travels through the Twitter platform about seven times faster (up to 13 times faster if we consider the upper margin of error) than the Instagram platform at scenario 3.

5. Discussion

Our 4-step research methodology and results presented here helped us obtain insights from which significant lessons could be learned.

Twitter vs. Instagram: Our experiments demonstrated that the Twitter platform presented an improved performance when the metrics of message completeness and latency are analyzed. However, user B friends who posted on Instagram did not necessarily make the posts on the Twitter platform. In other words, the "competition of posts" between platforms is not under control. We have to consider that Instagram allows fewer automated captures of messages per minute, which might be caused by a higher activity level of Instagram users than Twitter. Specifically, even though the percentage of monthly active users on Instagram and Twitter is comparable (33% vs. 32%), 61% of Instagram users visit the platform daily compared to 45% of Twitter users. Thus, we can infer that the competition of photos and videos on Instagram is higher since it is a photo-sharing app, while Twitter seems optimized for short text messages.

Twitter behavior: The Twitter dataset revealed some curiosities, e.g., reposting some messages up to 8 times, even though the user profile was configured for messages to be presented in chronological order. We can conclude that Twitter selects specific tweets, mainly ones with videos, to be retweeted in followers' timelines. The criteria are not clear since the messages contained the same type of content. The only difference was the posting time, which may be considered by the platform to decide whether to repost a message.

Observer effect: As we used different tools (Selenium, Gramblr, and our programs), our results might have been affected by them. In physics, this phenomenon is widely known as the observer effect, which also happens in active network and system measurements. This is a limitation of experimental methodologies. For example, we cannot quantify whether Gamblr introduced some significant additional delay to Instagram or if the computed delay is accurate to the time spent for a post to appear in a user timeline.

User profiles: Our experiments depicted a snapshot of Twitter and Instagram behavior when the data was collected. This behavior might change for other users and even for the same users at different circumstances according to the platforms' internal algorithm working, which is for us a black box. Our experiments were conducted with only two essentially anonymous and antisocial users, with few followers and following fellows. While the platforms' behavior may differ for users with a more intense record of interactions, conducting such experiments would require the OSN provider's cooperation, given the practical and ethical concerns involved. Therefore, despite these limitations, we believe our results are valid and useful for different purposes, as a first attempt to disclose and compare the behavior of two different OSNs.

Experiment automation: This research further contributed to the study carried out by Perera et al. [42] on the analysis of the tweet arrival rate. The use of an appropriate distribution for the message arrival rate allowed us to work stealthily with the Twitter and Instagram platforms outsmarting the detection of artificial bot behavior.

Platform constraints: We faced some constraints during the execution of the experiments. In step 2 of our methodology, we estimated spending 20 hours performing all experiments on the two platforms. However, in practice, we spent three times more because several replications were detected as unusual behavior by the platforms. For instance, the Twitter platform presented some instability, i.e., "*Internal server error*" and other messages of unclear errors, i.e., "*Your account may not be authorized to perform this action. Please refresh the page and try again*.". Once the user account is locked, it is necessary to execute a few steps to unlock it, including a verification code sent by e-mail or SMS to the user. These actions caused interruptions in the experiments, which frequently required the experiment replication to be restarted from scratch.

6. Conclusion

This study aimed to evaluate the performance of OSNs, given their increasing use in real-life event detection based on public data. We evaluated how the Twitter and Instagram platforms respond to their users when providing similar functionalities (e.g., message publications, receiving posts at the timeline). Our experiments allowed us to understand some of the platforms' behavior. When a user A posts a message, it appears in the timeline of another user B over a higher performance on Twitter than Instagram. More posts published by user A were available to user B on Twitter than on Instagram. Study findings also showed that both platforms offered a latency near real-time, making them adequate for real-time processing. However, when comparing platforms, Twitter outperforms Instagram in all metrics evaluated.

Future research should repeat the experiments considering users in different geographic locations since our experiments were performed with users in the same geographic location. Moreover, it is relevant to conduct a different set of experiments expanding the configuration settings, e.g., text, video, or even existing users with several followers and following of various users. This might allow investigating the role played by the platform algorithms on data completeness and latency.

Acknowledgements

This research is part of the INCT of the Future Internet for Smart Cities funded by CNPq proc. 465446/2014-0, Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001, FAPESP proc. 14/50937-1, and FAPESP proc. 15/24485-9.

References

[1] Achrekar, H., Gandhe, A., Lazarus, R., Yu, S. H., & Liu, B. (2011, April). Predicting flu trends using Twitter data. In 2011 IEEE conference on computer communications workshops (INFOCOM WKSHPS) (pp. 702-707).

[2] Alhabash, S., & Ma, M. (2017). A tale of four platforms: Motivations and uses of Facebook, Twitter, Instagram, and Snapchat among college students? Social Media+ Society, 3(1), 2056305117691544.

[3] Alkhatib, M., El Barachi, M., & Shaalan, K. (2019). An Arabic social media based framework for incidents and events monitoring in smart cities. Journal of Cleaner Production, 220, 771-785

[4] Ananny, M., & Crawford, K. (2018). Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. new media & society, 20(3), 973-989.

[5] Anthopoulos, L., & Fitsilis, P. (2015, October). Social networks in smart cities: Comparing evaluation models. In 2015 IEEE First International Smart Cities Conference (ISC2) (pp. 1-6). IEEE.

[6] Aramaki, E., Maskawa, S., & Morita, M. (2011, July). Twitter catches the flu: detecting influenza epidemics using Twitter. In Proceedings of the conference on empirical methods in natural language processing (pp. 1568-1576). Association for Computational Linguistics.

[7] Ayora, V., Horita, F. and Kamienski, C., Social Networks as Real-time Data Distribution Platforms for

Smart Cities. 10th Latin America Networking Conference (LANC 2018), October 2018.

[8] Batrinca, B., & Treleaven, P. C. (2015). Social media analytics: a survey of techniques, tools and platforms. Ai & Society, 30(1), 89-116.

[9] Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. Big Data & Society, 3(1), 2053951715622512.).

[10] Cerrone, D., Pau, H., & Lehtovuori, P. (2015). A sense of place: Exploring the potentials and possible uses of Location Based Social Network Data for urban and transportation planning in Turku City Centre. Turku Urban Research Programme's Research Report 1/2015.

[11] Constine J. Instagram hits 1 billion monthly users, up from 800M in September. TechCrunch. 2018. Available at: https://techcrunch.com/2018/06/20/ instagram-1-billion-users/ Accessed 30 September 2020.

[12] D'Andrea, A., Ferri, F., & Grifoni, P. (2010). An overview of methods for virtual social networks analysis. In Computational social network analysis (pp. 3-25). .

[13] Dayani, R., Chhabra, N., Kadian, T., & Kaushal, R. (2015, December). Rumor detection in twitter: An analysis in retrospect. In 2015 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS)(pp. 1-3).

[14] De Assis, L. F. F. G., de Albuquerque, J. P., Herfort, B., Steiger, E., & Horita, F. E. A. (2015). Geographical prioritization of social network messages in near real-time using sensor data streams: an application to floods. Revista Brasileira de Cartografia, 68(6).

[15] Doran, D., Gokhale, S., & Dagnino, A. (2013, August). Human sensing for smart cities. In Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (pp. 1323-1330).

[16] Doran, D., Severin, K., Gokhale, S., & Dagnino, A. (2016). Social media enabled human sensing for smart cities. AI Communications, 29(1), 57-75.

[17] Driscoll, K., & Walker, S. (2014). Big data, big questions| working within a black box: Transparency in the collection and production of big twitter data. International Journal of Communication, 8, 20.

[18] Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., ... & Sandvig, C. (2015, April). " I always assumed that I wasn't really that close to [her]" Reasoning about Invisible Algorithms in News Feeds. 33rd annual ACM conference on human factors in computing systems (pp. 153-162).

[19] Gilbert, S. (2016). Learning in a Twitter-based community of practice: an exploration of knowledge exchange as a motivation for participation in# hcsmca. Information, Communication & Society, 19(9), 1214-1232.

[20] Giridhar, P., Wang, S., Abdelzaher, T., Al Amin, T., & Kaplan, L. (2017, July). Social fusion: Integrating Twitter and Instagram for event monitoring. 2017 IEEE International Conference on Autonomic Computing (ICAC) (pp. 1-10).

[21] Gonawela, A., Kumar, R., Thawani, U., Ahmed, D., Chandrasekaran, R. & Pal, J. (2020, January). The Anointed Son, The Hired Gun, and the Chai Wala: Enemies and Insults in Politicians' Tweets in the Run-Up to the 2019 Indian General Elections. In Proceedings of the 53rd Hawaii International Conference on System Sciences (HICSS) (pp. 2878-2887).

[22] Goodchild, M. F. (2007). Citizens as sensors: the world of volunteered geography. GeoJournal, 69(4), 211-221.

[23] Gruzd, A., Lannigan, J., & Quigley, K. (2018). Examining government cross-platform engagement in social media: Instagram vs Twitter and the big lift project. Government Information Quarterly, 35(4), 579-587.

[24] Guidry, J. P., Jin, Y., Orr, C. A., Messner, M., & Meganck, S. (2017). Ebola on Instagram and Twitter: How health organizations address the health crisis in their social media engagement. Public relations review, 43(3), 477-486.

[25] Horita, F. E., de Albuquerque, J. P., Marchezini, V., & Mendiondo, E. M. (2017). Bridging the gap between decision-making and emerging big data sources: An application of a model-based framework to disaster management in Brazil. Decision Support Systems, 97, 12-22.

[26] Hammerl, T., Schwaiger, J. M., & Leist, S. (2019). Measuring the Success of Social Media: Matching Identified Success Factors to Social Media KPIs.

[27] Hu, Y., Manikonda, L., & Kambhampati, S. (2014, May). What we instagram: A first analysis of instagram photo content and user types. In Eighth International AAAI conference on weblogs and social media.

[28] Hutchinson, A., 2016. Here's why Twitter is so important, to everyone. Available at: https://www.socialmediatoday.com/social-networks/heres-why-twitter-soimportant-everyone, Accessed date: 10 June 2020.

[29] Joseph, K., Landwehr, P. M., & Carley, K. M. (2014, April). Two 1% s don't make a whole: Comparing simultaneous samples from Twitter's streaming API. In International conference on social computing, behavioral-cultural modeling, and prediction(pp. 75-83).

[30] Karlsson, M., & Sjøvaag, H. (2016). Content analysis and online news: epistemologies of analysing the ephemeral Web. Digital journalism, 4(1), 177-192.

[31] Instagram. Changes to Improve Your Instagram Feed. March 22, 2018. Available at: https://instagram-press.com/blog/2018/03/22/changes-to-improve-your-instagram-feed/. Accessed 10 June 2020.

[32] Instagram. Changes to Our Account Disable Policy. July 18, 2019. Available at: https://instagram-press.com/blog/2019/07/18/changes-to-our-account-disable-policy/. Accessed 10 June 2020.

[33] Li, R., Lei, K. H., Khadiwala, R., & Chang, K. C. C. (2012, April). Tedas: A Twitter-based event detection and analysis system. In 2012 IEEE 28th International Conference on Data Engineering (pp. 1273-1276). IEEE.

[34] Mohsin M. 10 Instagram Stats Every Marketer Should Know in 2019. Oberlo.2019. Available at: https://www.oberlo.com/blog/instagram-stats-every-marketer-should-know. Accessed 5 June 2019

[35] Mora, N., Caballé, S., Daradoumis, T., Barolli, L., Kulla, E., & Spaho, E. (2014, July). Characterizing social network e-assessment in collaborative complex learning resources. In 2014 Eighth International Conference on Complex, Intelligent and Software Intensive Systems (pp. 257-264).

[36] Morstatter, F., Pfeffer, J., Liu, H., & Carley, K. M. (2013, June). Is the sample good enough? comparing data from twitter's streaming api with twitter's firehose. In Seventh international AAAI conference on weblogs and social media.

[37] Moustaka, V., Vakali, A., & Anthopoulos, L. G. (2018). A systematic review for smart city data analytics. ACM Computing Surveys (CSUR), 51(5), 103.

[38] Moustaka, V., Theodosiou, Z., Vakali, A., Kounoudes, A., & Anthopoulos, L. G. (2019). Enhancing social networking in smart cities: Privacy and security borderlines. Technological Forecasting and Social Change, 142, 285-300.

[39] Nummi, P. (2019). Social media data analysis in urban e-planning. In Smart Cities and Smart Spaces: Concepts, Methodologies, Tools, and Applications (pp. 636-651).

[40] O'Neil E. API Updates and Importante Changes. Facebook.com. April 25, 2019. Available at: https://developers.facebook.com/blog/post/v2/2019/04/25/api-updates/. Accessed June 5, 2019.

[41] Panagiotou, N., Katakis, I., & Gunopulos, D. (2016). Detecting events in online social networks: Definitions, trends and challenges. In Solving Large Scale Learning Tasks. Challenges and Algorithms (pp. 42-84).

[42] Perera, R. D., Anand, S., Subbalakshmi, K. P., & Chandramouli, R. (2010, October). Twitter analytics: Architecture, tools and analysis. 2010 Military Communications Conference (pp. 2186-2191).

[43] Prakash, A., Caton, S., Haas, C.. (2019, January). Utilizing Social Media For Lead Generation. In Proceedings of the 52nd Hawaii International Conference on System Sciences (HICSS) (pp. 2304-2313).

[44] Rader, E., Cotter, K., & Cho, J. (2018, April). Explanations as mechanisms for supporting algorithmic transparency. In Proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1-13)).

[45] Rathnayake, C., & Suthers, D. D. (2018). Twitter issue response hashtags as affordances for momentary connectedness. Social Media+ Society, 4(3), 2056305118784780.

[46] Sakaki, T., Okazaki, M., & Matsuo, Y. (2010, April). Earthquake shakes Twitter users: real-time event detection by social sensors. 19th international conference on World Wide Web (pp. 851-860).

[47] Singh, P., Dwivedi, Y. K., Kahlon, K. S., Sawhney, R. S., Alalwan, A. A., & Rana, N. P. (2019). Smart Monitoring and Controlling of Government Policies Using Social Media and Cloud Computing. Information Systems Frontiers, 1-23.

[48] Smith, K., 2019. Marketing: 126 Amazing Social Media Statistics and Facts. Brandwatch blog. Available at. https://www.brandwatch.com/blog/amazing-social-media-statistics-and-facts/, Accessed date: 24 June 2019.

[49] Stieglitz, S., & Dang-Xuan, L. (2013). Social media and political communication: a social media analytics framework. Social network analysis and mining, 3(4), 1277-1291.

[50] Stieglitz, S., Mirbabaie, M., Ross, B., & Neuberger, C. (2018). Social media analytics–Challenges in topic discovery, data collection, and data preparation. International journal of information management, 39, 156-168.

[51] Thakur, M., Patel, D., Kumar, S., & Barua, J. (2014, December). Newsinstaminer: Enriching news article using instagram. In International Conference on Big Data Analytics(pp. 174-188). Springer, Cham.

[52] Wang, S., Giridhar, P., Kaplan, L., & Abdelzaher, T. (2017, April). Unsupervised event tracking by integrating twitter and instagram. In Proceedings of the 2nd International Workshop on Social Sensing (pp. 81-86).