Examining the intra-location differences among Twitter samples

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Abstract: In this paper, we explore Twitter data samples collected from five different geographical locations. For each of these geographical locations, we compare variations occurring within samples collected simultaneously from two different machines running Twitter API clients. In addition, we split the collected data samples into "complete" and "incomplete" datasets. An incomplete dataset is a collection of Twitter messages where at least one machine received a smaller data sample due to some interruption. A complete dataset is one that includes all tweets that Twitter's API delivers for a particular set of search parameters. Our findings indicate that 86% of the complete samples show some variations in the attribute values attached to extracted tweets. While the complete datasets show comparable attribute values and network characteristics, the incomplete data samples exhibit substantial differences. We arrive at recommendations for researchers on Online Social Networks on how to mine Twitter data while mitigating these risks.

1 INTRODUCTION

In the search for representative and freely accessible data on Online Social Networks (OSN), researchers frequently rely on datasets extracted from Twitter. Tweets (Twitter messages) have been utilized in various research fields from applied network science to medicine (Grinberg et al., 2019; Morone and Makse, 2015; Broniatowski et al., 2018; Boutyline and Willer, 2017; Kušen and Strembeck, 2021).

Twitter's well-documented and publicly available application programming interface (API) grants researchers automated access to large datasets, only requiring an existing Twitter account. As a major downside, Twitter data is only made available to researchers free of charge as a blackbox sample. Access types with fewer limitations (e.g., higher monthly rate limits, access to a full archive) are offered by Twitter either via commercial or special purpose accounts (e.g., for academic research). While these types of accounts are used in business and academic settings, they are either paid for or granted upon request after fulfilling specific criteria. In many cases, researchers may not be able to obtain an academic account or cannot afford paying to lift the paywall. This leaves researchers with free-of-charge API access to samples of Twitter data.

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Despite Twitter's popularity as a data source, there is still little awareness among OSN researchers of how this sampled data from Twitter may affect their research and how sampling has to be accounted for in their research designs. Regarding representativeness, Twitter data samples were found to potentially under- or over-represent certain user accounts (Pfeffer et al., 2018). Dataset sizes and the user accounts contained therein vary substantially based on the access types (Kim et al., 2020). Furthermore, Wang et al. (2015) found that the various access types result in different user-activity patterns and sentiments. Similarly, Morstatter et al. (2013) compared different Twitter API endpoints and discovered that Twitter data obtained via the free-of-charge API performs worse than other access types in terms of reflecting the statistical properties of Twitter activity. When comparing data samples collected using popular and non-popular search terms, Campan et al. (2018) revealed that only unpopular search terms lead to unbiased samples and that, otherwise, samples cannot be considered random. Recently, Pfeffer et al. (2022) found that approximately 10% of tweets are deleted in the short term and up to 30% over the period of four years. Moreover, Timoneda (2018) found that even in the short term, 20-30% tweets of strong political content could not even be recovered via the free-of-charge API.

In Ivanova et al. (2022), we investigated the differences in data samples that were collected from various geolocations. In this context, geolocations refer to network-topological locations (Internet nodes) that send requests to the free-of-charge Twitter API. In particular, we showed that data collections extracted from the same geolocation as well as the same network-topological zone may vary in terms of users and tweets collected, as well in terms of the associated metadata. As a consequence, we showed that the derived networks, such as retweet and mention networks, also exhibit substantial differences relevant to a research design.

This paper extends our previous study by examining the differences between data samples extracted from two different machines running at the *same* geographical location (i.e., *intra-location* differences). For this purpose, we distinguish between two types of data collections: 1) an *incomplete* collection results from at least one dataset not being fully retrieved due to various server errors; 2) a *complete* collection results from all available data having been received from the Twitter API endpoint in a proven manner.

The remainder of this paper is structured as follows. Section 2 gives an overview of the background information fundamental to this paper. Section 3 then describes our technical approach for mining Twitter data in an orchestrated manner. Next, Section 4 presents key findings and limitations. Section 5 concludes the paper.

2 BACKGROUND

2.1 Twitter data model

For each request, the Twitter Search API v1.1 returns tweets containing a wide variety of attributes. These attributes include data related to the tweet itself (e.g. creation time), geographical information (e.g. location), a collection of the entities within the tweet (e.g. urls), and data related to the user who published it (e.g. screen name). According to Twitter API's documentation[1 2] certain attributes are expected to change over time (e.g. retweet count) while others remain static (e.g. status id).

[1]https://developer.twitter.com/en/docs/twitter-api/v1/data-dictionary/object-model/tweet

[2]All links last accessed on March 7th, 2023

2.2 Network derivation

Combinations of the received attributes can be used to derive various types of networks (e.g., mention and retweet networks). Retweet networks represent retweet activity and retweet frequency. In a retweet network, each message (i.e., each retweet) is represented via a separate vertex and each retweet is connected to the original message being retweeted. Mention networks depict interactions between users based on the @-mentions included in their respective tweets. The derived networks can be used for performing different types of network analysis tasks (see, e.g., Kwak et al. 2010; Xiong et al. 2019; Gruzd and Roy 2014; Kušen and Strembeck 2021).

3 APPROACH

3.1 Infrastructure

For the simultaneous collection of multiple datasets, we created a distributed infrastructure of virtual machines (VMs) deployed in various geographical locations (see Figure 1). We created ten VMs in five availability zones offered by Amazon Web Services (AWS) at the time, each hosting two VMs (we will use the term *geolocation pair* for referring to the virtual machines running at the same geographical location): Frankfurt (Germany), Mumbai (India), Sydney (Australia), Seoul (South Korea), and Virginia (USA). The selection of these five availability zones followed the rationale of covering different geographical locations worldwide.

The collection process was coordinated by an additional host located in Vienna (Austria) acting as the orchestrator. Furthermore, a second host in Vienna served as a central and permanent storage device for the datasets collected from the five different geolocations (see Figure 1). Each collection was initiated via the orchestrator by sending collection scripts to each VM. The only variation in these scripts resulted from distinct Twitter developer credentials used for the individual API calls. We set all developer accounts' locations to correspond to the respective geolocations of the AWS VMs to reduce potential bias. The execution time for the collection procedure was synchronized within the infrastructure, meaning that all 10 VMs would begin requesting data from the Twitter API at the same time. The individual requests were done using the RTweet package[3], which by default collects a mixture of popular and most recent tweets.

[3]https://cran.r-project.org/web/packages/rtweet/rtweet.pdf

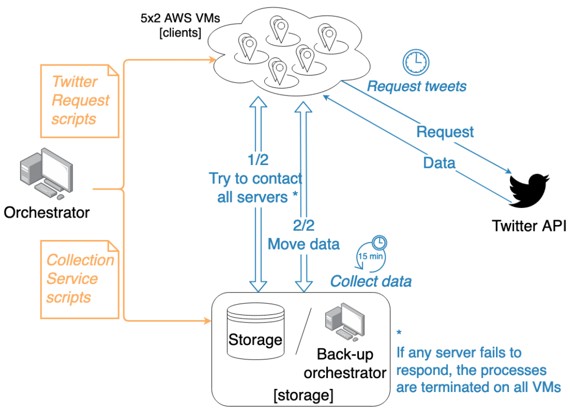


Figure 1: Infrastructure for multi-site Twitter mining; Adapted from Ivanova et al. (2022, Figure 1).

For the purposes of this paper, we assumed two general collection types: 1) "complete" collections and 2) "incomplete" collections. An incomplete dataset is a collection of Twitter messages where at least one machine received a smaller data sample due to some interruption (e.g. timeout, over capacity). A complete dataset is one that includes all messages that Twitter's API delivers for a particular set of search parameters.

3.2 Datasets

Table 1 depicts the 14 collections that have been extracted for our study, the requested hashtags, the maximum number of tweets received, the tweets' publication period, and the respective collection date. The hashtag selection aims to cover a wide variety of globally discussed topics (e.g. pop culture, conflicts) and dataset sizes. A detailed overview of the number of tweets collected per VMs for each topic is presented in Table 2. The asterisk superscript of the collection number indicates that at least one of the data samples was interrupted and the corresponding collection is incomplete.

4 FINDINGS

For the purposes of this paper, we analyze the data alongside the following aspects. First, we focus on the tweet IDs (i.e., unique tweet identifiers) in each collection. We then examine whether the tweet attributes are consistent. Finally, we explore the characteristics of retweet and mention networks derived from our collections.

4.1 Node level

Figures 2 and 3 depict the (dis-)similarities for the 14 data collections between the pairs of Internet nodes at each of the five geolocations in our study (Frankfurt, Mumbai, Sydney, Seoul and Virginia). The exact overlap (see Figure 2) refers to tweets that include the same attributes for the same tweet ID. In contrast, the partial overlap (see Figure 3) refers to tweets that have the same ID but exhibit partial differences in attribute values, such as unequal retweet counts.

The overlap values offer a clear glance into the similarities between intra-location datasets. Yet, it is essential to consider the effects of an incomplete dataset. For the interrupted collection C05*, we observe a considerable drop in the exact overlap value for all five locations. Furthermore, for the geolocation Seoul we find an even lower value of the exact overlap (i.e., $< 1\%$), which occurs because Seoul 1 received a considerably smaller dataset than Seoul 2. A relatively low exact overlap can also be found across all geolocations for C02, yet in this case all data samples are complete. However, the reason for the exact overlap varying from 26.29% for Seoul to 93.47% for Frankfurt remains unclear.

For the two locations without interruptions (i.e., Sydney and Virginia), the partial overlap is close to 100% for all collections. In some cases, such as the interrupted collection C09* in Frankfurt, we see a similar drop in the partial and the exact overlap percentages, affected by the incomplete collection for Frankfurt 1. However, in other cases, such as C05*, a similar correlation is noticeable despite the datasets within the geolocation pairs being complete. The location Seoul stands out in this regard, as we find the most differences in terms of varying overlap values for the individual collections, yet merely three collections have been categorized as being incomplete (i.e., C05, C10, and C13).

There is a noteworthy indication of a potential pattern in the overlap values, which can be found across all locations. Overall, we observe low exact-overlap values for the eight out of 14 collections: C02, C05, C06, C09, C11, C12, C13, C14. However, with the exception of C02 and C06, the rest of the collections appear to be prone to API errors.

4.2 Attribute level

We take a closer look at the partial overlaps by examining the individual attributes of the overlapping tweets. We match the tweets across databases based on their tweet IDs, thus assuming it to be a constant attribute. The frequent variation of attribute values in

Table 1: Summary of tweet collections including the used hashtag, maximum number of tweets collected (i.e., #T), time window for data collection, and date of collection. An asterisk denotes that the collection is incomplete. Adapted from Ivanova et al. (2022, Table 1).

Collection	Hashtag	#T (max)	From	Until	Collected on
C01	covid19	310.879	18.11.21	21.11.21	25.11.21
C02	BlackFriday	550.361	26.11.21	28.11.21	01.12.21
C03	Omicron	526.927	29.11.21	03.12.21	06.12.21
C04	HongKong	18.957	19.12.21	24.12.21	29.12.21
C05*	HappyBirthdayTaehyung	2.577.930	29.12.21	01.01.22	04.01.22
C06	Djokovic	218.966	04.01.22	08.01.22	11.01.22
C07	tsunami	125.793	14.01.22	20.01.22	24.01.22
C08	Ukraine	85.641	18.01.22	22.01.22	25.01.22
C09*	SuperBowl	1.826.490	13.02.22	15.02.22	20.02.22
C10*	Putin	197.941	21.02.22	23.02.22	27.02.22
C11*	Ukraine	436.420	21.02.22	23.02.22	25.02.22
C12*	Putin	590.680	23.02.22	25.02.22	01.03.22
C13*	Ukraine	1.144.923	10.03.22	13.03.22	17.03.22
C14*	Ukraine	1.474.915	15.03.22	20.03.22	23.03.22

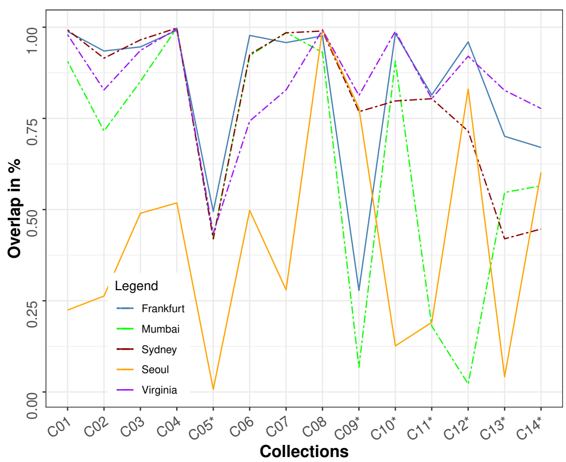


Figure 2: Exact intra-location overlap of the tweet populations per collection (i.e., identical attribute values)

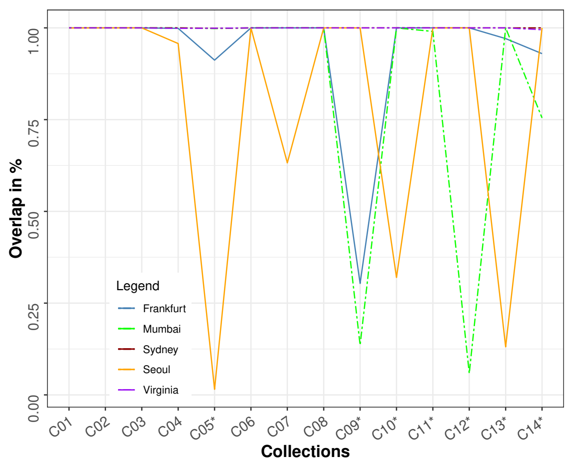


Figure 3: Partial intra-location overlap of the tweet populations per collection (i.e., same tweet id, variations of other attribute values)

tweets extracted at Seoul (as depicted by the orange line in Figure 3) is also visible within the attribute-level analysis. Table 3 depicts one such example of the count-related attributes (e.g. retweet count) in collection C10*. In this case, the number of differences found between the two VMs in Seoul is considerably higher than within the rest of the geolocations. A similar pattern can also be found in other collections such as collection C02 (see Table 4), which is categorized as a complete collection.

User object In addition to count variables (e.g. retweet count or like count) which are expected to have variations over time, we also examined the consistency of user-object attributes. Table 5 depicts the difference within these attributes based on collection C02. The column "Expected change" is based on the official Twitter's API documentation for the respective user-object attributes. This documentation characterizes attributes as either "relatively constant" or as expected to change frequently (over time), such as the number of tweets the account has posted "statuses_count" and its number of followers "followers_count"[4]. Based on the fact that some of the attributes are described as non-constant, we can safely assume that other count values are assumed subjected to changes over time (referred to via "1.yes" in the respective tables). The remaining attributes are marked as "unknown". The number of total changes for col-

[4]https://developer.twitter.com/en/docs/twitter-api/v1/data-dictionary/object-model/user

Table 2: Number of tweets collected per location per hashtag and their respective logged messages. An asterisk denotes that the collection is incomplete. Adapted from Ivanova et al. (2022, Table 2).

Coll.	Frankfurt 1	Frankfurt 2	Mumbai 1	Mumbai 2	Sydney 1	Sydney 2	Seoul 1	Seoul 2	Virginia 1	Virginia 2
C01	310.802	310.803	310.811	310.810	310.808	310.806	310.805	310.879	310.814	310.808
C02	550.321	550.312	550.361	550.361	550.332	550.339	550.330	550.313	550.310	550.304
C03	526.804	526.811	526.803	526.804	526.813	526.815	526.927	526.830	526.809	526.812
C04	18.886	18.868	18.366	18.366	18.371	18.371	**17.883**[1]	18.532	18.935	18.957
C05*	2.351.611	2.577.831	2.574.730	2.577.930	2.575.355	2.574.470	38.985[2]	2.577.219	2.575.290	2.576.477
C06	218.831	218.827	218.841	218.842	218.841	218.842	218.965	218.966	218.858	218.836
C07	125.789	125.793	**78.711**[1]	**78.711**[1]	**78.710**[1]	**78.712**[1]	124.518	**78.714**[1]	125.779	125.788
C08	85.640	85.637	84.406	84.406	84.409	84.412	85.622	85.622	85.640	85.641
C09*	554.498[4]	1.825.922	247.731[3]	1.825.615	1.825.616	1.825.577	1.826.056	1.826.146	1.826.476	1.826.490
C10*	197.909	197.910	197.937	197.941	197.939	197.932	197.939	63.356[2]	197.907	197.909
C11*	436.391	436.392	436.379	432.209[2]	436.401	436.409	436.420	436.399	436.409	436.409
C12*	590.543	590.548	34.577[2]	590.600	590.646	590.674	590.653	590.680	590.607	590.601
C13*	1.068.768	1.100.893	1.100.851	1.100.832	1.144.885	1.144.892	1.144.923	150.033[2]	1.100.894	1.100.907
C14*	1.309.517[5]	1.408.257	590.046[3]	445.348[3]	1.381.884	1.381.923	1.382.012	1.382.025	1.467.636	1.474.915

Logged messages:
[1] Two confirmations that the script exited correctly
[2] Error in curl::curl_fetch_memory(url, handle = handle) : OpenSSL SSL_read: SSL_ERROR_SYSCALL, errno 104
[3] Error in curl::curl_fetch_memory(url, handle = handle) : transfer closed with outstanding read data remaining
[4] Killed
[5] Over capacity - 130

Table 3: Absolute number of differences in count attributes of overlapping tweets among geolocation pairs for C10*. Note regarding abbreviations: FRA - Frankfurt, MUM - Mumbai, SYD - Sydney, SEL - Seoul, VA - Virginia, rt - retweet, qt - quoted.

Attribute	**FRA**	**MUM**	**SYD**	**SEL**	**VI**
rt_followers	520	1467	4288	18944	508
qt_followers	216	291	756	1893	217
favourites	69	358	1272	13659	102
statuses	62	282	1193	3104	78
rt_statuses	27	96	453	1775	40
followers	25	101	350	9144	38
rt_friends	22	45	116	5579	11
friends	7	34	119	6637	29
qt_statuses	5	9	37	171	8
retweet	3	1	14	73	1
rt_favorite	3	10	29	2158	7
rt_retweet	3	1	14	71	1
listed	1	1	9	1130	14
qt_favorite	1	6	42	391	1
qt_retweet		2	11	65	
favorite		1		39	3
qt_friends		1	4	340	1

Table 4: Absolute number of differences in count attributes of overlapping tweets among geolocation pairs for C02. Note regarding abbreviations: FRA - Frankfurt, MUM - Mumbai, SYD - Sydney, SEL - Seoul, VA - Virginia, rt - retweet, qt - quoted.

Attribute	**FR**	**MU**	**SY**	**SE**	**VI**
rt_followers	1826	9002	7926	67319	29239
favourites	1200	5081	4774	39875	14940
statuses	933	2740	2709	9855	14527
rt_statuses	480	1926	2125	8906	12494
qt_followers	399	900	899	3506	2297
followers	143	2508	2175	27482	3373
rt_favorite	89	1316	1020	13825	3344
friends	60	2061	1744	21030	1667
retweet	53	76	28	524	1006
rt_retweet	53	76	28	520	1003
listed	33	279	285	2761	401
qt_statuses	33	83	100	444	855
rt_friends	31	2471	2025	21622	1212
qt_favorite	19	84	106	713	440
favorite	1	7	8	76	17
qt_retweet	1	2	6	43	41
qt_friends		61	53	706	35

lection C02 per location and per user-object attribute is depicted in the respective columns.

4.3 Network level

To better understand how intra-location differences in the collected datasets may affect network analyses, we take a closer look at two selected network types that can be derived from the collected Twitter datasets. In particular, we examine retweet and mention networks. For each retweet or mention network, we counted the number of vertices and edges, calculated the number of connected components, and compared degree distributions. Degree distributions are contrasted using empirical quantile-quantile (QQ) plots to highlight the (dis-)similarity of the network structures.

Retweet networks We constructed retweet networks from all datasets and compared them per lo-

Table 5: User-object attributes as per Twitter's API documentation and their actual variation per geolocation pairs for CO2. Note regarding abbreviations: "l.yes" refers to a logically derived yes based on the Twitter API documentation.

Attribute	**Expected change**	**Frankfurt**	**Mumbai**	**Sydney**	**Seoul**	**Virginia**
id	no	assumed to be constant (see 4.2)				
screen_name	yes	-	-	-	-	-
location	yes	1	-	-	-	-
url	unknown	-	-	1	7	-
description	yes	1	-	-	-	5
verified	unknown	-	-	-	-	-
followers_count	yes	143	2508	2175	27482	3373
friends_count	l.yes	60	2061	1744	21030	1667
listed_count	l.yes	33	279	285	2761	401
favourites_count	l.yes	1200	5081	4774	39875	14940
statuses_count	yes	933	2740	2709	9855	14527
created_at	no	-	-	-	200	-
profile_banner_url	unknown	-	-	-	1	3
profile_image_url_https	unknown	-	1	-	-	9
default_profile	unknown	-	-	-	-	-
default_profile_image	unknown	-	-	-	-	-

cation in terms of their network characteristics. It is worth noting that we observe only *one* perfect match between the network characteristics across all collected complete collections (see C08)[5].

The remainder of the complete collections contain differences in at least one of the dataset pairs. Table 6 presents one such example based on collection C07. Here, five of the VMs (i.e., Mumbai 1, Mumbai 2, Sydney 1, Sydney 2, and Seoul 2) have retrieved less tweets even though Twitter's API did not produce any error messages. An analysis of the extracted retweet networks shows no differences between the datasets collected at Frankfurt and at Mumbai. In Seoul, however, we notice mismatches regarding all network descriptors. For the remaining two geolocations (Sydney, Virginia) the differences in the number of vertices and edges are comparatively minor (i.e., $< 1\%$).

Lastly, we found that all incomplete collections show differences in terms of all network characteristics for the respective geolocations. As expected, when a collection has been interrupted we found variations in all values and a mismatch in the graphical visualisation of the degree distributions. However, further network differences can also be observed for the geolocations with complete datasets.

Mention networks In addition to the retweet networks, we also derived mention networks and explore the same network characteristics (e.g., number of vertices). We established the existence of the same three groups of collections as for retweet networks: perfect match, complete collections with variations, incomplete collections with variations.

[5]Details on the exact network characteristics are available as supplemental material at https://rivanova.org/complexis2023.

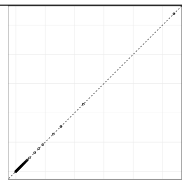
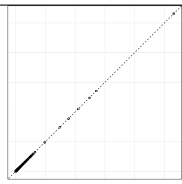
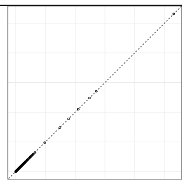
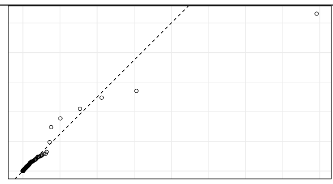
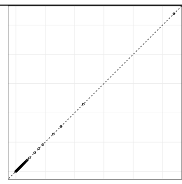
4.4 Limitations

This paper builds on our previous study (Ivanova et al., 2022) by reusing some of the datasets. When designing our infrastructure for tweet extraction (see Section 3), our main goal was to implement the experiment as reproducible as possible, while reducing collection bias. The variety in the geographical locations was achieved via the use of a commercial cloud platform (i.e., Amazon Web Services). We selected five of AWS availability zones to maximize diversity and global distribution (i.e., as many continents as possible). We assume that the setup behind the individual VMs is equivalent (i.e., we assume AWS is running comparable hardware at different locations), yet further comparative research is needed in order to conclude whether the use of another hosting platform may yield different results. Furthermore, we used an iterative collection approach. In particular, we collected 200 messages every 10 seconds. Another option would be to request larger batches of tweets using longer time intervals. Investigating these sources of possible variation is future work.

5 CONCLUSIONS

In this paper, we analyzed 14 Twitter data samples collected simultaneously from five pairs of virtual machines (VMs) running at five different geographical and network-topological locations (i.e., Frankfurt,

Table 6: Comparison of number of vertices, number of edges, number of connected components and degree distributions of retweet networks per geolocation pair (two virtual machines) for C07 (i.e., a complete collection with differences).

Virtual machine	**|V|**	**|E|**	**Connected Components**	**Degree distributions**
Frankfurt 1	124.704	118.296	6.408	
Frankfurt 2	124.704	118.296	6.408	
Mumbai 1[1]	78.221	72.995	5.226	
Mumbai 2[1]	78.221	72.995	5.226	
Sydney 1[1]	78.220	72.994	5.226	
Sydney 2[1]	78.221	72.995	5.226	
Seoul 1	123.464	117.067	6.397	
Seoul 2[1]	78.220	72.994	5.226	
Virginia 1	124.696	118.288	6.408	
Virginia 2	124.706	118.298	6.408	

[1] Two confirmations that the collection script exited correctly, yet less tweets

Mumbai, Sydney, Seoul and Virginia). We found variations among the data samples from the pairs running at the same geolocation. These differences manifest in terms of the collected tweet IDs, tweet attribute values, and the characteristics of the derived networks.

In addition, we split the collections into two groups – *complete* collections that contain all tweets provided via Twitter's API, and *incomplete* collections that stopped prematurely by Twitter's API throwing an error message.

Our findings show that complete collections tend to have a similar number of received tweets variations regarding the exact tweets (matched based on their tweet IDs) that have been collected. The overlap between the tweets has an observed range from 63.21% to 100% with a median of 99.97%. For incomplete collections, we confirmed that the resulting collections exhibited considerable differences in terms of number of collected tweets. In this case, the fractions of overlapping tweet IDs ranged from 1.51% to 99.98% with a median of 13.56%.

When looking at the attributes of the collected tweets, we found that count attributes, such as retweet count, may be different regardless of whether the collection was complete or incomplete. While Twitter's API documentation states that count attributes are expected to change over time, we found that there are no consistency guarantees when retrieving datasets even in a synchronized manner.

For our analysis, we also created retweet and mention networks from the collected datasets. Upon examining the networks' characteristics, we observed variations for complete and incomplete collection. Within the complete collections, we discovered exact intra-location matches for only one collection. For the remaining six collections, we found rather small, yet noticeable variations in the number of vertices, number of edges, number of connected components, and the degree distribution. As expected, all incomplete collections showed differences in terms of network characteristics. However, we also found smaller network-level differences regarding certain network characteristics for some complete collections.

Based on our study, we derive the following recommendations for researchers using Twitter's free-of-charge API. First, the status codes and error messages issued by Twitter's API must be handled and documented properly in order to avoid incomplete data samples. Second, we suggest researchers to be cautious when relying on attribute values which are expected to change in time and in space, such as count attributes (e.g. retweet count or like count). In addition, our previous research on (dis-)similarities between individual geolocations (see Ivanova et al. 2022) recommended the use of three or more geolocations for accessing the Twitter API in parallel, and the use of a three-day delay.

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