An examination of the #NGSSchat Storify database

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Abstract: Teachers frequently use Twitter to engage in professional learning activities. A prominent example of teachers' use of Twitter for such purposes is evident within the #NGSSchat community, which encouraged synchronous (at the same time) conversations between teachers and other educational stakeholders regarding the Next Generation Science Standards (NGSS) curriculum reform in the United States. Notably, #NGSSchat moderators archived the chats via the Storify platform, which has subsequently been used by researchers to understand science teachers' professional learning activities on Twitter. However, what has not been established is the representativeness of this archive of #NGSSchat tweets. In other words, whether those who archived #NGSSchat content selected only a (potentially biased) selection of tweets is as yet unknown. Thus, in this study, we examined the Storify #NGSSchat database and compared it with raw data requests using the Twitter API. We found that the synchronous chats most data was adequately achieved. Contrarily (but as anticipated given what distinguishes the #NGSSchat community-synchronous conversations), the Storify #NGSSchat database did not capture most data outside these synchronous chat sessions. Importantly, we did not find an indication of systematic content- or user-driven tweet exclusion within the synchronous NGSS chat sessions on Storify, suggesting that the #NGSSchat archive via Storify (and potentially others like it) may be used by researchers for most research-related purposes.

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Introduction

In times of rapid technological development online learning is gaining popularity across all domains in the educational landscape. Teacher education is no exception, with many online professional development (PD) activities being offered to and adopted by teachers (e.g., Dede et al., 2016). In particular, online teacher communities on social networking sites provide opportunities for informal teacher learning (e.g., Greenhow & Lewin, 2016; Greenhow et al., 2018). As costs and proximity of learning opportunities (e.g., McCoy et al., 2020) are important factors in teachers' PD selection, online communities seem appealing for engaging in professional learning. Notably, research examining the effectiveness of online teacher communities related to the Advanced Placement program found positive associations for teachers participating in online teacher communities on student performance (Fishman et al., 2014; Frumin et al., 2018). Besides these more formal online communities that are hosted from institutional stakeholders, teachers also self-organize on social networking sites such as Facebook (e.g., Ranieri, Manca, & Fini, 2012), Pinterest (e.g., Hu et al., 2018), Reddit (e.g., Staudt Willet & Carpenter, 2020), Twitter (e.g., Carpenter & Krutka, 2019; Fischer et al., 2019, Rosenberg et al., 2016), and others. Especially during early phases of curriculum reforms, when teachers may be looking for guidance in implementing reform, convenient access to opportunities for professional learning play an important role in successful reform efforts (Stiles et al., 2017).

This can also be seen in one of the largest curriculum reforms in the United States in recent years, the *Next Generation Science Standards* (NGSS; NGSS Lead States, 2013). In response, teachers (and other stakeholders, such as school- and school district-based

administrators) started organizing themselves on Twitter to discuss the reform, share ideas on potential instructional enactments, and to connect with one another. One of the most prominent hashtags used by teachers to discuss the NGSS was #NGSSchat (Carpenter et al., 2020). Teachers would set up a certain time to virtually meet up on Twitter, often in a bi-monthly frequency, and to discuss a certain topic in a synchronous fashion. Afterwards, the moderators of the #NGSSchat community chose to archive the chats on the Storify platform (<http://www.ngsspln.com/ngsschat.html>). Notably, the Storify platform itself is not active anymore and the database is only readily accessible through our versions of it (see Rosenberg et al., 2020, to access this data). Data from Storify has been used in several research projects (e.g., Rosenberg et al., under review). As this moderator-filtered approach to store Twitter data may have led to biased selection of tweets (e.g., removing presumably unwanted content, favoring tweets from more prominent users, tweets that received more likes/retweets, etc.), the purpose of this paper is to explore the quality and quantity of this Storify database. Thus, the core research question is as follows: *How does the Storify #NGSSchat database compare to raw #NGSSchat data requests?*

Methods

Storify database between #NGSSchat synchronous sessions

In order to evaluate the completeness of the Storify data between NGSS chat sessions, we extracted all timeframes from the Storify database in between no tweets were posted in 2014, 2015, and 2016. We then ordered these timeframes by size and started to download them beginning with the greatest gap in the Storify data. These time gaps were then ordered identifying 48 gaps with more than six hours between tweets in the Storify #NGSSchat. The timeframes of these 48 gaps were then used to download tweets using the `search_fullarchive()`

function from the R-package `rtweet` (Kearney, 2019). Afterwards we compared quantitative tweet characteristics (i.e., number of favorites and retweets) for the Storify data and the missing data between the synchronous NGSS chat sessions. The entire code used to conduct this analysis is included as an RMarkdown file in the appendix and to the repository.

Storify database within #NGSSchat synchronous sessions

In order to evaluate the completeness of the Storify data within NGSS chat sessions, we examined 9 random NGSS chat sessions (3 for each year). Therefore, the Storify data was divided into time frames of 24 hours that equaled a day in UTC time format. Then, all timeframes that consisted of at least 300 tweets were identified (10 days in 2014, 18 days in 2015, 5 days in 2016). This procedure ensured that we did not randomly select a day without a synchronous NGSS chat session. Afterwards, we randomly selected three days for each 2014, 2015 and 2016. For each of these nine timeframes, tweets were downloaded using the aforementioned method. This new downloaded data was then employed to assess the completeness of the Storify database within the synchronous chat sessions and investigated potential reasons for why data was missing. The entire code used to conduct this analysis is included as an R-markdown file in the appendix.

Results

Completeness of Storify data between #NGSSchat synchronous sessions

The original Storify database consisted of 17,226 tweets posted under the hashtag #NGSSchat between 2014 and 2016. The identification of time gaps results in 48 gaps that were greater than 6 hours (Figure 1). We considered this as sufficient, as we obtained less than 40 new tweets for the smallest three timeframes. The 48 download queries resulted in a total of 33,097 tweets. This estimate indicates that the Storify database consists of 34.2% of all tweets that could

have been obtained between 2014 and 2016 at highest. Notably, the chronologically latest of these gaps (the time gap between May 2016 and the end of 2016) amounted to 16,689 missed tweets in the Storify database, including full NGSS chat sessions. If this time gap were to be excluded from the calculation of the completeness of the Storify database, Storify would have a 51.2% completeness rate.

Figure 1. Number of tweets in Storify database for each day of the years 2014, 2015, and 2016.

Comparing the Storify database with the additional tweets that were obtained in between NGSS chat sessions, we investigated possible differences concerning favourite and retweet counts. The Storify database had a mean favourite count of $M = 1.20$, $SD = 1.75$, ranging from 0 to 38 while the additional tweets had a mean favourite count of $M = 0.93$, $SD = 2.66$, ranging from 0 to 248. Meanwhile, the Storify database included a mean retweet count of $M = 0.35$, $SD = 1.04$, ranging from 0 to 53 while the additional tweets included a mean retweet count of $M = 0.43$, $SD = 1.93$ ranging from 0 to 198.

Completeness of Storify data within #NGSSchat synchronous sessions

To examine the completeness of the Storify database within the NGSS chat sessions, we randomly selected three days for each year 2014, 2015 and 2016 that consisted of at least 300 tweets. Out of all 44 distinct days that were included in the Storify database, 33 day fulfilled this criterion, making up 68.8% of all days represented in the Storify database. The resulting nine days were downloaded and compared with the original data.

Overall, while the Storify database included 3,960 tweets, the re-download data yielded 6,263 tweets during these nine days. Assuming that no tweets were deleted between the two points of download, that would mean that the Storify database during these nine days would only be complete to 63.2%. Evaluating this assumption, we found that 43 tweets within the nine days were deleted from the Storify database such that they were not obtained through re-downloading. This makes up for 1.1% of tweets in the Storify database being deleted prior to our re-download. Assuming that these 43 would not have been deleted but rather re-downloaded, the aforementioned first estimate of the completeness of the Storify database amounts to 62.8%.

We considered that this discrepancy of 36.8% between the Storify database and the re-downloaded tweets within the selected nine days is due to the fact that we looked at 24 hour time frames rather than the NGSS chat sessions only. We therefore only looked at the two hours with most tweets in the Storify database (Figure 2), 1 and 3 AM UTC. Such an exclusion was achieved through filtering all tweets posted between 01:00 and 02:59 AM UTC by extracting the hour of the creation date of all tweets. This leads to an estimated completeness of the Storify database of 67.5% within NGSS chat sessions and indicates that the aforementioned discrepancy in data completeness seems to also hold true within NGSS chat sessions. On the other hand, when excluding retweets from the sample the completeness of the Storify database was estimated

at 80.8%. When additionally only looking at tweets posted between 1 and 3 AM UTC that were not retweets, the completeness of the Storify database was estimated at 84.0%.

Figure 2. Number of tweets in Storify data over time (UTC) by minutes of the day.

Identifying patterns of missing tweet data. Tweets in the Storify database were filtered from Storify moderators by certain criteria. As the Storify database within NGSS chat sessions seemed more complete when excluding retweets and tweets posted outside of 1 and 3 AM UTC, we examined these criteria. We found that while 60.4% of tweets that were excluded were retweets, only 1.1% of tweets in the Storify database were retweets. This seems to indicate that retweets were viewed as an exclusion criterion. Similarly, 22.3% of excluded tweets were not posted between 1 and 3 AM UTC while only 4.3% of tweets that were not excluded were not posted between 1 and 3 AM UTC. Together, 69.5% of all excluded tweets that can be explained by either being a retweet, being posted outside of 1-3 AM UTC or being both. Thus, we excluded all tweets that were retweets or posted outside of 1 and 3 AM UTC for all subsequent analysis

and further examined tweets in our re-downloaded sample to identify possible properties that could qualify as exclusion criteria.

Another potential exclusion criteria might be to exclude short tweets (with the assumption that they may not have sufficient content; e.g., "@Individual1 No limits? Tell me more. . . #NGSSchat"). Examining the length of tweets of the mentioned subset, we obtained a mean character length of $M = 91.57$, $SD = 35.83$, ranging from 23 to 151. For the length of tweets during the sampled days in the Storify database we obtained $M = 98.09$, $SD = 33.54$, ranging from 18 to 151. The length of tweets therefore seemed not to be a possible filtering criterion for Storify moderators.

Another possibility is that certain users were systematically excluded. We found that 17 users did not appear in the Storify database who contributed a total of only 3.4% missing tweets. Notably, none of the excluded users contributed more than four tweets. Thus, it seems unlikely that certain users were systematically excluded by Storify moderators.

Creating a full chronological list of tweets that were excluded while meeting the criteria of not being retweets and being posted between 1 and 3 AM UTC, we looked at further criteria of exclusion ourselves as algorithmic solutions seemed to not lead to any further explanation of exclusion criteria. Firstly, we found that some NGSS chat sessions started at 2 AM UTC and were preceded by a chat session called "High School NGSS chat" which included the hashtag #NGSSchat as well. These chat sessions were always excluded in the described subset and made up 302 tweets. The exclusion of tweets posted within HS NGSS chat sessions can therefore explain an additional 12.9% of all excluded tweets in our re-downloaded sample. Similarly, we found that many excluded tweets represented introductions of teachers and reactions to these introductions in the beginning of NGSS chat sessions (e.g., "Hi @username, great to see you!"),

“Jane Doe here, teaching Chemistry in New York”). We counted 118 of these tweets in the described subset such that additional 5.0% of all excluded tweets can be explained through excluded greetings and introductions of teachers. Also, we found that very short reactions like “Agreed. Thanks @username” were excluded 11 times, explaining additional 0.5% of exclusions. Thus, with these additional checks added to the other exclusion criteria we identified; we could explain 87.9% of all excluded tweets within our re-downloaded sample of NGSS chat sessions.

For the remaining 12.1%, we could not identify any consistent pattern that may explain exclusion criteria. For example, when re-examining the length of tweets as an exclusion criterion on this small subset, these remaining 12.1% of tweets had a mean length of $M = 92.47$ characters, $SD = 33.48$, ranging from 23 to 148, yet again similar to the tweets that were not excluded. It seems that these 12.1% of tweets were excluded by moderators seemingly at random when considering the entire Storify database. Also, there have been some inconsistencies in the enforcement of the aforementioned exclusion criteria. For instance, 1.1% of tweets during the sampled days in the Storify database were still retweets even though retweets seem to constitute an exclusion criterion. Also, we found that while introduction and greeting tweets were almost always excluded in some NGSS chat sessions, they were not excluded in other NGSS chat sessions (in our sample: all sessions that took place on January 22nd, 2016 or later). Such inconsistencies in tweet exclusion of tweets by NGSS moderators limit the ability to clearly identify further exclusion criteria.

Conclusion

Within the chat sessions, the Storify dataset includes about 80% of all original tweets. Out of the missing 20%, tweets mostly belonged to the “High School NGSS chat” sessions

(#hsNGSSchat) and included teachers introducing themselves or greeting each other. The exclusion of those tweets do not seem to harm the validity of analyses utilizing Storify data or introduce biases to potential analyses. The remaining approximate 10% of tweets in the Storify database seem to be missing at random. When examining quantitative tweet characteristics (number of favorites, retweets), we did not see substantial differences between the Storify database and the newly downloaded data between the synchronous NGSS chat sessions. The Storify data does not include data in between NGSS chat sessions (about 50% of tweets are missing between January 2014 and April 2016). Thus, we do not recommend using the Storify database for examining activity outside the synchronous NGSS chat session. In summary, the Storify data may be utilized to understand the synchronous NGSS chat sessions as it captures the most of the relevant tweet activity. That said, a redownload of the entire #NGSSchat community may be recommended if analyses intend to capture the full range of interactions within the NGSS chat session without the content filtering provided by the Storify moderators.

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Appendix

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Example of downloading tweets using rtweet

```
rm(list=ls())
library(lubridate, quietly = T, warn.conflicts = F) # function setdiff() masked
library(magrittr, quietly = T)

## rtweet's function search_fullarchive originally capped
## queries of tweet-downloads at 100 tweets. Since the
## premium Twitter API allows for up to 500 tweets,
## a user-created fix was used for downloading all tweets

library(devtools, quietly = T)

# remotes::install_github("kevintaylor/rtweet")

library(rtweet, quietly = T)

## Custom-made functions for file routines

## The following function was used to send queries
## to the Twitter API

# env_name <- "NGSSproject"

tweetdownload <- function(from, to){
  search_fullarchive(q="#NGSSchat", n=500, fromDate = from,
                    toDate = to, env_name = env_name)
}

## Download queries are done through timeframes of the format
## yyyymmddhhmm. The following function converts UCT timestamps
## to such timeframes which was later used to download gaps
## in between the storify data set.

UCT2frame <- function(datetime){
  frame <- strptime(datetime,"%Y-%m-%d %H:%M:%S", tz="UCT")
  frame <- substr(frame, 1, nchar(frame) - 3)
  frame <- gsub("-", "", frame)
  frame <- gsub(":", "", frame)
  frame <- gsub(" ", "", frame)
  return(frame)
}

## Through the following function, query results were saved
## in a .rda file format with a specific filename that comprised
```

```

## of the chronologically first and last tweets of the query.

save_rda_dl <- function(tweets_dl, stampstring=""){
  first <- tweets_dl$created_at %>% min() %>% UCT2frame()
  last <- tweets_dl$created_at %>% max() %>% UCT2frame()

  file_name <- paste(stampstring, "DATA_", first, "_TO_", last, ".rda", sep="")

  save(tweets_dl, file = file_name)
}

## Example usage

from <- as.POSIXct(1234, origin = "2020-01-01", tz = "UTC")
to <- as.POSIXct(9876, origin = "2020-01-01", tz = "UTC")

from # Format in data

## [1] "2020-01-01 00:20:34 UTC"

from <- UCT2frame(from)
to <- UCT2frame(to)

from # query format

## [1] "202001010020"

# tweets <- tweetdownload(from, to)

# save_rda_dl(tweets)

```

Calculating gaps in between Storify #NGSSchat database

```

## Read storify data set

storifydata <- readRDS("storify_data.rds")

## Range of tweets in Storify data set timewise

min(storifydata$created_at)

## [1] "2012-05-11 00:01:09 UTC"

max(storifydata$created_at)

## [1] "2017-11-17 04:08:07 UTC"

## Order tweets chronologically

storifydata <- storifydata[order(storifydata$created_at),]

## Only include tweets posted between 2014 and 2016

start <- min(grep("2014", storifydata$created_at))
end <- max(grep("2016", storifydata$created_at))

```

```

storifydata <- storifydata[start:end,]

## Calculate timegaps in between tweets

reference <- data.frame(
  t0 <- storifydata$created_at[1:nrow(storifydata)-1],
  t1 <- storifydata$created_at[2:nrow(storifydata)]
)
colnames(reference) <- c("t0", "t1")

## Adding the two time gaps from the beginning of 2014 to
## the first tweets in Storify data set of 2014 as well as
## from last tweet in Storify data set of 2016 to the end
## of 2016

start2014 <- as.POSIXct(strptime("2014-01-01 00:00:01",
                                format="%Y-%m-%d %H:%M:%S"), tz="UTC")

reference <- rbind(reference[1,], reference)

reference[1,1] <- start2014
reference[1,2] <- reference[2,1]

end2016 <- as.POSIXct(strptime("2016-12-31 23:59:59",
                                format="%Y-%m-%d %H:%M:%S"), tz="UTC")

reference <- rbind(reference, reference[nrow(reference),])

reference[nrow(reference),2] <- end2016
reference[nrow(reference),1] <- reference[nrow(reference)-1,2]

## Create time differences in between tweets

reference$delta <- seconds_to_period(reference$t1 - reference$t0)

## Order pairs of tweets by biggest time gaps

reference <- reference[order(reference$delta, decreasing = T),]

## Select the 48 biggest time gaps (effectively choosing all
## time gaps larger than 6 hours)

reference <- reference[1:48,]

## Order these 48 time gaps chronologically for better overview

reference <- reference[order(reference$t0),]

## Read in downloads of queries addressing these time gaps
## Note: Also ordered chronologically

fn <- list(
  "DATA_201401011738_T0_201404032154.rda",

```



```

"DATA_201404040214_TO_201404180058.rda",
"DATA_201404180247_TO_201405020054.rda",
"DATA_201405020209_TO_201405160017.rda",
"DATA_201405160207_TO_201405291751.rda",
"DATA_201405300204_TO_201406130059.rda",
"DATA_201406130213_TO_201406270054.rda",
"DATA_201406270211_TO_201407101021.rda",
"DATA_201407101310_TO_201407110048.rda",
"DATA_201407110202_TO_201408010054.rda",
"DATA_201408010243_TO_201408150059.rda",
"DATA_201408150201_TO_201408280927.rda",
"DATA_201408280947_TO_201408290020.rda",
"DATA_201408290207_TO_201409120057.rda",
"DATA_201410030134_TO_201410170056.rda",
"DATA_201410170223_TO_201410292040.rda",
"DATA_201410292101_TO_201410310059.rda",
"DATA_201411070232_TO_201411141125.rda",
"DATA_201411141412_TO_201411210159.rda",
"DATA_201411210314_TO_201412050159.rda",
"DATA_201412190303_TO_201501090159.rda",
"DATA_201501230255_TO_201502060159.rda",
"DATA_201503052243_TO_201503130039.rda",
"DATA_201503131023_TO_201503200059.rda",
"DATA_201503200223_TO_201504030059.rda",
"DATA_201505270116_TO_201506050057.rda",
"DATA_201506050240_TO_201506190059.rda",
"DATA_201506190201_TO_201507030056.rda",
"DATA_201507030211_TO_201507170058.rda",
"DATA_201507170213_TO_201507310058.rda",
"DATA_201507310230_TO_201508070057.rda",
"DATA_201508070201_TO_201508210004.rda",
"DATA_201508211409_TO_201509040100.rda",
"DATA_201509040200_TO_201509180059.rda",
"DATA_201509180200_TO_201510020056.rda",
"DATA_201510020225_TO_201510160100.rda",
"DATA_201510160942_TO_201511060154.rda",
"DATA_201511061825_TO_201511200159.rda",
"DATA_201511200307_TO_201512040200.rda",
"DATA_201512040303_TO_201512180200.rda",
"DATA_201512180306_TO_201601080159.rda",
"DATA_201601080311_TO_201601220159.rda",
"DATA_201601220356_TO_201602050201.rda",
"DATA_201602051650_TO_201602190200.rda",
"DATA_201602190314_TO_201603040159.rda",
"DATA_201604251954_TO_201605060103.rda",
"DATA_201605060227_TO_201605061332.rda",
"DATA_201605061353_TO_201612312335.rda"
)

## While combining queries to new data frame, count
## number of new tweets per query in time gaps

all <- data.frame()

```

```

len <- c()
for (name in fn){
  load(name)
  current <- tweets_dl
  len <- c(len, nrow(current))
  current <- current[order(current$created_at),]
  all <- rbind(all, current)
}

```

Assign number of new tweets to time gaps

```
reference$n_new <- len
```

Overview of new downloaded tweets in time gaps

```
reference
```

##		t0	t1	delta	n_new
## 1	2014-01-01 00:00:01	2014-04-03 23:38:12	92d 23H 38M 11S	282	
## 473	2014-04-04 02:14:45	2014-04-18 01:00:22	13d 22H 45M 37S	202	
## 814	2014-04-18 02:47:59	2014-05-02 01:01:46	13d 22H 13M 47S	164	
## 927	2014-05-02 02:09:30	2014-05-16 00:22:21	13d 22H 12M 51S	109	
## 1137	2014-05-16 02:07:46	2014-05-29 18:13:38	13d 16H 5M 52S	108	
## 1362	2014-05-30 02:04:04	2014-06-13 01:00:21	13d 22H 56M 17S	157	
## 1786	2014-06-13 02:13:29	2014-06-27 00:57:46	13d 22H 44M 17S	288	
## 2130	2014-06-27 02:11:25	2014-07-10 13:10:43	13d 10H 59M 18S	162	
## 2131	2014-07-10 13:10:43	2014-07-11 00:52:35	11H 41M 52S	26	
## 2333	2014-07-11 02:02:49	2014-08-01 00:59:44	20d 22H 56M 55S	224	
## 2660	2014-08-01 02:43:59	2014-08-15 01:00:22	13d 22H 16M 23S	260	
## 3086	2014-08-15 02:01:32	2014-08-28 09:47:14	13d 7H 45M 42S	194	
## 3087	2014-08-28 09:47:14	2014-08-29 00:23:06	14H 35M 52S	39	
## 3342	2014-08-29 02:07:48	2014-09-12 00:58:19	13d 22H 50M 31S	236	
## 3642	2014-09-12 02:10:30	2014-10-17 01:00:04	34d 22H 49M 34S	500	
## 3996	2014-10-17 02:23:30	2014-10-29 21:01:29	12d 18H 37M 59S	184	
## 3997	2014-10-29 21:01:29	2014-10-31 01:00:23	1d 3H 58M 54S	76	
## 4328	2014-10-31 02:17:00	2014-11-14 14:12:38	14d 11H 55M 38S	500	
## 4329	2014-11-14 14:12:38	2014-11-21 02:00:17	6d 11H 47M 39S	141	
## 4666	2014-11-21 03:14:24	2014-12-05 02:01:43	13d 22H 47M 19S	222	
## 4946	2014-12-05 03:02:49	2015-01-09 02:00:29	34d 22H 57M 40S	500	
## 5131	2015-01-09 03:11:47	2015-02-06 02:00:34	27d 22H 48M 47S	500	
## 5519	2015-02-06 02:57:39	2015-03-13 00:44:26	34d 21H 46M 47S	500	
## 6265	2015-03-13 10:23:32	2015-03-20 01:00:09	6d 14H 36M 37S	757	
## 7157	2015-03-20 02:23:47	2015-04-03 01:00:45	13d 22H 36M 58S	587	
## 7692	2015-04-03 02:02:48	2015-06-05 01:00:05	62d 22H 57M 17S	500	
## 8284	2015-06-05 02:40:44	2015-06-19 01:00:22	13d 22H 19M 38S	532	
## 8652	2015-06-19 02:01:28	2015-07-03 00:57:27	13d 22H 55M 59S	500	
## 9097	2015-07-03 02:11:10	2015-07-17 01:00:43	13d 22H 49M 33S	301	
## 9441	2015-07-17 02:13:01	2015-07-31 01:00:55	13d 22H 47M 54S	354	
## 10116	2015-07-31 02:30:55	2015-08-07 00:59:10	6d 22H 28M 15S	214	
## 10388	2015-08-07 02:01:10	2015-08-21 00:22:36	13d 22H 21M 26S	513	
## 10881	2015-08-21 14:09:56	2015-09-04 01:01:09	13d 10H 51M 13S	367	
## 11299	2015-09-04 02:00:03	2015-09-18 01:00:40	13d 23H 0M 37S	422	
## 11734	2015-09-18 02:00:53	2015-10-02 01:01:27	13d 23H 0M 34S	475	
## 12057	2015-10-02 02:05:25	2015-10-16 01:01:51	13d 22H 56M 26S	500	

```
## 12538 2015-10-16 02:18:45 2015-11-06 02:01:57 20d 23H 43M 12S 500
## 13009 2015-11-06 03:05:03 2015-11-20 02:00:52 13d 22H 55M 49S 500
## 13463 2015-11-20 03:07:44 2015-12-04 02:01:01 13d 22H 53M 17S 430
## 13959 2015-12-04 03:03:11 2015-12-18 02:01:12 13d 22H 58M 1S 442
## 14305 2015-12-18 03:06:25 2016-01-08 02:00:23 20d 22H 53M 58S 373
## 14727 2016-01-08 03:02:07 2016-01-22 02:00:42 13d 22H 58M 35S 500
## 15215 2016-01-22 03:56:12 2016-02-05 02:02:11 13d 22H 5M 59S 507
## 15932 2016-02-05 16:50:37 2016-02-19 02:01:52 13d 9H 11M 15S 569
## 16485 2016-02-19 03:14:59 2016-03-04 02:00:08 13d 22H 45M 9S 481
## 16946 2016-03-04 03:00:05 2016-05-06 01:04:15 62d 22H 4M 10S 493
## 17224 2016-05-06 02:27:31 2016-05-06 13:35:40 11H 8M 9S 17
## 172261 2016-05-06 13:53:14 2016-12-31 23:59:59 239d 10H 6M 45S 16689
```

```
nrow(storifydata) # Sum of tweets in storify data
```

```
## [1] 17226
```

```
nrow(all) # Sum of downloaded tweets in time gaps
```

```
## [1] 33097
```

Analysis of tweets downloaded between gaps in Storify #NGSSchat database

```
## Created data frames of statistics for favourites
## and retweets in storify data and gap data
```

```
favourites <- data.frame(
```

```
M = c(mean(storifydata$favorite_count), mean(all$favorite_count)),
Med = c(median(storifydata$favorite_count), median(all$favorite_count)),
SD = c(sd(storifydata$favorite_count), sd(all$favorite_count)),
Min = c(min(storifydata$favorite_count), min(all$favorite_count)),
Max = c(max(storifydata$favorite_count), max(all$favorite_count))
```

```
)
```

```
favourites$M <- round(favourites$M, 2)
favourites$SD <- round(favourites$SD, 2)
```

```
rownames(favourites) <- c("Storifydata", "Gapdata")
```

```
retweets <- data.frame(
```

```
M = c(mean(storifydata$retweet_count), mean(all$retweet_count)),
Med = c(median(storifydata$retweet_count), median(all$retweet_count)),
SD = c(sd(storifydata$retweet_count), sd(all$retweet_count)),
Min = c(min(storifydata$retweet_count), min(all$retweet_count)),
Max = c(max(storifydata$retweet_count), max(all$retweet_count))
```

```
)
```

```
retweets$M <- round(retweets$M, 2)
retweets$SD <- round(retweets$SD, 2)
```

```
rownames(retweets) <- c("Storifydata", "Gapdata")
```

```
favourites
```

```
##           M Med   SD Min Max
## Storifydata 1.20   1 1.75   0  38
## Gapdata     0.93   0 2.66   0 248
```

```
retweets
```

```
##           M Med   SD Min Max
## Storifydata 0.35   0 1.04   0  53
## Gapdata     0.43   0 1.93   0 198
```

Selecting tweets within rush hours to re-download and compare

```
set.seed(123)

## Select days with more than 300 tweets in storify data set

## Extract days from timestamps in storify data set

time <- storifydata$created_at

days <- format(time, format='%Y-%m-%d')

## Aggregate number of tweets over days

freq <- table(days)

## Exclusion of days with less than 300 tweets

freq <- freq[freq >= 300]

## For each year, sample three days by subsetting
## all days by year and sampling three days in each subset

freq <- data.frame(freq)

t2014 <- freq[grep("2014", freq$days),]
t2014 <- t2014[sample(nrow(t2014), 3), ]

t2015 <- freq[grep("2015", freq$days),]
t2015 <- t2015[sample(nrow(t2015), 3), ]

t2016 <- freq[grep("2016", freq$days),]
t2016 <- t2016[sample(nrow(t2016), 3), ]

result <- rbind(t2014, t2015, t2016)
colnames(result) <- c("Date", "Number of tweets")

result # Days that were redownloaded
```

```
##           Date Number of tweets
## 3  2014-06-13           424
## 10 2014-11-21           337
## 2   2014-04-18           341
## 28 2015-12-18           346
## 21 2015-09-04           418
```

```
## 15 2015-06-05          592
## 32 2016-02-19          553
## 30 2016-01-22          488
## 33 2016-03-04          461
```

Comparing re-downloaded tweets with the Storify #NGSSchat database

```
rm(list=ls())

## Timeframes and number of tweets in original data

days <- read.table(header=T, text="
day ntweets
2014-06-13 424
2014-11-21 337
2014-04-18 341
2015-12-18 346
2015-09-04 418
2015-06-05 592
2016-02-19 553
2016-01-22 488
2016-03-04 461"
)

## Read in storify data

storifydata <- readRDS("storify_data.rds")

## Order tweets chronologically

storifydata <- storifydata[order(storifydata$created_at),]

## Select days of re-downloaded days from storify data set

old <- data.frame()

for (day in days$day){
  index <- grep(day, as.character(storifydata$created_at))
  old <- rbind(old, storifydata[index,])
}

## Read in new data and order each data set chronologically

fn <- list(
  "DATA_201406130033_TO_201406132339.rda",
  "DATA_201411210000_TO_201411212212.rda",
  "DATA_201404180000_TO_201404182146.rda",
  "DATA_201512180030_TO_201512182355.rda",
  "DATA_201509040005_TO_201509042315.rda",
  "DATA_201506050002_TO_201506052015.rda",
  "DATA_201602190002_TO_201602192307.rda",
  "DATA_201601220009_TO_201601222320.rda",
  "DATA_201603040026_TO_201603042206.rda"
```

```

)

new <- data.frame()
for (name in fn){
  load(name)
  current <- tweets_dl
  current <- current[order(current$created_at),]
  new <- rbind(new, current)
}

new_n <- c()

## Compare number of tweets between both data sets for each day

for (day in days$day){
  new_n <- c(new_n, grep(day, as.character(new$created_at)) %>% length())
}

days$n_newtweets <- new_n
colnames(days) <- c("Day", "Storify", "Re_DL")
days$Estimate <- (as.numeric(days[,2]) / as.numeric(days[,3])) * 100

days

```

```

##           Day Storify Re_DL Estimate
## 1 2014-06-13      424   635 66.77165
## 2 2014-11-21      337   662 50.90634
## 3 2014-04-18      341   596 57.21477
## 4 2015-12-18      346   574 60.27875
## 5 2015-09-04      418   639 65.41471
## 6 2015-06-05      592   852 69.48357
## 7 2016-02-19      553   861 64.22764
## 8 2016-01-22      488   751 64.98003
## 9 2016-03-04      461   693 66.52237

```

```

sum(days$Storify) # Sum of tweets in storify data during selected days

```

```
## [1] 3960
```

```

sum(days$Re_DL) # Sum of tweets in re-downloaded data during selected days

```

```
## [1] 6263
```

```

sum(days$Storify) * 100 / sum(days$Re_DL) # % estimate

```

```
## [1] 63.22848
```

Have tweets been deleted since the download of the storify data set?

```

## With the function base::setdiff() the following sets are selected
## through looking at the tweet IDs of the given tweets

```

```

## 1) Tweets that are in old but not in new (deleted tweets) and
## 2) Tweets that are in new but not in old (tweets missing in Storify #NGSSchat database)

```

```

## Old and not in new (deleted tweets)

deleted <- base::setdiff(old$status_id, new$status_id)
length(deleted)

## [1] 43

(length(deleted) / nrow(old)) * 100 # %

## [1] 1.085859

## Corrected estimate of completeness of storify data set assuming no tweets
## would have been deleted

sum(days$Storify) * 100 / (sum(days$Re_DL) + length(deleted)) # % corrected estimate

## [1] 62.79734

## This corrected estimate can also be reformulated by counting
## the number of tweets that are in the new, but not in the storify data set

missing <- base::setdiff(new$status_id, old$status_id)
length(missing)

## [1] 2346

(nrow(old) / (nrow(old) + length(missing))) * 100

## [1] 62.79734

```

Which kind of data within rush hours misses in the Storify #NGSSchat database?

```

## Possibility: Data sets differ in inclusion of retweets

## Exclude manually copy-pasted retweets "RT @" and automatically
## created retweets (indicated by the variable is_retweet)

new2 <- new[new$is_retweet==F, ]
new2 <- new2[!grep("RT @", new2$text),]

old2 <- old[old$is_retweet==F, ]
old2 <- old2[!grep("RT @", old2$text),]

new_n2 <- c()
old_n2 <- c()

for (day in days$Day){
  new_n2 <- c(new_n2, grep(day, as.character(new2$created_at)) %>% length())
  old_n2 <- c(old_n2, grep(day, as.character(old2$created_at)) %>% length())
}

days$Storify_noRT <- old_n2
days$Re_DL_noRT <- new_n2
days$Estimate2 <- (as.numeric(days[,5]) / as.numeric(days[,6])) * 100

```

```
days
```

```
##           Day Storify Re_DL Estimate Storify_noRT Re_DL_noRT Estimate2
## 1 2014-06-13      424   635 66.77165           406         451  90.02217
## 2 2014-11-21      337   662 50.90634           321         484  66.32231
## 3 2014-04-18      341   596 57.21477           333         433  76.90531
## 4 2015-12-18      346   574 60.27875           346         480  72.08333
## 5 2015-09-04      418   639 65.41471           418         488  85.65574
## 6 2015-06-05      592   852 69.48357           592         640  92.50000
## 7 2016-02-19      553   861 64.22764           553         684  80.84795
## 8 2016-01-22      488   751 64.98003           488         609  80.13136
## 9 2016-03-04      461   693 66.52237           461         537  85.84730
```

```
sum(days$Storify_noRT) # Sum of tweets in storify data during selected days without retweets
```

```
## [1] 3918
```

```
sum(days$Re_DL_noRT) # Sum of tweets in re-downloaded data during selected days without retweets
```

```
## [1] 4806
```

```
sum(days$Storify_noRT) * 100 / sum(days$Re_DL_noRT) # % estimate
```

```
## [1] 81.5231
```

```
## Corrected estimate assuming no tweets would have been deleted
```

```
missing2 <- base::setdiff(new2$status_id, old2$status_id)
(nrow(old2) / (nrow(old2) + length(missing2))) * 100 # % corrected estimate
```

```
## [1] 80.83351
```

```
## Conclusion: Storify data set is still not complete but seems
## more complete when excluding retweets (80.83%)
```

Is the storify data set complete during the most busy hours of #NGSSchat?

```
## Possibility: Most hours of the days that were looked at were not
## busy and excluded from storify data set (see download of time gaps)
```

```
## Only looking at tweets between 01:00 and 03:00 UTC (most activity)
```

```
## Subsetting data sets
```

```
old3 <- old[which(hour(old$created_at) %in% 1:2),] # 01:00-02:59 UTC
new3 <- new[which(hour(new$created_at) %in% 1:2),]
```

```
old_n3 <- c()
```

```
new_n3 <- c()
```

```
for (day in days$Day){
  new_n3 <- c(new_n3, grep(day, as.character(new3$created_at)) %>% length())
  old_n3 <- c(old_n3, grep(day, as.character(old3$created_at)) %>% length())
}
```

```
## Estimate
```



```

sum(old_n3) * 100 / sum(new_n3) # % estimate

## [1] 68.04383
## Corrected estimate assuming no tweets would have been deleted

missing3 <- base::setdiff(new3$status_id, old3$status_id)
(nrow(old3) / (nrow(old3) + length(missing3))) * 100 # % corrected estimate

## [1] 67.52228
## Conclusion: Dataset during rush hours and between 01:00 and 03:00 UTC more
## complete than whole days but still only 67.5% complete.

## Subsetting retweets only *and* tweets between 01:00 and 03:00 UTC

new4 <- new3[new3$is_retweet==F, ]
new4 <- new4[-grep("RT @", new4$text),]

old4 <- old3[old3$is_retweet==F, ]
old4 <- old4[-grep("RT @", old4$text),]

new_n4 <- c()
old_n4 <- c()

for (day in days$Day){
  new_n4 <- c(new_n4, grep(day, as.character(new4$created_at)) %>% length())
  old_n4 <- c(old_n4, grep(day, as.character(old4$created_at)) %>% length())
}

## Estimate

sum(old_n4) * 100 / sum(new_n4) # % estimate

## [1] 84.75113
## Corrected estimate assuming no tweets would have been deleted

missing4 <- base::setdiff(new4$status_id, old4$status_id)
(nrow(old4) / (nrow(old4) + length(missing4))) * 100 # % corrected estimate

## [1] 83.9722

```

Summary of estimates of completeness of Storify data set within NGSS chat sessions

The storify data is incomplete within rush hours. The share to which the storify data set is complete increases slightly when only looking at data during the most busy hours and increases drastically when excluding retweets. This points to the fact that different exclusion criteria were applied. Furthermore, the data is incomplete to similar degrees between all re-downloaded days.

```

## All estimates

## All data

days[1:4]

```

```
##           Day Storify Re_DL Estimate
## 1 2014-06-13      424   635 66.77165
## 2 2014-11-21      337   662 50.90634
## 3 2014-04-18      341   596 57.21477
## 4 2015-12-18      346   574 60.27875
## 5 2015-09-04      418   639 65.41471
## 6 2015-06-05      592   852 69.48357
## 7 2016-02-19      553   861 64.22764
## 8 2016-01-22      488   751 64.98003
## 9 2016-03-04      461   693 66.52237
```

```
sum(days[2])
```

```
## [1] 3960
```

```
sum(days[3])
```

```
## [1] 6263
```

```
(sum(days[2]) / sum(days[3])) * 100
```

```
## [1] 63.22848
```

```
(nrow(old) / (nrow(old) + length(missing))) * 100 # % assuming no tweets have been deleted
```

```
## [1] 62.79734
```

```
## Without retweets
```

```
days[c(1, 5:7)]
```

```
##           Day Storify_noRT Re_DL_noRT Estimate2
## 1 2014-06-13      406      451  90.02217
## 2 2014-11-21      321      484  66.32231
## 3 2014-04-18      333      433  76.90531
## 4 2015-12-18      346      480  72.08333
## 5 2015-09-04      418      488  85.65574
## 6 2015-06-05      592      640  92.50000
## 7 2016-02-19      553      684  80.84795
## 8 2016-01-22      488      609  80.13136
## 9 2016-03-04      461      537  85.84730
```

```
sum(days[5])
```

```
## [1] 3918
```

```
sum(days[6])
```

```
## [1] 4806
```

```
(sum(days[5]) / sum(days[6])) * 100
```

```
## [1] 81.5231
```

```
(nrow(old2) / (nrow(old2) + length(missing2))) * 100 # % assuming no tweets have been deleted
```

```
## [1] 80.83351
```

```
## Without most busy hours
```

```
days[2] <- old_n3
```

```
days[3] <- new_n3
days[4] <- days[2] / days[3]
days[1:4]
```

```
##           Day Storify Re_DL Estimate
## 1 2014-06-13      424   594 0.7138047
## 2 2014-11-21      303   587 0.5161840
## 3 2014-04-18      341   552 0.6177536
## 4 2015-12-18      316   497 0.6358149
## 5 2015-09-04      418   603 0.6932007
## 6 2015-06-05      592   790 0.7493671
## 7 2016-02-19      491   734 0.6689373
## 8 2016-01-22      444   622 0.7138264
## 9 2016-03-04      459   588 0.7806122
```

```
sum(days[2])
```

```
## [1] 3788
```

```
sum(days[3])
```

```
## [1] 5567
```

```
(sum(days[2]) / sum(days[3])) * 100
```

```
## [1] 68.04383
```

```
(nrow(old3) / (nrow(old3) + length(missing3))) * 100 # % assuming no tweets have been deleted
```

```
## [1] 67.52228
```

```
## Without retweets nor most busy hours
```

```
days[2] <- old_n4
days[3] <- new_n4
days[4] <- days[2] / days[3]
days[1:4]
```

```
##           Day Storify Re_DL Estimate
## 1 2014-06-13      406   441 0.9206349
## 2 2014-11-21      287   440 0.6522727
## 3 2014-04-18      333   412 0.8082524
## 4 2015-12-18      316   432 0.7314815
## 5 2015-09-04      418   471 0.8874735
## 6 2015-06-05      592   619 0.9563813
## 7 2016-02-19      491   608 0.8075658
## 8 2016-01-22      444   532 0.8345865
## 9 2016-03-04      459   465 0.9870968
```

```
sum(days[2])
```

```
## [1] 3746
```

```
sum(days[3])
```

```
## [1] 4420
```

```
(sum(days[2]) / sum(days[3])) * 100
```

```
## [1] 84.75113
```

```
(nrow(old4) / (nrow(old4) + length(missing4))) * 100 # % assuming no tweets have been deleted
```

```
## [1] 83.9722
```

Considering different possible criteria of exclusion by Storify administrators

```
## Further analyzing tweets, that could possibly have been sorted out by  
## certain criteria by Storify administrators
```

```
## Sorted out is defined as existing in re-downloads but not in Storify data set  
## Not sorted out is defined as existing in Storify data set
```

```
sorted_out <- new[!new$status_id %in% old$status_id,]  
not_sorted_out <- old
```

```
## Possibility: Retweets have been sorted out predominantly by being a retweet
```

```
## Get retweets by the variable is_retweet as well as pattern search in text  
## (manual retweeting with RT @)
```

```
c(which(sorted_out$is_retweet==T), grep("RT @", sorted_out$text)) %>%  
  unique() %>%  
  length() * 100 /  
  nrow(sorted_out)
```

```
## [1] 60.40068
```

```
c(which(not_sorted_out$is_retweet==T), grep("RT @", not_sorted_out$text)) %>%  
  unique() %>%  
  length() * 100 /  
  nrow(not_sorted_out)
```

```
## [1] 1.060606
```

```
## Conclusion: 60.4% of tweets that were sorted out were retweets. Only  
## 1.1% of tweets that were not sorted out were retweets. Still, there were  
## possibly more criteria of exclusion.
```

```
## Possibility: Tweets that were not posted between 1 and 3 UTC (most  
## activity) were sorted out
```

```
which(!hour(sorted_out$created_at) %in% 1:2) %>% length() * 100 / nrow(sorted_out)
```

```
## [1] 22.33589
```

```
which(!hour(not_sorted_out$created_at) %in% 1:2) %>% length() * 100 / nrow(not_sorted_out)
```

```
## [1] 4.343434
```

```
## Conclusion: 22.3% of tweets that were sorted out were not posted between.  
## 1 and 3 UTC. Only 4.3% of tweets that were not sorted out were not posted between  
## 1 and 3 UTC. Still, there were possibly more criteria of exclusion.
```

```
## Excluding all retweets and posts outside of 1-3 UTC from sorted out tweets  
## for further analysis
```

```

rt_index <- c(which(sorted_out$is_retweet==T), grep("RT @", sorted_out$text)) %>% unique()
time_index <- which(!hour(sorted_out$created_at) %in% 1:2)

sorted_out2 <- sorted_out[-unique(c(rt_index, time_index)),]

(1 - nrow(sorted_out2) / nrow(sorted_out)) * 100

## [1] 69.52259
## Retweets and timeframe 1-3 UTC explains 69.5% of all sorted out tweets
## Possibility: Short tweets with no rich content have been sorted out

not_sorted_out$text %>% na.omit() %>% nchar() %>% mean()

## [1] 98.09318
not_sorted_out$text %>% na.omit() %>% nchar() %>% sd()

## [1] 33.54303
not_sorted_out$text %>% na.omit() %>% nchar() %>% summary()

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      18.00   71.00  103.00   98.09  129.00  151.00
sorted_out2$text %>% na.omit() %>% nchar() %>% mean()

## [1] 91.57343
sorted_out2$text %>% na.omit() %>% nchar() %>% sd()

## [1] 35.83203
sorted_out2$text %>% na.omit() %>% nchar() %>% summary()

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      23.00   59.00   94.00   91.57  126.00  151.00
## Conclusion: Length of tweets does not seem to have been
## an exclusion criterion for Storify administrators

## Possibility: Certain users were systematically excluded

users_in_sorted_out2 <- sorted_out2$user_id %>% unique()
users_in_not_sorted_out <- not_sorted_out$user_id %>% unique()

## User that were only in the sorted out tweets

possibly_excluded_users <- base::setdiff(users_in_sorted_out2, users_in_not_sorted_out)

## Get amount of tweets posted by these users in sorted out tweets

amount <- c()

for (i in 1:length(possibly_excluded_users)){
  amount <- c(amount, length(grep(possibly_excluded_users[i], sorted_out2$user_id)))
}

```

```
data.frame(possibly_excluded_users, amount)
```

```
##    possibly_excluded_users amount
## 1          2740332152         1
## 2          2618716136         1
## 3          485723891         1
## 4          242535287         1
## 5          735163872         1
## 6          18603531         1
## 7          437791317         2
## 8          1388220798         4
## 9          341617430         1
## 10         2988710739         3
## 11         1671862620         1
## 12         3074511560         1
## 13           7032662         1
## 14         2760083384         1
## 15         1305350636         2
## 16         1093562454         1
## 17         235769765         1
```

```
sum(amount) * 100 / nrow(sorted_out2)
```

```
## [1] 3.356643
```

```
## Excluded users can only account for 3.4% of all excluded tweets
## (without retweets and tweets outside of 1-3 UTC).
## No user with more than 4 tweets has been excluded in this subset.
## It is not likely that certain users have been systematically excluded by
## Storify administrators

## End of algorithmic reconstruction of exclusion criteria for tweets
```