ABSTRACT

Social media data is now widely used by many academic researchers. However, long-term social media data collection projects, which involve collecting Twitter data from Twitter's public-use APIs, often encounter various issues when they try to collect streaming social media monitoring data from local-area network servers (LANs). In this technical report, we discuss some of the issues that we have encountered in our Twitter data collection project. We present a cloud-based data collection, pre-processing, and archiving infrastructure which we argue mitigates or resolves the problems we have encountered, at minimal cloud-computing costs. We show how this approach works in different cloud computing architectures.

Keywords Social media · Cloud computing · Twitter · Time series

1 Introduction

Social media data is now widely used in many studies in computer and social science [1]. Many of these studies collect short-term cross-sectional samplings of social media data, while others take advantage of free-access social media APIs and attempt to build longer-term time series that monitor discussion and behavior online. However, in our experience conducting long-term social media data collection projects, which involve collecting Twitter data from Twitter’s public-use APIs, there are various issues involved in collecting a reliable and consistent pipeline of social media monitoring data from local-area network servers (LANs). In this technical report, we begin by discussing some of the issues that we have encountered in our Twitter data collection project (which at this point has been ongoing since 2014). We then present a cloud-based data collection, pre-processing, and archiving infrastructure which we argue mitigates or resolves many of the problems we have encountered, at minimal cloud-computing costs.

2 Problems collecting streaming social media

If a researcher is interested in quickly collecting cross-sectional social media data from Twitter, use of the so-called “streaming” and “REST” APIs are relatively straightforward [2][3]. Subject to rate limits, Twitter allows researchers
to get access to a great deal of current data from Twitter, including the content that is being discussed as well as data from individual user accounts. In our application, where we are interested in studying the online conversations with respect to different political and social topics, collecting data from the Twitter Streaming API by keyword or hashtag data filtering over a brief window of time is relatively straightforward, and is the type of data that many scholars use in their research [4, 5, 6, 7, 8].

This situation becomes more complicated if the research project involves longer-term monitoring of conversations and discussion on Twitter. For example, one of our ongoing projects involves monitoring Twitter mentions of voter issues during elections, requiring us to collect data continuously in the weeks before, during, and after an election. Ever since beginning this project in 2014, we have worked to refine and improve our methodology for collecting these data [9, 10]. Our process focuses on searching for specific keywords that are associated with topics including election fraud, voting by mail, and registering to vote. In another example of long-term social media monitoring, we are developing methods for collecting Twitter conversations using dynamic keyword selection in situations where the discussion might be rapidly-evolving over long periods of time [11].

In attempting to build long-term, multi-year, social media data collection projects on local machines, several prominent problems emerge. In our experience, simple issues can crop up. Our early work used python scripts running on local university servers, connected to local-area networks. We found these scripts could often encounter issues accessing the Twitter APIs, have trouble with network access, or compete with other processes running on the servers. Good programmers can often tests scripts collecting longer-term social media data, identify some of these issues, and revises code to pause collection or restart [9].

However, even good programmers will have trouble resolving systems failures. First, relying on local hardware introduces difficult, and in some cases impossible-to-anticipate, system failures. Power outages can knock systems offline, and without a secondary local system in place, data in a time series will be lost. Network instability can also undermine data collection efforts, especially during peak-use hours or if network infrastructure is temporarily down for maintenance. Furthermore, if there is permanent system damage to a local system, it can be difficult if not impossible to recover data.

Second, setting up LANs can also potentially limit future collection efforts. As a collection project naturally expands, computational power, active memory, and storage considerations may change. In many settings, scripts that are running in the background to collect streaming social media data may compete for system resources with other users and other processes, which can limit their ability to collect all of the available data. Also, local systems can be difficult, expensive, and time-intensive to upgrade, especially if one needs to address these concerns repeatedly in a multi-year project.

Finally, the kinds of local systems most researchers have accessed to are not designed for the specific needs of collecting real-time streaming data. Collecting these data requires a system to quickly and effectively obtain, buffer, process, and store large continuous streams of incoming information. Collecting this type of high-frequency, continuously streaming data involves specific computational considerations, with specialized algorithms designed to best capture these data [12]. Without a good system designed for these tasks, processing and saving files can temporarily interrupt the Twitter stream and limit the amount of data gathered. Given these interruptions are most likely to occur during periods of heavy Twitter traffic, the censored Twitter data may not be missing at random, with systemic omitted Twitter data from the streaming API potentially adding bias to an analysis [13].

### 3 Cloud-based social media monitoring

In this paper, we present specific solutions to data collection on two popular cloud computing services: Amazon Web Services (AWS) and Oracle Cloud. While we illustrate two specific solutions, the methods and processes we outline can be generally applied to other cloud services. While we do not claim here that we are the first to develop this type of workflow, we want to provide details about how our long-term social media data collection solution operates for other researchers to evaluate and utilize in their own work. Essentially we built a process that solves or mitigates the problems that we encountered using LANs, by moving the data collection and pre-processing steps onto cloud-computing platforms [2].

In the next section of this paper we describe how our process works in AWS, before outlining a similar process works in Oracle Cloud.

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2In order to reduce cloud-computing data storage costs, and to make the social media data we collect more readily accessible to our research group, we outline a process of piping the pre-processed data to cheap, secure, and easy-to-use data storage applications (here Box). Note that budget allowing, all data can be stored on a single platform.
3.1 AWS Workflow

We developed a serverless architecture using AWS to tackle the problems discussed in the previous section. This system collects tweets in a stable and failure-tolerant manner.

As shown in Figure 1, the AWS Twitter Monitor consists of four parts: the data producer, AWS Kinesis services, the data consumer, and user-friendly data storage. Specifically, this Twitter monitoring process involves the following steps:

1. The data producer, a program located on an EC2 instance, requests tweets of interest from the Twitter Streaming API and puts them in the Kinesis Stream.
2. The Firehose collects records in the Kinesis Stream, saves them as buffer files, and stores them temporarily in an S3 bucket.
3. The data consumers, such as Lambda functions or programs on the EC2 instance, process and analyze the S3 file.
4. The raw tweets are then piped to a Box folder and the processed data to an RDS MariaDB for final data storage.

![Figure 1: AWS Twitter Monitor Overview](image)

In the following discussion, we describe each of these Twitter monitoring processes in detail.

**Data Producer**

First, we run Python scripts using the AWS Elastic Computing Cloud (EC2) to connect the two parts of our data pipeline: the Twitter Streaming API and AWS Kinesis Stream.

The Python scripts:

- Use the `boto3` and `TwitterAPI` packages.
- Connect to the Twitter Streaming API using Twitter Developer credentials.
- Connect to the AWS Kinesis Stream using AWS credentials.
- Sends requests to the Twitter Streaming API.
- Puts tweets one by one into the Kinesis Stream.

The Twitter Streaming API has a rate limit that does not allow the API to deliver more than one percent of all tweets being posted. There are on average 6,000 tweets being posted every second, so the rate limit is usually around 60 tweets/second. We use track queries, user IDs, or locations to filter the tweets and keep the number of tweets obtained for each set of Twitter Developers credentials from exceeding the rate limit.

**Table 1: Comparison of System Specifications**

| Spec                  | AWS EC2 EC2 t3.medium | EC2 t3.micro | Oracle Compute VM.Standard.E2.2 |
|-----------------------|-----------------------|--------------|-------------------------------|
| **CPU Series**        | Intel(R) Xeon(R)      | Intel(R) Xeon(R) | AMD EPYC                     |
| **CPU Model**         | Platinum 8175M CPU    | Platinum 8175M CPU | 7551                         |
| **Core Clock**        | 2.50GHz               | 2.50GHz      | 2GHz                          |
| **Core Count**        | 2 Cores               | 2 Cores      | 2 Cores                       |
| **Baseline performance (per CPU)** | 20%            | 10%          | 100%                          |
| **Memory**            | 4 GB                  | 1 GB         | 15 GB                         |

* CPU performance is restricted if average CPU usage exceeds the baseline.
Selecting the suitable EC2 type is important, as it ensures that the instance provides sufficient computing power, at the lowest cost. We choose one t3.medium instance because its 2-core CPU and 4 GB memory enable us to collect tweets at the rate limit and implement moderate analysis at the same time. We skip the free-tier instances (e.g. t3.micro) since their baseline performance is 10%, which means if the average CPU usage (per core, over time) exceeds the baseline, the performance of the instance will be restricted\(^3\). Our programs use 10%-20% per CPU core so that the free-tire "t3.micro" instance is not enough. For more details about the comparison of system specifications, please see Table\(^4\).

### Kinesis

The Kinesis Stream is a temporary streaming data storage service. It involves specifying a selected number of computational shards. One shard is an independent storage timeline, in which the records are ordered by the timestamps of the "Put" events. Each shard supports up to 1,000 records or 1 MB of data per second for writes. It is easily scalable when the Twitter monitor is approaching the rate limits. By default, users can read records that were put in the shards no more than 24 hours ago. This 24-hours trace-back feature provides extra failure tolerance comparing to running Twitter Stream API alone. Kinesis Stream is also more reliable since it seldom suffers from power outages, system failures, or network instability.

We use a Python script and the AWS Cloudwatch services to monitor the usage of the Kinesis Stream and automatically scale the number of shards. Once the per-shard ingesting data exceeds 800 KB/s in size, or 800 records/s in counts, the program immediately creates a new shard to prevent the Twitter monitor from hitting the rate limits. To be more conservative in deleting data, the program only closes a shard when the per-shard incoming data are less than 500 KB/s and 500 records/s for more than 3 hours.

We use the AWS Firehose to read records from the Kinesis Stream and save them temporarily in an S3 bucket. Records stored in the Kinesis Stream can usually be extracted and saved in various programming languages. But since streams use independent sequence numbers to organize the stored records, it is not straightforward to merge records from two shards in chronological order. Compared to reading records from shards using Python script, AWS Firehose is a more natural way to connect the Kinesis Stream and storage since it reads records from all shards at the same time and merge them automatically. In addition, it has lower latency and higher stability.

The records in the Firehose are saved as buffer files and stored in a Simple Storage Service (S3) bucket. Storing data temporarily in S3 acts as a reservoir and provides extra data safety. It is also easy to trigger analysis tools, such as Lambda functions, for data transfer and analysis.

### Data Consumer

In this part of our process, we can analyze and process our collected data. For example, in this stage researchers can add tags, labels, or transformations of the features in the raw data. We use Lambda functions and Python programs to process, analyze, and transfer data files in the S3 bucket.

A Lambda function is a short piece of code that serves as a fast solution of data processing and analysis. The Lambda functions are automatically triggered once a file is created in our S3 bucket. We use them to split tweets according to keyword groups, extract hashtags, count the number of tweets, infer the locations of tweets, and for other tasks. A Lambda function is executed on AWS in parallel. For instance, if there are five files created in the S3 bucket at time \(t\), they will be processed/analyzed at the same time.

We use Python scripts to conduct non-recursive analyses and data transfers. The Lambda function is designed to be fast and simple, and the pricing depends on run time and storage use. It is not cost efficient to transfer data files via Lambda functions. In our Twitter monitor, Python scripts with nested try-except structures are used for complicated analyses and data transfers.

### Data Storage

After data processing and analyses, we store the aggregate level results in a Relational Database Service (RDS) MariaDB for easy data extraction, and compress the raw tweets and send them to Box FTP for long-term storage.

The RDS instance has great accessibility and supports SQL queries. We use a MariaDB to store frequently used data such as hashtags, counts of tweets across states, and frequent user information. This data is most useful for exploratory analysis of the collected data, as SQL queries make it possible to pull and analyze specific subsets of data.

\(^3\)https://docs.aws.amazon.com/AWSEC2/latest/UserGuide/burstable-credits-baseline-concepts.html

\(^4\)
Although it is entirely possible to store the data in directly in AWS, given many of these projects involve long-term data collection efforts, it is not always cost efficient to store data on in the cloud computing environment for long periods of time. Thus, we use a Python script to compress raw S3 files into .7z format (avoiding the high data transfer cost of AWS) and send them to Box every hour. This Box folder is shared with members of the research group and is backed up regularly.

### 3.2 Oracle Cloud Workflow

In addition to the AWS monitors, we developed an alternative serverless architecture on Oracle Cloud. As shown in Figure 2, the Oracle Twitter monitor also consists of four parts: the data producer, Oracle Analytics, the data consumer, and user-friendly data storage. Specifically, this Twitter monitoring process on Oracle involves the following steps:

![Figure 2: Oracle Twitter Monitor Overview](image)

1. The data producer, a program located on an Oracle compute instance, requests tweets of interest from the Twitter Streaming API and puts them in the Oracle Stream.
2. Another program on the Oracle compute instance reads the tweets from the Oracle stream, saves them into JSON files and compresses the JSON files into 7z format.
3. An analysis program on the Oracle compute instance reads the JSON files, processes the tweets and extracts text from them.
4. The raw tweets are then piped to a Box folder and the extracted text to an Oracle Object Storage bucket.

Next, we describe each of these Twitter monitoring processes in detail.

**Data Producer**

We run Python scripts using Oracle Compute Instance to request tweets from the Twitter Streaming API and to put them in Oracle Stream.

The python scripts:

- Use oci and TwitterAPI packages.
- Connect to the Twitter Streaming API using two sets of Twitter Developer credentials and create two Twitter streams, one active and the other for redundancy.
- Connect to the Oracle Stream using registered key pairs.
- Send requests to the Twitter Streaming API through the active stream.
- Puts tweets in the Oracle Stream.

The Twitter Streaming API has a rate limit that does not allow the API to deliver more than one percent of all tweets being posted. There are on average 6,000 tweets being posted every second, so the rate limit is usually around 60 tweets/second. We use track queries, user IDs, or locations to filter the tweets and keep the number of tweets obtained for each set of Twitter Developers credentials from exceeding the rate limit.

Since there is no concept of CPU credits for Oracle Compute Instance, an instance of type "VM.Standard.E2.2" that has 2 CPU cores and 15 GB memory is enough to execute our scripts for this process.

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4 Other cloud-based storage solutions could be used in lieu of Box (i.e. Dropbox and Google Drive.)
Oracle Analytics

We use one Oracle stream partition for each monitor to ingest incoming tweets from the Twitter Streaming API. The Oracle stream partitions are similar to the shards of AWS Kinesis stream. Each partition allows up to 1,000 records/s or 1 MB/s for writes and up to 5 requests/s for reads. The records stored in the Oracle stream are available to read if they were put in within the last 7 days. According to the summary statistics of the tweets collected by the AWS Twitter monitors, one Twitter stream that uses one set of developer’s credentials can produces up to 50 tweets/s or 300 KB/s tweets, which are within the rate limit of one Oracle stream partition. Therefore, we do not use programs to scale the number of partitions for the Oracle Twitter monitors.

Data Consumer

In this part of our process, we use python scripts to read tweets from the Oracle stream, extract text from tweets, and save both the raw tweets and text into data files.

The Python scripts:

- Use the oc1 package.
- Use "TYPE_AFTER_OFFSET" cursors to read tweets from Oracle stream in order.
- Extract "text" and "full_text" fields from tweets.
- Save raw tweets and text into JSON files.
- Compress raw tweets JSON files into 7z files.

Data Storage

After reading data from Oracle stream and extracting text from tweets, we store the text files in Oracle Object Storage for easy extraction and push the compressed JSON files to a Box folder for long-term storage.

The Oracle Object Storage is similar to the AWS S3. It provides great accessibility to users who possess key pairs that are registered in the Oracle Cloud account. We use Object Storage as an temporary data storage for the research team to share data between compute instances within the Oracle network.

The Box folder is shared with members of the research group and is backed up regularly.

4 Discussion and Conclusion

Many research groups are using social media data in their studies of political, social, and economic attitudes and behavior. Interest is increasing in the development of longer-term datasets that can be used to analyze changes over time in attitudes and behavior [3]. However, in our efforts to collect longer-term social media datasets from local servers using local-area networks, we have encountered important limitations in the availability and reliability of those systems for these purposes.

To improve the reliability of our longer-term social media data collections process, we have developed the two different cloud-based infrastructures discussed in above in our paper. By moving the data collection and pre-processing stages into the cloud, we can avoid many of the problems that we and others have encountered using local servers and local-area networks. We designed our process to make the collected and pre-processed data more easily available to our research group, but moving the data to a secure and usable storage solution like Box.

There are many opportunities for researchers who are interested in using social media data for studying the longer-term dynamics of political, social, and economic attitudes and behavior. We hope that by providing the details of our process we allow others to evaluate the best practices in collecting these data, and perhaps provide other researchers initial guidance in adopting a cloud-based process to improve their ability to collect similar datasets.

References

[1] Marko Klasnja and Pablo Barbara and Nicholas Beauchamp and Jonathan Nagler and Josh Tucker. Measuring public opinion with social media data. In The Oxford Handbook of Polling and Survey Methods, edited by Lonna Rae Atkeson and R. Michael Alvarez, pages 555–582. Oxford University Press, 2018.
[2] Matthew A. Russell. *Mining the Social Web: Analyzing Data from Facebook, Twitter, LinkedIn, and Other Social Media Sites*. O’Reilly Media, Inc., Second Edition, 2014

[3] Zachary Steinert-Threlkeld *Twitter as Data*. Elements in Quantitative and Computational Methods for the Social Sciences. Cambridge University Press, 2018

[4] Brendan O’Connor, Ramnath Balasubramanyan, and Bryan R. Routledge. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media, 2010

[5] Michael D. Conover, Bruno Gonçalves, Alessandro Flammini and Filippo Menczer. Partisan asymmetries in online political activity. EPJ Data Science 1 (6), 2012.

[6] Pablo Barberá and Gonzalo Rivero Understanding the political representativeness of Twitter users. Social Science Computer Review, 33 (6), 2014.

[7] Nicholas Beauchamp. Predicting and Interpolating State-Level Polls Using Twitter Textual Data. *American Journal of Political Science*. 61 (2), 2017

[8] Nicholas Adams-Cohen. Policy Change and Public Opinion: Measuring Shifting Political Sentiment with Social Media Data. *American Politics Research*, forthcoming 2020.

[9] Nicholas J. Adams-Cohen and Clare Hao and Cherie Jia and Nailen Matschke and R. Michael Alvarez. Election Monitoring Using Twitter. Caltech/MIT Voting Technology Project Working Paper 129, 2017. [vote.caltech.edu/working-papers/129](http://vote.caltech.edu/working-papers/129)

[10] R. Michael Alvarez, Nicholas Adams-Cohen, Seo-young Silvia Kim, and Yimeng Li. *Securing American Elections: How Data-Driven Election Monitoring Can Improve Our Democracy*. Elements in Campaigns and Elections. Cambridge University Press, Forthcoming.

[11] Anqi Liu and Maya Srikanth and Nicholas Adams-Cohen and R. Michael Alvarez and Anima Anandkumar. Finding social media trolls: Dynamic keyword selection methods for rapidly-evolving online debates. AI For Social Good Workshop, NeurIPS 2019. [arXiv:1911.05332[cs.LG]](https://arxiv.org/abs/1911.05332)

[12] Brian Babcock, Shivnath Babu, Mayur Datar, Rajeev Motwani, and Jennifer Widom. Models and issues in data stream systems. SIGMOD/PODS02: International Conference on Management of Data and Symposium on Principles Database and Systems, 2002.

[13] Fred Morstatter, Jürgen Pfeffer and Huan Liu When is it biased?: assessing the representativeness of Twitter’s streaming API. Web Science Track at WWW, 2014.