Exploring Bot Pervasiveness in Global Cities using Publicly Available Volunteered Geographic Information

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Abstract: Effective crisis management and response heavily relies on up-to-date and trustworthy information. Near real-time, volunteered geographic information (VGI) has previously been shown to be instrumental during disaster response by helping direct resources, create communication channels between the affected, etc. Trustworthiness continues to be a challenge when leveraging crowd sourced data, as quality information directly impacts the effectiveness of response. Previous research has demonstrated cloud-based VGI collection, storage, presentation, and bot mitigation using open source technologies and freely available web services. Alas, the technology was deployed as a prototype for small urban areas in the United States. This research explores bot pervasiveness in several global cities that have previously suffered a catastrophic event and/or are at risk for a future crisis event. The existence of non-trustworthy information in social media data has always been a known issue, taking steps to quantify the presence of bots in Twitter data can allow an end-user to more holistically understand their dataset.

1 INTRODUCTION

As human-caused global warming and worldwide socio-political tensions continue to increase, humanitarian and weather-related emergencies dominate world news headlines; examples include California (CA) rebuilding after the devastating Woolsey and Camp Fires, Puerto Rico (PR) continuing to repair infrastructure that was damaged during the 2017 hurricane season, and a migrant caravan stalling at the Mexican border with the goal of attaining asylum in the United States (US). While each of these scenarios are unique, they all exhibit some or all parts of the emergency response timeline: situational analysis, initial/ongoing response, and reconstruction (Jennex, 2007).

The rapid growth in functionality/connectivity of modern consumer products has greatly enhanced communication at all stages of the response timeline. Social media services, combined with Internet-connected smart phones, are especially powerful tools that enable emergency communication as well as adhoc communities to develop. Social media users can generate volunteered geographic information (VGI) (Aubrecht et al., 2017) which leverages a device's onboard positioning suite to annotate the data with location information. Device/user location can be ascertained through a global positioning system sensor, Wi-Fi networks, Bluetooth, cellular networks, or through a combination of the technologies.

The generated VGI can then be integrated into existing geographic information sytems (GIS) to supplement situational awareness (Sui and Goodchild, 2011). From desktop thick clients like ESRI's ArcGIS to web based clients like the Google Maps JavaScript Application Programming Interface (API), the data can be easily displayed with existing maps and layers, and updated as necessary during a developing event. While this work focuses on developing crisis situations, GIS tools and volunteered data are also useful in routine work such as urban planning (Spivey and Valappil, 2018) and risk assessment (Antoniou et al., 2017).

One of the largest challenges of using VGI, for any purpose, is trustworthiness (Moturu and Liu, 2011). The data is not guaranteed to be authored by a human, nor is human-generated information always pertinent to the specific situation at hand. Adjudication of VGI is a temporally/computationally expensive process but is vital when coordinating disaster response. Misdirection of supplies or spreading fake narratives can hamper rescue efforts and put lives at

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risk.

The following sections explore the fusion of open source technologies and openly available web services to improve the trustworthiness of streaming social media data. Findings will show a quantification of bot pervasiveness in Twitter data from selected global cities, for the exploration time-period, using the selected bot-detection algorithm.

2 BACKGROUND

The US Global Change Research Program is mandated by The Global Change Research Act of 1990 to deliver climate assessment reports to Congress and the President at least every four years (Reidmiller and (eds.), 2018). The Fourth National Climate Assessment was released in late 2018, and contains alarming results in the areas of coastal effects, energy supply/delivery/demand, air quality, and the health of tribes/indigenous peoples. To broadly summarize the extensive report: global warming is human-caused and the worldwide population has severe challenges ahead. While mitigation/prevention are critical, the planet is already responding with a greater number of fires, hurricanes, and coastal inundations than in previous years (Emanuel, 2011). Compounding these challenges are global socio-political crises that put many at risk of death, displacement, and/or having inadequate food/shelter/resources.

While prevention of these scenarios is ideal, it is not always possible, and crisis mitigation is required. To increase response success, the emergency management community continues to integrate modern technology into its capability suite. Two major technologies, smart phones and social media services, have created a myriad of opportunities to reach those in need.

Modern smart phones are inexpensive, readily accessible to the general population and are richly outfitted with large screens, powerful cameras, and wireless connectivity. They are lightweight, portable, readily interoperate with different Internet sources and can have custom applications installed. For a person in a disaster situation, the smartphone can be a lifeline and function as a sensor (Avvenuti et al., 2016) for social media communities.

Social media services, e.g. Twitter, Instagram, Facebook, and WhatsApp, can be utilized via web browsers or through applications installed on the ubiquitous smart phone. Generated VGI can include text-based messages through Tweets, ad-hoc communities offering local support on Facebook, to geospatially tagged Instagram photos, etc.

The combination of smartphones and social media services has already been leveraged to great success in recent years for crisis response. The Twitter API has been used as a real-time sensor to detect earthquakes in Japan, and using a spatiotemporal algorithm, determine their centers/trajectories (Sakaki et al., 2010). Facebook network analysis has shown how groups of entities emerge/communicate in emergency situations, namely during the 2016 flood in Louisiana, US (Kim and Hastak, 2018). Twitter has also been used to estimate structure damage during a hurricane by analyzing the drop in steady-state Twitter traffic; this deceleration creates 'data shadows' (Shelton et al., 2014) and is indicative of areas of high damage (Samuels et al., 2018).

Determining trustworthiness/pertinence of a Tweet, and/or the account from which it was generated, is a complicated task. To enable informed decision making for emergency managers/responders, Tweets must contain salient information, and be generated by a human. Tweet adjudication has been explored in different ways including using convolutional neural networks to inspect Tweet content (Caragea et al., 2016), investigating a cross-platform believability framework (Reuter, 2017), by performing topic summarization (O'Connor et al., 2010), mapping perceived emotions to usefulness/trustworthiness (Halse, 2016), and inspecting interconnected network patterns of Twitter users (Stephens and Poorthuis, 2015).

Using a combination of heuristics, researchers at the Observatory on Social Media, a collaboration between the Indiana University Network Science Institute and the Center for Complex Networks and Research Systems (Davis et al., 2016) have created an algorithm called Botometer that can estimate how bot-like or human-like Twitter accounts appear. Numerous characteristics are used for the adjudication including: user-related metadata, consideration of connected friends, the content/sentiment of the Tweets, network considerations and Tweet-timing (Varol et al., 2017). To attain the bot adjudication, a user's last 200 Tweets, last 100 mentions and built-out user data are required. Botometer is accessible as a microservice from Mashape (Botometer, 2018a); the online platform handles security, billing, failover and elasticity. An end-user can create a request to the Botometer service using their programming language of choice and send pertinent information for an account in JavaScript Object Notation (JSON) format. The service will return a JSON response with all pertinent bot information, allowing the researcher to focus on their use case, and not have to consider the implementation of the underlying service.

The Botometer response includes float values for the different aspects of consideration and overarching combined values. The values used in this work are the:

- Bot score, created from combining content/friend/etc. scores and ranging from [0.0] to [5.0]. The lower score indicates that an account exhibits fewer bot-like attributes, a higher score is more indicative that the account is automated. There are two bot scores returned, one utilizes the English language, and all aspects of bot consideration; the other is universal and does not consider content/sentiment values.
- Complete automation probability (CAP) value, one of Botometer's newer features; Bayes' theorem is used to generate an overarching percentage probability that an account is completely automated; like the bot scores, an English and universal version of the value is generated (Botometer, 2018b). Both scores are on a linear scale, and there are no delineated sub-categories.

Once these values are retrieved and annotated to each Tweet, the dataset can be filtered based on the different bot levels. By setting a cut-off threshold based on the scores, any query, map layer, generated data, etc. can be affected to only use human generated Tweets. The increased human-ness of the resulting data can increase confidence for the end-user that the data will be useful and pertinent.

Previous work in cloud-based VGI collection with bot mitigation (Toepke, 2018a) has leveraged hand-picked cities, mainly on the west coast of the US. The cities are urban, have a high population density, and contain inhabitants that heavily utilize social media services. While useful for initial research, it is necessary to explore larger global cities, to exercise true utility of the software stack. Six new cities were selected, for the following reasons:

- Each of the cities rate highly according to the Globalization and World Cities Research Network, which provides city rankings focusing on the amount of integration to the world economy that each city maintains (GaWC, 2017) (Beaverstock et al., 1999). While all the cities are historically/culturally/politically significant, any large disruption in these cities will have global economic impact; thus, this metric is sufficient for this work. Four of the cities rate at the 'Alpha' level, and two rate at the 'Beta' level; which are relational classifications, 'Alpha' indicating higher than 'Beta'.
- Each city has recently experienced a crisis, and/or is at high risk of a future disaster.
- The investigation area for each city-space is much larger than in previous work, which focused on only the downtown cores of each city. In the case of San Diego, CA, the exploration area was only 3.61845 km^2. The current areas of interest are also of differing population densities; ranging from empty (water/wilderness), to highly populated urban centers.
- Being global cities, social media services will receive Tweets in varying languages. Exploring how the software stack can process/display that data to end-users allows for deeper insight into pertinent information.

Metrics for each city can be found in Table 1, and a sample overlay map of the investigation area for Tokyo can be found in Figure 1; the other cities have similar rectangular investigation areas of varying sizes.

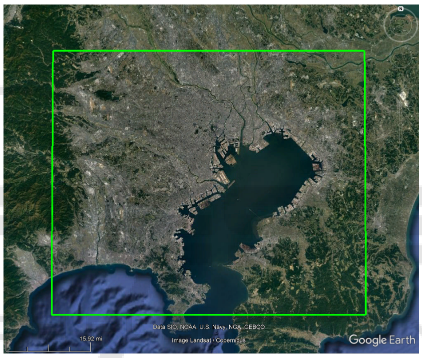

Figure 1: Area of Investigation for Tokyo, Japan.

The cities are as follows:

- Houston, Texas, US. In 2017, Hurricane Harvey stalled over the Houston metropolitan area in late summer. The unprecedented amount of precipitation from the Category 4 hurricane damaged/destroyed over 200,000 structures at an estimated cost of over $125 billion (NOAA, 2018). Without immense infrastructure changes, Houston will continue to be vulnerable to mass-precipitation events.
- Lisbon, Portugal Metropolitan Area (LMA). Due to its seaside location, the LMA is at risk of a tsunami, similar to the 1755 6-meter inundation which caused a large loss of life (Freire and Aubrecht, 2011). Rapid population growth also introduces the risk of many buildings not being constructed to safe seismic standards (Costa et al., 2008).
- Paris, Île-de-France, France. Increased worldwide tensions resulted in two separate terrorist attacks

occurring in 2015; which left hundreds of people dead, and many more grievously injured. Social media was critical for communications support immediately during/after the November attack (Petersen, 2018), and will continue to be instrumental in future crisis management plans.

- San Francisco, California, US. The nearby Hayward and San Andreas faults threaten the city with large earthquakes, the most recent being the Loma Prieta earthquake in 1989. The disaster caused 62 deaths, 3,757 injuries, and left thousands of people homeless (Nolen-Hoeksema and Morrow, 1991). San Francisco is also at risk of a tsunami caused by a large earthquake from the Cascadia subduction zone (Workgroup, 2013), which will affect water-adjacent neighborhoods.
- San Juan, PR. The island was battered sequentially by Hurricanes Irma and Maria in 2017; with the national power grid being mostly destroyed during Hurricane Maria, exacerbating the destruction to lives, homes, infrastructure and economy (Gallucci, 2018). The compounding challenges on the island continue to make the island vulnerable to future weather events (Purohit, 2018).
- Tokyo, Kanto, Japan. The densely populated area is situated on the western end of the Pacific Ring of Fire, an area of high seismic and volcanic activity, and is at high risk of being affected by earthquakes and tsunamis.

Table 1: Cities of Interest.

City	GaWC Rating	Area, km^2
Houston, US	Beta+	1811.97
Lisbon, Portugal	Alpha-	693.96
Paris, France	Alpha+	114.82
San Francisco, US	Alpha-	151.29
San Juan, PR	Beta-	534.69
Tokyo, Japan	Alpha+	7501.44

3 ARCHITECTURE

The social media service of choice for this work, Twitter, publishes a public API that is accessible via web services. The data is freely available for non-commercial use and is accessible via any compatible programming language.

A custom software solution was created using openly available libraries, web services and technologies. While the stack is fully discussed in previous work (Toepke, 2018a), the following is an overview of critical components, which can be seen in Figure 2.

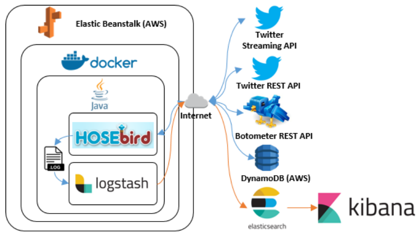

Figure 2: Architecture Diagram (Toepke, 2018a).

- Java is the primary programming language that affects all Tweet-consumption, and Hosebird Client (Hosebird, 2014), is an open source library that manages the connection to the Twitter Streaming API.
- Amazon Web Services (AWS) provides a high-uptime execution environment via the Elastic Beanstalk service and a Docker container.
- The Elastic Cloud provides the ELK stack via a software-as-a-service model, which is comprised of Logstash, Elasticsearch and Kibana. These technologies implement the transport, indexing/searching and visualization of Twitter data, respectively. Information overload is a critical problem when processing a high volume of social media data (Hiltz, 2013), and the ELK stack helps to provide a responsive and stable interface to the end-user.
- The Botometer web service takes into consideration key aspects of a Twitter user's account, timeline and mentions, processes them via machine learning algorithms, and generates information indicating how bot-like an account appears.

The consumer code is deployed via AWS, which collects the streaming Twitter data from specific geospatial boundary boxes, gathers/inserts bot data for each Tweet, then ships each annotated Tweet to the Elasticsearch instance. The end-user can then use Kibana's web interface to explore the underlying Elasticsearch data via dynamic queries, maps, and/or visualizations.

One of the benefits of the consumer code is the modularity in which new investigation areas can be added, or existing ones can be expanded. In the Java Tweet-consumer code, the latitudes/longitudes are stored in a configuration file; with a small code change, a new package can be rapidly redeployed to production. Using Elastic Beanstalk also provides seamless flexibility in choosing the size of the underlying compute infrastructure. In this case, a t2.small instance, which includes 1 virtual processor and 2 gigabytes of memory is adequate for the expected volume of Twitter data. If the investigator needed to expand areas, or expected a massive amount of Tweet volume, they could easily choose a configuration with more adequate specifications.

Similarly, the Elastic Cloud provides Elasticsearch/Kibana as a service, which abstracts the infrastructure layer. The implementor can decide between different levels of performance/cost, and the underlying instances will resize in-flight, simplifying administration, so the user can focus on the data. For this investigation, an aws.data.highio.i3 instance with 4 gigabytes of memory and 120 gigabytes of storage is adequate for the frequency/volume of Tweets.

While the architecture described is designed to process in-flight Twitter data, Botometer can certainly be used on static data sets. Annotating previously collected Twitter data to include bot information can greatly increase confidence for urban planning, historical event analysis, land-use tracking, etc.

To affect near real-time translation, the Google Translation API is utilized. It provides quality translations to/from many world languages (Google, 2018), and has shown previous utility in the exploration of social media for the purpose of bot detection (Hegelich and Janetzko, 2016). The service is available via a web API and is functionally a programmatically accessible version of the popular Google Translate website. Due to cost, $20 per 1,000,000 characters, this functionality is utilized for only a few hours; and is enabled/disabled via the Twitter data consumer source code.

4 RESULTS/DISCUSSION

For the six cities, the collection code was run for slightly over eight weeks, which will provide a minimum adequate amount of data for the purpose of this investigation (Toepke, 2018b). The Tweets were collected between September 1, 2018 (2018-09-01T00:00:00.000Z) and October 27, 2018 (2018-10-27T23:59:59.999Z); and all upcoming results are generated from the perspective of an end-user executing the dynamic queries using the Kibana web interface. The total number of geospatially annotated Tweets collected for the cities over that time period was 1,394,851 and can be visualized by city in Table 2.

Table 2 also displays the average Tweet density for each city, over the investigation areas. It can be seen that Paris and San Francisco have a very high Tweet density; as both investigation spaces encompass smaller areas and are of a dense urban composition. The densities for Tokyo and Lisbon are affected by the considerable presence of water cover, careful selection using polygon spaces would allow exclusion of uninhabited areas. The density values are not directly pertinent to bot pervasiveness but provide value in understanding each investigation space. The raw count for Tokyo is approximately an order of magnitude larger than that of the rest of the cities, as the investigation area is markedly larger.

Table 2: Tweet Count and Density for the Six Cities, September 1, 2018 to October 27, 2018.

City	Total Count	Tweets/km^2
Houston, US	91,156	50.31
Lisbon, Portugal	24,307	35.03
Paris, France	87,679	763.62
San Francisco, US	87,360	577.43
San Juan, PR	32,682	61.12
Tokyo, Japan	1,071,667	142.86

Approximately 20-30% of the Tweets do not have populated Botometer data; which can be because of rate limiting for the Twitter representational state transfer (REST) API, the user having their privacy such that their profile data cannot be accessed via the REST API, etc. It is of note that San Juan has a substantially larger number of null Botometer values, almost twice as many as the rest of the cities. Cursory inspection of Tweets shows no immediate reason for this disparity, and future investigation of this imbalance is of interest.

Figure 3 shows normalized Botometer score counts for each of the six cities. Normalization is achieved by dividing the count of each category of Botometer score by the total sum of Tweets for that city; this normalization allows for trend comparison despite differences in total count for each city. Bot-english values are utilized for Houston and San Francisco, while bot-universal values are used for the other four cities, which do not consider content/sentiment of the Tweet text, as they are not in the English language.

It can be seen that all the cities contain a non-negligible number of Tweets that are indicated to be from accounts with bot-like characteristics. It is also of note that the cities where the bot-universal values are used show a substantial percentage of Tweets that are not bot-like, much more so that the cities that leverage the bot-english values. This may be indicative that there are less bots targeting non-US cities, though the results might also indicate that the actual content/sentiment of Tweets are critical for a precise bot estimation. The Botometer algorithm may be conservative on assigning high bot scores to a Twitter account without considering the actual Tweet text. Indeed, creating the same graph for Houston and San Francisco using the corresponding bot-universal values shows the lowest bot scores (0.0 - 1.0) growing for

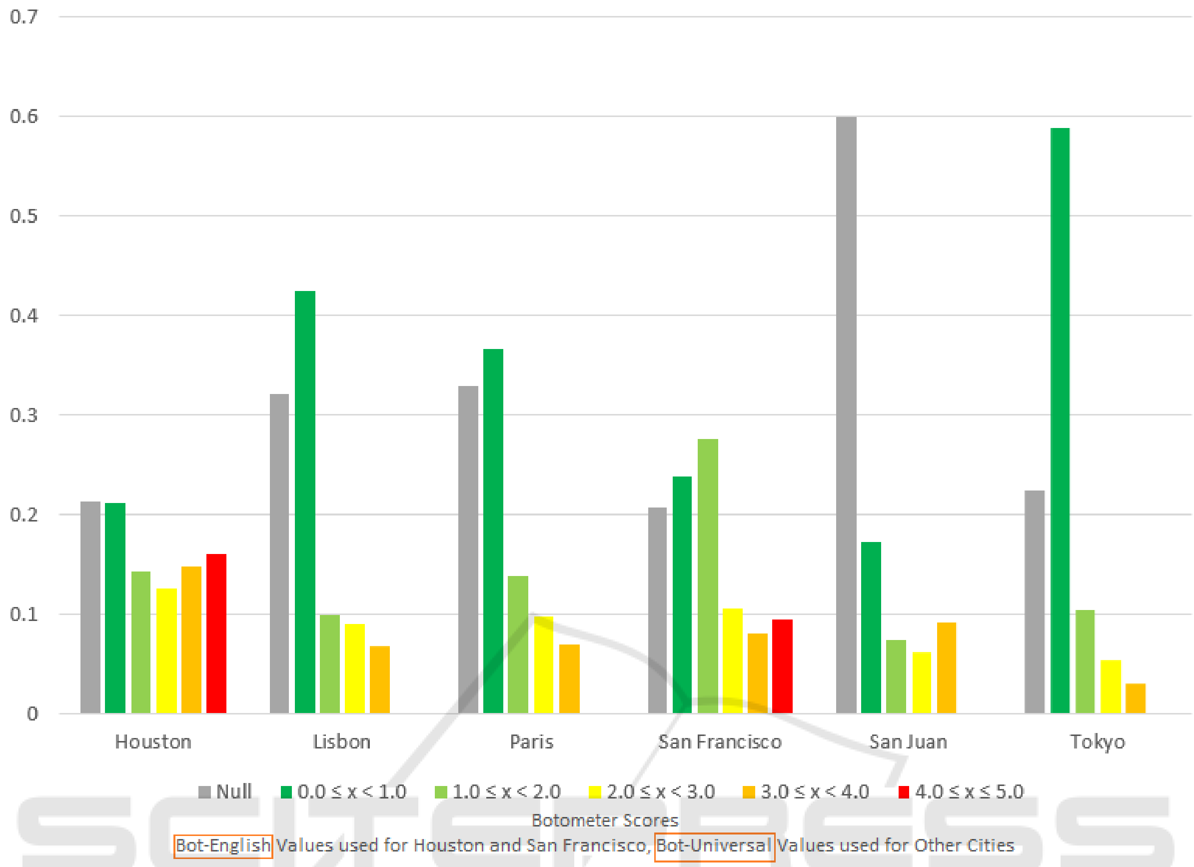

Figure 3: Normalized Botometer Score Counts for Tweets in the Six Cities, September 1, 2018 to October 27, 2018.

both cities, and the highest bot scores (4.0 - 5.0) being reduced/absorbed amongst the other values such that the results are more in-line with results from the other four cities. These bot-universal results are visualized in Figure 4.

For the four non-US cities, if they have a high enough density of English tweets, it may be beneficial to simply utilize the bot-english values. The percentage of English Tweets can be visualized in Table 3 and range from 2.96% in Tokyo to 45.99% in San Juan. Figure 4 also shows the normalized Botometer score counts for the non-US cities, using bot-english values. All cities show an increase in the (4.0 - 5.0) category, with Lisbon showing a substantial increase, and San Juan showing a massive increase. Using bot-english results in international cities may be adequate for a developing emergency response situation, but this approach disregards the local population and would not provide true introspection for ongoing use.

A more comprehensive solution would include real-time translation of each Tweet's text/location/hashtags, where applicable, to the local language of the end-user. As a proof-of-concept, translation functionality was implemented

Table 3: Percentage of English Tweets for non-US Cities, 2018-09-01 to 2018-10-27.

City	% English Tweets
Lisbon, Portugal	26.35
Paris, France	29.16
San Juan, PR	45.99
Tokyo, Japan	2.96

using the Google Translate API, a web-based translation service. The functionality was enabled for a short period and translated Japanese characters to English for the Tokyo investigation zone and functioned without issue. While used for in-flight data during this investigation, the Google Translate API can also be used to annotate existing historic social media datasets.

Figures 5 and 6 show the results for normalized CAP values across the cities. Figure 5 uses CAP-english values for Houston and San Francisco while using CAP-universal results for the rest of the cities; Figure 6 utilizes the opposite languages for each city. Results show an overwhelming percentage of all results showing a low probability of totally non-human

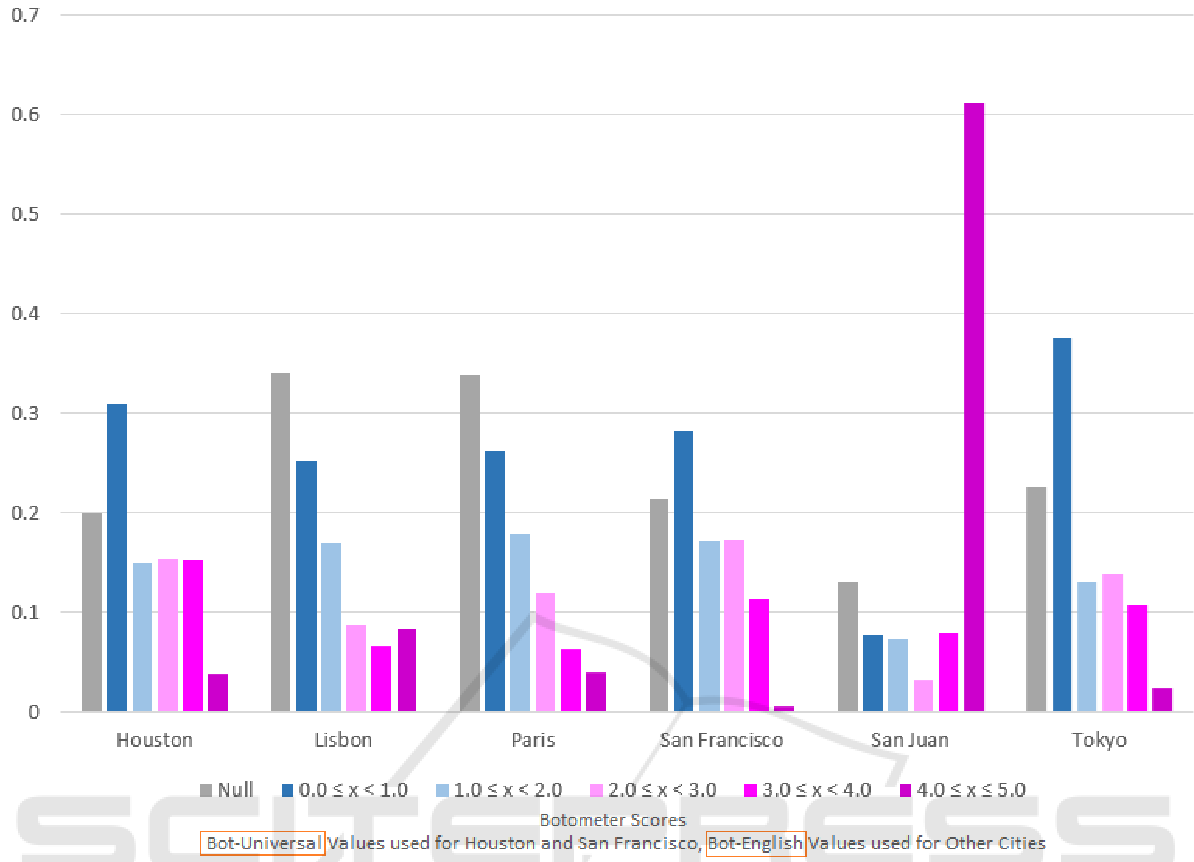

Figure 4: Normalized Botometer Score Counts for Tweets in the Six Cities Using Opposite Language Scores, September 1, 2018 to October 27, 2018.

accounts. One outlier is San Juan, which indicates a large amount of likely totally automated Twitter accounts. Upon further inspection, the entirety of these Tweets have authoring accounts that are affiliated with a job staffing firm, corroborated by the content of the Tweets containing job postings. The results from Figure 5 and 6 do not vary as widely as the bot scores, and likely do not rely as heavily on content/sentiment.

Deciding on a cutoff value for the bot scores and CAP values is arbitrary and can depend on application. E.g., if an end-user wants to be very sure they're considering only human-like data, they can filter out Tweets that have a bot score above 1, which is 20% of the maximum value of 5. For the purpose of this investigation, 40% is chosen as the cutoff value, which will return mostly human-like Tweets, but may have Tweets from bots present in the result set. Table 4 shows the percentages of bot-like Tweets, over the Tweets that have non-null bot/CAP values, based on the 40% cutoff, for the six cities, using English values for Houston and San Francisco while using the universal values for the other four cities, over the investigation timespan.

Table 4: Percent of Bot-like Tweets for the Six Cities Using Local Language Values across Tweets w/ Non-null Values by Bot Score and CAP Value, September 1, 2018 to October 27, 2018.

City	Bot $\geq$ 40%	CAP $\geq$ 40%
Houston, US	55.05%	33.13%
Lisbon, Portugal	23.04%	10.61%
Paris, France	24.70%	8.03%
San Francisco, US	35.30%	19.20%
San Juan, PR	38.39%	58.05%
Tokyo, Japan	10.93%	4.27%

For the bot scores, the minimum bot presence is estimated to be 10.93%, the maximum is 55.05% with an average estimation of 31.24%. For the CAP values, the minimum bot presence is estimated to be 4.27%, the maximum is 58.08% with an average estimation of 22.22%. Comparison against an objective marker of bot-permeation in an area would be ideal, unfortunately, such a measure does not currently exist. Nonetheless, it is apparent that a significant num-

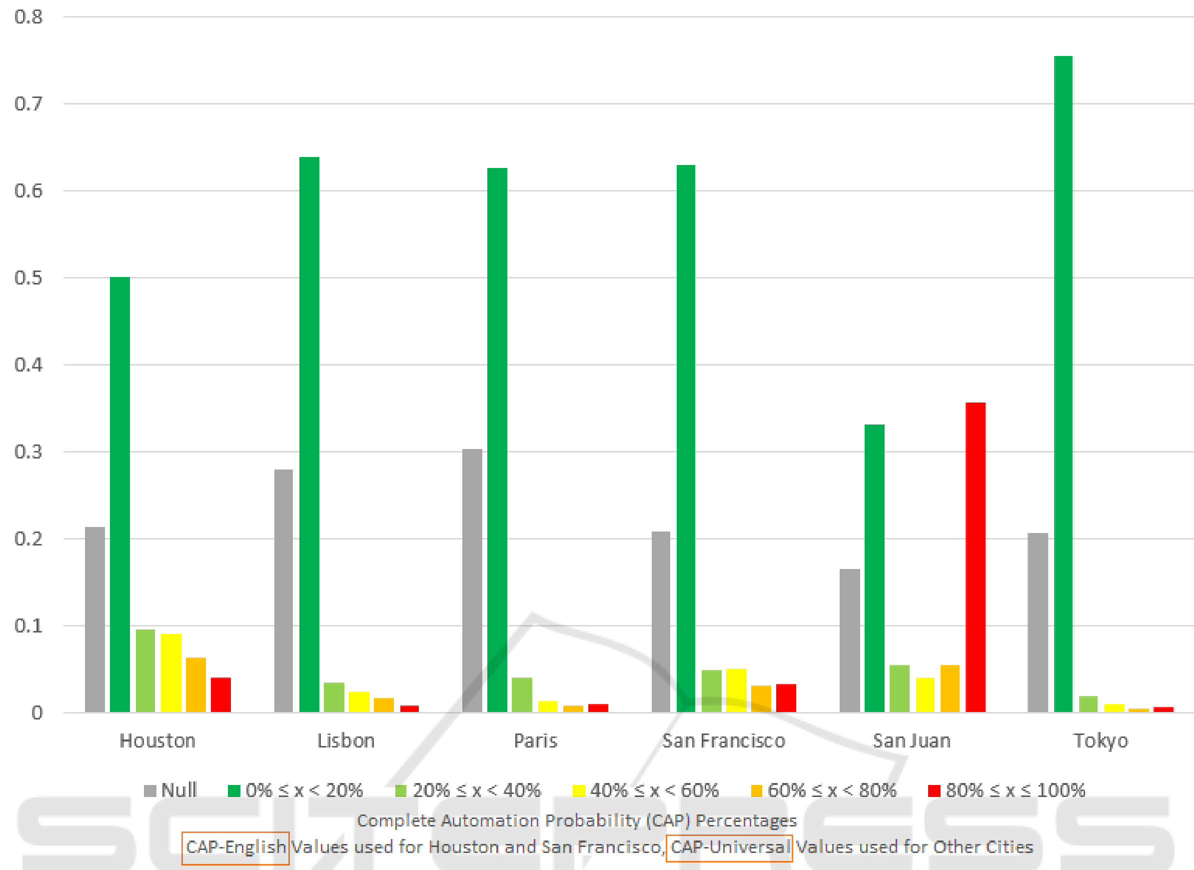

Figure 5: Normalized CAP Values Counts for Tweets in the Six Cities, September 1, 2018 to October 27, 2018.

ber of Tweets from accounts that exhibit bot-like characteristics exist in publicly available Twitter data, and adjudication/mitigation is recommended before using for emergency response and disaster recovery.

5 FOLLOW-ON WORK

- This investigation is performed experimentally and is not actively being used in the response realm. Partnerships with emergency response and disaster recovery practitioners are required for field-level deployment, evaluation and improvement. Generation of Open Geospatial Consortium Web Map and Web Feature layers, such that this data can be integrated into other GIS products, is another possible way forward.
- One of the weaknesses of this method is utilizing one social media service, and one bot-detection algorithm. Incorporation of data from other services can create a more complete operational picture of a geographic space. Also, receiving bot data from a single service/algorithm creates a possible point of failure; fusion/integration with other bot mitigation methods would increase resilience and data quality.
- Near real-time translation is investigated in this work, but no best path forward is apparent. With rapid movement in the cloud-services space, continued consideration is required to find the best-in-class translation solutions that combine high accuracy/throughput with low price/latency for this need.
- While the selected cities are more pertinent that cities selected in previous work, many more global cities, of varying sizes, need considered to reliably quantify the amount of automated data present in the sample set.
- It would also be of interest to perform testing by providing two different data streams to end-users during a pertinent event; one would be full-stream, the other would have the bot-like Tweets removed using this algorithm. After the event, error rates could be compared between the different sets of users, exploring the practical utility of this bot mitigation process.

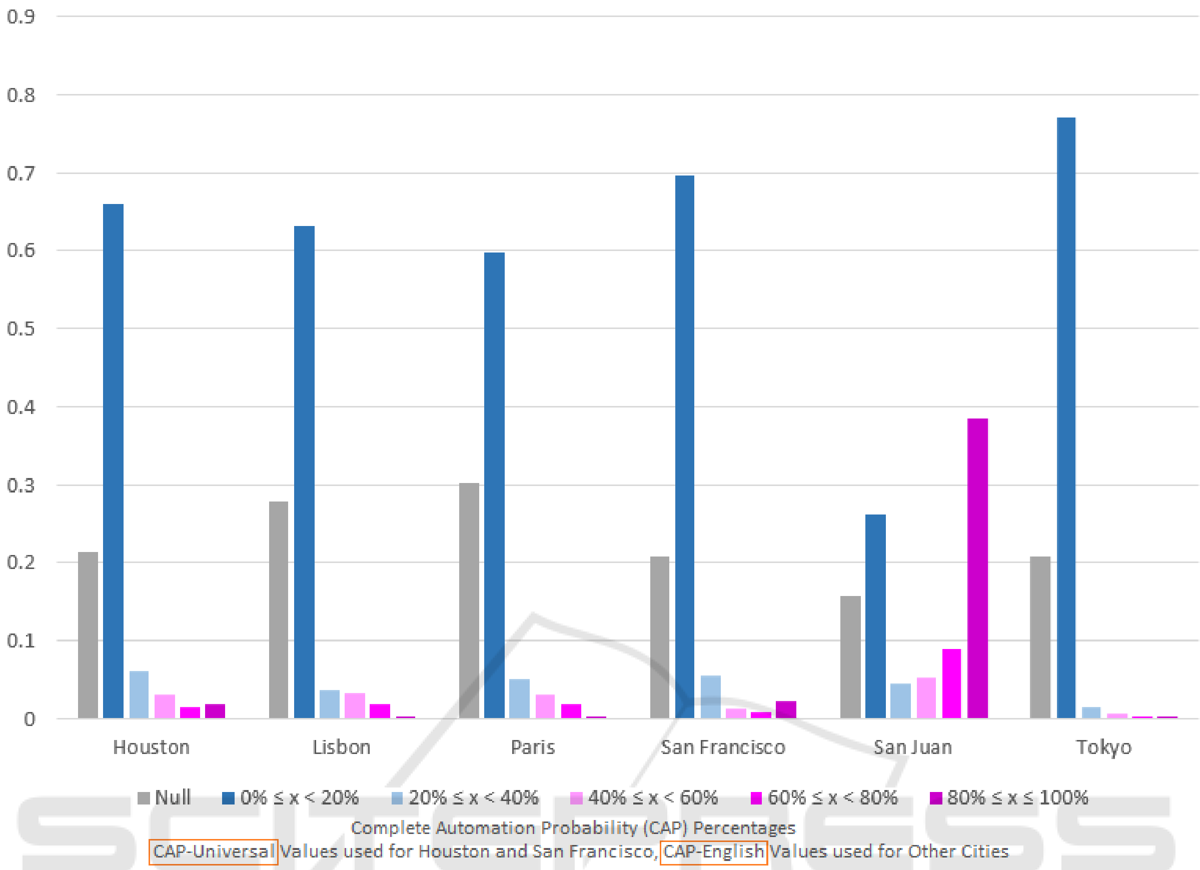

Figure 6: Normalized CAP Values Counts for Tweets in the Six Cities Using Opposite Language Scores, September 1, 2018 to October 27, 2018.

6 CONCLUSIONS

A software stack that was previously developed as a prototype has been extended to monitor Twitter bot pervasiveness in several global, linguistically non-homogenous cities that are at risk for, or that have recently suffered a crisis. Bot presence is investigated through different metrics which take local language into consideration. It has been found for these cities, using publicly available Twitter data, this specific bot detection algorithm, and local language values over the eight-week investigation period; that on average, an estimated 31.24% of Tweets are generated by automated accounts, with an estimated complete automation probability of 22.22%. Quantifying that nearly a third of the data is questionable gives an end-user a more holistic view of the dataset and is critical when integrating volunteered geospatial data into decision making processes.

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