Social Resilience and Collective Memory

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This manuscript was compiled on December 11, 2018

Social resilience is a community's capacity to prepare, adapt and get over a crisis such as those due to natural disasters which are disrupture events that can lead to a significally drift in the urban homeostasis, thus measure the time and effort that takes to recover to normal patterns can be a good parameter of resilience. Through the social responses to aliviate damages and victims in the 19S earthquake in Mexico City such as shelter allocation, and Twitter mentions as in news reports, we measure the impact of the event and how it drove the mobility in the most damaged area by analizing the behaviour of a bike sharing service. We also compare how the memory of the event last longer than it takes to recover normal pattern levels.

urban | resilience | natural | disaster | cohesion | solidarity | collective | memory

Natural dissasters represent a major disruptive event for a city's homeostasis (1) driving the collective behaviour patterns to change, but while they are in all cases with regretful consequences they are also emergence motors for cooperation and non-central coordination which impacts directly to their resilience. In the recent years there has been great efforts to assess damage by natural dissaster through social media (2) as well as studies on their role in social coordination having The Arab Spring (3) as it's most famous representation. But natural disasters affects more than one layer of the striked place and thus to measure the impact on several areas becomes of great importance to understand the complexity of the society's response. Is for that reason that in this paper we make a study of the latest major earthquake in Mexico City that took place in September 19 2017, using; official, crowdsourced, social media, mobility, news and wikipedia data for gaining insights not only in the immediate effect but in the collective memory (4) in the subsequent year.

September 19 is a date that will always be part of the mexican culture as it is dramatically and coincidentally the host of the 2 deadliest and most damaging earthquakes in the recent history. Around the 07:00 hours of 11/19/1985 an $8.1M_w$ earthquake with origin in the Pacific Ocean stroke Mexico City (5), being at that moment the most powerful one that had ever impacted the zone with an official count of 12,843 deceased due the damages of that day and the posterior aftershakes. On midnight 11/07/2017, a telluric fracture near the Chiapas coast (6) originated an $8.2M_w$ earthquake that caused enormous damages in the Chiapas, Oaxaca and Tabasco area with a death count of 102, even though it was felt on Mexico City there weren't major damages. Two weeks later and exactly on the 32nd anniversary of the "Terremoto del 85" at about the 13:15 hours (7), just two hours after the annual eartquake simulacrum to commemorate the victims a $7.1M_w$ intraplaque earthquake happened near the city of Puebla in the center of Mexico. The proximity of the origin along the simulacrum feeling made imposible the correct action and a complete building evacuation. Even when it wasn't as powerful as the previous one, the trepidation nature of the interplaque earthquakes and the proximity to the origin made huge damages to Mexico City. With 5,765 damaged households from which 2,273 were total and 3,492 partial and a total of 44 collapsed buildings the number of people that went homeless across the country was above 250,000 increasing the heritage poverty of the nation. The official numbers throw a deceased count of 225 in Mexico City out of a 369 total, which suggest that even when there are areas of improvement, the measures taken in the past 32 years in building regulation and civil instruction had a positive impact on the human lost relative to the one from 1985 even when the estimate of earthquake driven homeless people on the first one was of 150,000 which is a ratio of 0.60 while the death count one is 34.80.

Besides the catastrophe and the date, there's a major similarity in both events which is the civil response for the sake of aid (8). In both events within a half of an hour there were already very organized brigades at the collapsed areas with the difference of the government aid playing a crucial role in the later event while it was perceived null in the first one. The fast organization and fearless actions of volunteers in both cases are to be mention. An important difference in the capacity of organization of big masses in this 32 year time span is internet access which opens the door of fast spreading news through social media but also to crowdsource information allowing to direct and distribute efforts in a more optimal way. This way, efforts like #Verificado19S (9) played a valuable role by verifying the information that was broadcasted by individuals via social media and creating a map of dissasters, this model was fast adopted by government dependencies allowing a fast mapping of damages and concentrate efforts of verification and aid given the likelihood of having a vulnerable area (10).

Mobility data is hard to capture and in must cases rely on statistical experiments such as polls (11) but they fail to capture pattern shifts of a given event and instead they capture the overall behavior in a given time span. New technologies like GPS' devices embeded in cellphones, NFC/magnetic cards

Significance Statement

The understanding societies has been one of the motor drivers of science for a long time and the data collection and generation that has been arising from the last decades opens new hypothesis testing and conducts data driven research. In this context we take advantege of novell techniques and computation power to analize amounts of data that would had been impossible in previous times in order to get insights from three major questions in social systems; resilience, organization and collective memory and the connection between them. For that purpose we make use of of multiple datasets of different nature around the 19S Mexican Earthquake in 2017.

for public transportation and app cabs could be the solution to tackle this problems but being sensitive and highly revenueble data makes it very difficult to be realeased. In the last decade the use of bicycle-sharing services have increased in the whole globe (12) and a fair amount of them makes public a subset of information they collect making possible to detect patterns and change of them in real time data (13). As in year 2018, three different bike-sharing services exist in Mexico City but at the time of the earthquake there was the only one named Ecobici which depends directly on the city's government and makes it's anonymized usage data freely available (14). There are 3 types of mobility sensors; airborne, drive-by and stationary (15) and even when stationary sensors such as bike-sharing stations are not the best way to map a city they provide enough resources to test the homeostasis in the system. Although it doesn't correspond to the geographical center of the city, the area where this service is spread is popularily considered as so since it host the historical downtown and the Palacio de Gobierno. The three mayoralties where Ecobici is present are Cuauhtémoc, Miguel Hidalgo and Benito Juárez where a big amount of damages during the earthquake were concentrated also allowing us to analyze the usage in the pre and post event times.

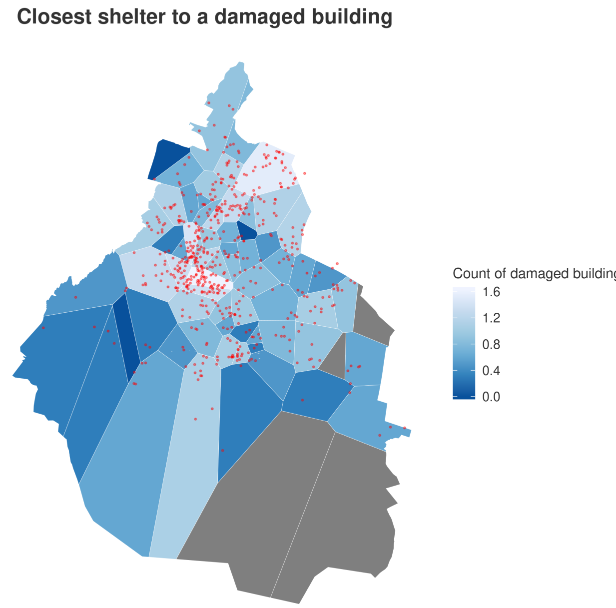

Fig. 2. Voronoi cells representing shortest distance to a shelter colored by the log10 count of damaged buildings inside each of them. The gray areas are shelter allocation voronoi cell where no damages where registered.

Damage Response Spatial Distribution

The dataset gather at (10) contains 695 records of damaged buildings that comprise information about; complete address, adjacent streets, neighborhood, mayoralty, quadrant, damage type, latitude, longitude and accuracy parameter. Out of those, only 569 are from Mexico City as the Valley of Mexico Metropolitan Area or Greater Mexico City besides the 16 mayoralties from Mexico City, is formed by 59 municipalities of Mexico State and 1 from Hidalgo. In this study we'll focus on the mean Mexico City solely as it was where the greater damages happened.

For the collapsed buildings we have 39 records with information that includes; address, building type (household, school, hospital, etc.), damage type (collapsed), adjacent streets, district, abstract of damages, process (current status), number of deceased, number of rescued, responsible institution of aid, responsible governmental entity, google maps link, latitude, longitude, report type (civil protection), entity, update date. In counterpart, the civil response given by shelter allocation has the following on the 74 shelters across Mexico City; entity, mayoralty, district, place (sports gym, school, government palace, etc.), type (civil or official), adjacent streets, address, needs, google maps link, latitude, longitude.

Figure 1 shows the high density of damages around the so called City's Center where are also located all the Ecobici stations. An interactive version of the image where deceased and rescued people along with location information can be found here.

As we're interested on the response of the society to the damages trying to keep the city's homeostasis as much as possible we compute the ratio of damages by square kilometer in each cell giving this a parameter of the aid distribution in function of the number of damages and compare them on a log10(rank) vs log10(damages frequency).

The empiric Zipf's law is a usual scale study of these type of systems as it measures a rate of innovation but although it has been tested on multiple geographical datasets (16), there's been reported cases where it reaches a saturation point (17)(18) showing a structure where no extra elements are needed or the marginal gain of adding a new one is very small as is presented in (17) for mapping a city through urban ride sharing. An overview of these emergin distributions is done in (19) claiming that these can be obtained by a Pólya's Urn with an adjacent possible restriction, meaning that in some cases innovation can only be achieved to a fixed amount. It's also shown in (19) that the Zipf's law fails to describe the scaling law of the complete dataset of city sizes in Brazil and only fits if we take the for the largest cities subset.

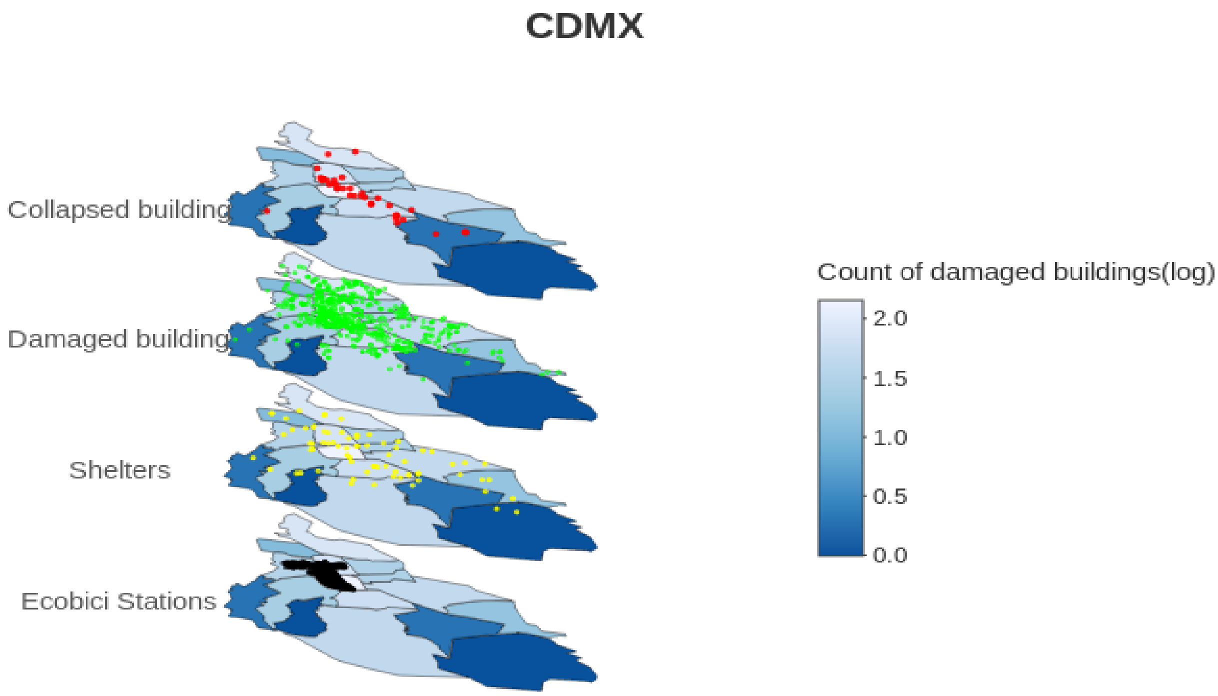

Fig. 1. Stacked map showing the spatial distribution of the collapsed and damaged buildings, shelters and Ecobici stations in Mexico City. The geometrical polygons represents the area of the 16 mayoralties colored by the amount of damages on each in log10 scale.

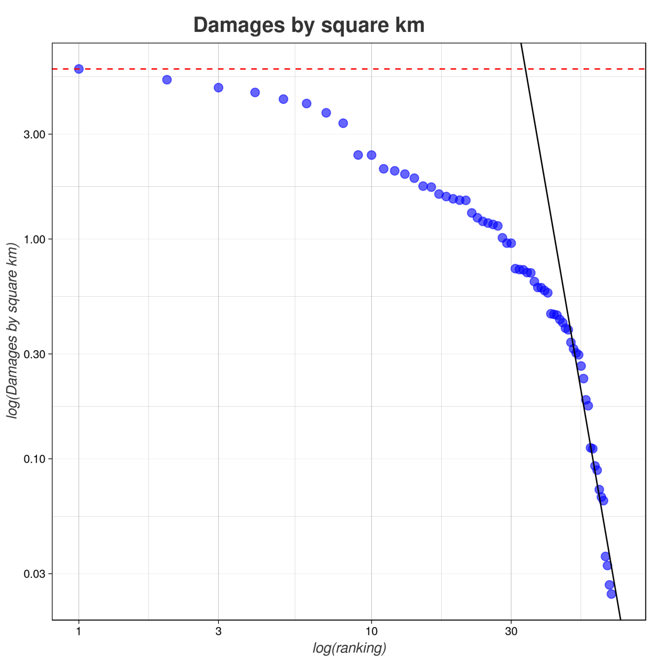

Fig. 3. Logarithmic distribution of the number of damaged buildings in a Voronoi cell in function of rank. A notorious saturation is taking place so a regression line on the Zipf's regime is drown in black along the maximum value in dotted red. This is a way to obtain the typical value of a saturated distribution.

We show in figure 3 that our system presents such behavior, reaching a fast saturation, and considering the fact that the damaged buildings were known beforehand the shelters were placed we could asume that an adjacent possible process was taking place. In (18) the meaning of a parameter of the scaling law in these distributions can be replaced by a typical or characteristic size since there's no longer a scale-free process. These characteristic size can be measured by a geometric mean:

$$S_0 = \sqrt[N_0]{\prod_{j=1}^{N_0} S_j} \quad [1]$$

where N_0 is the number of observations and S_j represent the values for each one, in this case the damages by square kilometer, resulting in a value for the characteristic number of damages by square kilometer by shelter of $S_0 = 0.6198$ which neglects to zero values for the multiplication but takes them in consideration for the root.

Mobility and Homeostasis

As we can see from 1, there is a major overlap in the most affected regions and the Ecobici range of service. This way it makes sense to use the usage data to measure the homeostasis of the system and by that, the resilience of the city.

We collected the Ecobici usage from February 2010 to October 2018 to analize if there's a clear tendency on behavior ever since the service started so we could compare to the one around the 19S event. The data gathers the information of 24,547,550 travels over 451 stations in 3183 days, having the following information; user genre, user age, bicycle, initial station, destination station, initial date, final date, initial hour, final hour.

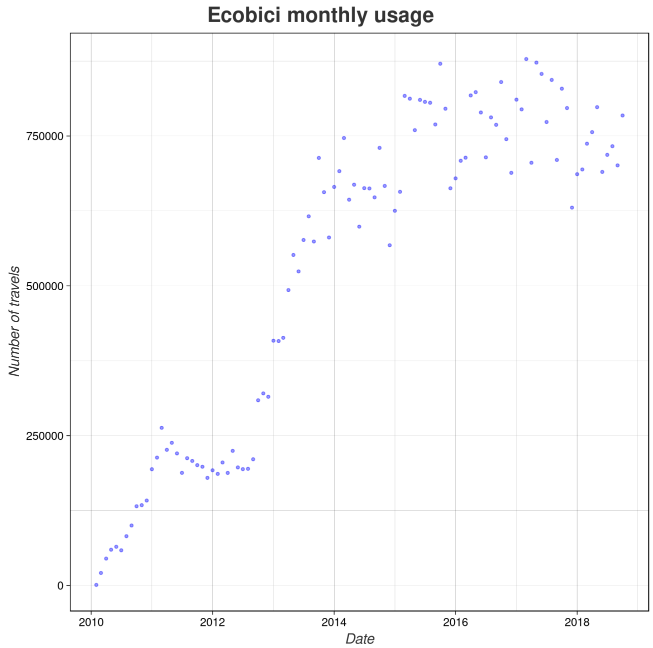

Fig. 4. Aggregated monthly usage of Ecobici service.

We can see from figure 4 that the usage of the service was rapidly adopted but drecreased after between the second and the third year just to take off again until 2016 where it seems to reach a steady state and even a second drop in usage which could be explained by the arrival of two other bikesharing services.

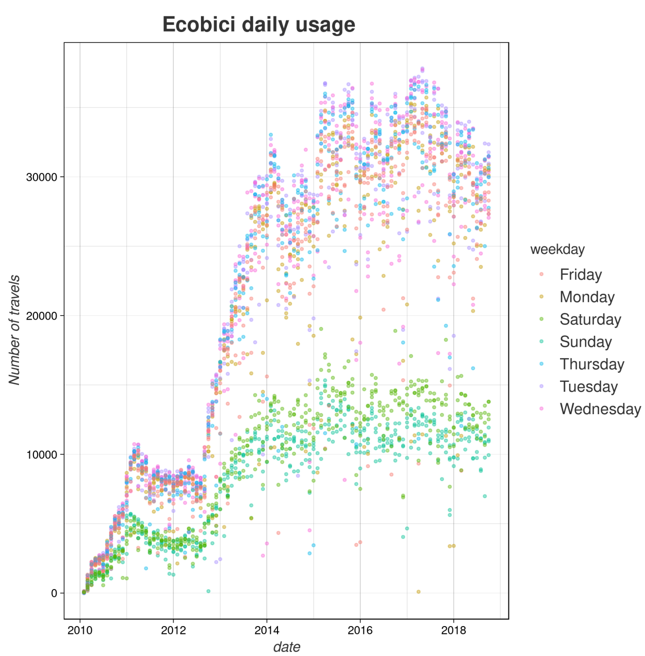

Fig. 5. Aggregated daily usage of Ecobici service colored by weekday. We can see that the weekend usage distribution is much lower than in weekdays. The daily usage shows a more evident drop in usage since late 2017 during weekdays while mantaining a steady pattern for weekends.

A more detailed look is needed to understand the dichotomy of the usage between the weekdays and the weekends. Figure 5 shows the different patterns between days, which suggest that the greater input comes from the work/school related travels and less from leisure. We can also see that the historical maxima of daily travel counts happened on 2017 and started a decline from there.

Figure 6(a) agrees with the hypothesis of the service being used for work communte as it's primarly purpose as we can clearly see that the peak usages on weekdays correspond to home-work-home commutes and a smaller one at lunch hour.

In 6(b) is possible to observe that in the week of the earth-aquake the main pattern remains but the median of usage is higher for lunch hour than the work-home commute, and also there's an evident decrease in the overall usage. But one interesting thing is that travels arises at the 1-4 a.m. time lapse, this is due an extended service took place until September 28th, having a 24h service and removing the 45 minutes limit per travel.

On 7 the hourly usage of each week from the previous to earthquake to 4 after are displayed, showing interesting patterns. On Friday September 15 7(a) there are 2 peaks instead of 3 because it is Mexico's Independence day and most places only work half a day. The earthquake week started normal, even on the 19th morning but from there the patterns change dramatically. Until the second and third week of October when shapes and amount of travels returned to it's regular. It's worth to mention that at that time most schools returned to classes (20).

Homeostasis was first introduced by Cannon (21) in 1932 defining it as the ability of an organism to maintain steady states of operation, in view of the internal and external changes but in 1962 Ashby (22) defined it as an adaptive reaction to maintain "essential variables" within a range, and thus we can view homeostasis as a capacity of a system to remain within a viability zone (1) and for that reason is closely related to robustness (23).

We use homeostasis as defined by Gershenson (1)

$$H = 1 - d(I_{in}, I_{out}) \qquad [2]$$

with d the Hamming distance between two sets, i.e.

$$d(A, B) = \frac{\sum_{i=0} a_i \oplus b_i}{|A|} \qquad [3]$$

being $\oplus$ the xor operator which gives a zero value if $a_i = b_i$ and 1 if $a_i \neq b_i$ and by that $d(A, B) = 0 \Leftrightarrow A = B$. We only use the norm of one set because we asume that both have the same cardinality.

The I in equation 2 are "information" and I_{in} or "input information" can be seen as the initial state or conditions and I_{out} or "output information" or the final state after I_{in} got into a transformation procees, i.e. $f(I_{in}) = I_{out}$. Another intersting metric also proposed in (1) in how to quantify self-organization S, defined as:

$$S = I_{in} - I_{out} \qquad [4]$$

Meaning that self-organization occurs if there's a process that reduces information ($S > 0$). On the other hand "emergence" is their ratio, as:

$$E = \frac{I_{in}}{I_{out}} \qquad [5]$$

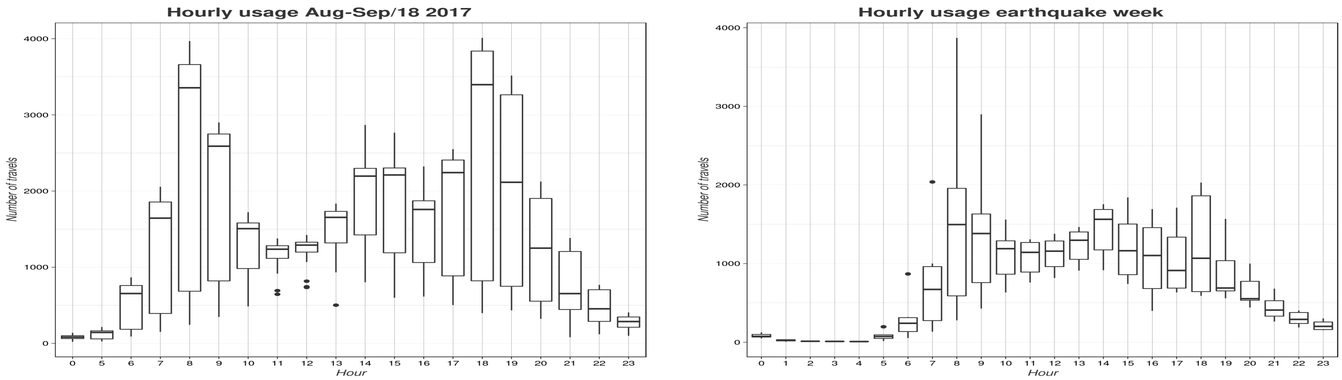

Fig. 6. Hourly usage of Ecobici service on weekdays in the period of August to September 18 2017 (left) which is about a month and a half before the earthquake stroke the city. There are three clear usage peaks around 8,14-15 and 16 hours, which can be thought of home-work-lunch-work-home commutes. Contrasting is the usage of Ecobici service on the period of September 19 to September 22 2017 (right) which are the weekdays of the earthquake's week

We'll define a more relaxed homeostasis than the one from equation 2, as we're computing ranks a better fit for our problem is to use the Kendall rank correlation coefficient $(1-\tau)$ as our distance, where

$$\tau = \frac{\sum_{i<j}(sign(x_j - x_i) * sign(y_j - y_i))}{n(n-1)/2} \qquad [6]$$

With this we can review the rank of station pairs by number of travel for each day and have relate them with an information base I_{in} of a long period.

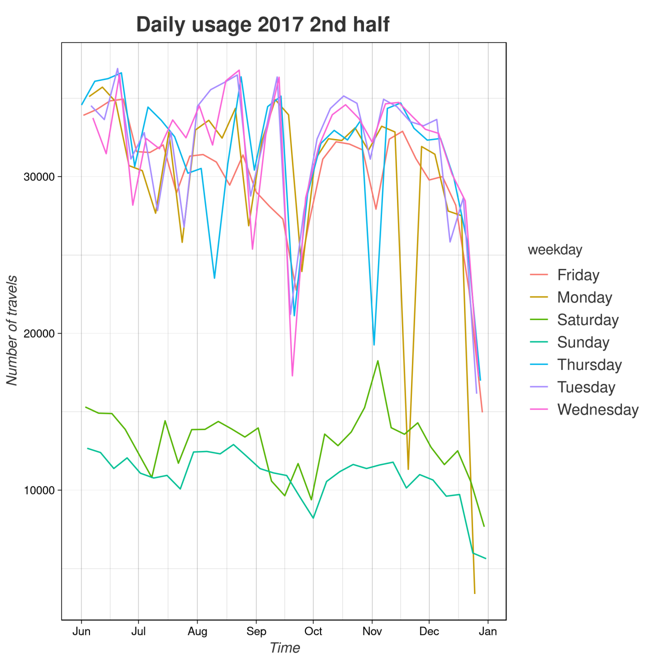

Fig. 8. Daily usage for the second half of 2017. Dates like November 2nd and 20th as mexican festivities have very evident decay on usage.

In order to understand the system we can see at the daily behavior of the whole 2nd half of 2017 in figure 8 which is notably noisy. We have major decays on festivities, even grater than those from the earthquake as we can see on both of the low peaks in November compaired to the one in September, but it's important to notice that in September the decay lasted longer than just one day.

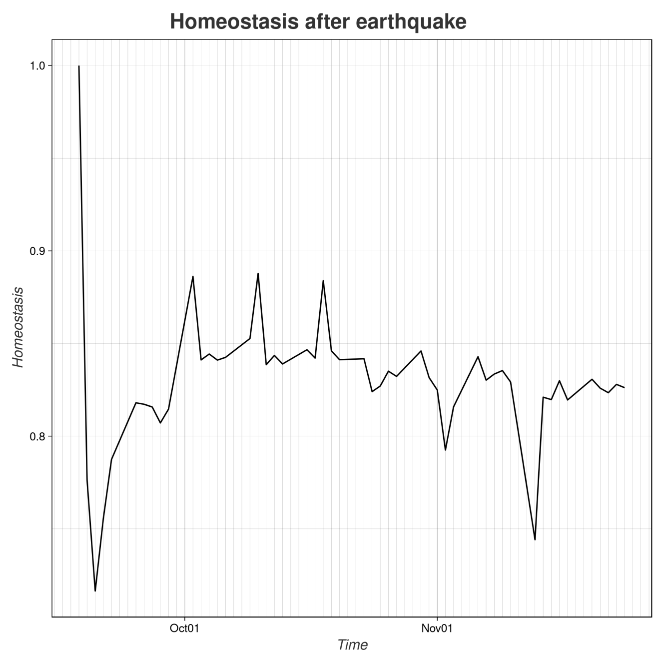

Fig. 9. Homeostasis from September 19 to November 30

Now looking at the bahaviour of the homeostasis in 9 is evident that something happend to the system. We took the whole August month and until September 19 to fix the basis of usage I_{in} ranking from most to least popular pair of stations that gets connected through a ride. And we can see that not only the number of travels dropped in 8 but the patterns in most common pairs of stations changed. We set the homeostasis from September 18 as our maximum homeostasis and measure relative to that as there's a considerable level of noise in an absolute scale. It's important to note that the lowest level of homeostasis happend on September 20 as the earthquake happened after the 9 a.m. peak use of the 19 and that even when the usage on November 20 was less than any

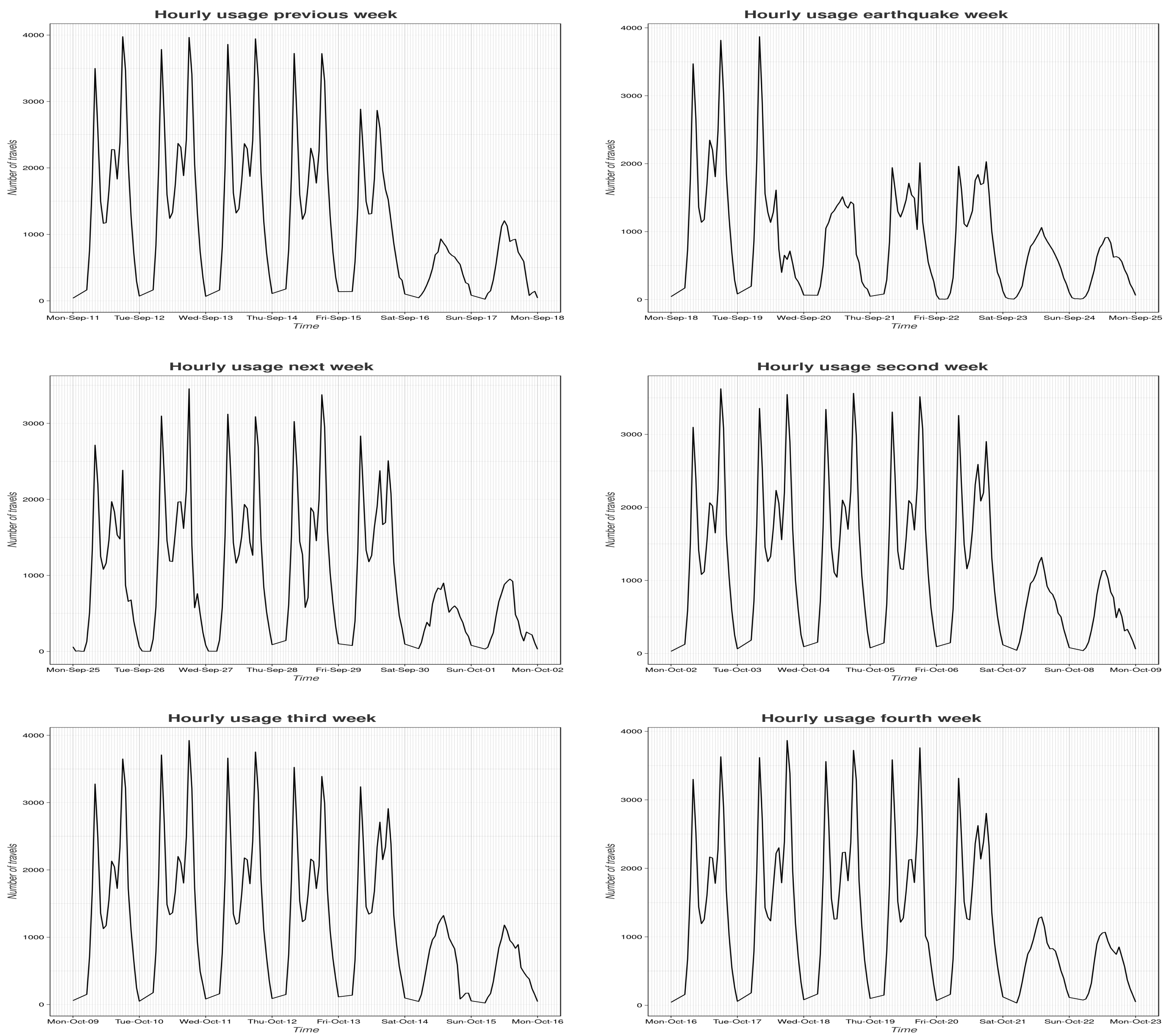

Fig. 7. Hourly usage of Ecobici service on by day from the previous week to the earthquake until the fourth subsequent one. On Friday September 15 there are 2 peaks instead of 3 because it is Mexico's Independence day and most places only work half a day. The earthquake week started normal, even on the 19th morning but from there the patterns change dramatically. Until the second and third week of October when shapes and amount of travels return to regular basis, it's worth to mention that at that time most schools returned to classes.

day around the earthquake and on November the 2nd was almost as low as the lowest in September, the homeostasis didn't drop as much as it did on the week of the event. Both the number of rides and the homeostasis reach a relative steady state at the second week of October, that corresponds to the return to classes of more than the 75% of the schools between October 9 and 13.

News Events

The Gdelt project (24) is a huge database of information which monitors all must broadcast, print and web news in 65 languages and makes an in-time translation and stores the event and important metadata around it as the entities and contries envolved, the number of mentions in the first 15 minutes of the event first appereance in one database and all the historical mentions in another, it also stores the URL of the information and performs sentiment analysis and the Goldstein Scale.

The Goldstein Scale is a measure of Conflict-Cooperation described in (25) and it is automatically assigned by the Gdelt project to every event given the likelihood of it's nature. The scale runs from -10 for the most conflictive or disruptive events to 10 for the most cooperative ones. Thus, as we wan't to measure cooperation in Mexico City after the Earthquake we will use this information. The Gdelt project stores all the information it collects in a columnar file allowing to query the files in an easy way. For this study we gather the information related to earthquakes in Mexico since 2015 until October 2019.

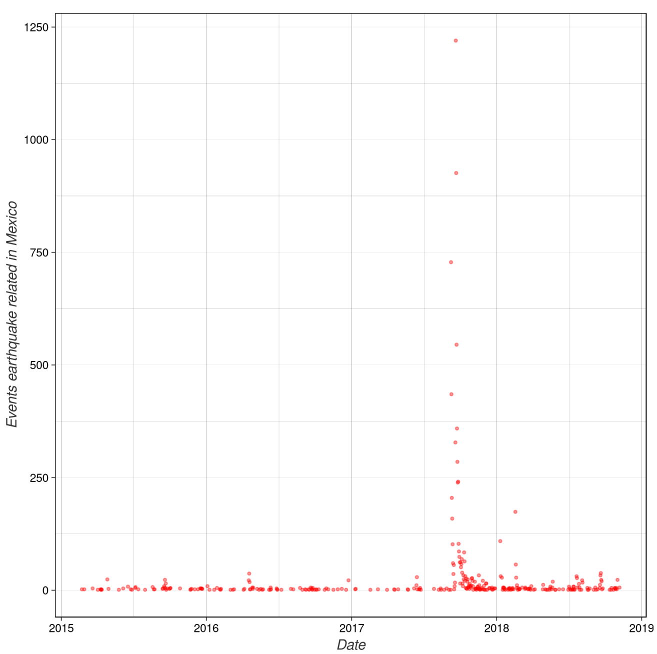

Fig. 10. Number of events realted to earthquakes in Mexico per day since the first day of 2015 until October/31/2017. It's is possible to observe that there are events along most of the entire time series but there is an important peak in September 2017 that correspond to the two major earthquakes in the last years.

Mexico is a seismic zone and hosts several important movements a year and figure 10 allows us to understand the importance of the 19S one. A very useful characteristic of the Gdelt project data is that it doesn't take into account mentions of previous events as new ones but instead they have it's own database for measure them. That way we can know that there's no event information of the 1985 earthquake in our query data.

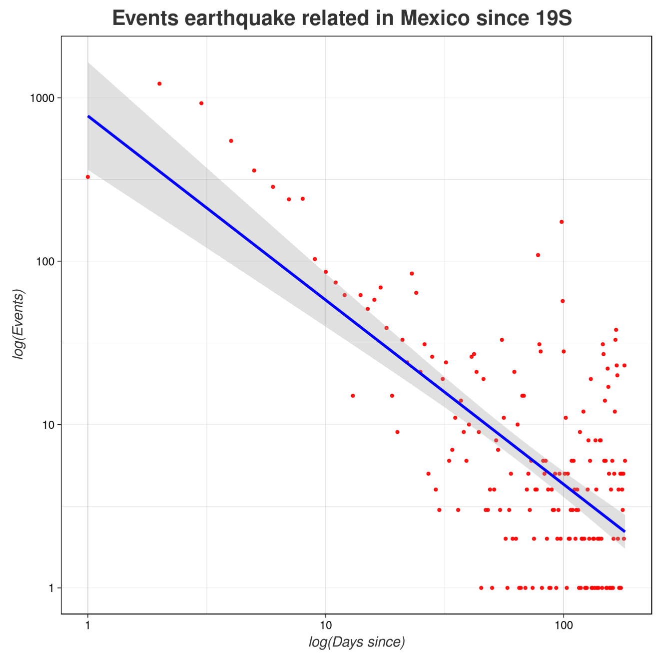

Fig. 11. Number of new earthquake related events in Mexico since 9/19/2017. The behavior obeys a power law $f(x) = cx^{-\gamma}$ with $\gamma = 1.127$

The figure 11 represents the number of events in Mexico related to earthquakes showing a power law decay which means that the system is cooling off linearly in the log-log space. A power law is a relationship between two quantities where a relative change in one results in a proportional relative change in the other specifically as a power of the first.

$$f(x) = cx^{-\gamma}$$

For this particular system we have a parameter $\gamma = 1.127$ which means that decays isn't very fast, i.e. new events still happens even long after the main one.

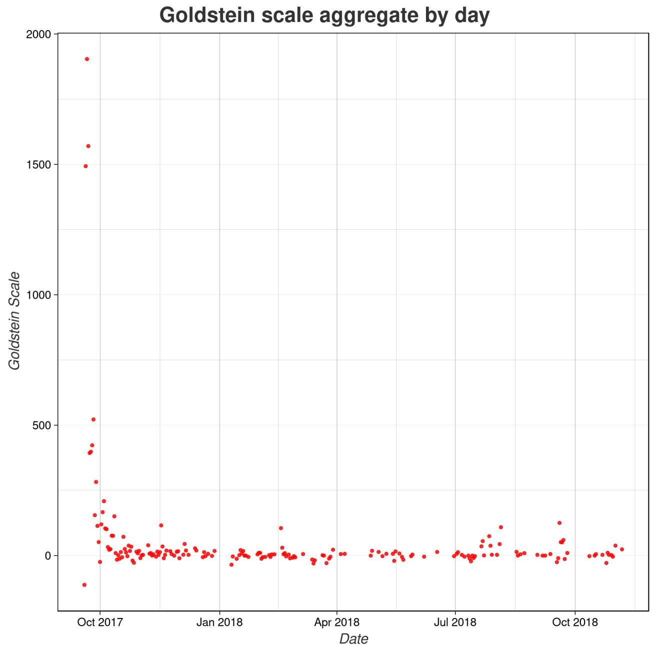

Fig. 12. Aggregation of Goldstein Scale by day on earthquake related events in Mexico from 09/19/2017 to 10/31/2018, showing that there has been more positive days than negative ones.

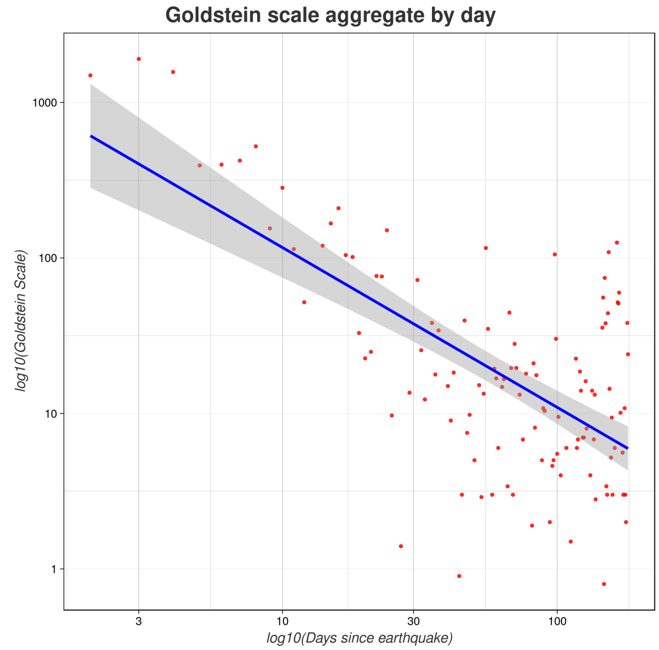

Fig. 13. Aggregated Goldstain Scale only on positive days on earthquake related events in Mexico from 09/19/2017 to 10/31/2018 on log-log scale.

Figure 12 shows the cummulative Goldstein scale by day for earthquake related events on Mexico from 09/19/2017 to 31/10/2018. The decision of using a sum of all the events instead of a statistic aggregation such as the mean or median is because we don't want to lose the information of the number of events. The whole dataset has 181 records, meaning that the other days didn't have events with the constrains we're studying and therey were only 54 negative records, thus we'll focus on the positive ones that contains the other 127.

The regression line on figure 13 shows a power law decay with $\gamma = 1.028$, this means that the number of related events decrease faster than their cooperative nature.

Collective Memory and Crowdsourced Coordination

The social media Twitter was a fundamental tool to coordinate the civil response as it was possible to crowdsource the information and validate it through the same mechanism. This way the knowledge of where aid was needed and the nature of it. In order to analize the evolution of this system we made use of the Twitter Gardenhouse feed which represent a random sample of the 10% of the entire public tweets. We made two collection runs as described next:

- Collected all the tweets containing the case and accent insensitive hashtags (09/01/2017-31/10/2018):
  - #PrayForMexico
  - #FuerzaMexico
  - #AquiSeNecesita
  - #AquiNecesitamos
  - #AquiYaNoSeNecesita
  - #Verificado19S
- Count hashtag repetition and add the most popular ones:
  - #SismoCDMX
  - #AyudaCiudadana
  - #TenemosSismo
    - Neglected:
      - #CDMX
      - #Mexico

The final dataset contains 1,300,863 tweets from 519,959 distinct users with 43,617 different hashtags.

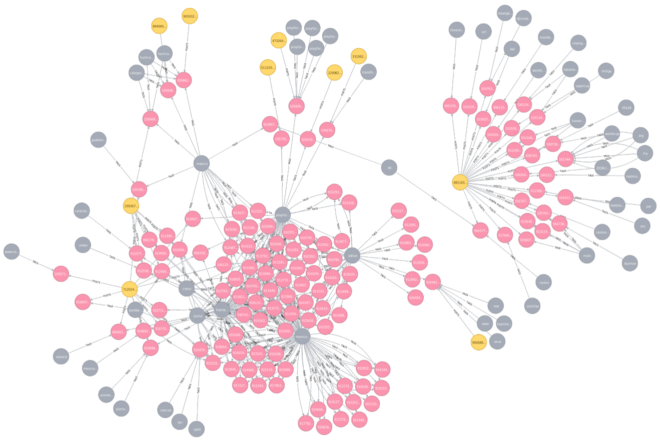

Fig. 14. Network showing a subset of Hashtags (grey) and their tagged Tweets (pink) and the Users who tweeted them (yellow).

We want to measure collective memory and we'll be doing this by looking at the collective behavior on this social media platform. There are two main parameters we're interested in, the overall tweets in time and individual adoption in order to review how long did the.

On figure 15 we can see the behavior of the collective memory about the earthquake. The historical maxima is on the day before the event, which is 09/20/2017 and starts a slow decline with $\gamma = 1.338$ for new users and $\gamma = 1.015$ for the overall tweets, this means that the adoption has a faster decay than the overall oblivion which is very simmilar to Golden scale one but even faster. On the other hand Wikipedia page visits 16 show a much slower decay with $\gamma = 0.552$.

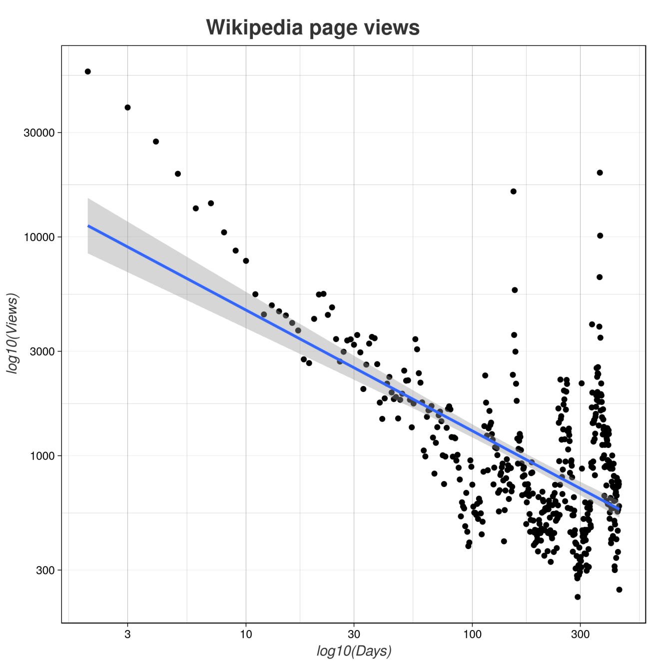

Fig. 16. Number of view of the Wikipedia site for the earthquake with $\gamma = 0.552$.

Another interesting thing to look at is as stated before, the trend adoption. This is, when do individual users starts posting tweets with these hashtags and how long do they keep doing that. This is shown in 17, particularly on 17(b) where we can see the individual users and how many days they have posted a tweet with any of the set of hashtags. In both 17(a) and 17(b) we can see by the days range (pink) a multimodal distribution, with the first peak around the 20-30 days, another at 365 days for the anniversary and the last for the maximal distance between days in our dataset. If we focus on the green points on 17 we can notice that the upper part has a different behavior than most of the users, the decay is much slower. By manual inspection we could corroborate that these were in fact automatic accounts and newspapers, since they don't provide an organic decay (they have used any of the seed tweets almost everyday since the event) we neglected those accounts for the regression analysis. In figure 17(a) we can see that there are accounts above the days range distribution, this is because those users on average have tweeted more than one tweet a day with the hashtags, the meaning of these on 17(b) is a little different since that represents users that only tweeted for consecutive days. The slopes for these are $\gamma = 0.635$ for the total tweets, and $\gamma = 0.517$ for the days tweeting. These is another parameter to measure collective memory as it quantifies the rate of abandon of the hashtags, meaning that every day 2 users stop tweeting about it, and it is to note the closeness to the Wikipedia rate.

Conclusions

We made an extensive analysis on an altered urban system as it is Mexico City after the 19S earthquake, we took a close look into different related datasets. First we measure the distribution of shelters given the damaged buildings and found that there's a saturation of shelters in function of the damages by square kilometer, these because of geographical constrains and the beforehand knowledge of the location of the damages, the charachteristic number of damages by square kilometer by shelteer is 0.6198 meaning that is lower than one. Then we analyse the bike sharing service "Ecobici" and look at the regular usage patterns to contrast with the ones in the days around the earthquake, for this a homeostasis measure based on information was used and finding that it took about 3 weeks to recover the normal patterns. We also used the Gdelt Project data to quantify the events and the emergence of cooperation by the Goldstein scale that is provided by them and also the number of events, we found that the cooperation decays slower than the number of events. To measure the collective memory we used a Twitter database to test how people talk about the event in function time and also looked at the number of visits to the Wikipedia page of the earthquake (in Spanish) finding that the oblibion rate is very similar in both systems, which is very slow compared to the homeostasis recovery being around 10 months for the stable state in the first one and three weeks for the later.

ACKNOWLEDGMENTS. I want to recognize the work of every person and dog who abandoned their comfort to help those in need, who sacrificed nights of sleep so that others could have a roof under which they could do so and a new day to breathe. Also to all of those who collect and share information.

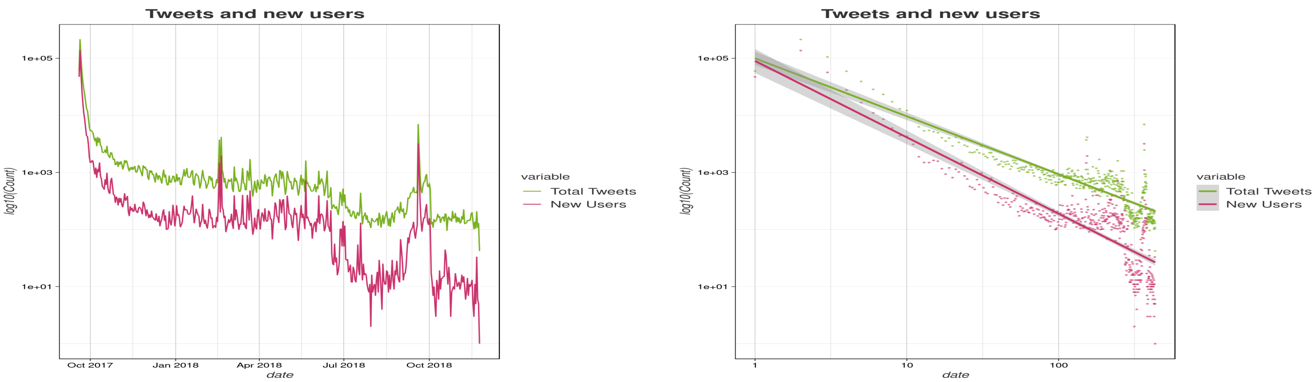

Fig. 15. Time series of the overall tweets containing any of the seed hashtags and the new users by day and number of tweets and new users by day in log-log scale. The trend indicates the decay rate with $\gamma = 1.338$ for new users and $\gamma = 1.015$ for total tweets. The slump matches the presidential elections period and the new peak is an anniversary event.

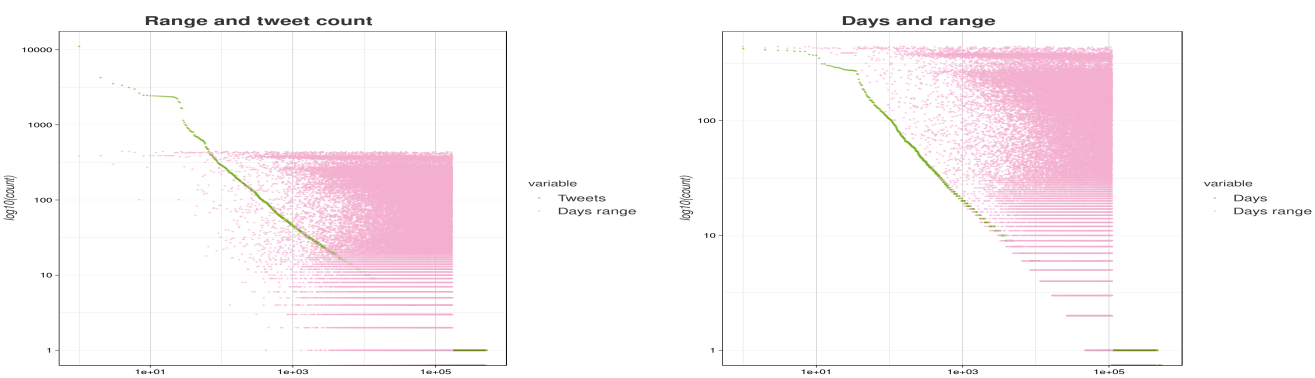

Fig. 17. The first plot shows the number of tweets by user ordered by its rank and the number of days between their first tweet and their last. The second figure shows the number of days a single user posted a tweet and also the range between first and last tweet. There's a clear change of regime in the green plots, the higher ones are from automatic accounts and newspapers. For the regression we didn't take them into account. For the number of tweets by user we got $\gamma = 0.635$, for the number of days tweeting $\gamma = 0.517$

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