Evidence of a common pattern in social explosions

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Motivation

- In recent years, our society has experienced the rise of new ways of interactions through virtual media.
- One of the most crucial consequence is that any person has the power to induce social destabilizations.
- Under critical circumstances, it can take dimensions of the whole country, causing political instability.
- Twitter is the most common virtual social network used as a platform for social movements and/or demonstrations $\longrightarrow$ 'Twitter revolutions'.

Some theoretical considerations

- **The success of an on-line movement:** the shift of scale and the later massive off-line protests.
- **The role of the social media:** to facilitate the transformation of small or local feelings of disagreement into large-scale social actions.
- **The way how social media achieves that effect:** growing clusters of people and groups with similar effervescent feelings.
- **Which in another case would never be in communication by several constraints, for instance, geographical distance.**

Why percolating properties?

- Social phenomena are mainly the emergent result of the interactions between their participants.
- It is natural to think that any macro-social action, as a consequence of spontaneous and massive interactions between all individuals, will have as a consequence the growth and divergence of the correlation between them.
- At the critical point, the correlation length is expected to grow.
- If the correlation length attains a power-law shape, then power-laws dominances are expected to happen on the cluster's statistics forms.
- We propose that the transition online-offline protest is characterised by signs of criticality, as the expected consequences from the divergence on the correlation length at the critical point.

The data-sets: Four different large-scale manifestations:

- The Spanish Indignados movement. Critical point: 15th of May 2011.
- The second and third data sets were taken in Argentina in 2019: A protest against high taxes between January 4th and 6th, and a mobilization asking for justice on November 9th.
- The Occupy Wall Street massive demonstrations, around May 2012.

		Same time		Same nº of hashtag usages	
Dataset	**Event day/s**	*N. Tweets*	*N. Hashtags*	*N. Tweets*	*N. Hashtags*
noaltarifazo/ruidazonacional	Jan. 4th-6th 2019	81,516	20,059	97,315	22,813
9n/9ngranmarchaporlajusticia	Nov. 9th 2019	136,367	15,266	165,461	18,193
15m	Mar. 15th 2011	39,704	2,991	49,612	3,674
occupy Wall Street	Dec. 5th 2010, Feb. 23th 2011	- (*)	14,788	- (*)	14,787

TABLE I. Datasets composition. (*) For the Occupy Wall Street dataset, tweet ids were not available, but only hashtags usage by users on a daily basis.

Daily activity: same time-window

Number of tweets per day, on the data-windows "before", "during", and "after" the online-offline transition point.

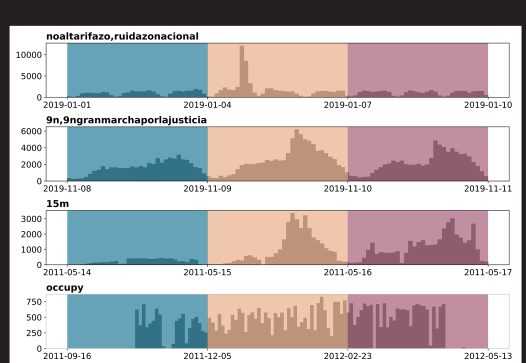

Figure 1:Each segment has the same time-window.

Daily activity: Same number of hashtag usages

Number of tweets per day, on the data-windows "before", "during", and "after" the online-offline transition point.

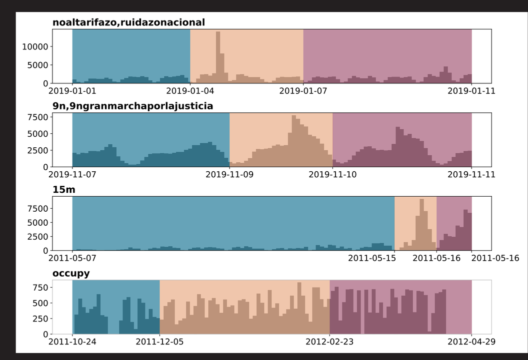

Figure 2:Each segment has the same number of hashtag usages.

No similarities beyond the highest activity on the data-windows "during".

Fits $X_{min}x^{-\alpha}$

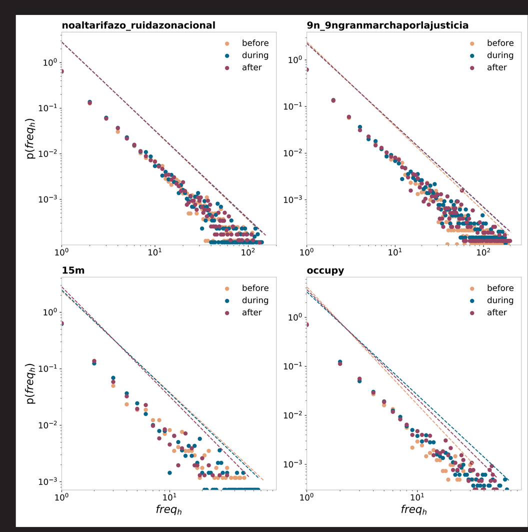

Figure 3:The power law exponents were fitted by the maximum likelihood method for discrete power laws, and all fits passed the Kolmogorov-Smirnov goodness-of-fit test at p=0.05.

Results

For each social movement, we fitted a power law distribution for the hashtags' frequencies, for the data-sets "Before" and "During". Namely, on both edges of the critical point.
As some users might use the same hashtag many times, we consider two different ways of building the hashtag frequency distribution inside each period: *(a)* counting the number of hashtag usages and, *(b)* counting the number of unique users using that hashtag.
These are denoted as "Hasht." and "User" in the first column of the table, respectively.

Level	Dataset	Same time		Same nº of hashtags	
		Before	*During*	*Before*	*During*
Hasht	noaltarifazo/ruidazonac..	1.957(0.011)	1.943(0.011)	1.955(0.011)	1.943(0.011)
	9n/9ngranmarchaporlaj..	1.822(0.011)	1.760(0.010)	1.818(0.009)	1.760(0.010)
	15m	1.960(0.046)	1.825(0.023)	1.793(0.020)	1.825(0.023)
	occupy Wall Street	2.402(0.025)	2.107(0.013)	2.402(0.025)	2.107(0.013)
User	noaltarifazo/ruidazonac..	1.994(0.012)	1.989(0.011)	1.989(0.012)	1.989(0.011)
	9n/9ngranmarchaporlaj..	1.788(0.010)	1.758(0.010)	1.822(0.009)	1.758(0.010)
	15m	2.125(0.054)	1.870(0.024)	1.840(0.020)	1.870(0.024)
	occupy Wall Street	2.074(0.018)	1.959(0.012)	2.074(0.018)	1.959(0.012)

Figure 4:Discrete power law exponents for the frequency distribution of hashtags, fitted by max-likelihood for each event and time periods "Before" and "During".

- The first point to notice is the lowest values for the exponents on the data-set 'During' for all the events.
- Lowest values of that negative exponent mean highest heterogeneity on the distribution. That could be expected for the case of the same-time data-windows (then varying the number of hashtags), given the higher activity as shown in figure 1.
- However, this is maintained also when the data is divided by having the same number of hashtags, then varying the time.
- Furthermore, let us notice that the last result is still robust whenever we count each hashtag in both ways: only once per user or each time that a user post it.
- The power-laws exponents for the distributions of the 'before' data-windows, are the same in each social movement (within their low values of error), whenever the distributions are done either counting the same number of hashtags or the same time-windows.
- The last phenomena are also robust in both cases: whether the data is taken either counting the number of hashtag usages or counting the number of unique users using that hashtag.

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