Heterogeneous pausing-time modelling for human response to gender violence situations

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Abstract: Citizen science practices can also approach physics to social psychology contexts. This study is based on time data extracted from a public experiment where participants have to decide whether to respond to a gender violence situation in public context. First we model interevent times as a Poissonian variable and then find heterogeneity in the dataset. As a way to overcome limitations of the Poisson model analysis, we perform a multifractal approach through q-moment analysis.

I. INTRODUCTION

Science is the result of a continuous and collective effort that has led to cross unimaginable frontiers. It would not have been possible without multidisciplinary and groundbreaking work brought from many different fields [1]. The study of complex systems draws this interdisciplinary domain, with contributions from physics, social sciences, mathematics, biology, and many others. As an alternative paradigm to reductionism, sometimes this cross-disciplinary endeavor leads to give up conventional methodologies. Highly controlled contexts can alter the outcomes of the study around human behavior [2]. In order to deal with these limitations citizen science changes the basis of usual research by allowing people to participate actively in an experiment. By doing this, it is possible to create an environment that is closer to real life world and also enables citizens to participate actively in research, making it more democratic [3]. Citizen science is done with volunteers partner with scientists to front real-world questions and facing present social needs. Moreover, this transformation leads to raise awareness about citizens role as an active part of technological society. Some examples advocating for a lab-in-the field approach are experimental economics, the design of financial trading floors, human mobility or social interactions dynamics. In this context, physics applied to social psychology is a new approach to study real life conflicts. It is known that social norms influence decision making and human behaviour, sometimes in a perjudicial way [4]. In public space, decisions might be based on arbitrary signals that favour certain norms of behaviour and not others. This leads critical consequences when gender norms and stereotypes constrain freedom and enjoyment of specific social groups [4].

Using standard methodologies in statistical physics we can examine how social norms affect human intercommunications. A way of studying cooperation parameters in urban conflict contexts is by modeling the intervention response time as a form of a queuing process. In particular, we study the response time assuming an homogeneous Poisson distribution. Being aware of the social heterogeneity of people participating in the public experiment allow us to find a more accurate response time distribution. It is therefore possible to perform a multifractal analysis through the so-called q-moments analysis [5]. Many physical and natural systems exhibit probability density functions that are different from the commonly used distributions, characterized by having "heavy tails". Sometimes, the large events often play an important role [1] and this behaviour can be better handled by analyzing q-moments.

The study is based on collected data from the citizen science public experiment called *Consciències la plaça* that took place in 2019. The aim of the experiment was to find out how we face social dilemmas about gender violence of different presented monologues by professional actors. The project is co-created by the research group OpenSystems from University of Barcelona, the feminist group of Elisava and NUS Teatre.

II. RESULTS

A. Data acquisition

The empirical data used in this study was obtained within the citizen science public experiment held at *Biennal de Ciutat i Ciència* of Barcelona city on the occasion of the International Day of Women and Girls in Science and was completed with *Calidoscopi Festival* public experiment. The location of *Biennal* was in three emblematic squares such as Mercat de Sant Antoni, Sortidor and J.M. Folch i Torres. *Calidoscopi* was carried out in Orfila square in Sant Andreu's neighbourhood. 39 groups of 6 people (234 individuals in total) were exposed in front of four types of different gender violence situation. Briefly, these situations are the following:

- *"I don't know what you're complaining about"* (A): Natalia watches discomfort of a girl sitting on the bench in front the harassment of a boy, which he justifies by saying that he only is telling her he likes her.
- *"Everyone is free to do what they want (in privacy)"* (B): Alex observed a situation where one

man showed his discomfort on the terrace of a bar where two boys were kissing.

- *"From the corner of her eye"* (C): Raquel was in the women's bathroom when she hears a girl comment to one person that that toilet is not what it belongs to, that should go to the other as it bothers the rest of people.

- *"The limits of the breast"* (D): Sandra is in the library when a person complains to the librarian of a mother breastfeeding her child.

The possible answers were: act decisively (C), intervene prudently (I), not to intervene in the situation of violence (D) or not to decide if the time limit for choosing an answer was exhausted (T). The experimental device consisted of 6 digital tablets. The 4 monologues were performed alternately in front of 6 participants randomly recruited in three different public spaces of Barcelona. After the performance, about 5-10 minutes, the participants decided individually and through a tablet where all other participant's actions were available on real time, how they would intervene in front of them of that situation. One part of the annotated data was descriptive information regarding age range and gender. The data collected showed which decision was made and also the response time by each participant.

B. Statistical approach

The study is based on the response time of participants when monologue finished. Without any social conditioning one should expect similar patterns in repeated situations. Our hypothesis is that social differences such as gender or age lead to act differently in front of a gender violence situation. In order to verify this hypothesis, our first approximation is a statistical approach. We have grouped response times conveniently by situation (A, B, C, D), decision (C, I, D), gender (Women, Men, Other) and age (Young 0-17, Adult 18-44, Old 45-99). The longest mean response time for stories corresponds to Story A (13 ± 1 s), for decisions the longest corresponds to Decision D (13 ± 2 s), for gender corresponds to Women (11.8 ± 0.6 s) and for age ranges corresponds to Young (16 ± 2 s). Differences can be appreciated better by observing box-plots in Figure 1. The statistical approach not allow us to find statistically relevant situation and gender differences in response time. However, some studies claim that traditional gender stereotypes makes different genders act differently. In some contexts, self-interested decisions require longer strategic reasoning [4]. Additionally, one perceive shorter time response in the decision to intervene (C) which is consistent with previous studies [4] while youngest and oldest are spending more time which is again consistent with literature [4].

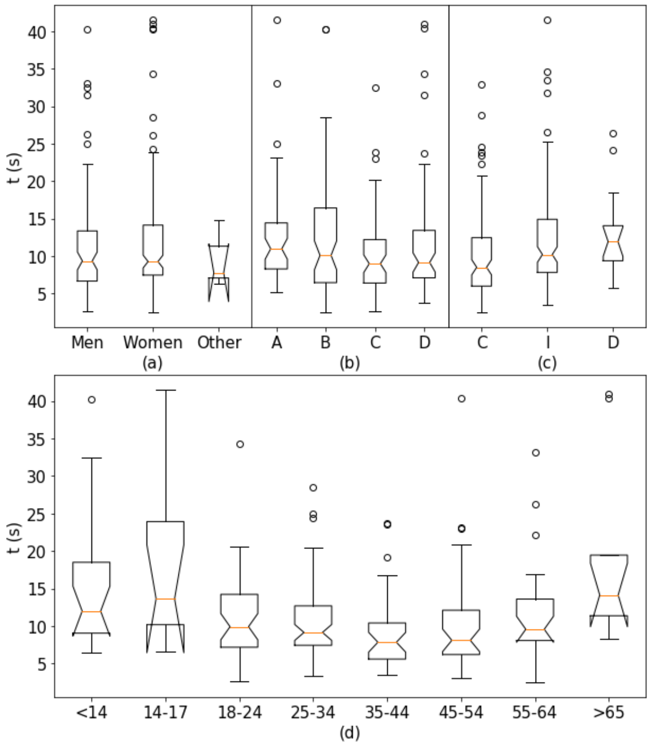

FIG. 1: Box-plot of response time for gender (a), situation (b), decision (c), and age (d). IQR=(Q3-Q1) covers the central 50% of the values. Error bars indicate values below Q3+1.5IQR and above Q1−1.5·IQR. Notches indicate the 95% CI for the median.

C. Poisson process

In order to delve deeper into the study of response time we introduce Poisson process. The homogeneous Poisson point process is a special case of a Markov renewal process [6]. The number of events in an interval of length t $(N(t), t \geq 0)$ is a Poisson random variable with parameter λ. A key variable in the Poisson process is the interevent time τ. Interevent times are defined as the difference between decision time of a participant and the following one of the same session group. Poissonian interevent times which are equally distributed and decumulative distribution [5] reads

$$\Psi(\tau) = e^{-\lambda\tau}, \tag{1}$$

where the average interevent time is $\langle\tau\rangle_{exp} = 1/\lambda$. Using this relation we define the characteristic time of the distribution as $\langle\tau\rangle_{exp}$. The square root of the variance is also characterized for $\sigma = \sqrt{\langle\tau^2\rangle - \langle\tau\rangle^2} = \langle\tau\rangle_{exp}$.

Assuming heterogeneity in total interevent time distribution and presupposing that these differences come from the socio-demographic heterogeneity we have divided interevent times by gender, decision and age. In Figure 2, we have plotted the decumulative density distribution of interevent times regarding different groups.

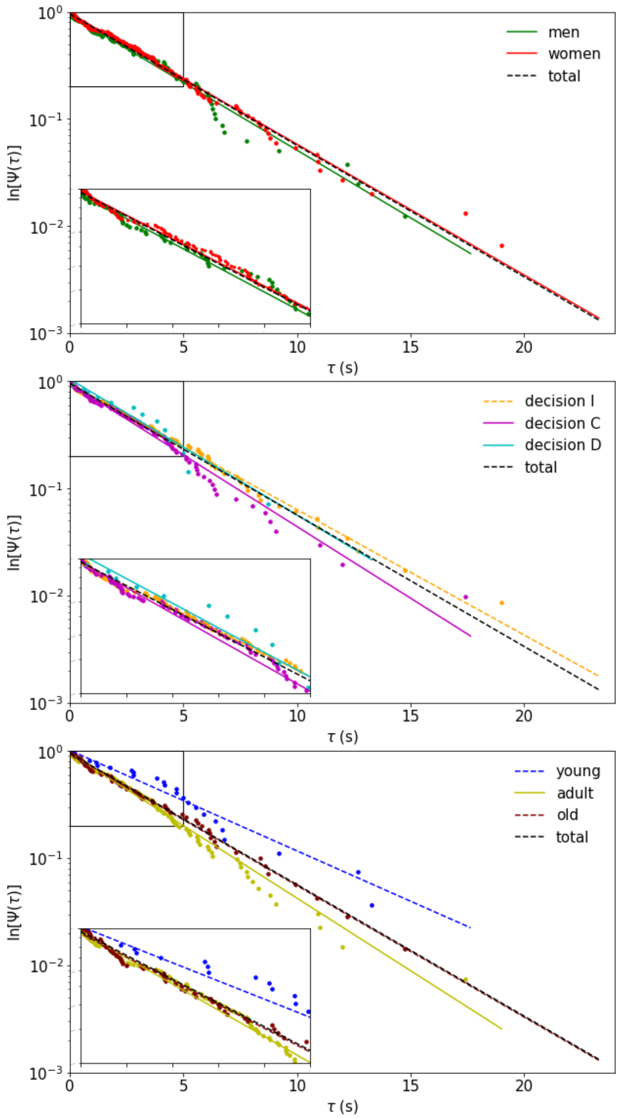

FIG. 2: Semi-logarithmic rank-plot for decumulative density distribution for social groups with Poisson regression adjust. Gender (a), Decision (b) and Age (c).

In Figure 2, we have estimated Poisson regression coefficients from Eq. (1) by using Maximum Likelihood (MLE) method. This allow us to find $1/\lambda = \tau_c$ with an alternative method, collected in Table I. Errors of τ_c are computed by propagating standard error. We confront the linear fit with direct estimation of the first moment $\langle\tau\rangle_{exp}$ whose error is considered to be the standard error of the mean. If interevent times were homogeneous Poissonian random variables τ_c should be similar to $\langle\tau\rangle_{exp}$ for every group. Following our initial hypothesis they all coincide within error range. However, τ_c from groups: Men, Decision D and Young have a relative error greater than 30%. The biggest discrepancy between τ_c and $\langle\tau\rangle_{exp}$ is for Decision D group. The pseudo-R^2 value, tells us that the best adjust is for Decision D although data is very limited and the worst adjust is from the total data together. This last finding confirms the social heterogeneity present in the experiment.

Group	N	$\langle\tau\rangle_{exp}$ (s)	τ_c (s)
Total	230	3.4±0.2	3.5±0.7
Men	77	3.3±0.4	3±1
Women	150	3.5±0.3	3.6±0.8
Dec. I	115	3.6±0.4	4±1
Dec. C	101	3.1±0.3	3.3±0.9
Dec. D	14	3.9±0.9	3±2
Young	27	4.8±0.8	5±2
Adult	133	3.1±0.3	3.2±0.8
Old	70	3.5±0.5	4±1

TABLE I: N shows group sample, $\langle\tau\rangle_{exp}$ is the experimental mean of interevent times and τ_c corresponds to the Poisson MLE regression shown in Figure 2. Time measured in seconds.

D. Valley Model

The Valley Model was proposed by Scher and Montroll [7] and it is based on the existence of heterogeneous potential wells of depth ϵ for trapped electric carriers. After a time interval each carrier jumps to another potential valley [5]. The energy is a random variable described by a energy density $\rho(\epsilon)$. Hence, PTD is defined as

$$\Psi(\tau) = \int_{-\infty}^{\infty} \Psi(\tau|\epsilon)\rho(\epsilon)d\epsilon, \tag{2}$$

where the conditional PTD is given by: $\Psi(\tau|\epsilon) = e^{-\frac{\tau}{\tau_0(\epsilon)}}$. Here, the characteristic time of the distribution is defined as $\tau_0(\epsilon) = Ae^{\beta\epsilon}$ where β is related with the thermal energy $\beta^{-1} = K_B T$. Without leaving the Poissonian context, it can be demonstrated that long tails in PTD can emerge, due to the heterogeneous form of the energy density $\rho(\epsilon)$. A remarkable property of a power law distribution is the "scale invariance" or the "self-similarity". The influence of scale symmetry on objects is reflected in the emergence of power laws and criticality [1].

E. Multifractal analysis

The multifractal formalism is a statistical description that provides global information on the self-similarity properties of fractal objects [1]. Self-similarity is expressed in the geometrical domain with application to fractals. A multifractal is in contrast a local quantity and is a generalization how self-similarity changes from point to point. The standard method to test for multifractal properties consists in calculating the so-called moments of order q:

$$\langle \tau^q \rangle = \int_0^\infty \tau^q \psi(\tau) d\tau = \int_0^\infty \tau^q d\tau \int_{-\infty}^\infty \psi(\tau|\epsilon)\rho(\epsilon) d\epsilon \quad (3)$$

where $\psi(\tau)$ is $d\Psi/d\tau$ defined in Eq. (2). The process will show multifractality if q-moments have the form:

$$\langle \tau^q \rangle \sim L^{f(q)} \quad (4)$$

when $f(q)$ is a nonlinear function of q. When $f(q)$ is linear, the process is monofractal. In order to study the multifractality of our system, we use here the generalized form of q moments given by [5]:

$$\langle \tau^T \rangle \sim \begin{cases} L^q l^{q^\alpha} & \text{when} \quad q < 1, \\ L^q & \text{when} \quad q \gg 1. \end{cases} \quad (5)$$

The $\alpha \neq 1$ is a parameter accounting for the multifractal behaviour in our system and that can be related to the density $\rho(\epsilon)$, l and L are exponential functions related with system scales. In Figure 3, we have plotted q-moments for interevent time groups in order to study the heterogeneity of our data through a fractal analysis. We observe a recognizable monofractal behaviour for all data groups starting from $q = 7.5$. In the first column of Table II, we have collected the slopes from linear regressions for monofractal behaviour plotted in Figure 3. We observe general significant differences between values of three columns. However, if we pay attention on the errors we see that in some cases exceed the value itself, this is the case of series Decision D, Young and Old. Coinciding $\ln(L)$ and $\ln(\tau_c)$ (see Eq. (1)) within the error range is a way to see how values are widespread inside a group. Another possibility to observe multifractality, is by plotting $f(q)/q$. Monofractal data should converge monotonically around 1 [5]. As we see in Figure 4, we may say that only for values of q greater than 10 data start to converge.

Group	$\ln(L)$	$\ln(\tau_c)$	$\ln\langle\tau\rangle_{exp}$
Total	3.1285 ± 0.0009	1.3 ± 0.5	1.23±0.07
Women	3.1337 ± 0.0006	1.2 ±0.9	1.2± 0.1
Men	2.8540 ± 0.0006	1.3± 0.6	1.25± 0.09
Dec. I	3.1372 ± 0.0004	1.3 ±0.7	1.3 ±0.1
Dec. C	2.8635 ± 0.0001	1.2 ±0.8	1.1± 0.1
Dec. D	2.5862 ± 0.0001	1± 2	1.4± 0.2
Young	2.8629 ± 0.0004	2± 2	1.6 ±0.2
Adult	2.9253 ± 0.0003	1.2 ±0.7	1.13± 0.09
Old	3.1473 ± 0.0001	1± 1	1.3± 0.1

TABLE II: $\ln(L)$ corresponds to the slopes of the monofractal range for Figure 3, $\ln(\tau_c)$ and $\ln\langle\tau\rangle_{exp}$ are the logarithms of values from Table I.

Paying attention in Figure 3, we can observe that smaller q values differ from linear behavior. As shown in Figure 4, data series for small q values behave slightly different from each other. These are multifractal behaviour indicators. In order to test multifractality, Figure 5 adjusts a curve for the smaller q values with a polynomial form of $aq + bq^\alpha$ (see Eq. (5)). The parameters of adjusted curves are reported in Table III, where coefficient a corresponds to $\ln(l)$ using definitions from Eq. (5).

Figure 5 allow us to confirm multifractal behaviour of interevent response time. This plot confirms that we can reach to new information using multifractal analysis. We see that the higher α exponents, further diverging from monofractal behaviour is for Old people and Decision D groups.

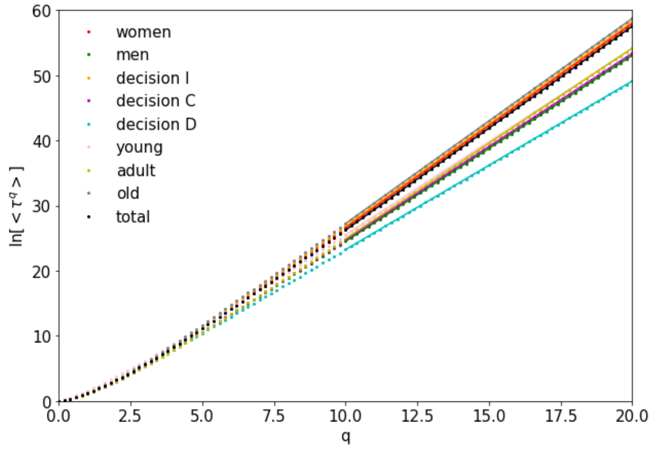

FIG. 3: Interevent time q-moments as a function of q with linear regressions in the range between 10 and 20 q values.

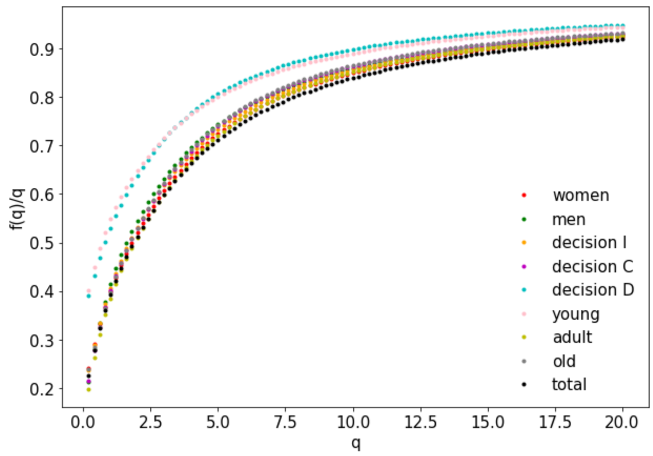

FIG. 4: Modified interevent time q-moment as a function of q. It shows $f(q)/q$ as a function of q.

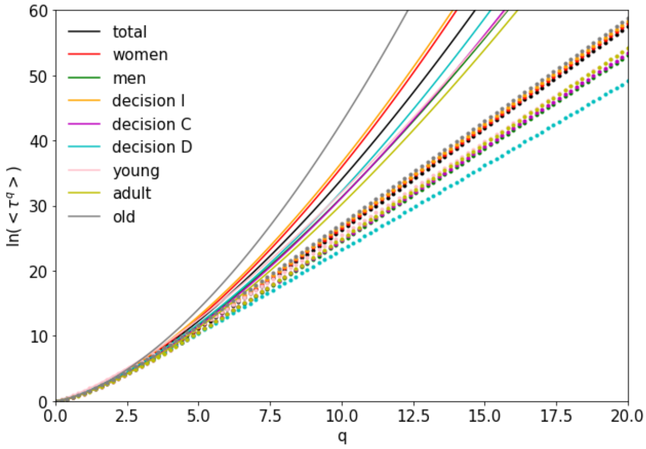

FIG. 5: Fitted polynomial curves with the form $aq + bq^{\alpha}$ as a function of q for multifractal behaviour in $q < 1$.

Group	a	b	α
Total	0.30 ± 0.03	0.93 ± 0.03	1.52 ± 0.02
Women	0.43 ± 0.02	0.82 ± 0.02	1.59 ± 0.02
Men	0.003 ± 0.045	1.18 ± 0.04	1.42 ± 0.02
Decision I	0.36 ± 0.03	0.91 ± 0.03	1.56 ± 0.02
Decision C	0.14 ±0.03	1.00 ±0.03	1.47 ± 0.02
Decision D	0.80 ± 0.01	0.57 ± 0.01	1.63± 0.02
Young	0.80 ±0.03	0.77± 0.03	1.49 ± 0.03
Adult	0.04 ± 0.03	1.08 ± 0.03	1.44 ± 0.02
Old	0.51 ± 0.02	0.75 ± 0.02	1.70 ± 0.02

TABLE III: Parameters of fitted curves for multifractal behaviour for $q < 1$ from linearizing Eq.(5) using a polynomial fit $aq + bq^{\alpha}$.

III. CONCLUSIONS

Citizen science experiments have opened the door to explore using physical approaches the social behaviour in urban contexts. In a gender violence situation, response time is crucial because not acting or doing it too late makes us complicit. In this work we have made use of several known procedures common in physics to test interevent time models. Studying the same phenomena from different perspectives allow us to identify valuable information in human decision making in crowded environments.

We noticed that using a decumulative rank plot distribution for separated groups already warns us about how interevent times are distributed. Deciding not to intervene (D) requires in general more time than to intervene (C) by looking in the mean, although Poisson regression analysis would give us a longer mean rate for Decision C than for Decision D. This may indicate that long-tails in homogeneous Poisson regression modify the adjust due to the presence of subgroups that take much more time (much longer than the mean) to decide. The appearance of long tails and extreme events can be studied further by a multifractal analysis. The Valley Model formalism enables the appearance of long tails by changing the form of the energy density even we have a limited data set. We found a multifractal behaviour for low range of q values. With the adjusted curves we have been able to model a non-linear function that characterizes this behaviour. In this context, a multifractal analysis is a useful tool to start characterizing criticality with the purpose of understanding better human behaviour in social contexts.

Gender-based violence in public space is a reality that affects many people every day but it is highly invisible and normalized because it is a structural phenomenon deeply attached in our society that sustains and legitimizes it. Awareness and information are key to identify and combat these prejudices. Therefore, one way to move towards a fairer and less violent society may be to work on strategies to identify them.

Acknowledgments

I would like to thanks my advisor Josep Perelló for his dedication and guidance and also to Andrea Calsamiglia for her attention introducing me the social psychology context of the study.

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