How Long are Real-Life Events?

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Abstract

Research in event cognition has focused on how people perceive and remember events under experimental conditions. This research study aims to explore the temporal duration of self-reported events from daily life (Sreekumar, et al., 2018; Zhuang, et al., 2012). The small amount of prior work that exists suggests that daily event durations have a Gaussian distribution and that people have prior beliefs that reflect this reality (Griffiths & Tenenbaum, 2006). Forty-eight participants provided activity duration data as they went about their everyday lives for 14 days. Descriptive analyses and activity duration modeling (mixture models of gaussian, gamma, normal and exponential distributions) were used to characterize event durations within activity types. Results show that most of the events present an exponential pattern of durations, while others show a bimodal pattern. Although some preplanned events have a characteristic time, many daily events have a substantial exponential component.

Keywords: Event duration; Smartphone data; Sampling methods; Cognition.

Introduction

Events occur all around us in a constant swirl of activity and yet we think and talk about them as discrete units. These event segmentations are the building blocks of our understanding of what is happening, our memories of what happened, and our plans for the future (Zacks & Tversky, 2001). While the formation of these conceptual event units is influenced by external reality, it is a cognitive process and depends on how people segment the stream of experience. Or in the words of Schwartz (2008:54), "Events are not simply out there and ready-made, waiting to be seen, recognized, or described; they are what we make of them".

In this paper, we investigate the duration of conceptual event units. Events can span wide temporal scales from the formation of star systems through to the hit of a tennis ball against a glass window. However, almost all event segmentation research has been carried out at the scale of seconds to minutes. This restriction is largely due to the methodological constraints of lab-based experimental research. How long are the events which people create as they go about their daily lives and how are these durations distributed?

There has been very little research on event durations. Griffiths & Tenenbaum (2006) asked individuals to make predictions about numeric quantities of everyday phenomena, of which two were of daily routines: baking a cake and watching a movie. They inferred participants' prior beliefs about the distribution of the numeric quantities using a Bayesian model. Participants were given a reference time point, and asked to estimate how long it would continue. They found that people's beliefs about these event durations were Gaussian.

A second study on daily events by Lewandowsky, Griffiths & Kalish (2009) also asked people to predict outcomes of two everyday events: cake baking and movie watching. They used a within-subject version of the prediction task and iterated learning. Also, they analyzed the individual level and not the aggregate level. Their responses were consistent with Griffiths & Tenenbaum (2006); the two events, cake baking and movie watching, presented Gaussian distributions. However, these studies considered only two types of events, both of which are likely to have clearly defined expectations of duration and end-point.

Zhuang et al. (2012) used a lifelogging device and sensors to measure daily activities, not only for seconds or minutes but

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also for hours and days. They asked participants to wear an Android phone to capture GPS location, audio, and capture images while participants performed their daily activities. Participants collected daily events through their smartphones for four weeks. They were also asked to segment their images into different events and then tag each episode with a set of tags. Using data from Zhuang et al. (2012), we plotted the distribution of event durations. The results showed that duration did not have a Gaussian distribution; indeed, it seems they have a skewed distribution (see Figure 1 and Figure 2).

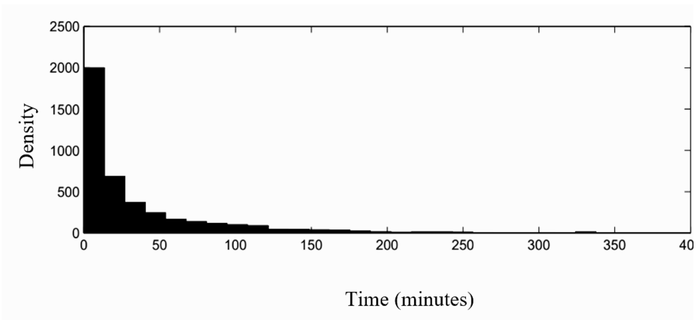

Figure 1: Daily activity distribution from Zhuang et al. (2012) study.

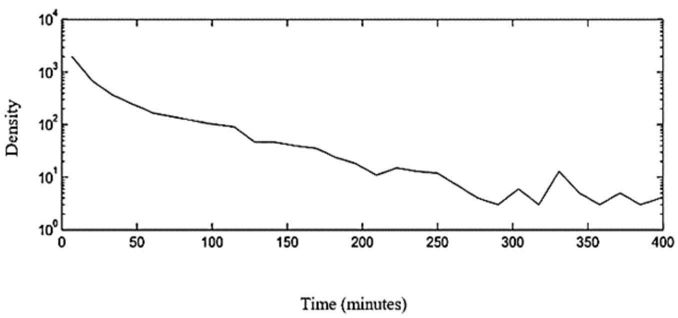

Figure 2: Event distribution histogram on a log scale from Zhuang et al. (2012) study.

None of these studies were primarily aimed to investigate event duration and they all have clear limitations when reexamined for this purpose. Griffiths & Tenenbaum (2006) and Lewandowsky, Griffiths & Kalish (2009) found a consistent Gaussian distribution, but this was only with two specific types of events. Zhuang et al. (2012) included a broad range of everyday events and found a skewed distribution. However, as there was no breakdown by event types, it is possible that the skewed pattern is a consequence of combining events of many types, each of which has its own distribution. In this paper, we aim to explore the temporal duration of self-reported daily events using contemporary sampling methods and differentiating event type categories.

Method

Participants

A group of 48 participants over the age of 18 were recruited from the Unforgettable Research Services pool (www.unforgettable.me) and Facebook student groups. Unforgettable.me is an experience-sampling platform that allows users to collect and analyze private data from participants' daily lives without viewing it (Dennis, Yim, Garrett, Sreekumar, & Stone, 2019).

Participants were compensated between \$60.75 and \$97.50 AUD depending on how many surveys were completed. Due to a lack of Wi-Fi, five of the participants were excluded; three of them withdrew, and one participant was excluded because their phone was not compatible with the study requirements. The final sample included forty participants (28 females, 12 males, mean age = 30.4). All participants gave written informed consent.

Materials

Participants received microsurveys as they went about their normal lives. Each survey asked four questions about the immediately preceding event: When did the event start?; What sort of event was it?; Where was the event located?; Who did you do the event with? Participants were instructed to fill out the survey when they had finished what they were doing and to answer the survey in relation to the immediately preceding event. The time of the survey was thus taken to be the end time of the event and the event duration was calculated as the difference between this survey time and the participant provided start time.

The Activity type, Location, and People questions required multiple choice responses with options based on Sreekumar et al. (2018). There were 15 subcategories of Activity type, 17 for Location, and 10 for People, listed in Table 1. Each question included an "other" response option which allowed participants to enter a free text description. Order of options was randomized in each survey. Participants could select more than one option for the Activity and People categories. However, for the Location category, they could only select one option. For this study, we only considered and analyzed the activity category.

Table 1: Events segmentation survey categories.

Categories	Tags
Events (15)	- Watching movies/TV/listening to a concert/other performance - Exercising/playing sport/ dancing/walking/running - Reading/writing - Eating/drinking - Work (studying, working at a desk) - Other non-desk work (e.g. bar-tending, paramedic, carpenter, vendor) - Meeting/talking/chatting/discussing - Chores (cooking, cleaning, laundry) - Transiting (drive/fly/bus/taxi, other vehicles) - Shopping - Using social media - Praying/meditating - Sleeping/napping - Personal grooming/hygiene (e.g. brushing teeth, showering, doing hair) - Other activity
People (10)	Alone, Family, Friends, Colleagues, Classmates, Pet(s), Strangers, Crowd, Partner, Other
Places (17)	Home, Work, Store, Library, Park, Restaurant/café, Office, Gymnasium, Garden, Church, Beach, School, Farm, Sports field, Street, In transport (car/airplane/ship/truck and rail), Other places.

Procedure

Participants were prompted to fill out the survey using an ecological momentary assessment (EMA) application called SEMA3 (Koval, Hinton, Dozo, Gleeson, Alvarez, Harrison, & Sinnott, 2019). Seven survey notifications were semi-randomly distributed between 8:00am and 8:00pm each day for 14 consecutive days. On average, survey notifications were separated from each other by 2 hours. Following the notification, participants had around 80 minutes to complete each survey. Compliance was high: overall, participants responded to 91.45% of the surveys (M=8,963 surveys, SD = 13).

Data analysis

Activity duration modeling was used to identify the distribution of event durations within activity types. The present study considered five different models; the first one is the Gaussian model which was included based on the in which there is evidence that people believe that daily events have a normal distribution (Griffiths & Tenenbaum, 2006). The second model that we explored was an exponential distribution, which we chose to capture the skewed pattern found in the Sreekumar et. al (2018) data. One conceptual peculiarity of choosing an exponential model is that it assumes that the most probable event duration is 0. To allow for a non zero mode, we also included the gamma distribution. Finally, we also included mixture models of the exponential and normal and exponential and gamma distribution as some categories (e.g. sleep) had distributions that seemed to have both a standard time as well as a skewed component.

For each type, we fit five models as follows:

Normal:
$duration[i] \sim Norm(\mu, \sigma)$
$\mu \sim Norm(400)$
$\sigma \sim Norm(100)$

Exponential:
$duration[i] \sim Exp(\lambda)$
$\lambda \sim Exp(1)$

Gamma:
$duration[i] \sim Gamma(\alpha, \beta)$
$\alpha \sim Exp(2)$
$\beta \sim Gamma(1, 0)$

Exponential Normal Mixture:
$duration[i] \sim ExpNormal(\lambda, \mu, \sigma, mix)$
$\lambda \sim Exp(1)$
$\mu \sim Exp(400)$
$\sigma \sim Exp(100)$
$mix \sim Uniform(0, 5)$

Gamma Normal Mixture:
$duration[i] \sim GammaNormal(\alpha, \beta, \mu, \sigma, mix)$
$\alpha \sim Exp(2)$
$\beta \sim Gamma(1, 0)$
$\mu \sim Exp(400)$
$\sigma \sim Exp(100)$
$mix \sim Uniform(0, 5)$

The estimation was conducted in nimble R version 0.12.1 (Nimble, 2021). For each model, 11000 MCMC samples were taken. The first 1000 were discarded. The widely applicable information criterion (WAIC) was used to select the best model (Watanabe, 2013).

Results

Table 2 shows the WAICs for each model for each activity. Bolded results indicate the best fitting model. When the differences between models were less than five we have bolded all results as the data does not clearly distinguish them

Table 2: WAIC score for four distribution models.

	WAIC				
	Normal Model	Exponential Model	Gamma Model	Exponential Normal Mixture Model	Gamma Normal Mixture Model
All Data	25810	22797	22775	22577	**22564**
Watching movies/TV / listening to a concert	2546	2223	2222	**2191**	2210
Using social media	2646	2314	2317	**2299**	2304
Sleeping/napping	1864	1672	1666	**1631**	1639
Eating/drinking	5073	3983	3986	**3973**	**3974**
Work (studying, working)	7078	5271	5273	**5253**	**5252**
Meeting/talking/ chatting	4463	3372	3375	**3358**	**3360**
Chores	1742	1428	1433	**1389**	**1391**
Personal grooming/hygiene	1280	**1161**	1167	**1163**	1169
Exercising/play sport	1129	**1024**	**1029**	**1026**	1031
Reading/writing	731	**690**	**695**	**692**	704
Transiting	1726	**1642**	**1644**	**1645**	1648
Shopping	877	**770**	**774**	**769**	778
Other non-desk work	767	**690**	**691**	**693**	**693**

Note: We decided to exclude two events in the analysis process: 'Praying/meditating' due to lack of data and 'Other activity' because it included qualitative data.

Table 3: Parameters of mixed models

	Exponential Normal Mixture Model								**Gamma Normal Mixture Model**									
	λ	SD	μ	SD	σ	SD	mix	SD	α	SD	β	SD	μ	SD	σ	SD	mix	SD
All Data	0.017	<.001	449.4	27.7	174.6	16.7	0.953	0.006	1.106	0.033	0.019	0.001	436.9	25.9	176.1	15.2	0.949	0.007
Watching movies/TV/ listening to a concert	0.018	0.002	436.8	61.9	163.5	45.8	0.926	0.023	0.740	0.154	0.008	0.004	145.5	182.7	53.1	62.0	0.732	0.139
Using social media	0.019	0.002	409.6	102.6	175.8	87.3	0.965	0.017	0.975	0.091	0.016	0.002	420.6	129.3	189.5	157.3	0.970	0.020
Sleeping/napping	0.016	0.002	420.6	22.7	106.1	18.0	0.739	0.041	0.837	0.109	0.009	0.002	434.4	22.7	91.9	21.1	0.791	0.050
Eating/drinking	0.020	0.001	447.5	231.4	429.2	362.0	0.990	0.006	1.031	0.065	0.020	0.002	453.6	227.5	438.6	364.3	0.991	0.006
Work (studying, working at a desk)	0.013	0.001	516.0	79.6	175.5	58.8	0.966	0.013	1.074	0.071	0.013	0.001	514.3	81.0	175.3	66.0	0.965	0.013
Meeting/talking	0.016	0.001	500.7	194.5	344.3	303.7	0.980	0.012	1.015	0.076	0.016	0.002	509.7	206.3	341.5	245.8	0.982	0.011
Chores	0.025	0.002	539.3	222.2	388.3	297.6	0.970	0.015	1.045	0.106	0.022	0.003	568.1	214.0	353.8	256.0	0.971	0.015
Personal grooming/hygiene	0.019	0.002	266.5	258.0	523.0	862.5	0.963	0.043	0.862	0.101	0.013	0.002	314.2	349.9	782.1	1133	0.979	0.031
Exercising/play sport	0.017	0.002	311.4	313.0	639.7	826.5	0.973	0.033	0.818	0.105	0.012	0.002	319.7	363.3	716.1	900.1	0.967	0.054
Reading/Writing	0.017	0.002	276.9	316.2	639.3	814.0	0.943	0.087	0.598	0.180	0.006	0.003	59.3	11.4	33.8	11.4	0.454	0.211
Transiting	0.018	0.002	215.5	282.5	412.1	617.3	0.930	0.096	0.970	0.139	0.016	0.003	173.0	252.5	282.5	467.2	0.886	0.129
Shopping	0.018	0.002	373.2	291.0	595.8	655.2	0.964	0.043	0.579	0.235	0.003	0.002	49.4	5.6	31.5	5.373	0.193	0.137
Other non-desk work	0.007	0.002	476.5	303.6	611.0	737.5	0.921	0.064	0.739	0.121	0.004	0.001	378.7	366.7	653.6	801.6	0.945	0.063

The best fit for the data aggregated across all event types was provided by the gamma normal mixture model. However, this was not a clearly dominant pattern for any of the individual event type categories.

The exponential normal mixture model was either the preferred model (three event types) or one of the preferred models (12 event types) for all event type categories. An example of this pattern can be seen with the sleeping and napping events. Figure 3 shows the histogram of duration values with the line showing the fit of the exponential normal mixture model. There are two clear components: an exponential in the left part of the graph and a normal around a duration of approximately 7 hours towards the right. These two components likely correspond to naps and overnight sleeps respectively, two subtypes which are likely to have distinct temporal structures.

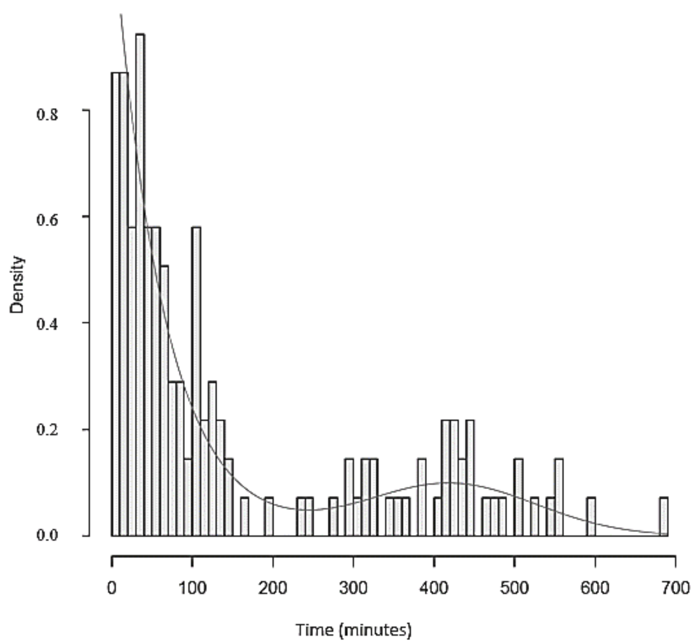

Figure 3: Histogram of the durations of sleeping and napping events measured in minutes. The black line is the fit of the exponential normal mixture model with the mean parameter.

In five cases, the mixture models were preferred over the exponential, normal or gamma models, but there was no clear discrimination between the mixture models. An example of the fit of a gamma normal mixture model can be seen for the working and studying event category in figure 4.

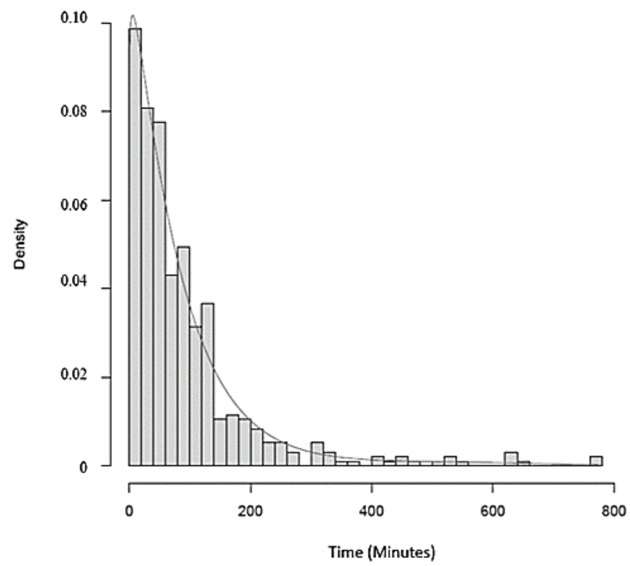

Figure 4: Histogram of the durations of working and studying events measured in minutes. The black line is the fit of the gamma normal mixture model with the mean parameter.

In reality, it is highly unlikely for events to actually have zero durations, so the gamma model is theoretically more motivated. However, the difference between an exponential model and a gamma model with an alpha value near 1 are difficult to discriminate and this seems to have led to widespread indiscriminability between the exponential and gamma models across many of our event types, see Table 3 for model parameters.

A simple skewed model was among the preferred models for eight of the event type categories: grooming, exercising, reading/writing, transiting, shopping, praying/meditating, other non-desk work, and other. While it was not possible to discriminate between the simple skewed model and the exponential normal mixed model in these cases, the normal component was relatively flat. This can be seen in figure 5 showing the exponential normal mixture model for exercising (figure 5A) and grooming (figure 5B). See also the model parameters in Table 3.

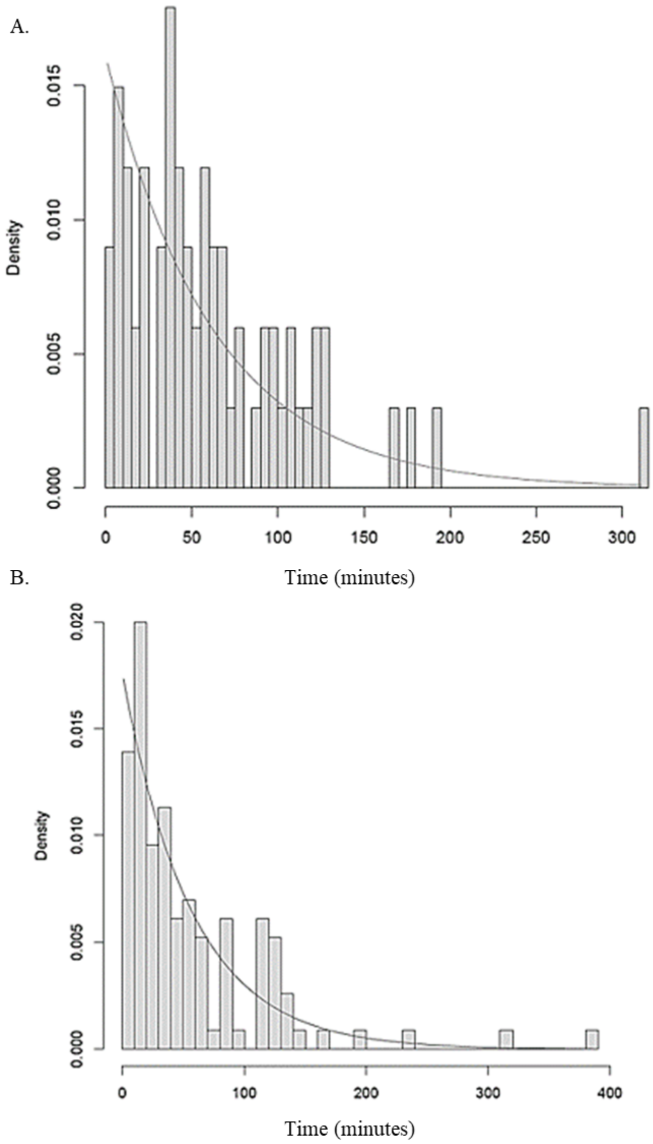

Figure 5: These density histograms for duration measured in minutes illustrate the exponential normal mixture model. The black line is the fit of the model with the mean parameter. Figure 5A shows the event distribution of exercising/playing a sport, and 5B represents grooming.

Conclusion

The results of this experiment are consistent with previous studies by Zhuang, et al. (2012) and Sreekumar, et al. (2018). In all event type categories, the durations of people's reported daily events featured a skewed, exponential or gamma distribution. Even when a mixture model involving a normal distribution was preferred, the mixture parameters (see Table 3) were often close to one, indicating that the normal component of the mixture was contributing less than the skewed distributions.

This difference and tendency towards shorter events with a substantial exponential component in their distribution could be due to several factors. It could be that our event categories are still too coarse, containing many subtypes each consisting of different distributions. It could also be due to a real difference in event properties: where planned events with well-defined durations independent of the observer show a normal distribution and unplanned, sporadic events show a more exponential distribution. The truth likely lies in a combination of these factors. This is well-illustrated with our sleeping and napping category. Here we do indeed see two distinct subtypes, and one of them (sleeping) is well-fit by a normal distribution. However, the napping events have a skewed distribution and do not seem likely to resolve into distinct subtypes of normally distributed event durations. Instead, it seems that the duration of a nap can vary but is skewed towards shorter durations.

Additionally, to assume that the duration of events can only fit in Gaussian or exponential distribution models is to assume a dichotomic posture. Our study found that events are dynamic, so event durations not only have an exponential distribution; some of them fit the mixture of exponential plus normal model and the mixture gamma plus normal model. These findings are significant because when events are divided into different types, we see that some events have a normal distribution, which could be because they are part of planned events such as baking a cake. Alternatively, many events are very brief and their durations have a skewed distribution, for instance chatting. This variation likely occurs within the real-life tokens of many event categories, even ones with well-defined expected durations.

What is clear is that when one examines real life events at the scale of minutes and hours, there is substantial heterogeneity. Existing models of event segmentation (e.g. Franklin, Norman, Ranganath, Zacks, & Gershman, 2019) will require extension to capture the range of events that people commonly perceive.

To conclude, we have found that people regularly segment their daily lives into events ranging from seconds through to hours. All of the event type categories we examined showed a substantial exponential component suggesting that many daily events do not have a particular characteristic duration.

Acknowledgments

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