Engaging narratives evoke similar neural activity and lead to similar time perception

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Abstract:

It is said that we lose track of time - that "time flies" - when we are engrossed in a story. How does engagement with a story cause this distorted perception of time, and what are its neural correlates? People commit both time and attentional resources to an engaging stimulus. For narrative videos, attentional engagement can be represented as the level of similarity between the electroencephalographic responses of different viewers. Here we show that this measure of neural engagement predicted the duration of time that viewers were willing to commit to narrative videos. Contrary to popular wisdom, engagement did not distort the average perception of time duration. Rather, more similar brain responses resulted in a more uniform perception of time across viewers. These findings suggest that by capturing the attention of an audience, narrative videos bring both neural processing and the subjective perception of time into synchrony.

Keywords: Inter-subject correlation; EEG; naturalistic stimuli; engagement

We operationally define engagement as the commitment to devote inherently limited resources to a stimulus. Unlike self-report assessments, commitment can be estimated objectively using the resources (time, money, etc.) that an individual is willing to allocate to a stimulus. Engagement can therefore be assessed like other value-based decisions using a comparison between the worth of the narrative stimulus and that of possible alternatives (Rangel, Camerer, & Montague, 2008).

Time commitment can be calculated from an online video's ability to retain viewers. For a large enough audience, this can be measured from viewership survival, $S(t)$, defined as the fraction of the audience that "survives" until time, t, in the video. The rate at which the audience shrinks is the risk of viewership loss ($\lambda(t)$). When the stimulus evokes a high level of engagement, the risk of losing viewers is low. Conversely, when the audience is not engaged, the risk is high. Behavioral engagement is therefore defined quantitatively for the first time as the inverse of the risk of losing viewers:

$$E(t) = 1/\lambda(t)$$

Raw viewership survival data, $S(t)$, from which engagement is derived, was acquired for online videos in both the real-world (courtesy of StoryCorps) and in an experimental condition.

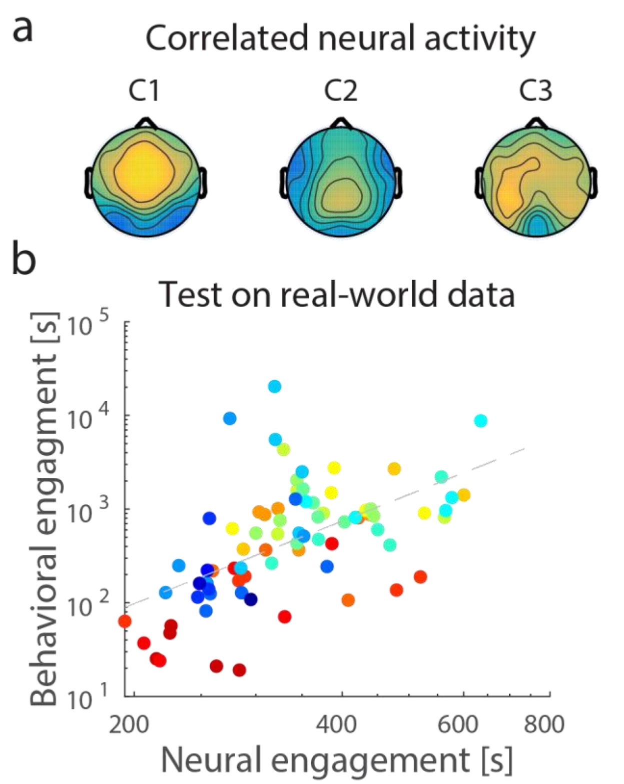

Figure 1: Neural Engagement predicts Behavioral Engagement.

The similarity of electroencephalographic (EEG) evoked responses across viewers may be a neural marker of engagement (Dmochowski, Sajda, Dias, & Parra, 2012). To test this with the proposed behavioral measure of engagement, inter-subject correlation (ISC), measured using components of EEG that strongly correlate across viewers, was extracted from the neural activity of 20 individuals who watched the same videos for which behavioral engagement had been assessed (data and methods the same as in Cohen & Parra, 2016). Time resolved ISC in the *i*-th correlated component is denoted as $x(t) = [x_1(t), x_2(t), x_3(t)]$ for the three strongest components used to predict behavioral engagement (scalp topographies are shown in Figure 1a).

A model was fit to the experimental behavior data, and this model's predictive ability was tested on the real-world behavior data. Here, following the survival analysis literature, a proportional hazard model was used (Cox, 1972), resulting in a regression of engagement, $E(t)$, with a time dependent covariate, $\gamma(t)$, that depends on $x(t)$, and a constant baseline engagement, E_0:

$$E(t) = E_0 \gamma(t) \,.$$

Following the traditional form of the proportional hazard model (Cox, 1972) the time dependent covariate, $\gamma(t)$, equals the exponentiated weighted sum of the predictor variables:

$$\gamma(t) = exp\left[\sum_{i=1}^{3} \beta_i x_i(t)\right] = \prod_{i=1}^{3} \gamma_i\,(t)$$

For the experimental data, approximately 30% of the commitment to watch the stimuli can be attributed to the variation in "neural engagement," $E_0\,\gamma(t)$. This contribution was mainly explained by the second component of the ISC (Figure 1a, C2). To test the neural predictor on unseen data, we compared neural engagement to the real-world audience engagement and find a strong correlation (r = 0.56, p = 0.003, N=78, Figure 1b).

After establishing the validity of both the behavioral and neural measures of engagement, the relationship between stimulus engagement and time perception was assessed. An additional cohort of viewers provided subjective estimates for the durations of brief periods of time during the videos. These time segments judged corresponded to the time intervals over which behavioral and neural engagement were assessed Despite prevalent theories that stimulus engagement induces time distortion (Nakamura & Csikszentmihalyi, 2002), there was no correlation between the mean estimates of time duration and engagement, measured either behaviorally or neurally (p > 0.3). Interestingly, however, neural engagement correlated with the variability of time estimates across viewers (Figure 2, Pilot: r = - 0.27, p=0.0009, N = 129, Replication: r = - 0.23, p = 0.05, N = 129).

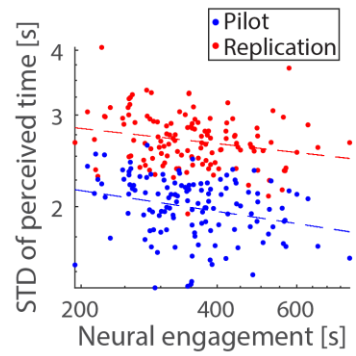

Figure 2: Engagement predicts the variability of time perception.

We conclude that if viewers are similarly entrained by the stimulus (or activity), thus eliciting a high level of ISC, they will be immune to extrinsic costs such as the time or money that they are sacrificing for the current moment's enjoyment. Their perception of time, one of the many valuable resources that they are sacrificing, will thus be driven by the stimulus, and consistently so across viewers.

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