Engagement synchronizes brains and warps time

Samantha S. Cohen[1], Simon Henin[2], and Lucas C. Parra[2]
[1]The Graduate Center at the City University of New York, [2]The City College of New York

Introduction

- What is Engagement?
  - Transportation (Green & Brock, 2000)
  - Identification (Cohen, 2001)
  - Presence (Biocca, 2002)
  - Flow (Csikszentmihalyi, 1997)
- How to measure engagement?
  - Self Report Questionnaires
  - Online: re-tweets, re-postings, comments, click-rate, total audience size

Objective

1. Provide a formal definition for Engagement
2. Develop a quantitative behavioral metric
3. Validate a postulated neurological correlate

Engagement Definition

Proposed definition: The commitment to devote scarce resources to a stimulus.

- Commitment can be estimated objectively using the resources (time, money, etc.) that an individual is willing to allocate
- Here: Measure engagement online using the likelihood that audience members will be retained for an interval of time

Methods

Behavioral Engagement:

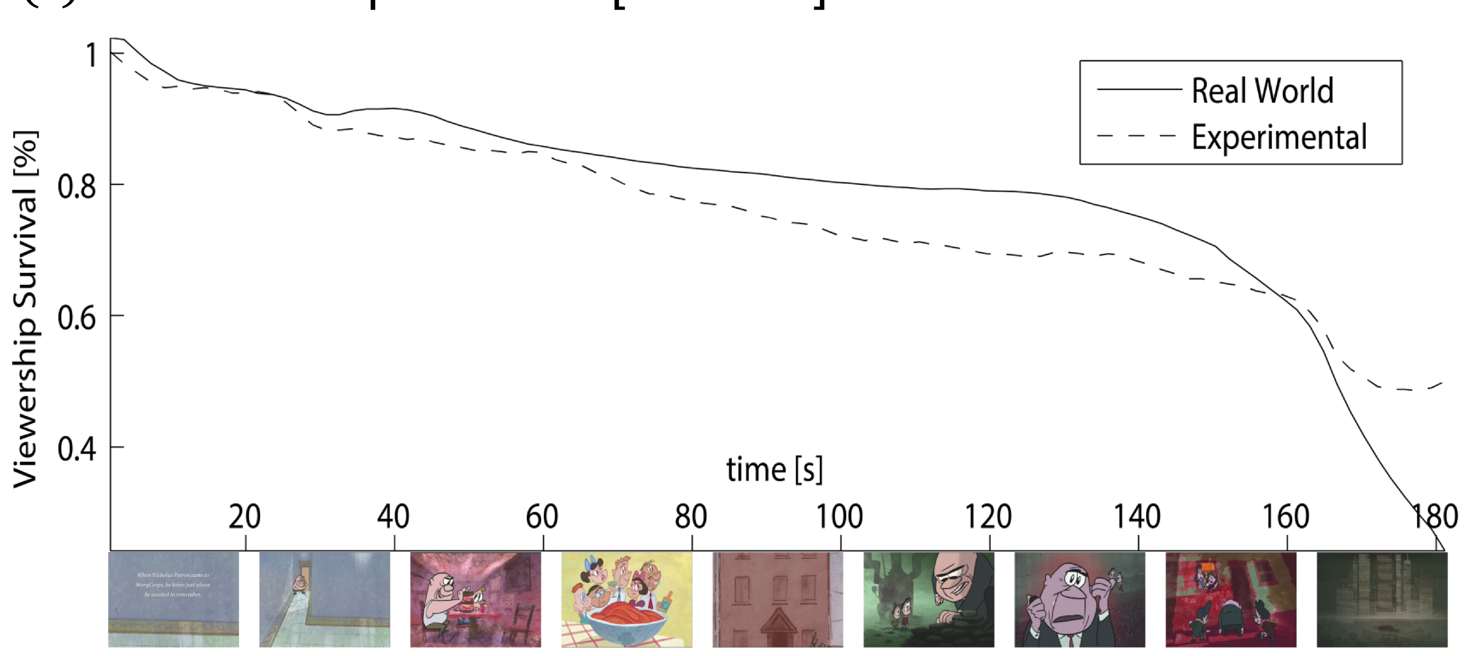
Experimental Data:

- 10 videos
- 1,000 viewers recruited via Amazon's MTurk
- Given an artificial time limit (15 min) to watch videos (27 min total)
- Total data collection duration: ~ 1 hour

Real World Data:

- 5 videos
- Provided by content generator (StoryCorps)
- Total data collection duration: 2.6 +/- 0.8 years (since each video was originally posted online)

$S(t)$ = Viewership Survival [Fraction]:



$\lambda(t)$ = Hazard [1/s]:

$$\lambda(t) = -\frac{1}{S(t)}\frac{\partial S(t)}{\partial t} \approx \frac{1}{S(t)}\frac{S(t) - S(t+\Delta t)}{\Delta t} \qquad (1)$$

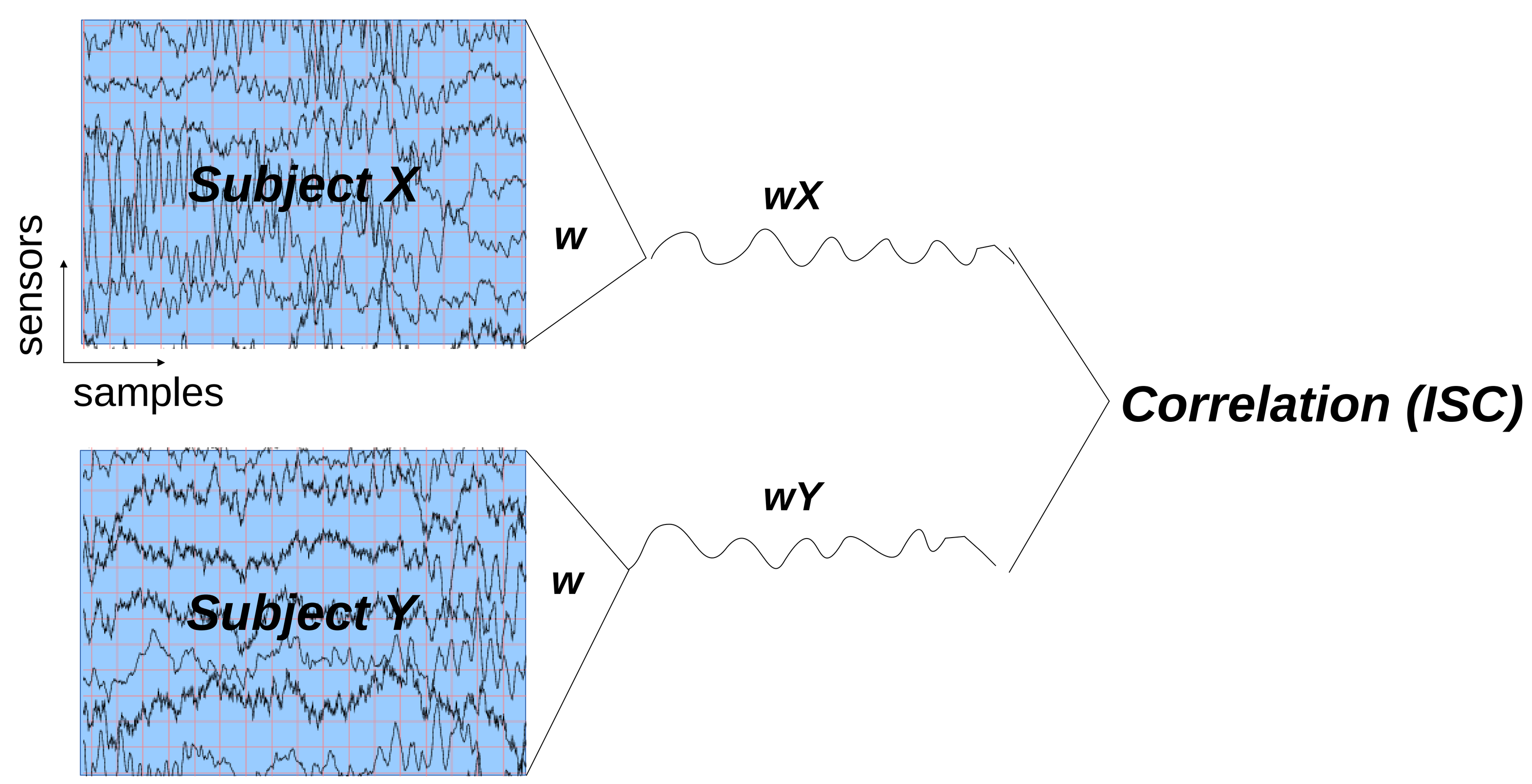
$E(t)$ = Engagement [s]:

$$E(t) = \frac{1}{\lambda(t)} \qquad (2)$$

Neural Engagement:

- EEG evoked by 10 videos (N=22)

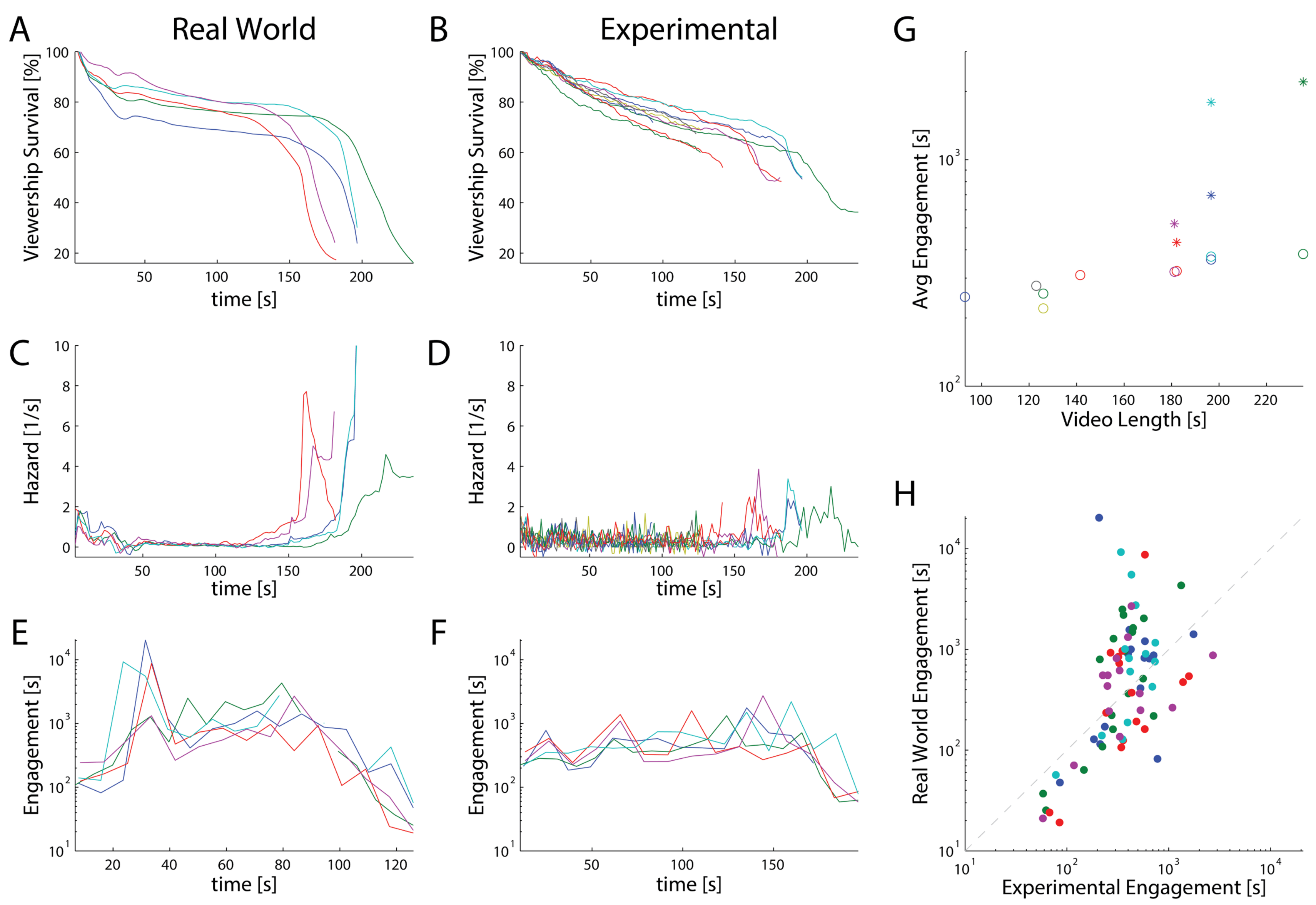
Find Components with Maximal Inter-Subject Correlation (ISC)



Goal: Find spatial projections w such that resultant 1D temporal fluctuations are maximally correlated in time, i.e. evoked responses are reliably reproduced in two datasets

Results

"Experimental" engagement data mimics "Real World."



"Real World" (online viewers, watching at their discretion, left column) vs. "Experimental" (viewers recruited on MTurk, middle column).

- A/B: Survival curves (S(t)).
- C/D: Hazard (Equation 1).
- E/F: Engagement (Equation 2, plotted on a log scale)
- G: Average engagement relative to video duration.
- H: Engagement correlated between "Real World" and "Experimental" data. (Color indicates one of five videos, Points represent Δt=12s)

Can ISC explain variation in engagement?

Hypothesis:

Engagement → Reliable processing → Synchronize brain activity

Use three most correlated components resolved in time (Dmochowski et al., 2012, Ki et al., 2016):

$$x(t) = [x_1(t), x_2(t), x_3(t)]$$

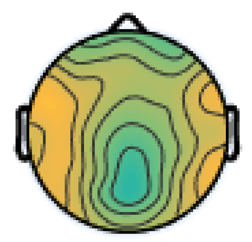
Proportional Hazard Model:

$$E(t) = E_0\,\gamma(t) \qquad (3)$$

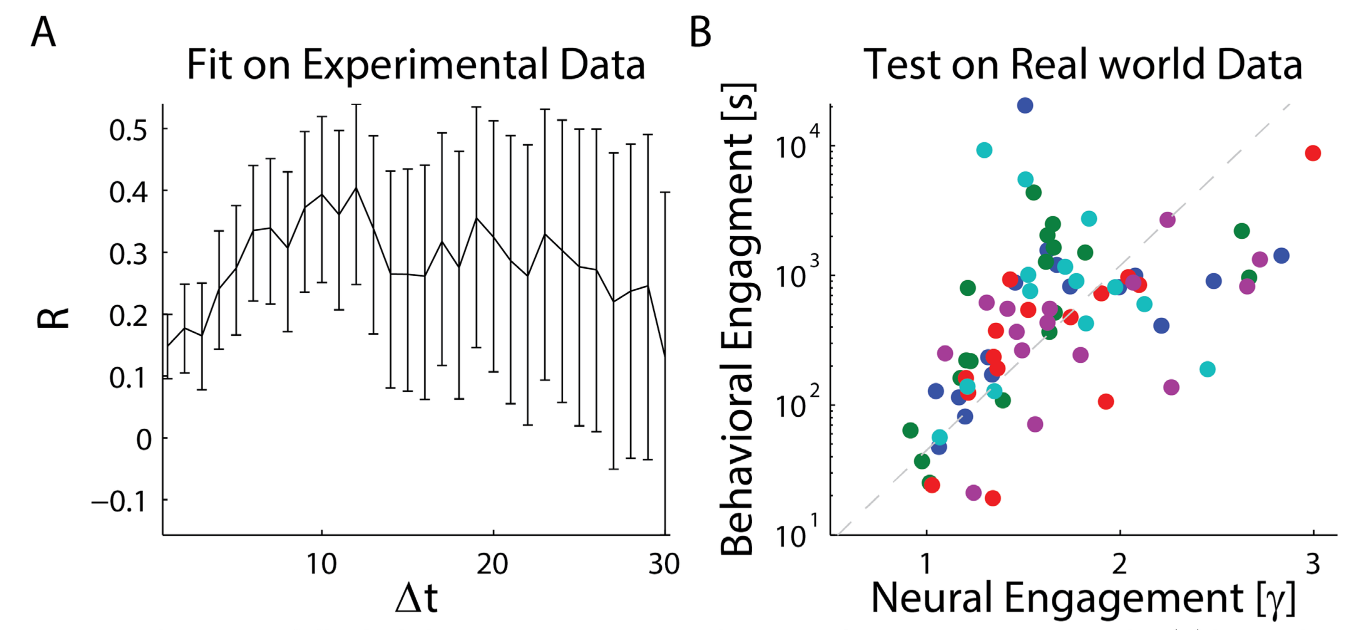
$$\gamma(t) = exp\left[\sum_{i=1}^{3}\beta_i x_i(t)\right] = \prod_{i=1}^{3}\gamma_i(t) \qquad (4)$$

Neural vs. Behavioral Engagement

- Δt = 12 s
- E_0 = 212 s
- $\overline{\gamma_1}(t) = 1.0$, $\overline{\gamma_2}(t) = 1.5$, $\overline{\gamma_3}(t) = 1.1$



Component 2 scalp topography



- A: Goodness of fit (R) between "Experimental" engagement ($E(t)$) and neural engagement ($\gamma(t)$, Equation 3) for different time intervals Δt.
- B: Predictive ability of neural engagement ($\gamma(t)$) on the "Real World" engagement data using the model developed on the Experimental engagement data in the best fitting window of Δt=12s.

Conclusions

- $E(t) = \frac{1}{\lambda(t)}$ = "mean time between failures"
  - Renewal Process
  - An estimate of the level of commitment, not an estimate of expected viewing time
- $\gamma(t)$ may explain the warping of time experienced during engagement
  - Component 2 of ISC contributes most strongly
- Can ISC be used to measure *purely* endogenously motivated attention?

References

Biocca, F. (2002). The evolution of interactive media. Toward being there in non-linear narrative worlds. In M. Green, J. Strange & T. Brock (Eds.), Narrative impact, social and cognitive foundations (pp. 97–130). Mahwah, NJ: Erlbaum.

Cohen, J. (2001). Defining identification: A theoretical look at the identification of audiences with media characters. *Mass Communication & Society*, 4, 245–264.

Csikszentmihalyi, M. (1997). Finding flow: The psychology of engagement with everyday life. New York: BasicBooks.

Dmochowski, J. P., Bezdek, M. A., Abelson, B. P., Johnson, J. S., Schumacher, E. H., & Parra, L. C. (2014). Audience preferences are predicted by temporal reliability of neural processing. *Nature Communications*, *5*(4567), 1–9.

Dmochowski, J. P., Sajda, P., Dias, J., & Parra, L. C. (2012). Correlated components of ongoing EEG point to emotionally laden attention – a possible marker of engagement? *Frontiers in Human Neuroscience*, *6*(112), 1–9.

Green, M. C., & Brock, T. C. (2000). The role of transportation in the persuasiveness of public narratives. *Journal of personality and social psychology.*

Ki, J., Kelly, S., & Parra, L. C. (2016). Attention strongly modulates reliability of neural responses to naturalistic narrative stimuli. *Journal of Neuroscience*.

Acknowledgements: We thank the members of the Parra lab and DARPA for support (Project Title: From Neural to Social Networks, Contract/Grant Number: ARO:W911NF-14-1-0157)