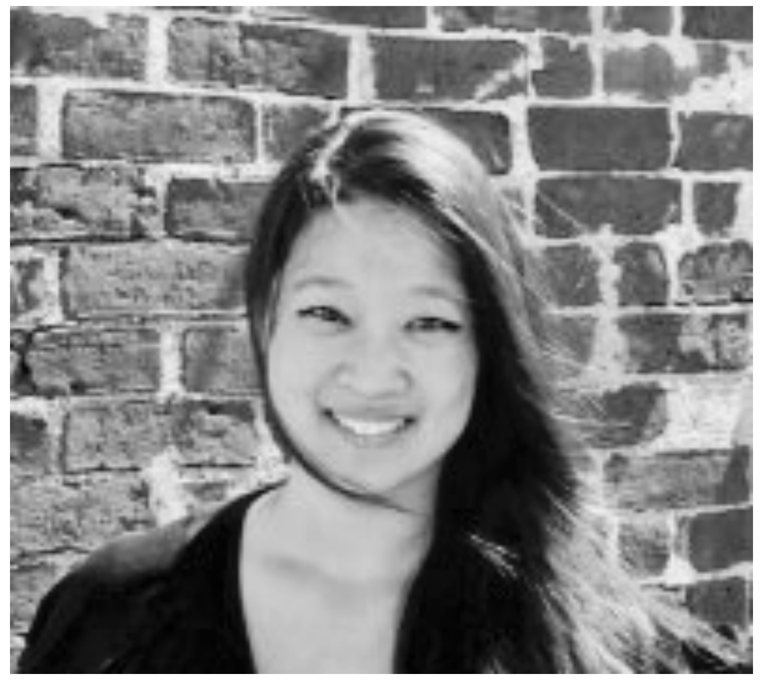
Collective Neuroscience

Thalia Wheatley
Dartmouth
Santa Fe Institute

CSSS 2023

Dartmouth Social Systems Lab


Carolyn Parkinson
Assoc Prof UCLA


Olivia Kang
Director of Learning, Lucid


Adrienne Wood
Asst Prof UVA


Kelly Finn
postdoc


Beau Sievers
postdoc

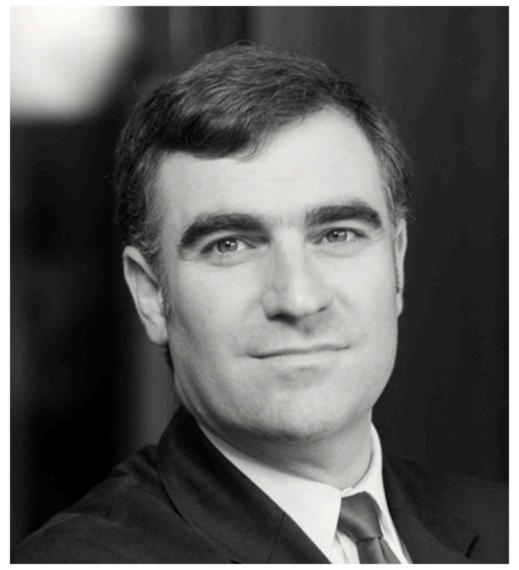

Emma Templeton
graduate student


Sophie Wohltjen
graduate student


Chris Welker
graduate student


Caitlyn Lee
graduate student


Uri Hasson, Princeton


Adam Kleinbaum, TUCK


Adam Boncz. CEU

NSF

NIMH
National Institute of Mental Health

SANTA FE INSTITUTE

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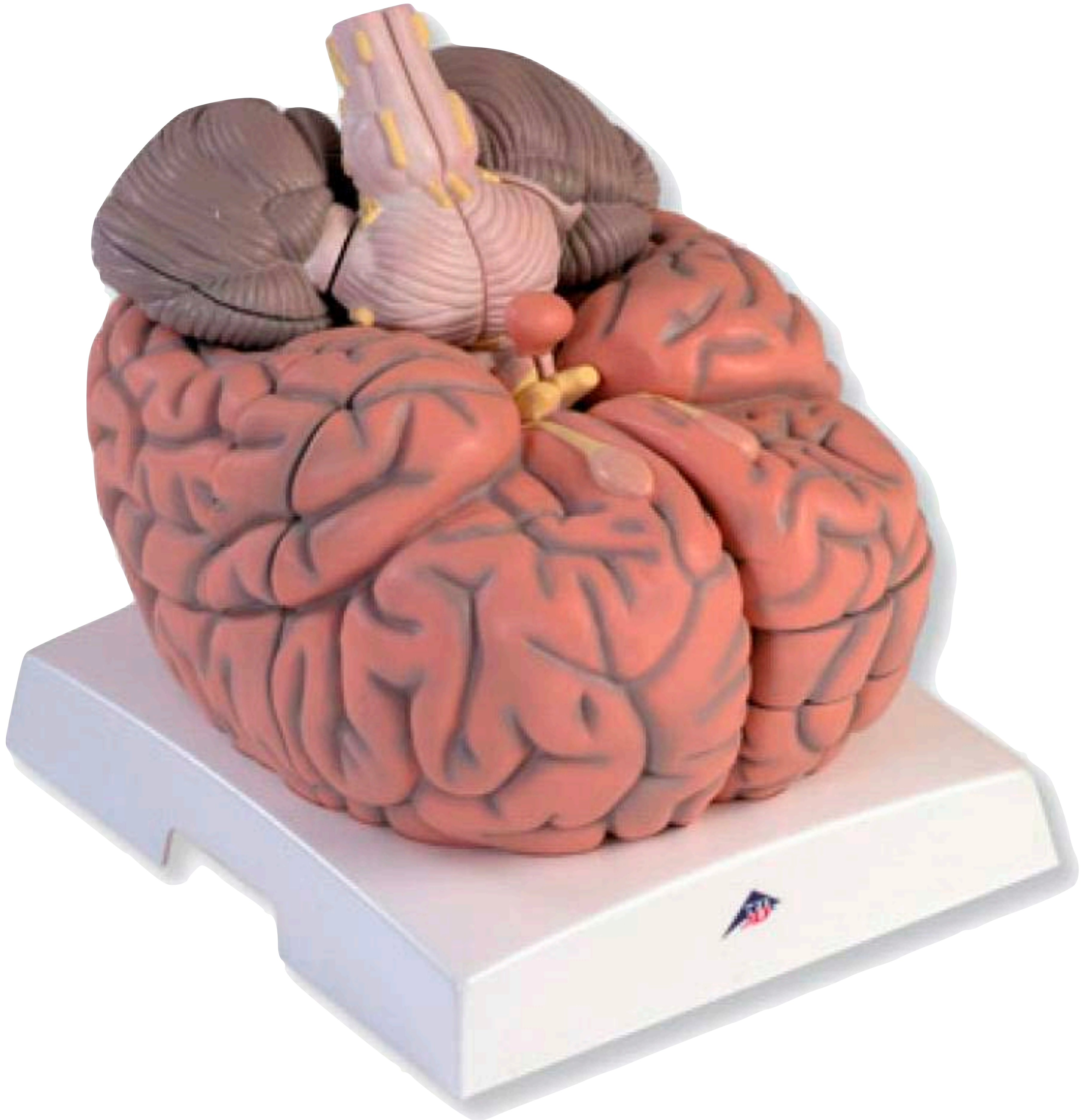
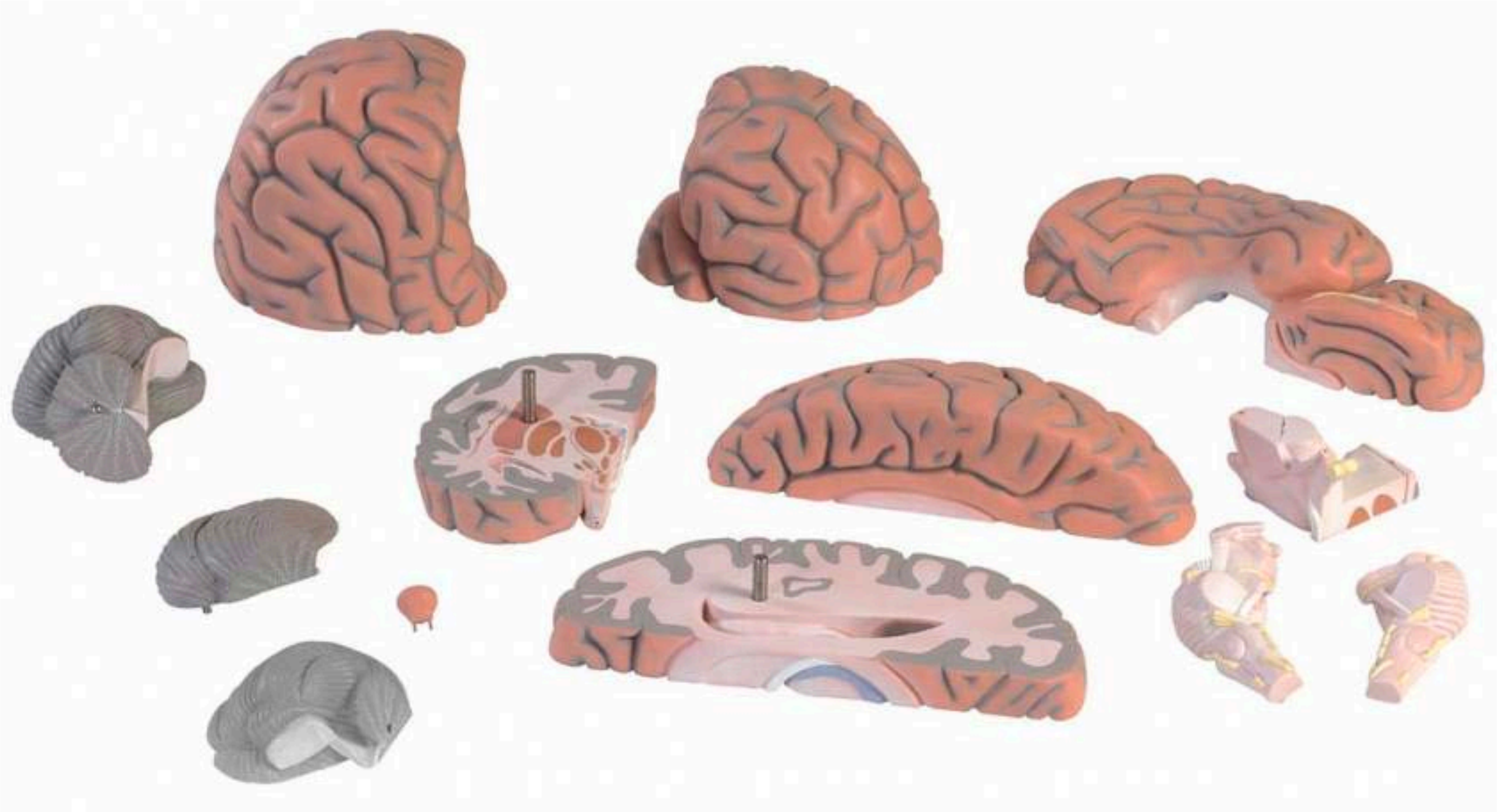
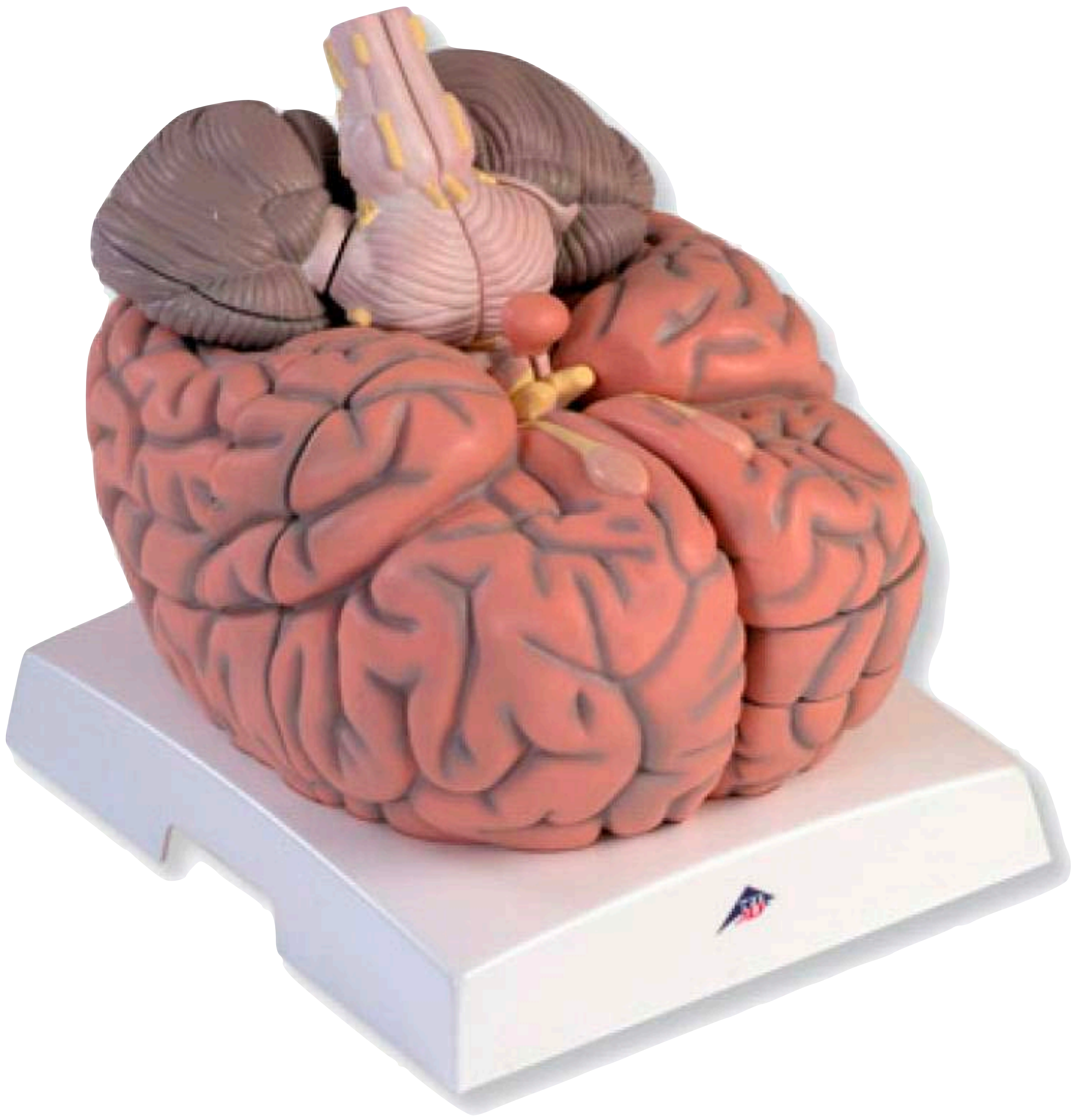
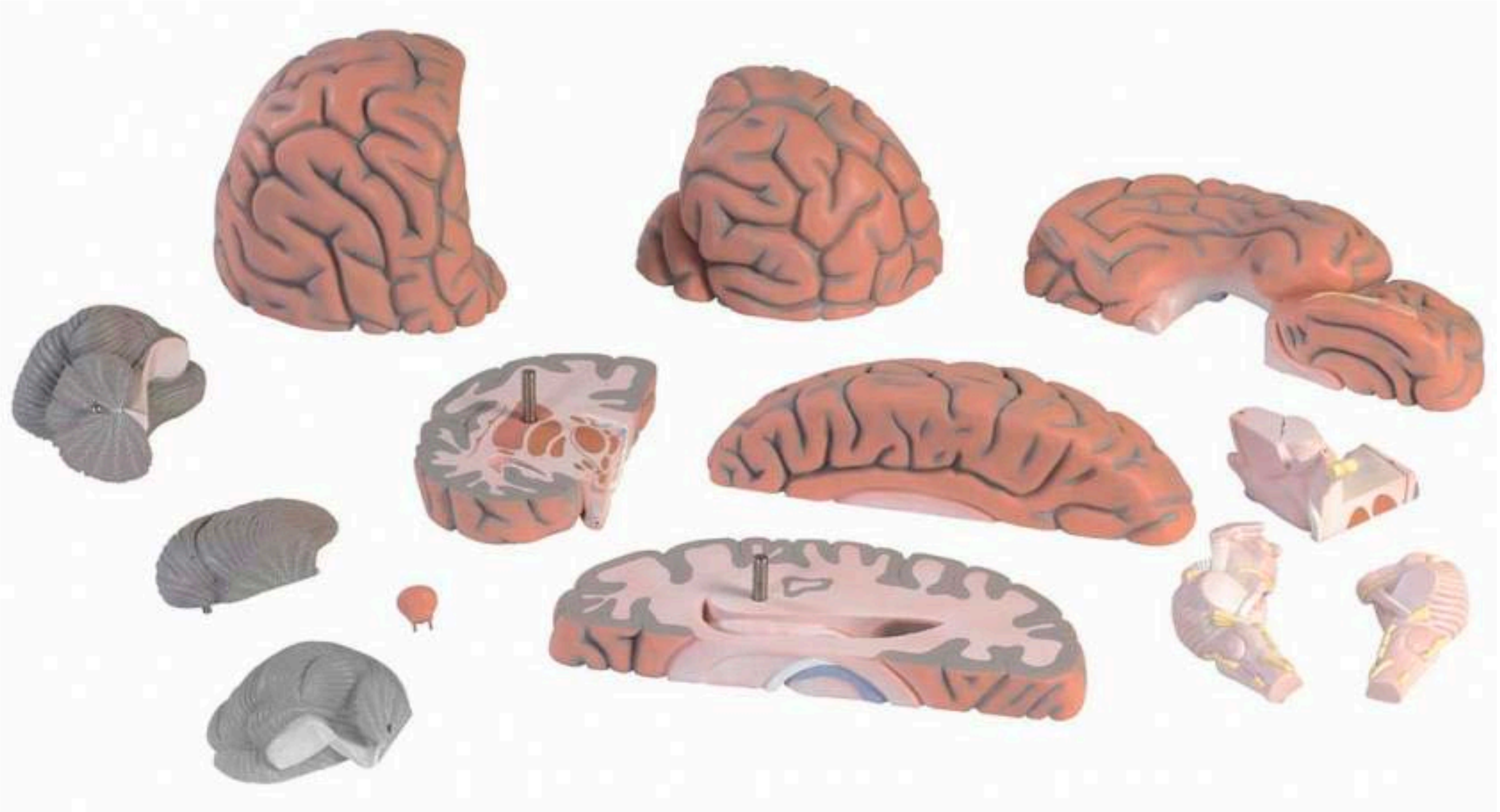
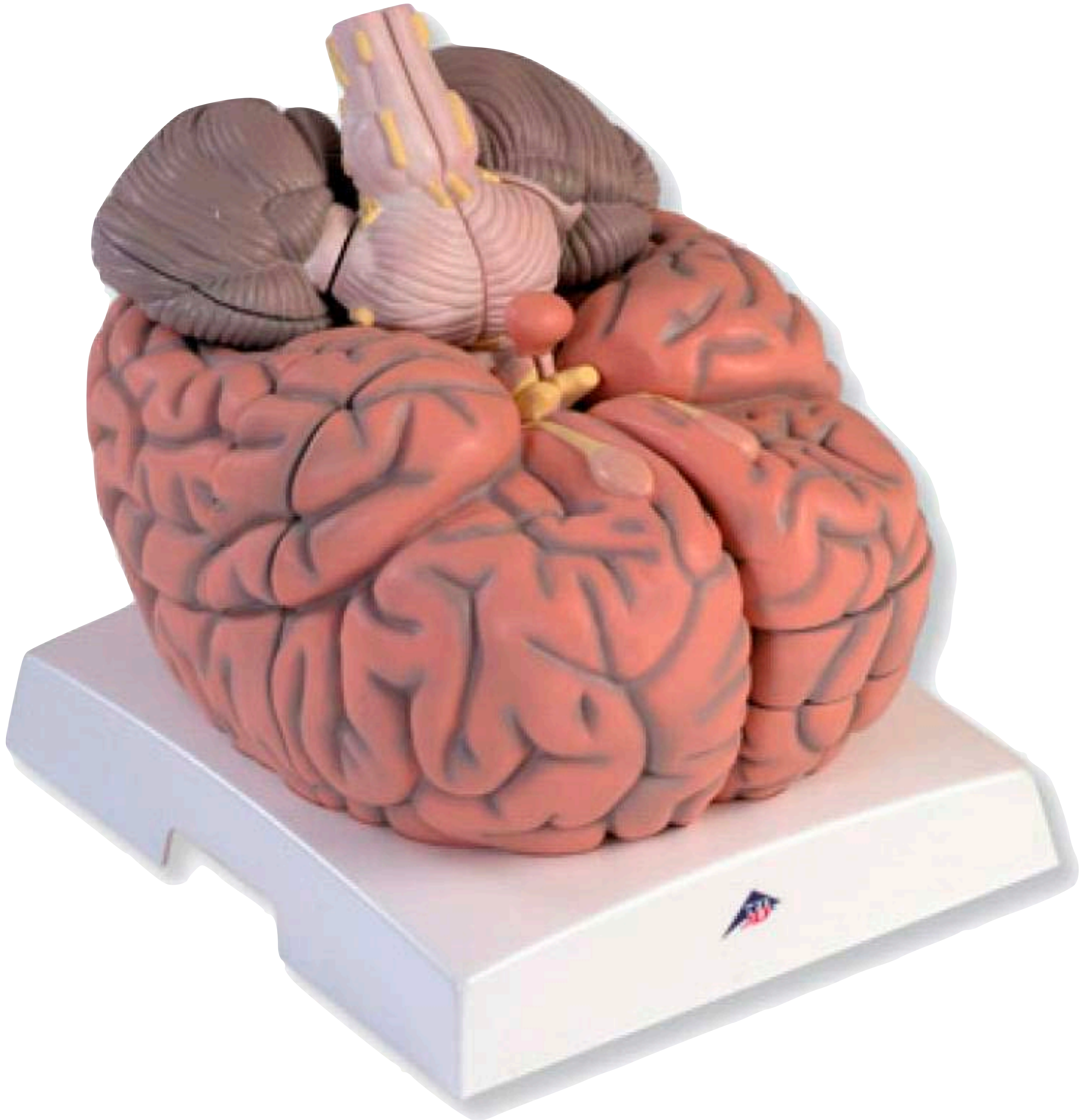
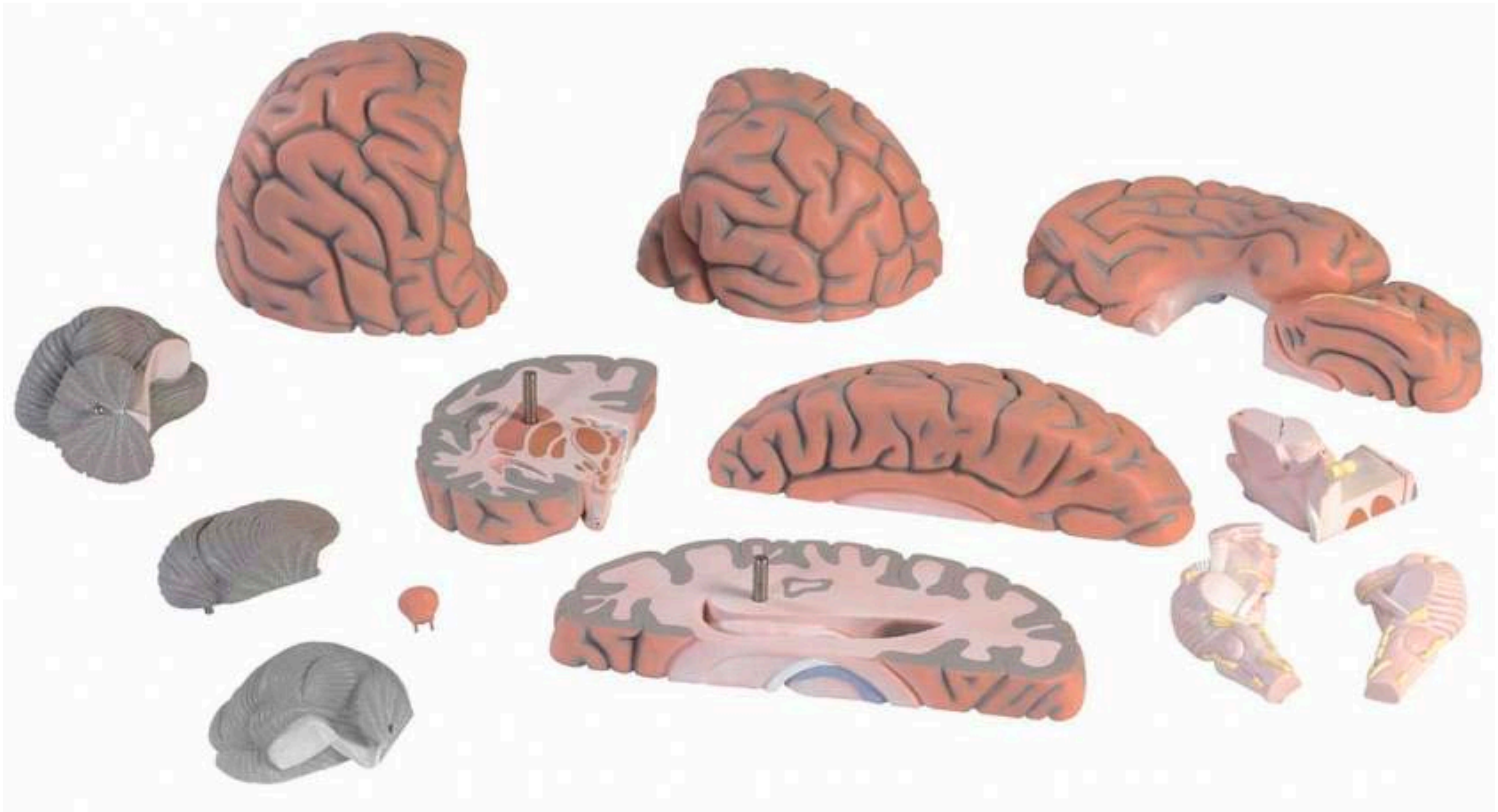
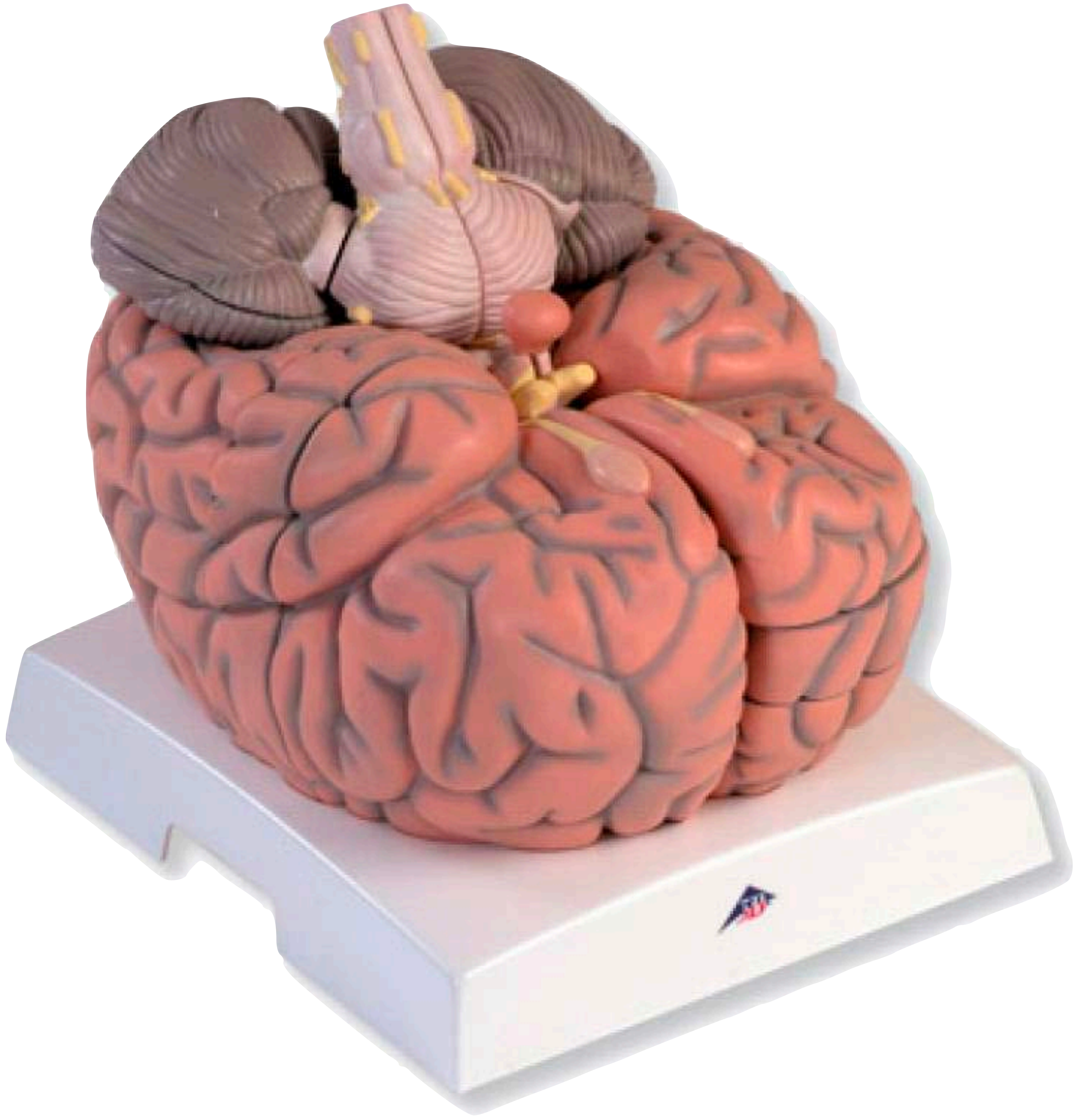
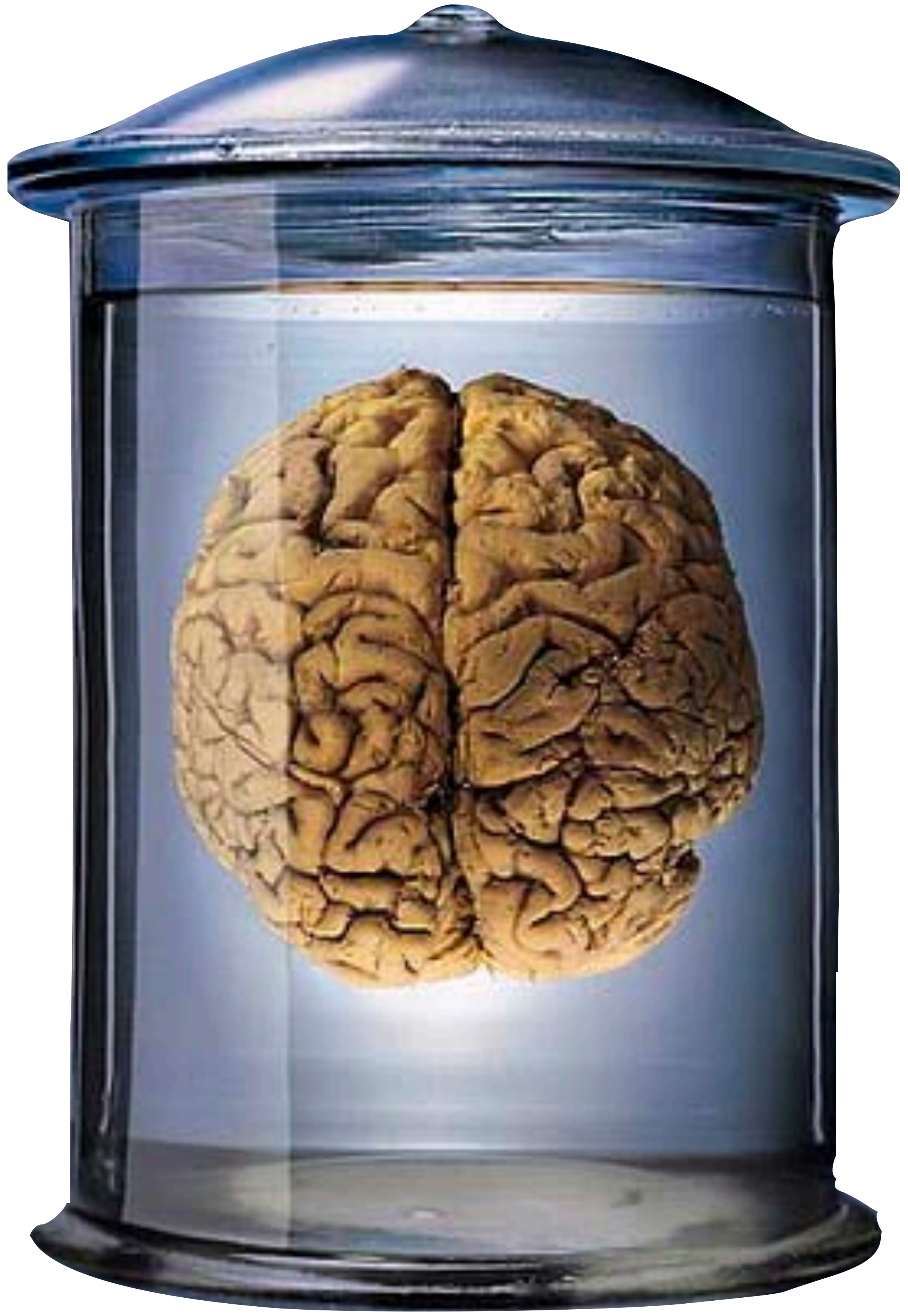












P-Curve: A Key to the File-Drawer
UtahState

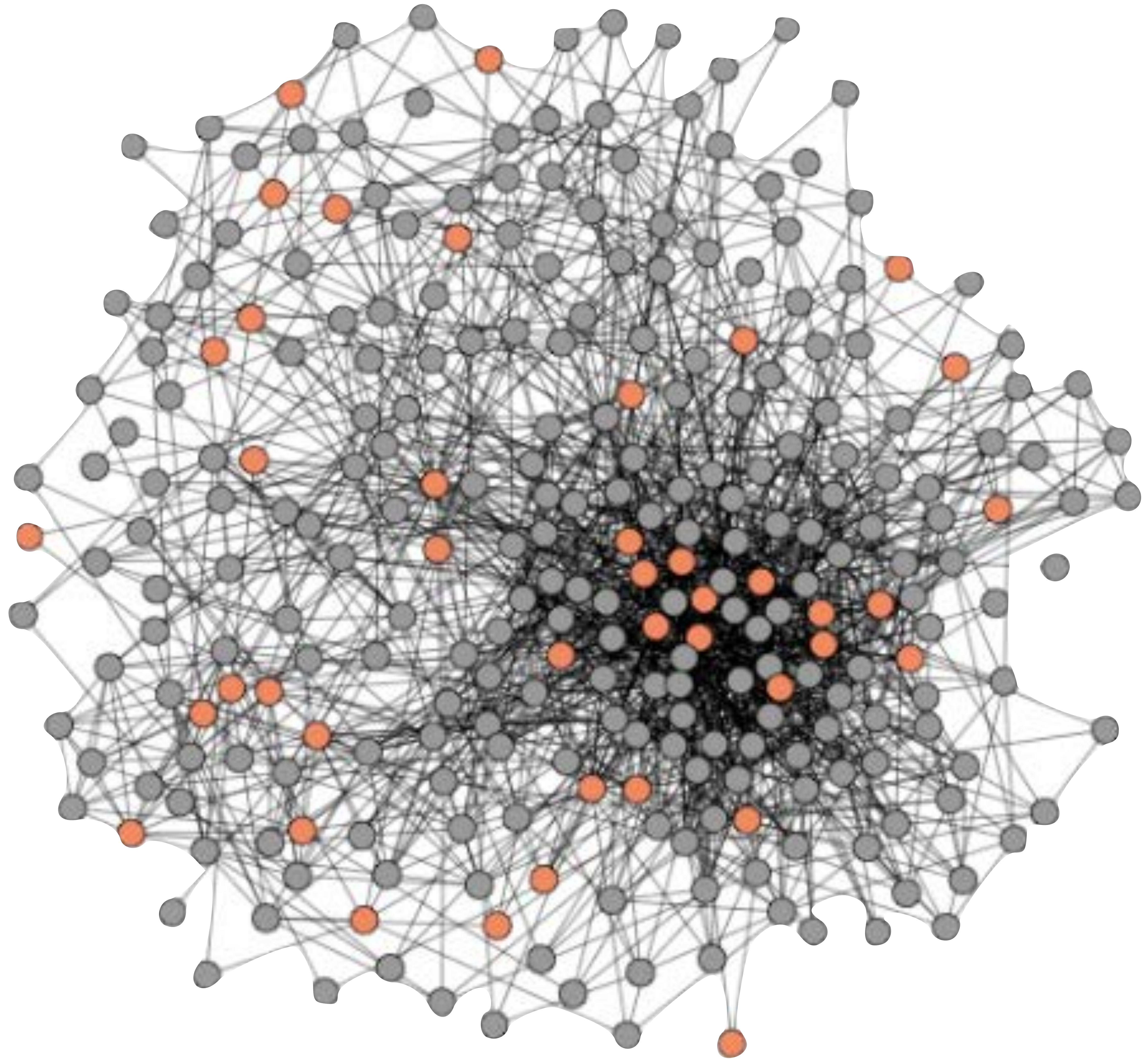
Designing a study

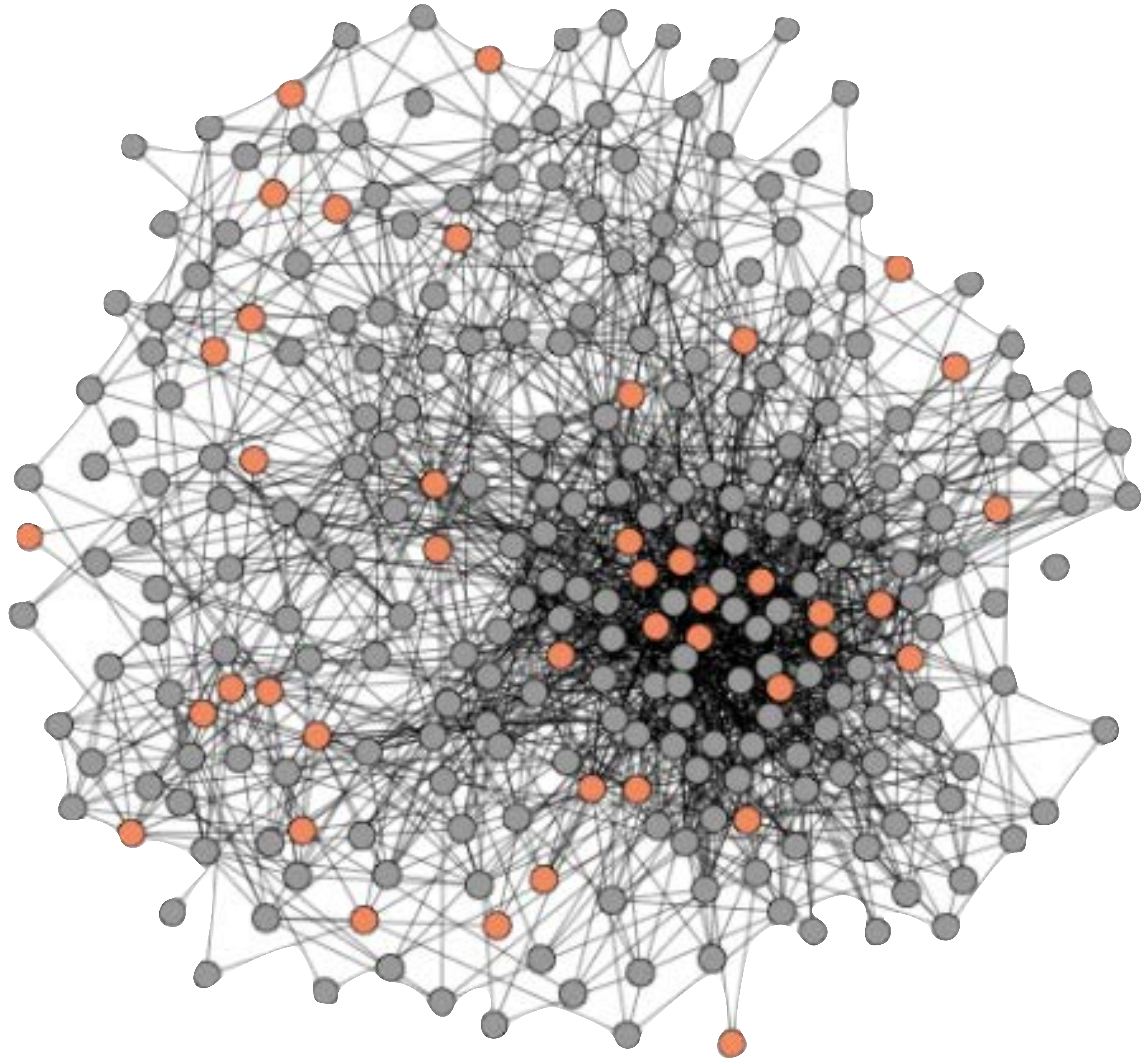
Designing a study

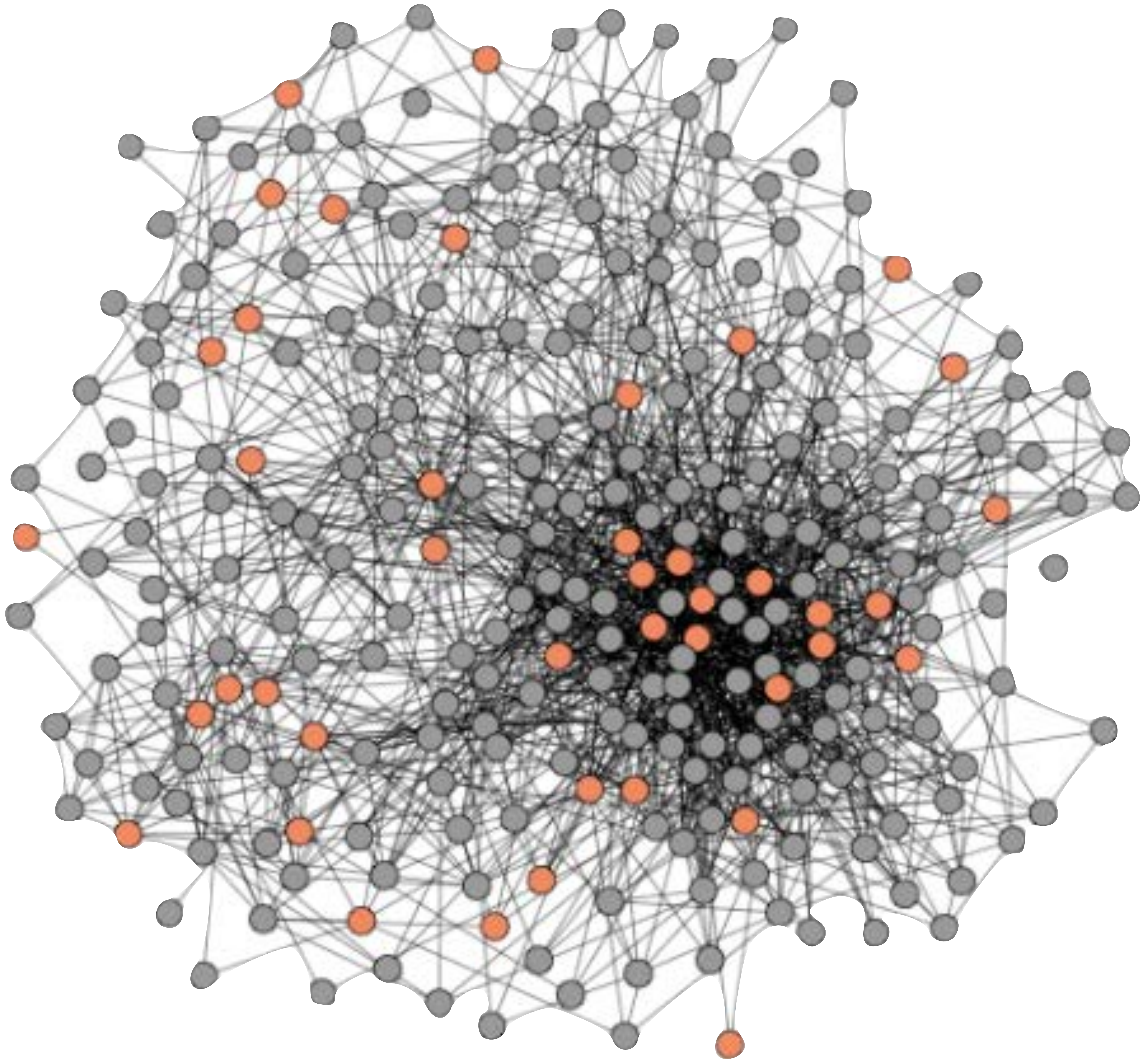
Participating in a study

Designing a study

Participating in a study

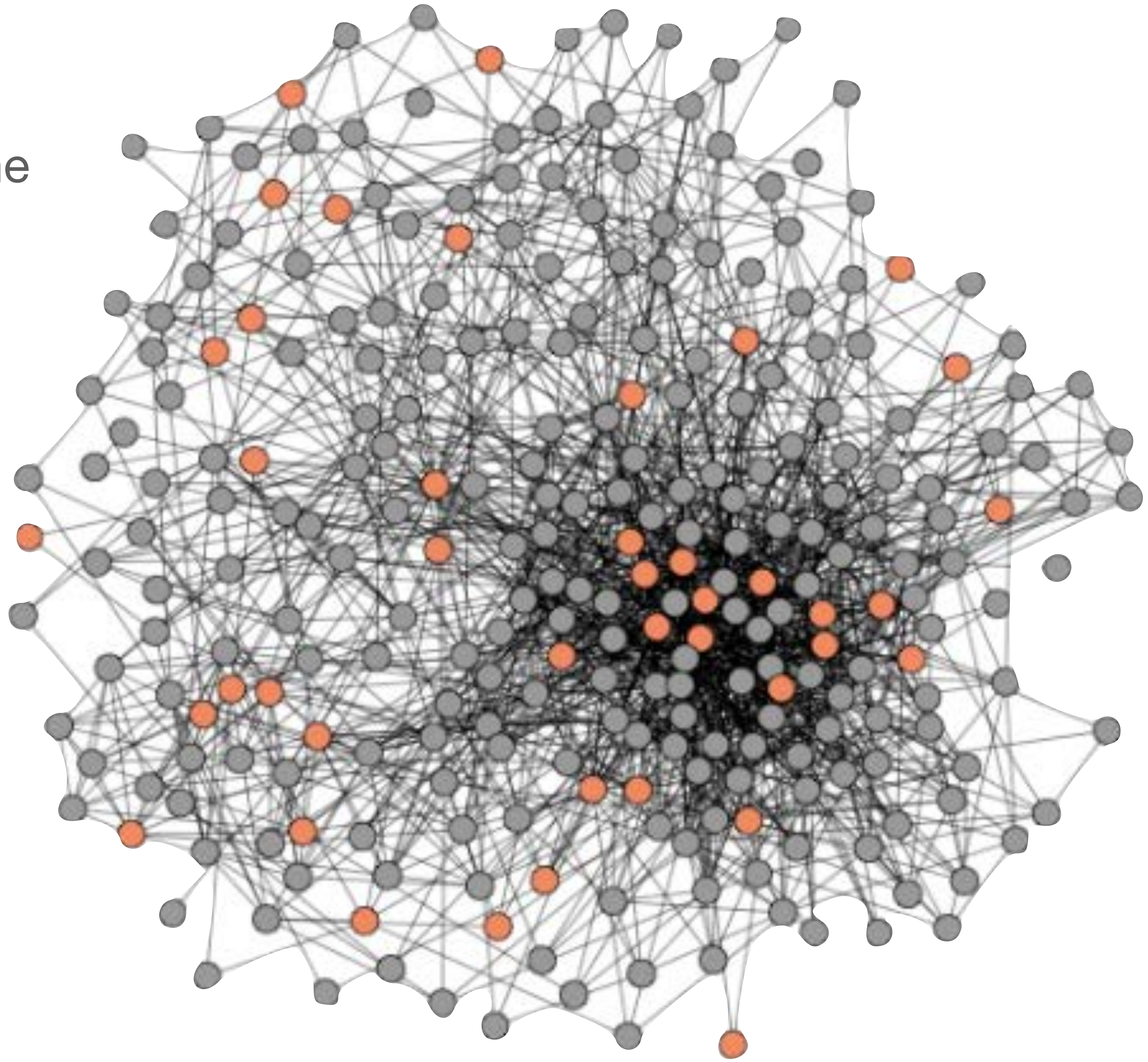






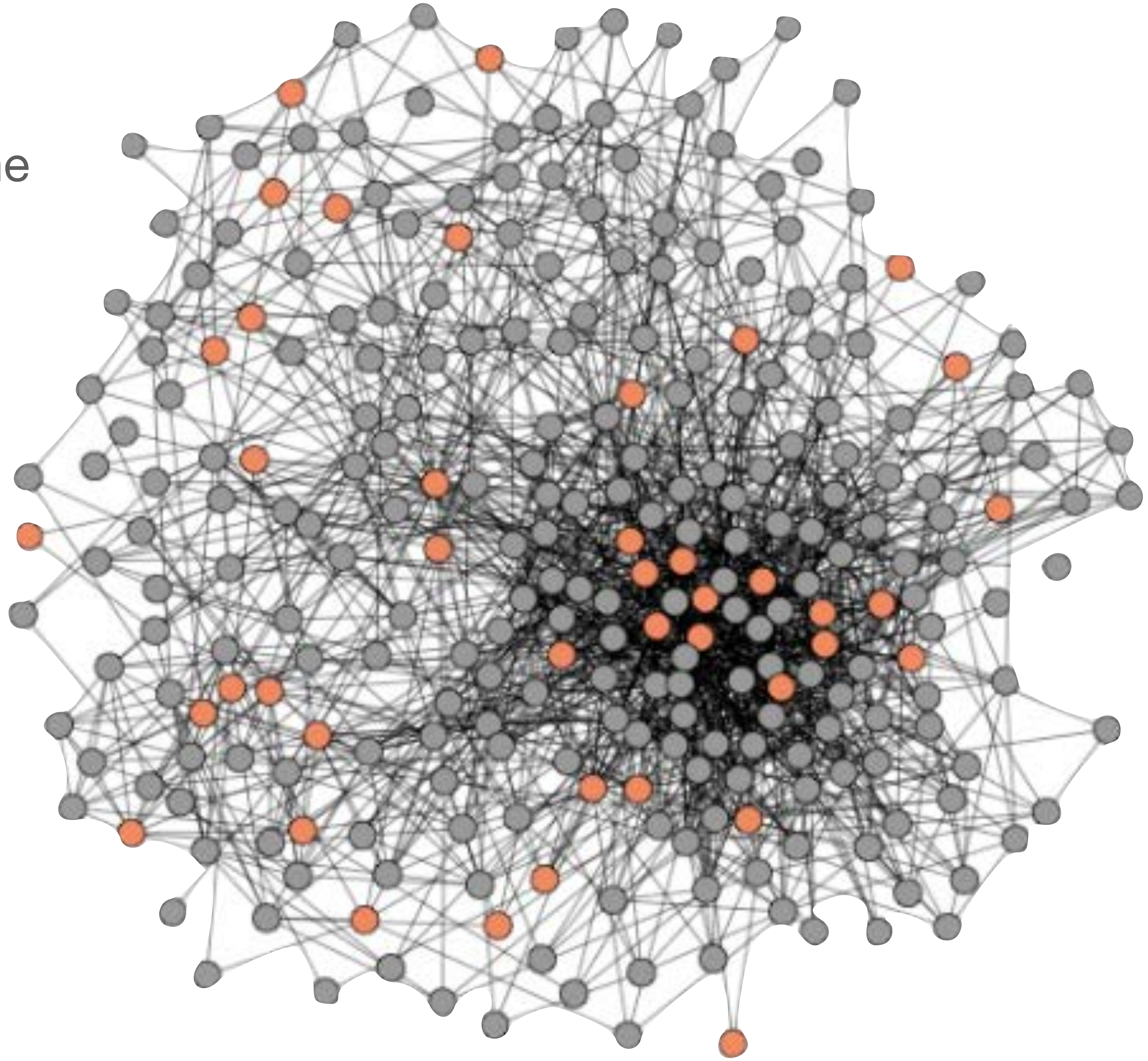
Homophily

Tendency of nodes to connect to others of the same type



Homophily

Tendency of nodes to connect to others of the same type

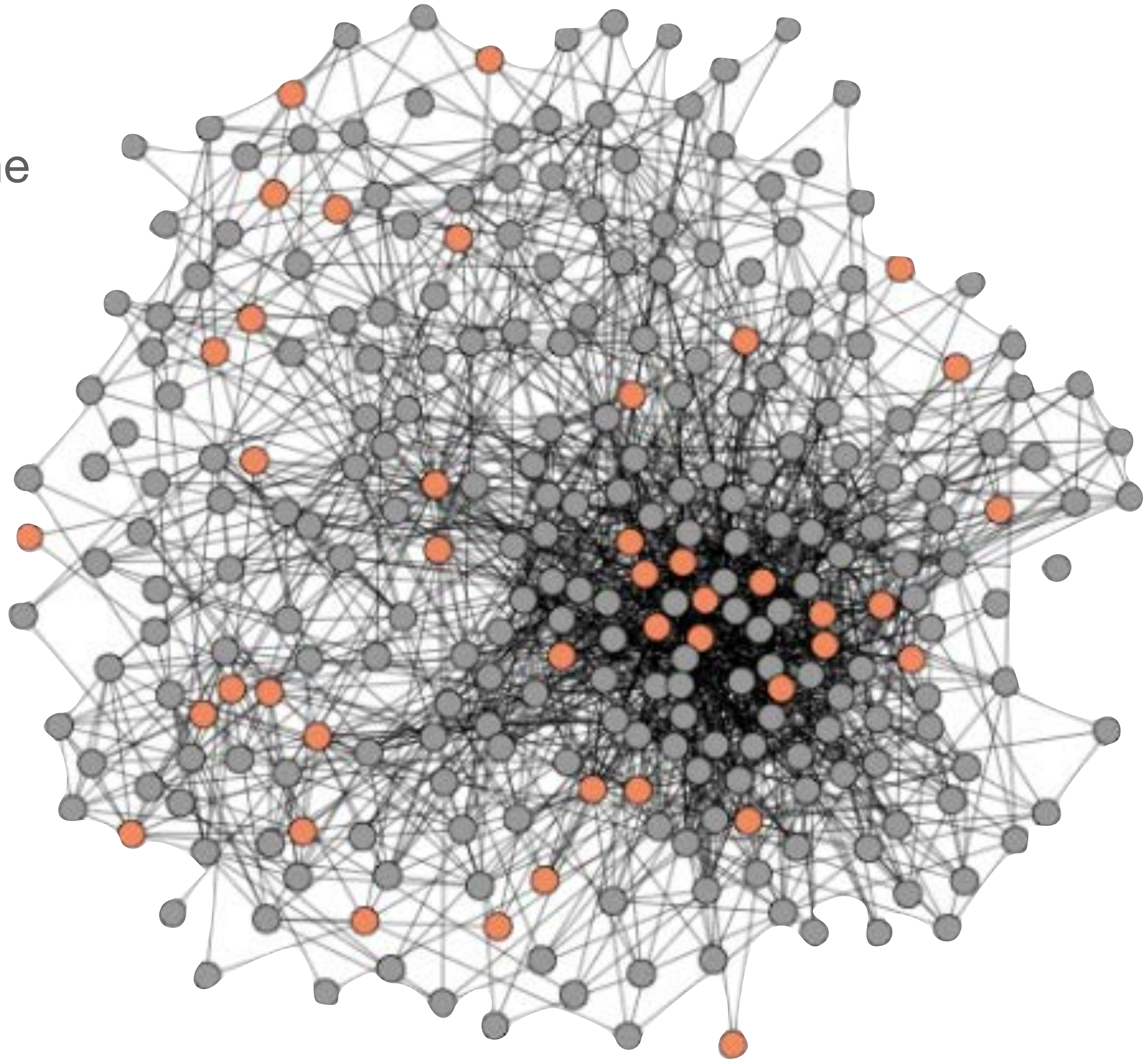


Influence

Tendency of nodes to influence each other such that they become more similar

Homophily

Tendency of nodes to connect to others of the same type

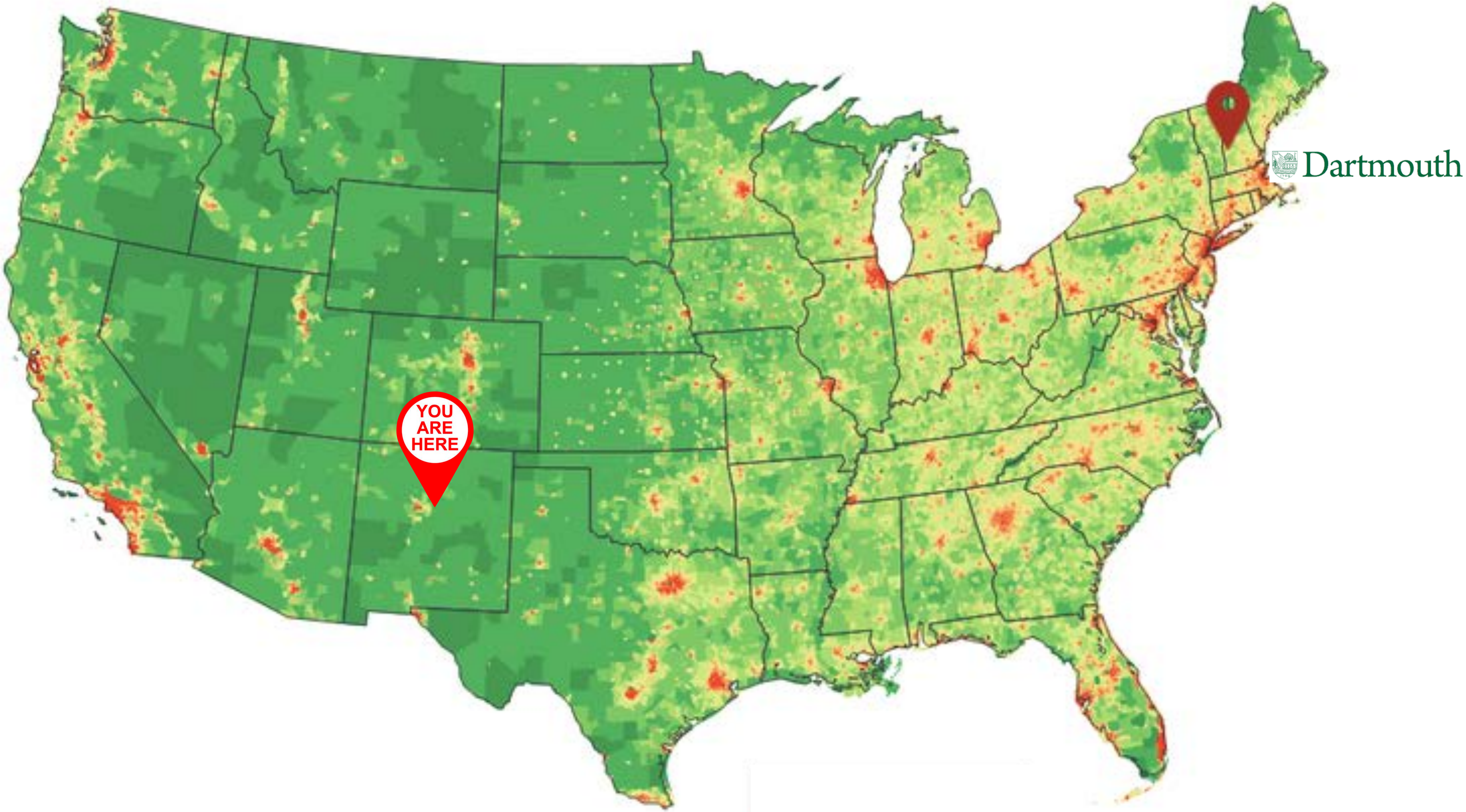


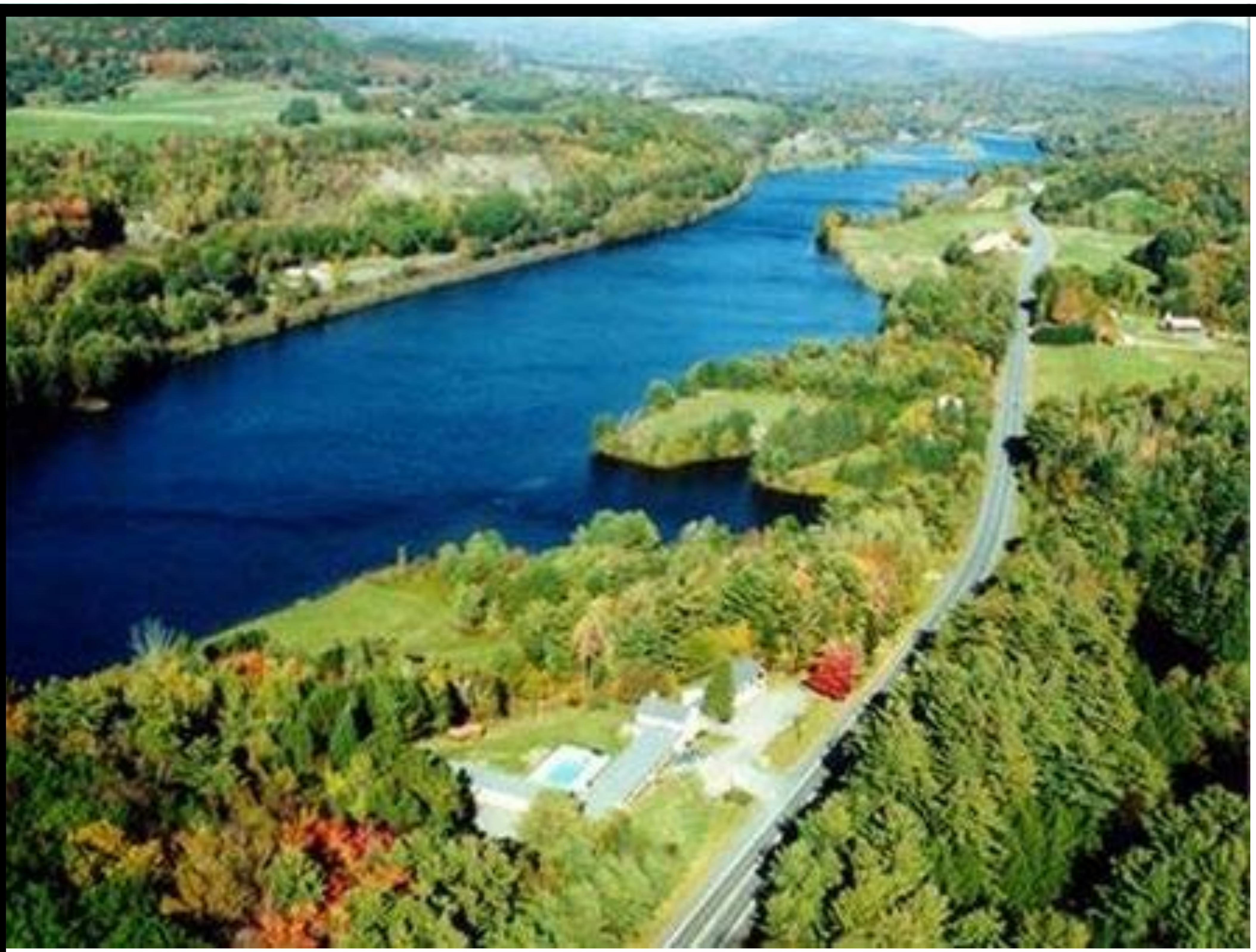
Byrdes of on kynde and color flok and flye always together




Carolyn Parkinson
UCLA

Adam Kleinbaum
Tuck School of Business
Dartmouth


YOU
ARE
HERE
Dartmouth





TUCK

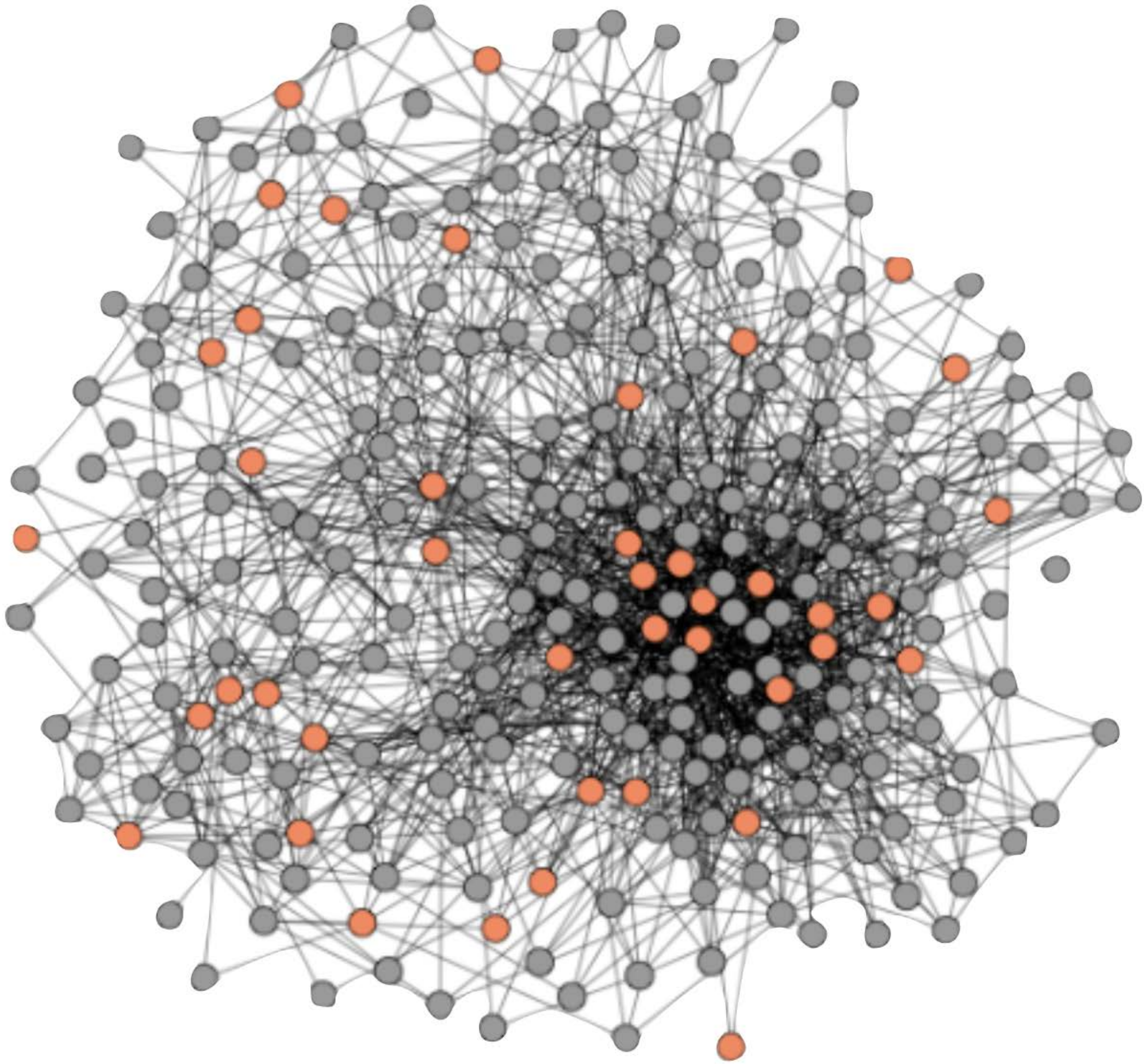

TUCK

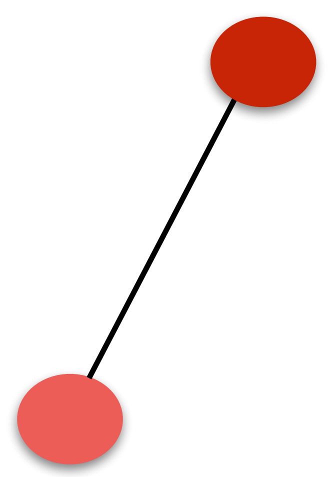

TUCK


TUCK

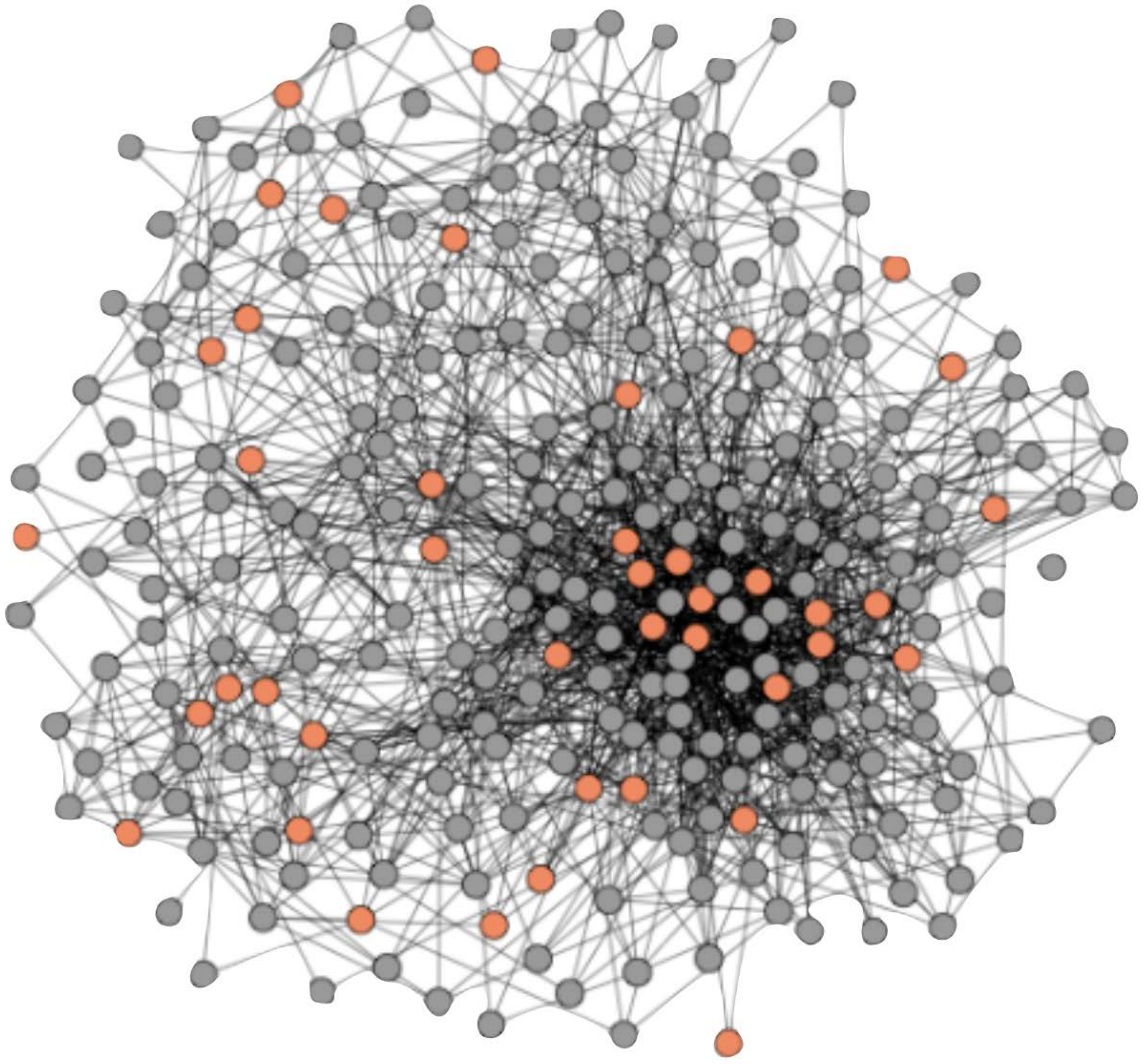

TUCK

“Consider the people with whom you like to spend your free time. Since you arrived at Dartmouth, who are the classmates you have been with most often for informal social activities such as going out to lunch, dinner, drinks, films, visiting one another’s homes, and so on?”

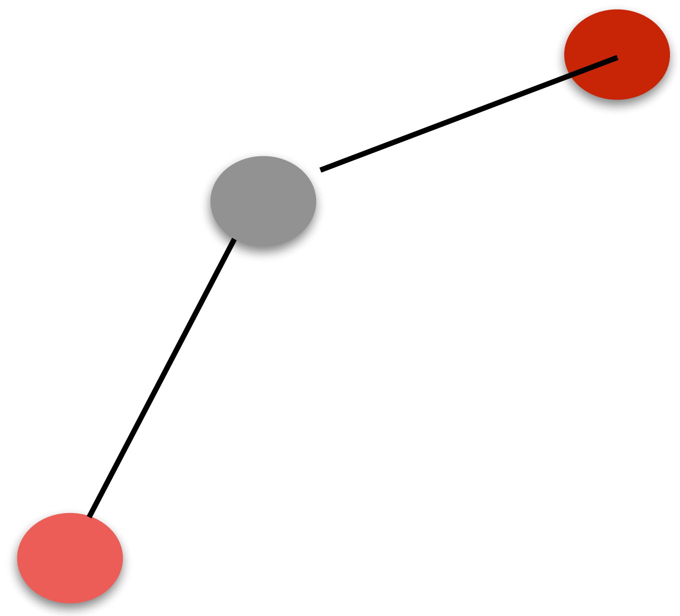




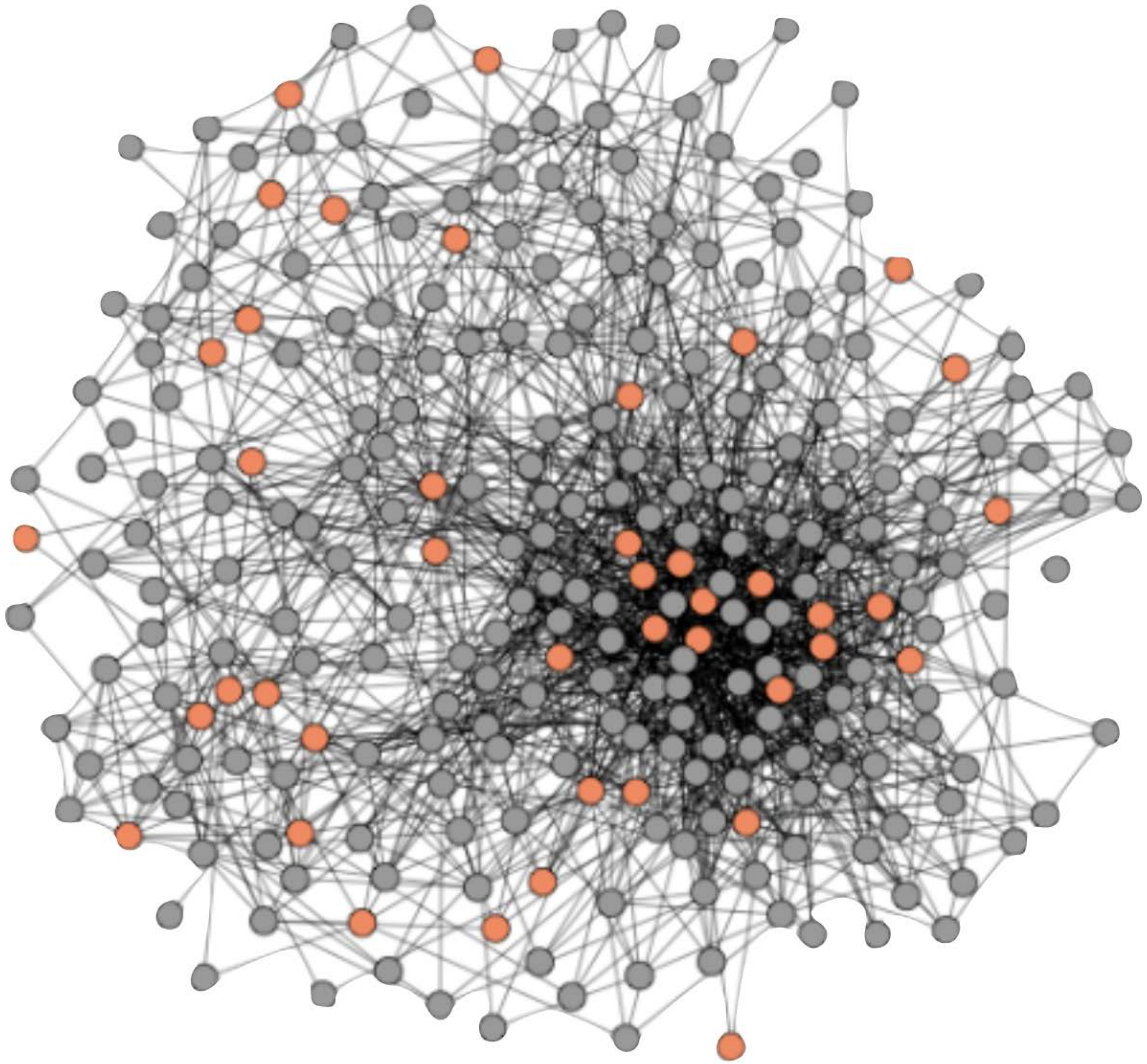
Parkinson et al., Nature Comms, 2018



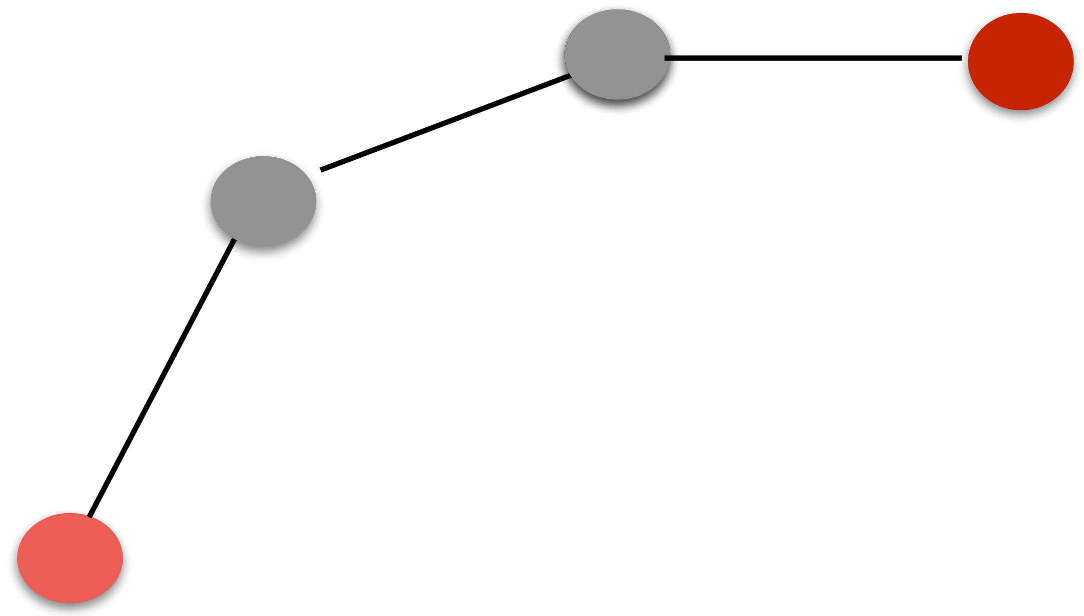
friends of friends



Parkinson et al., Nature Comms, 2018

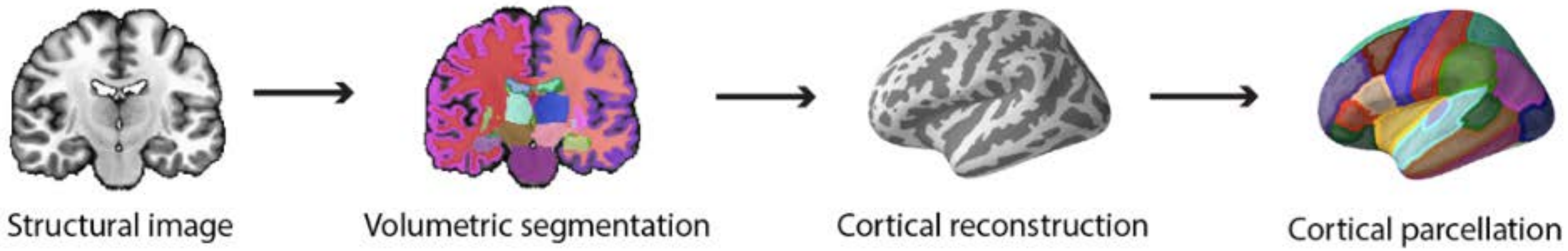


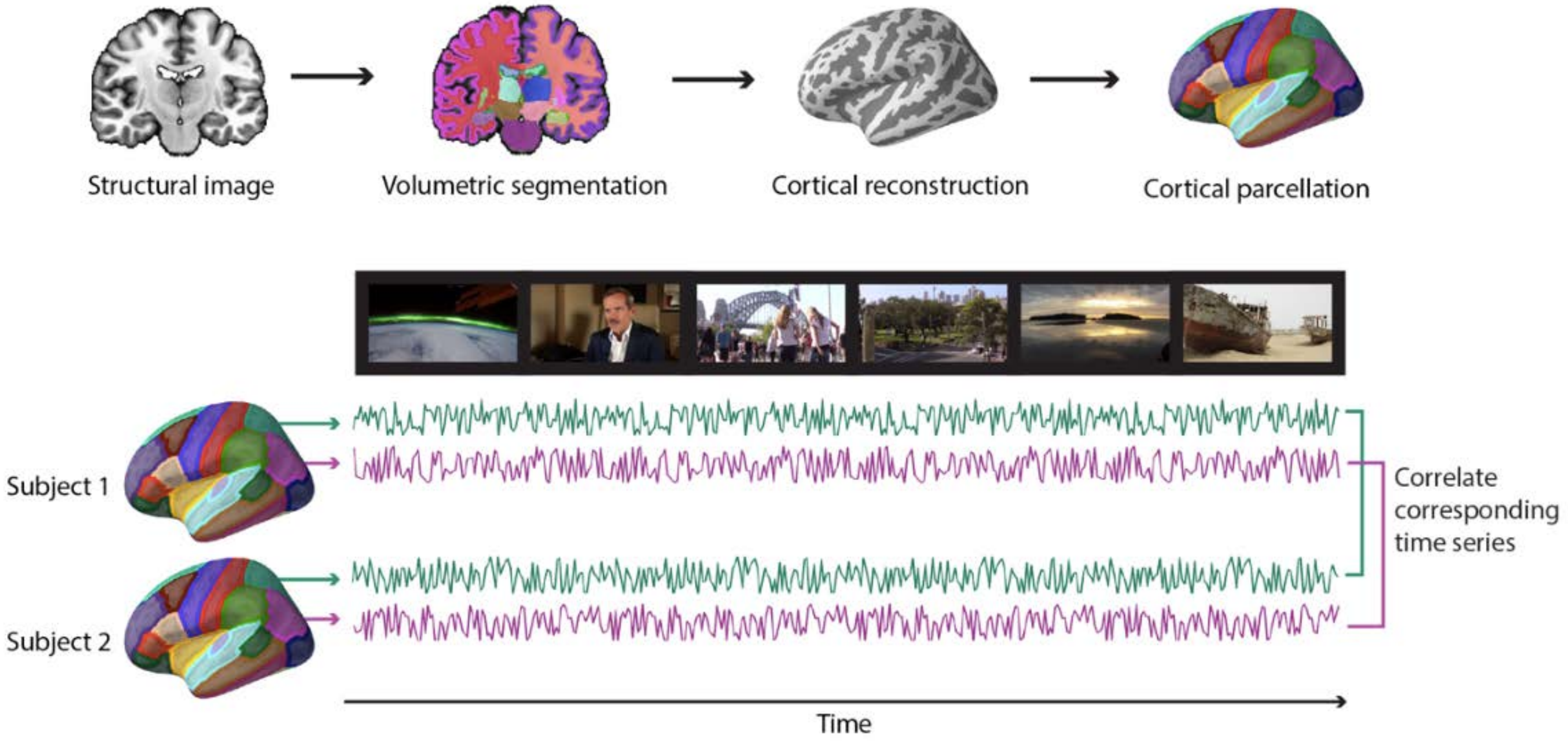
friends of friends of friends



Parkinson et al., Nature Comms, 2018

Show People Movie Clips


Structural image
Volumetric segmentation
Cortical reconstruction
Cortical parcellation


Structural image
Volumetric segmentation
Cortical reconstruction
Cortical parcellation
Subject 1
Subject 2
Correlate corresponding time series
Time

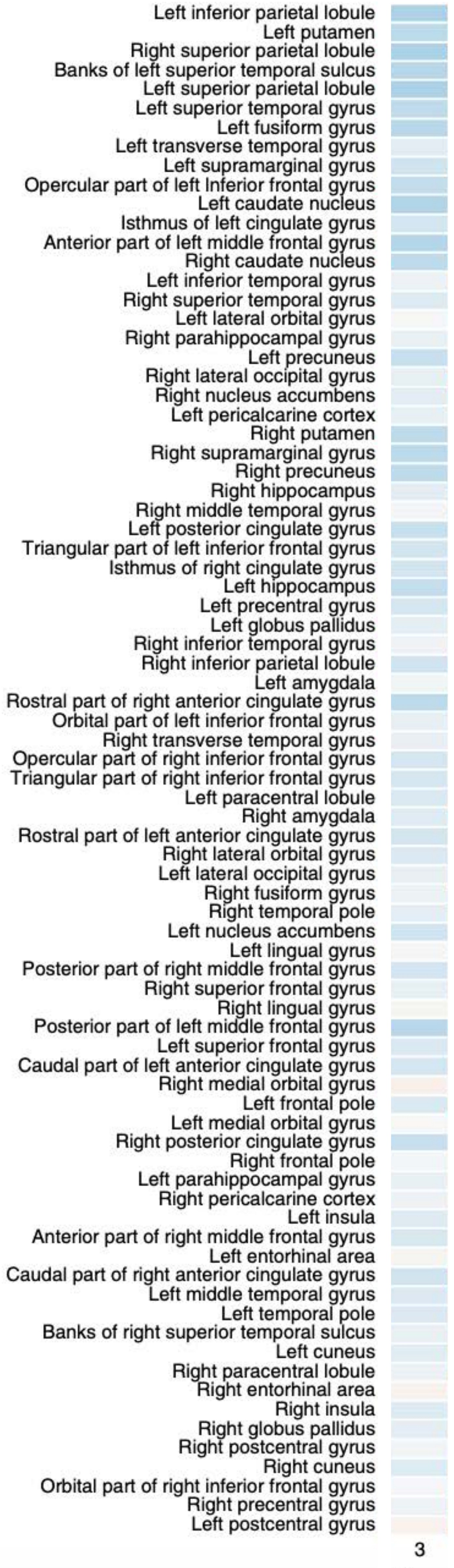
Similar Neural Responses Predict Friendship

Parkinson, Kleinbaum, Wheatley, Nat Comms, 2018

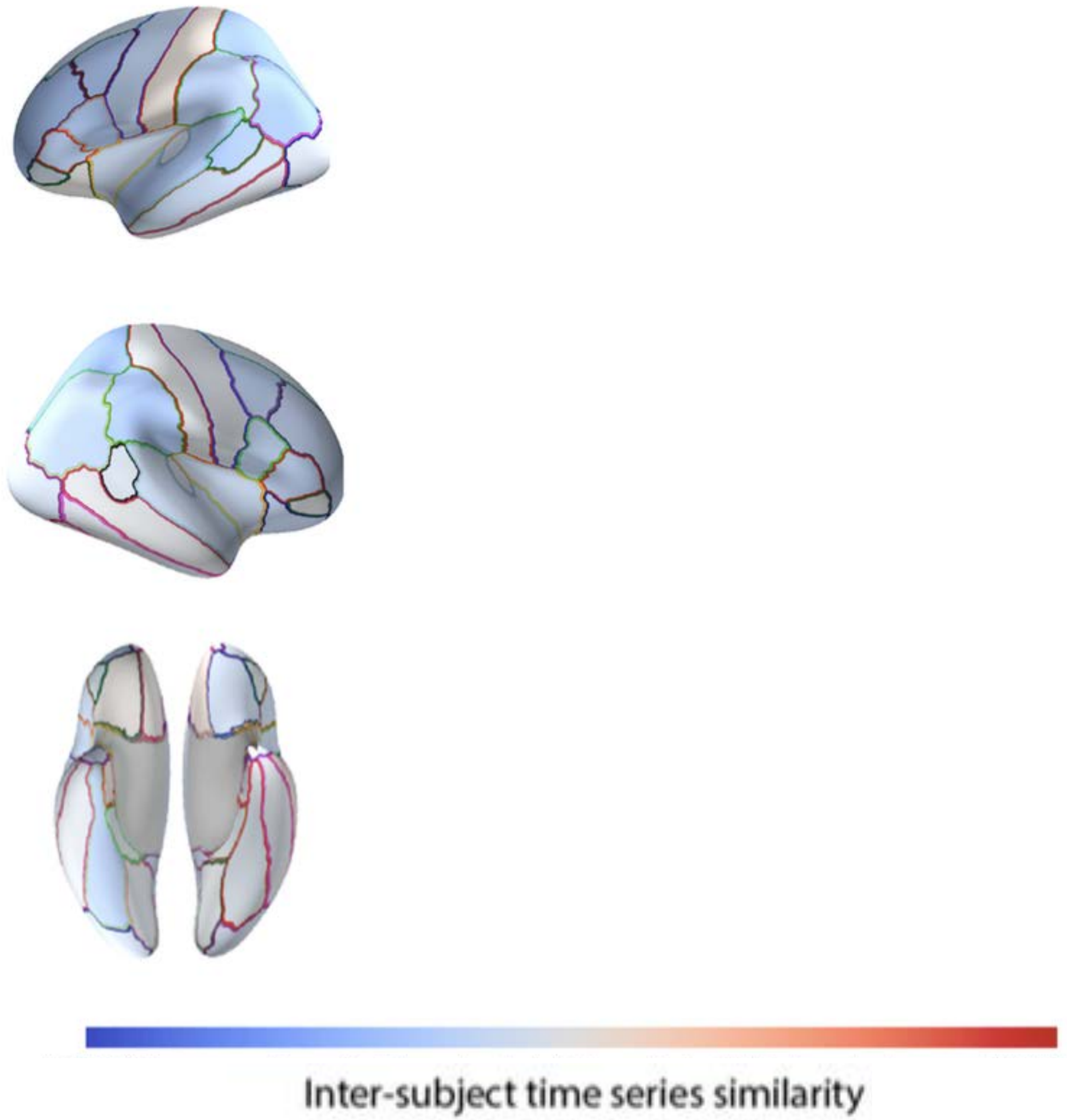
Left inferior parietal lobule
Left putamen
Right superior parietal lobule
Banks of left superior temporal sulcus
Left superior parietal lobule
Left superior temporal gyrus
Left fusiform gyrus
Left transverse temporal gyrus
Left supramarginal gyrus
Opercular part of left Inferior frontal gyrus
Left caudate nucleus
Isthmus of left cingulate gyrus
Anterior part of left middle frontal gyrus
Right caudate nucleus
Left inferior temporal gyrus
Right superior temporal gyrus
Left lateral orbital gyrus
Right parahippocampal gyrus
Left precuneus
Right lateral occipital gyrus
Right nucleus accumbens
Left pericalcarine cortex
Right putamen
Right supramarginal gyrus
Right precuneus
Right hippocampus
Right middle temporal gyrus
Left posterior cingulate gyrus
Triangular part of left inferior frontal gyrus
Isthmus of right cingulate gyrus
Left hippocampus
Left precentral gyrus
Left globus pallidus
Right inferior temporal gyrus
Right inferior parietal lobule
Left amygdala
Rostral part of right anterior cingulate gyrus
Orbital part of left inferior frontal gyrus
Right transverse temporal gyrus
Opercular part of right inferior frontal gyrus
Triangular part of right inferior frontal gyrus
Left paracentral lobule
Right amygdala
Rostral part of left anterior cingulate gyrus
Right lateral orbital gyrus
Left lateral occipital gyrus
Right fusiform gyrus
Right temporal pole
Left nucleus accumbens
Left lingual gyrus
Posterior part of right middle frontal gyrus
Right superior frontal gyrus
Right lingual gyrus
Posterior part of left middle frontal gyrus
Left superior frontal gyrus
Caudal part of left anterior cingulate gyrus
Right medial orbital gyrus
Left frontal pole
Left medial orbital gyrus
Right posterior cingulate gyrus
Right frontal pole
Left parahippocampal gyrus
Right pericalcarine cortex
Left insula
Anterior part of right middle frontal gyrus
Left entorhinal area
Caudal part of right anterior cingulate gyrus
Left middle temporal gyrus
Left temporal pole
Banks of right superior temporal sulcus
Left cuneus
Right paracentral lobule
Right entorhinal area
Right insula
Right globus pallidus
Right postcentral gyrus
Right cuneus
Orbital part of right inferior frontal gyrus
Right precentral gyrus
Left postcentral gyrus

Similar Neural Responses Predict Friendship

Parkinson, Kleinbaum, Wheatley, Nat Comms, 2018

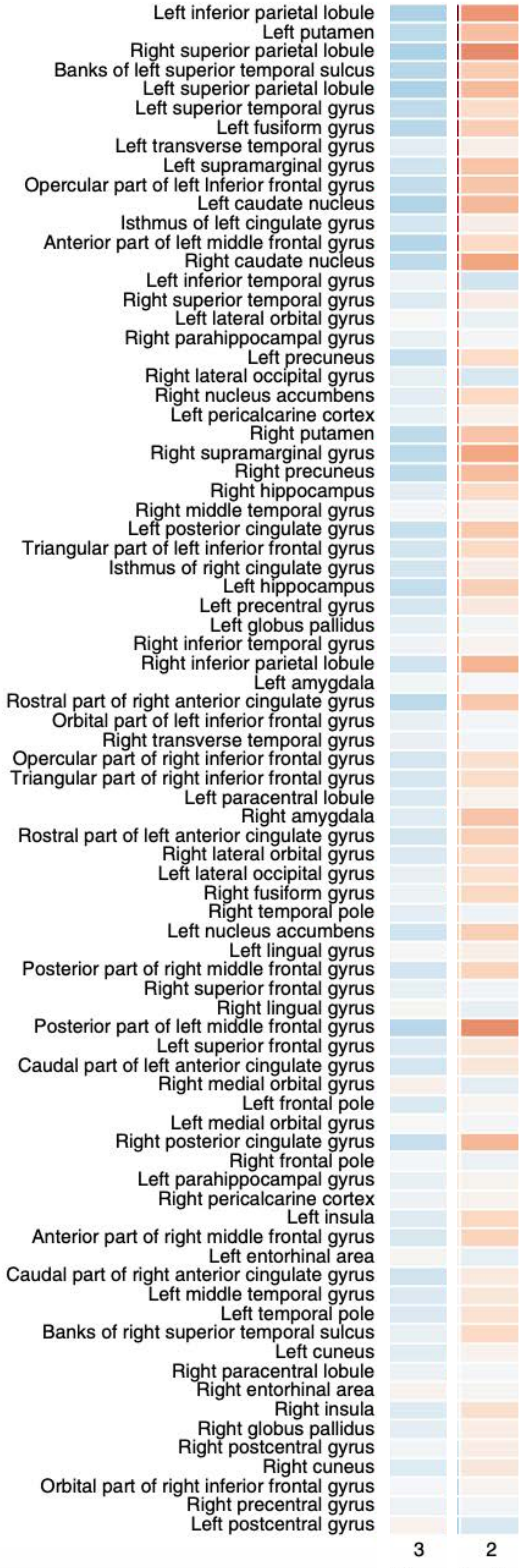


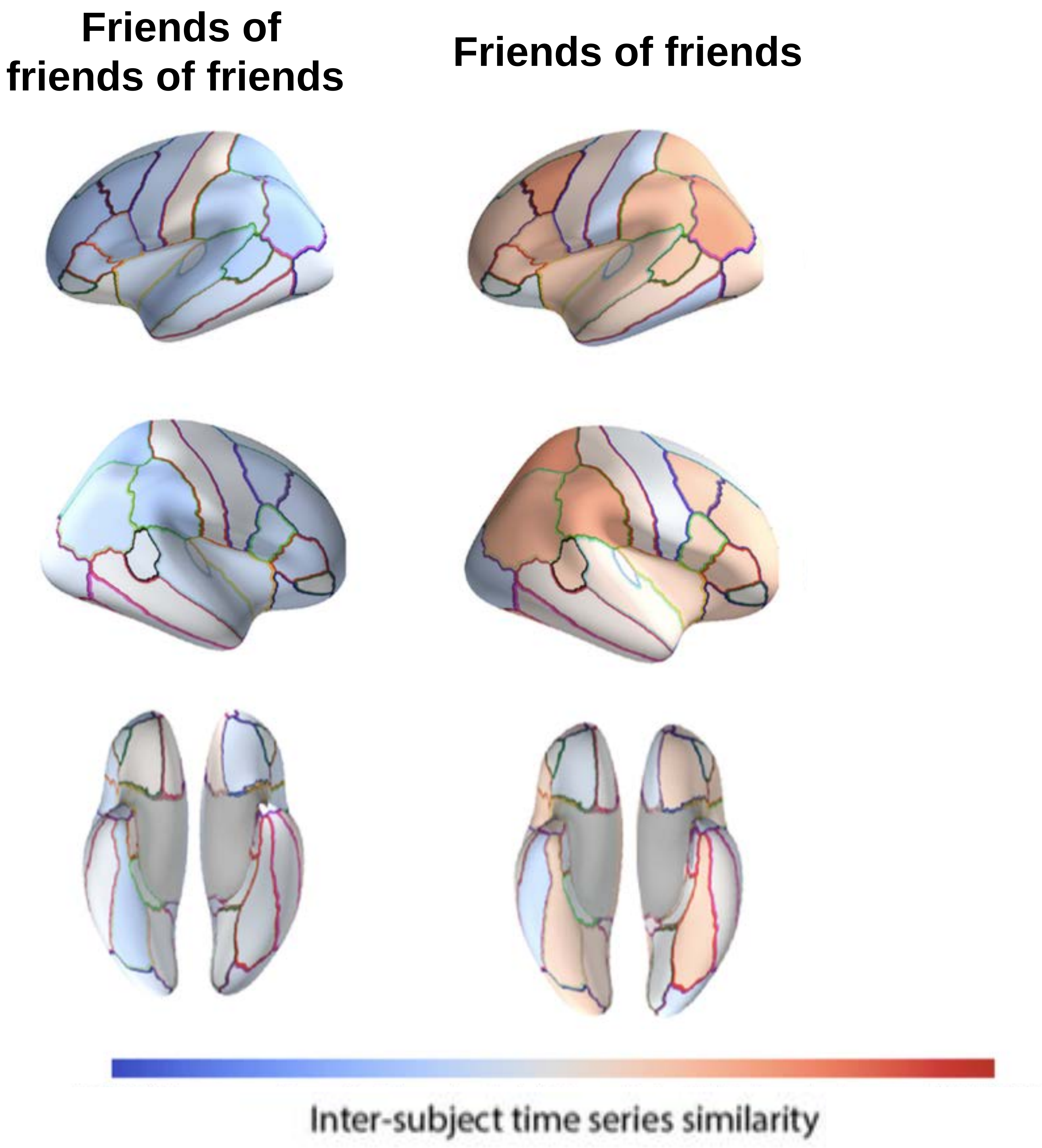
Friends of friends of friends



Similar Neural Responses Predict Friendship

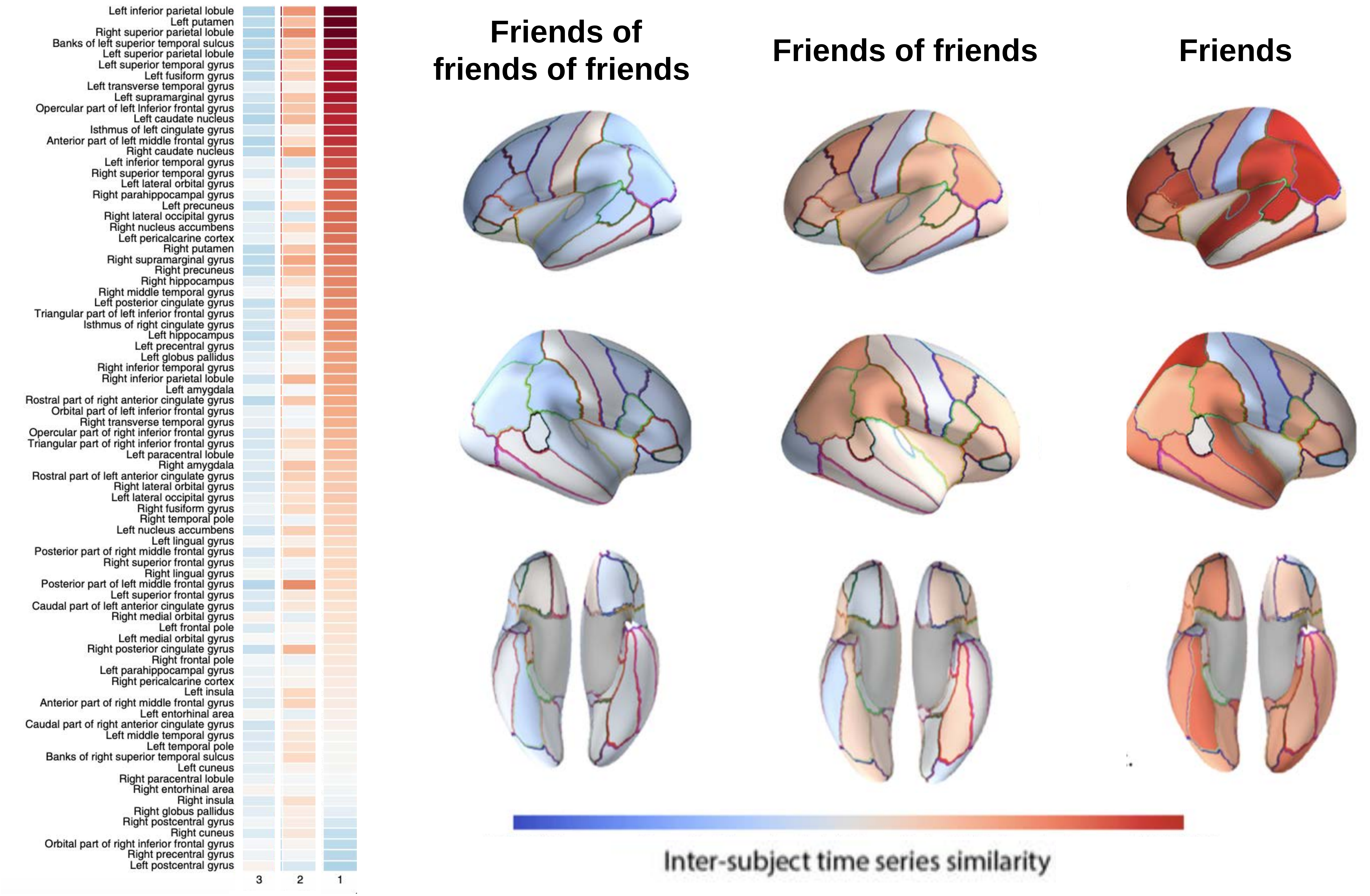
Parkinson, Kleinbaum, Wheatley, Nat Comms, 2018



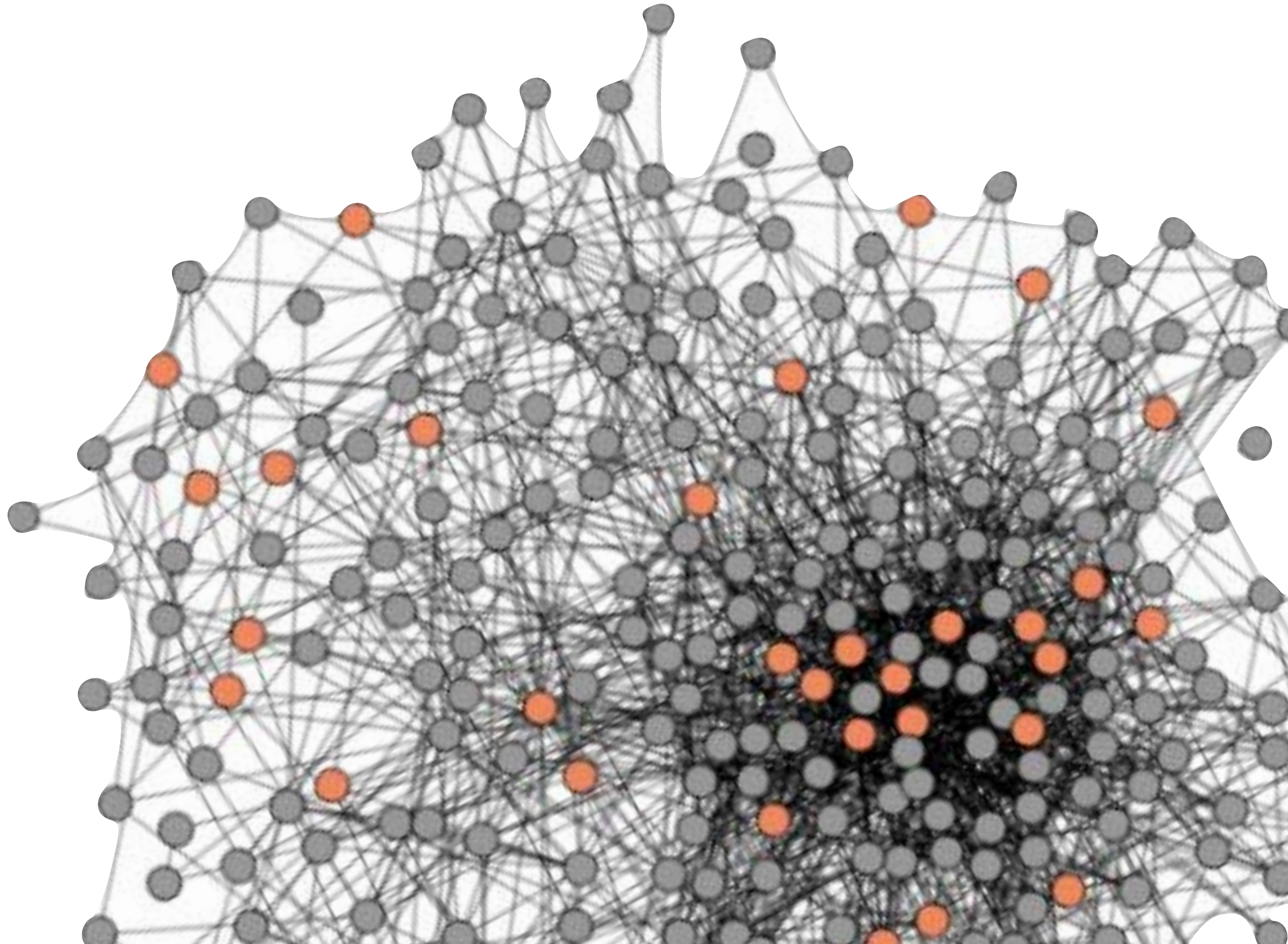


Similar Neural Responses Predict Friendship

Parkinson, Kleinbaum, Wheatley, Nat Comms, 2018



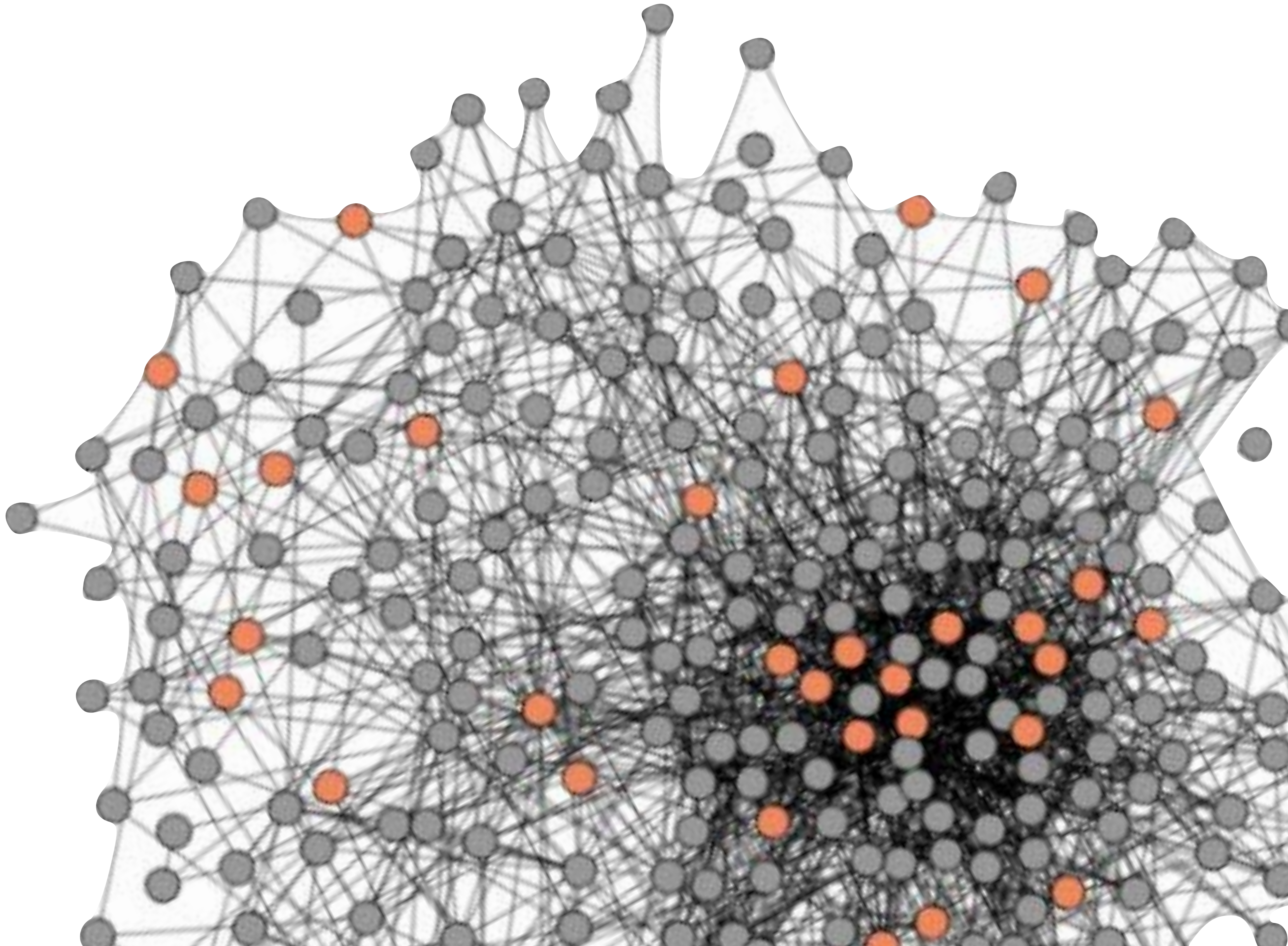
Cross-sectional data



Cross-sectional data

Did these friends think alike from the start?

(vs. become more similar due to shared experience)



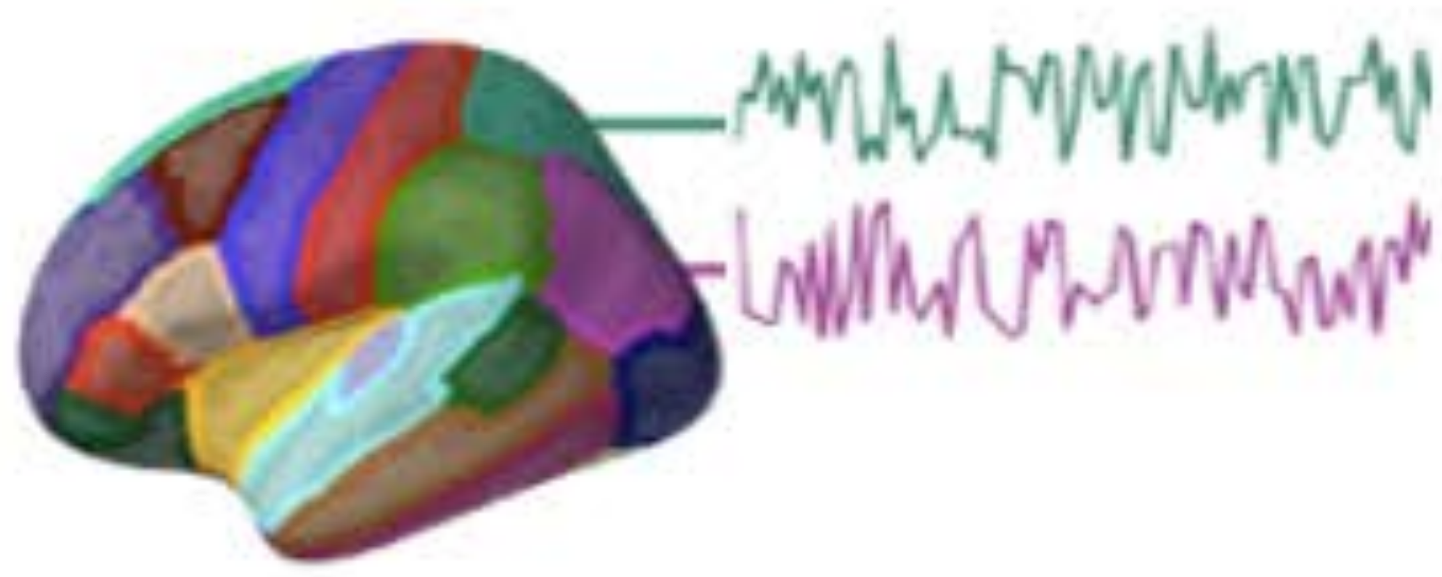
Follow up (under review)

Before meeting each other…

Follow up (under review)

Before meeting each other…

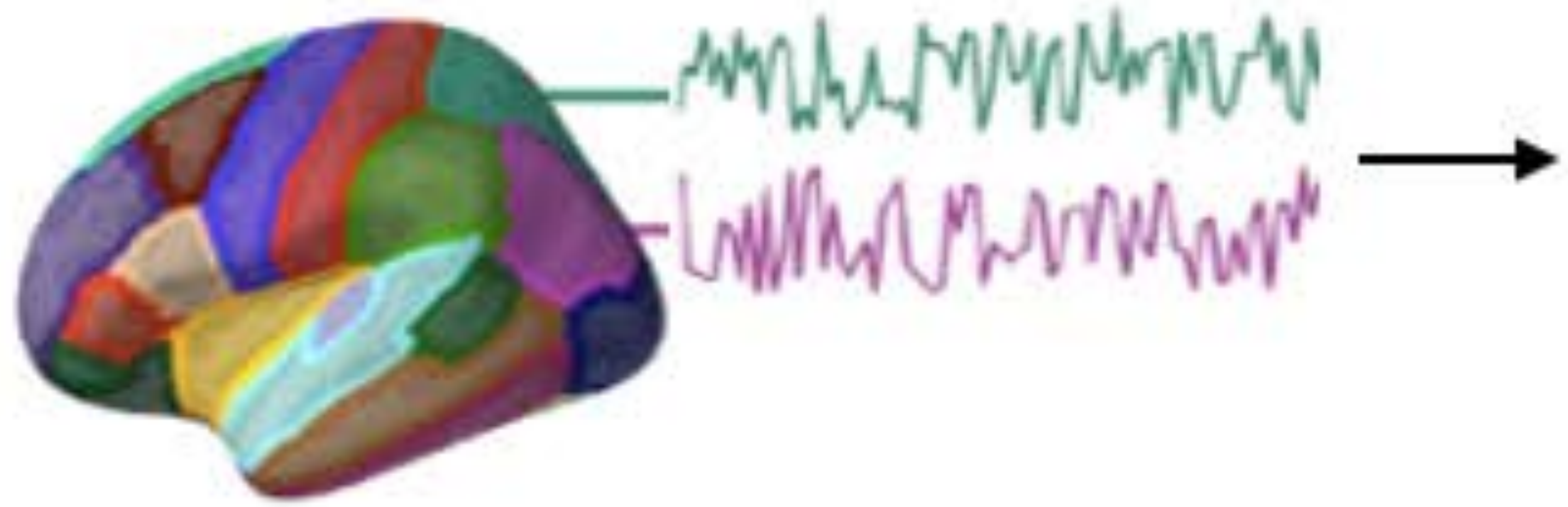
Follow up (under review)



Brain responses to clips (before meeting each other)

Hyon et al., under review

Follow up (under review)

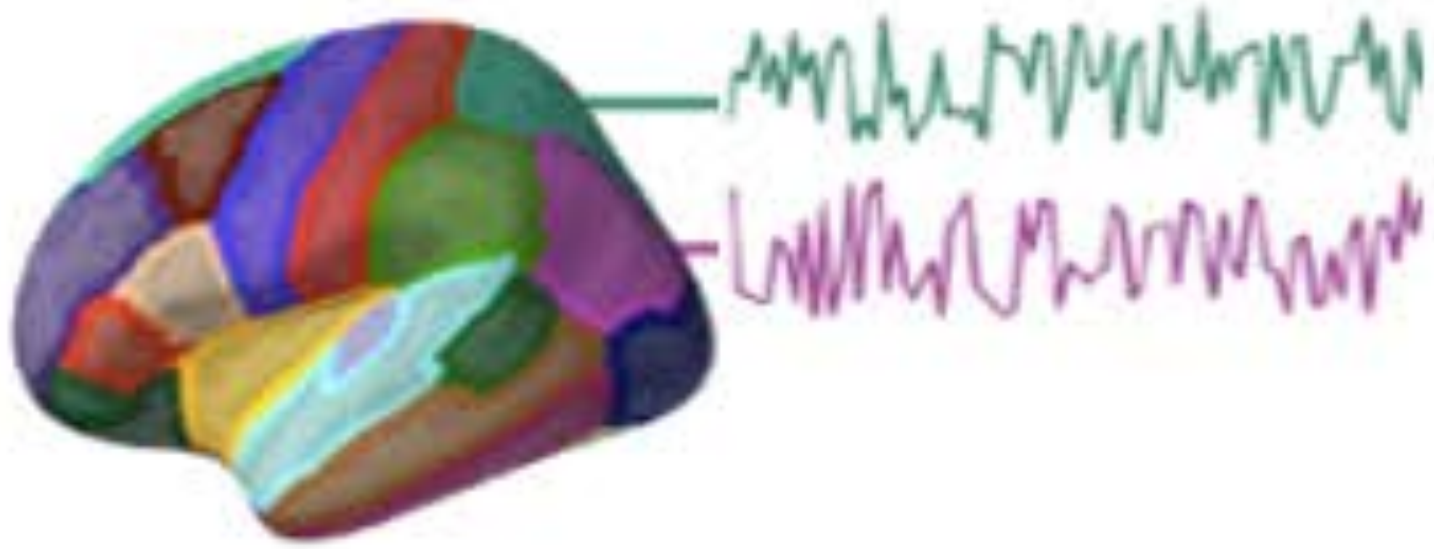


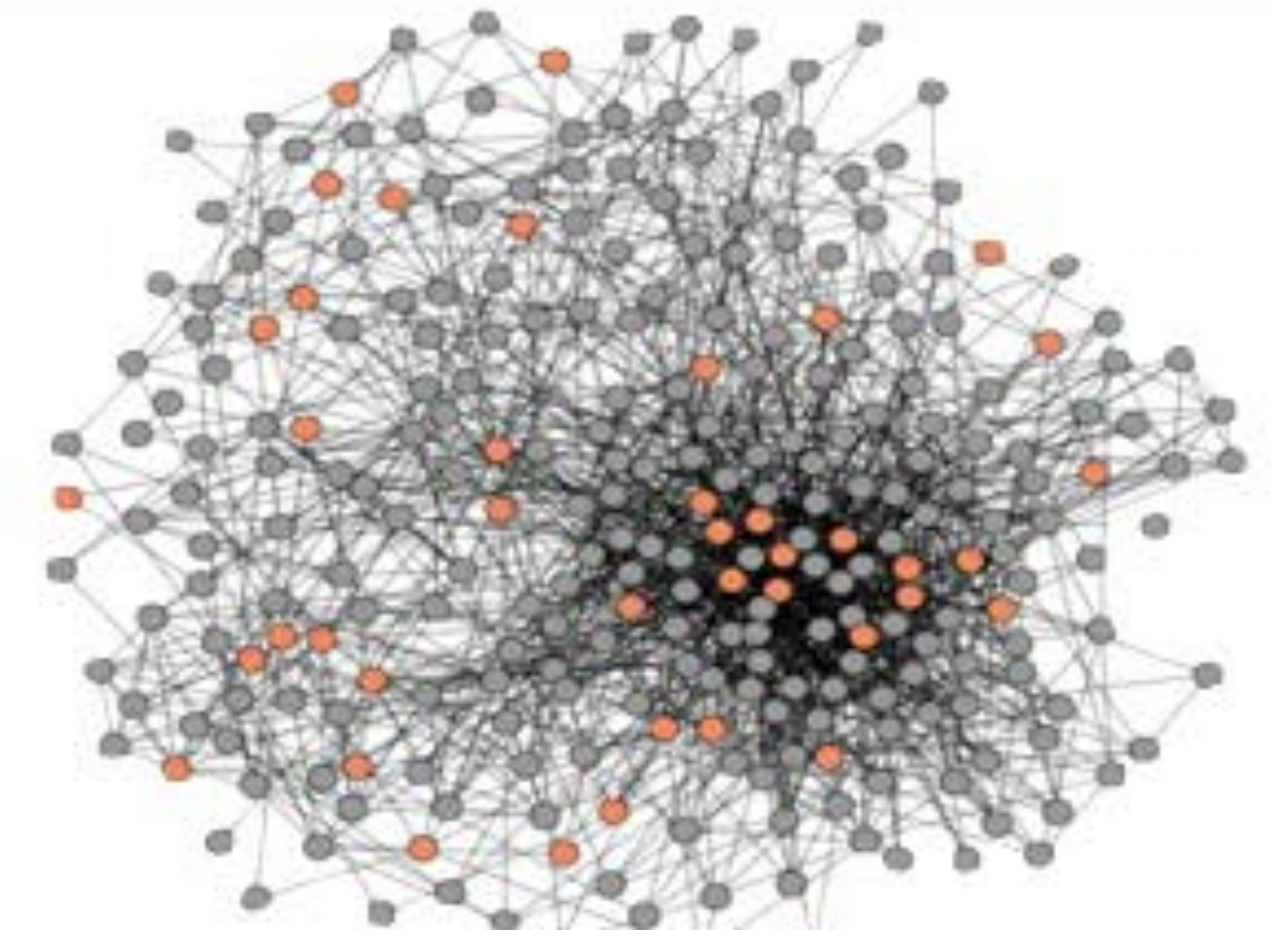
Brain responses to clips
(before meeting each other)

wait for social network
to stabilize

Hyon et al., under review

Follow up (under review)



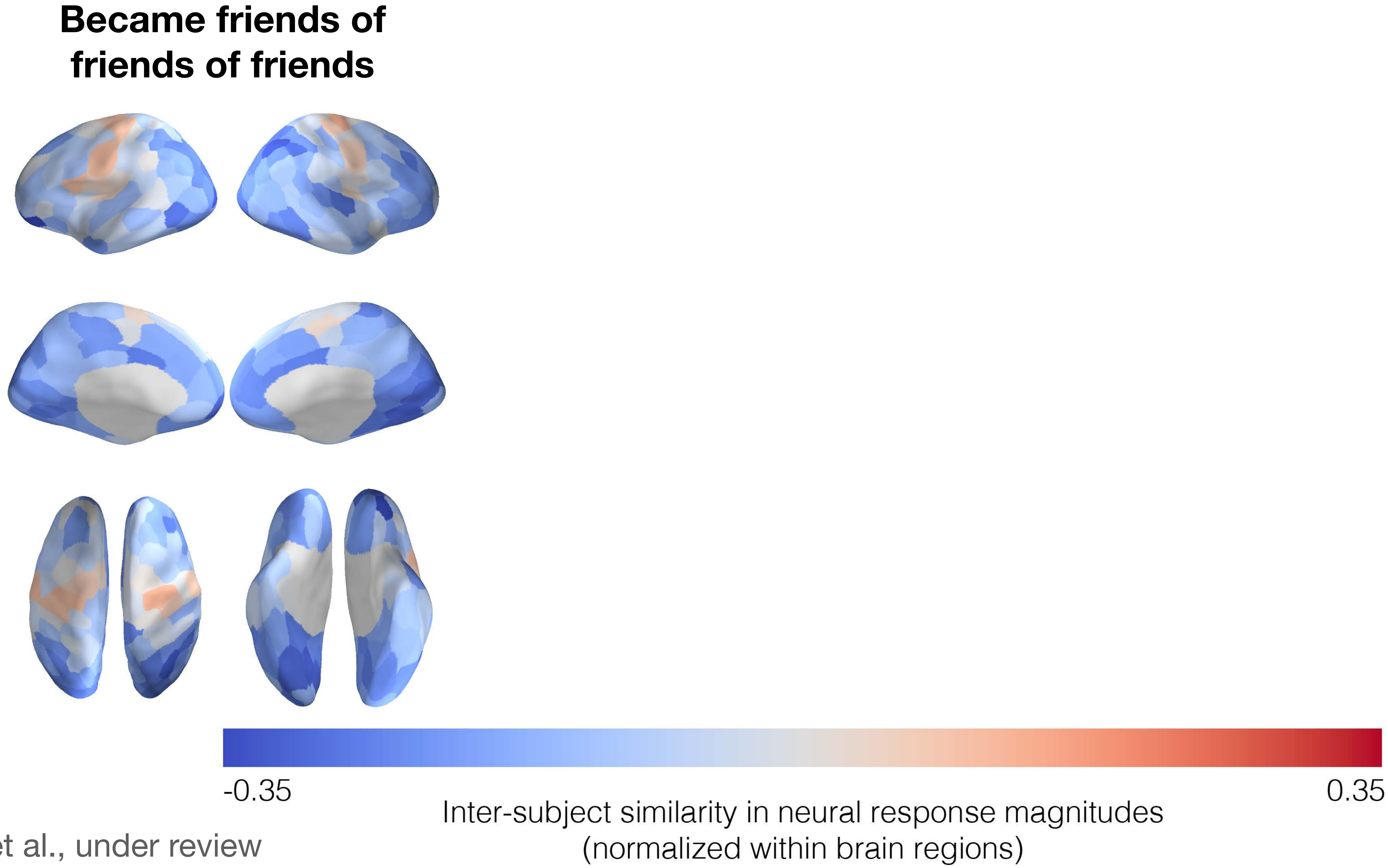


Brain responses to clips (before meeting each other)

wait for social network to stabilize

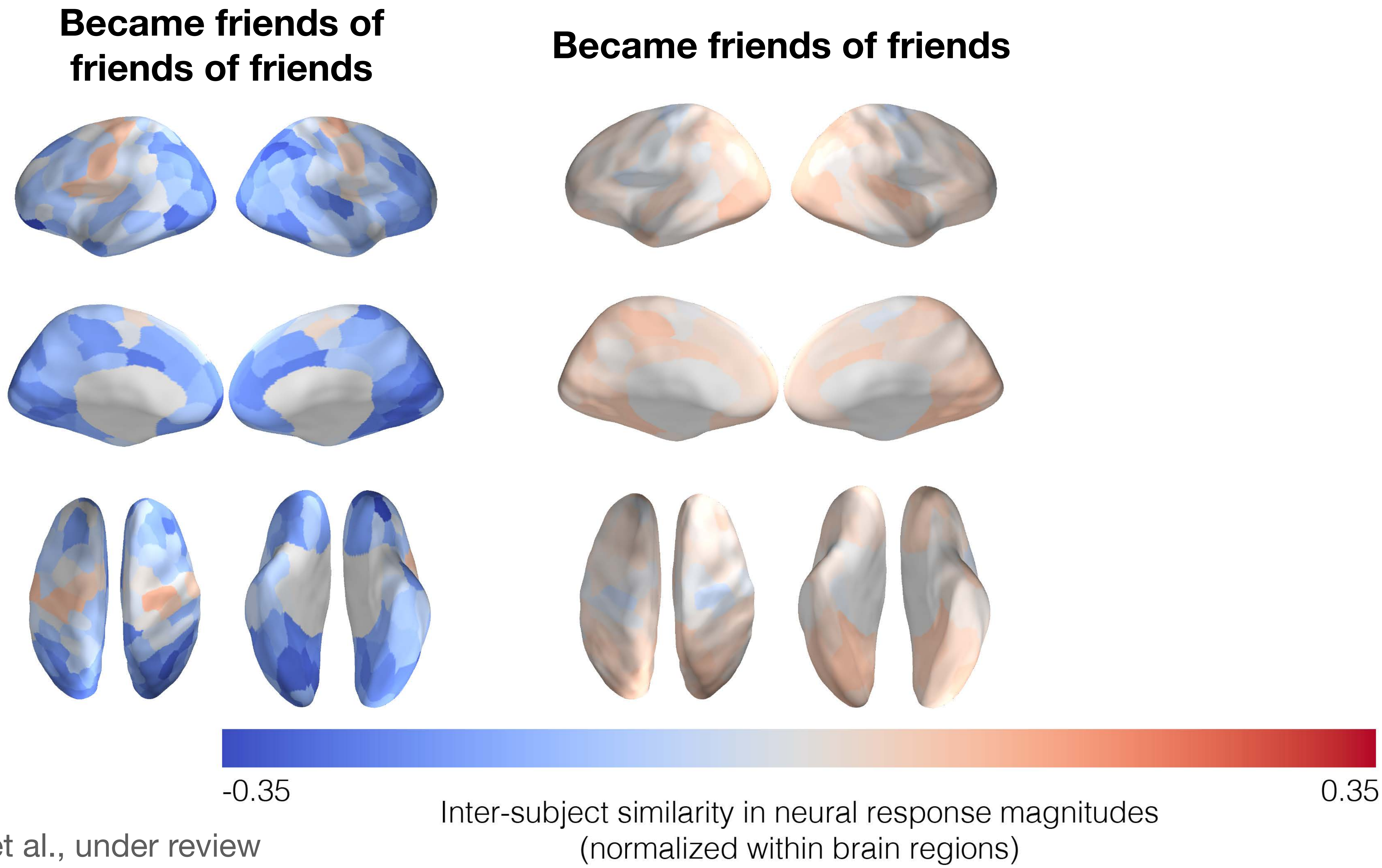
Hyon et al., under review

Brain activity of strangers predicts later friendship



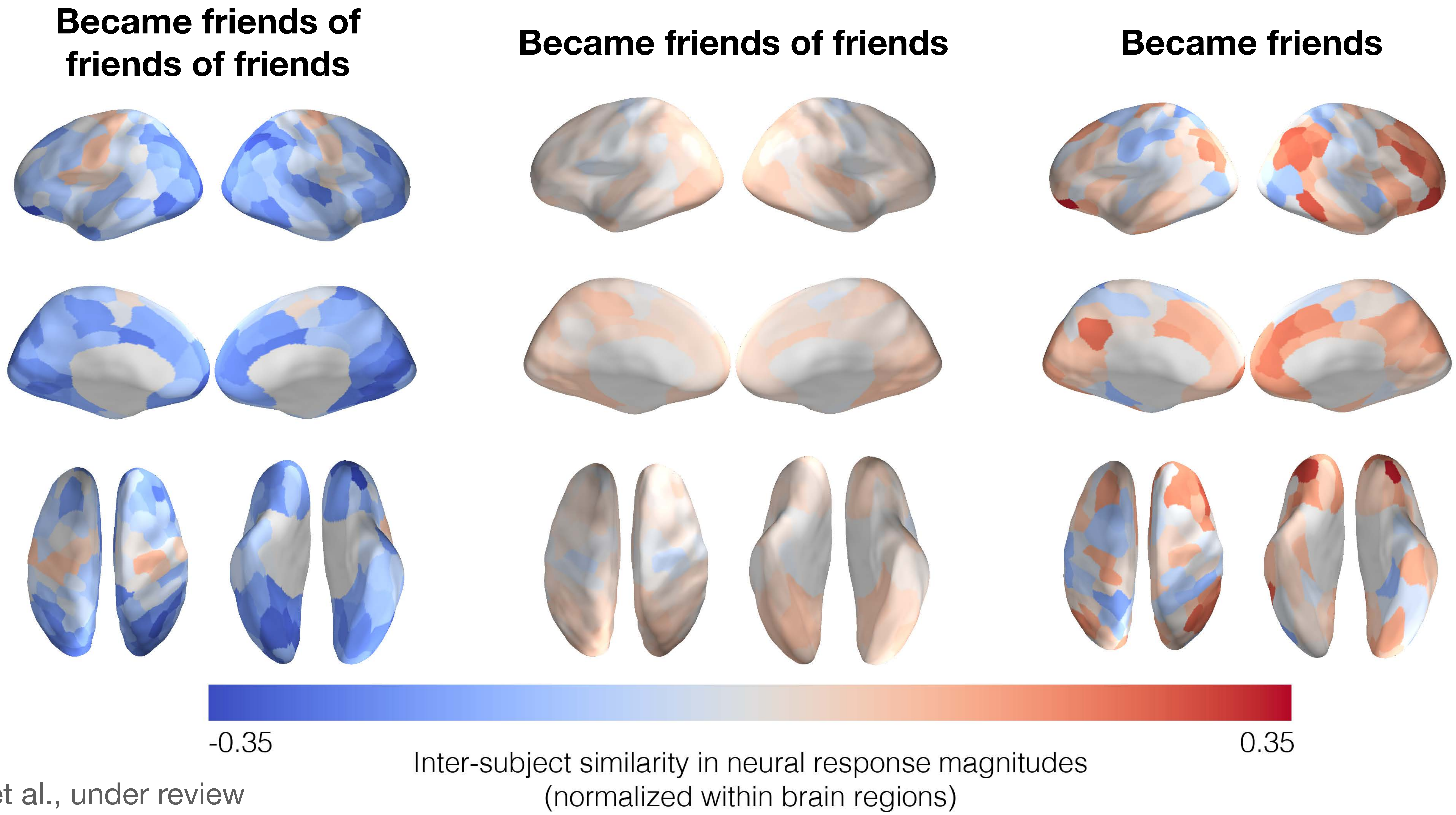
Hyon et al., under review

Brain activity of strangers predicts later friendship



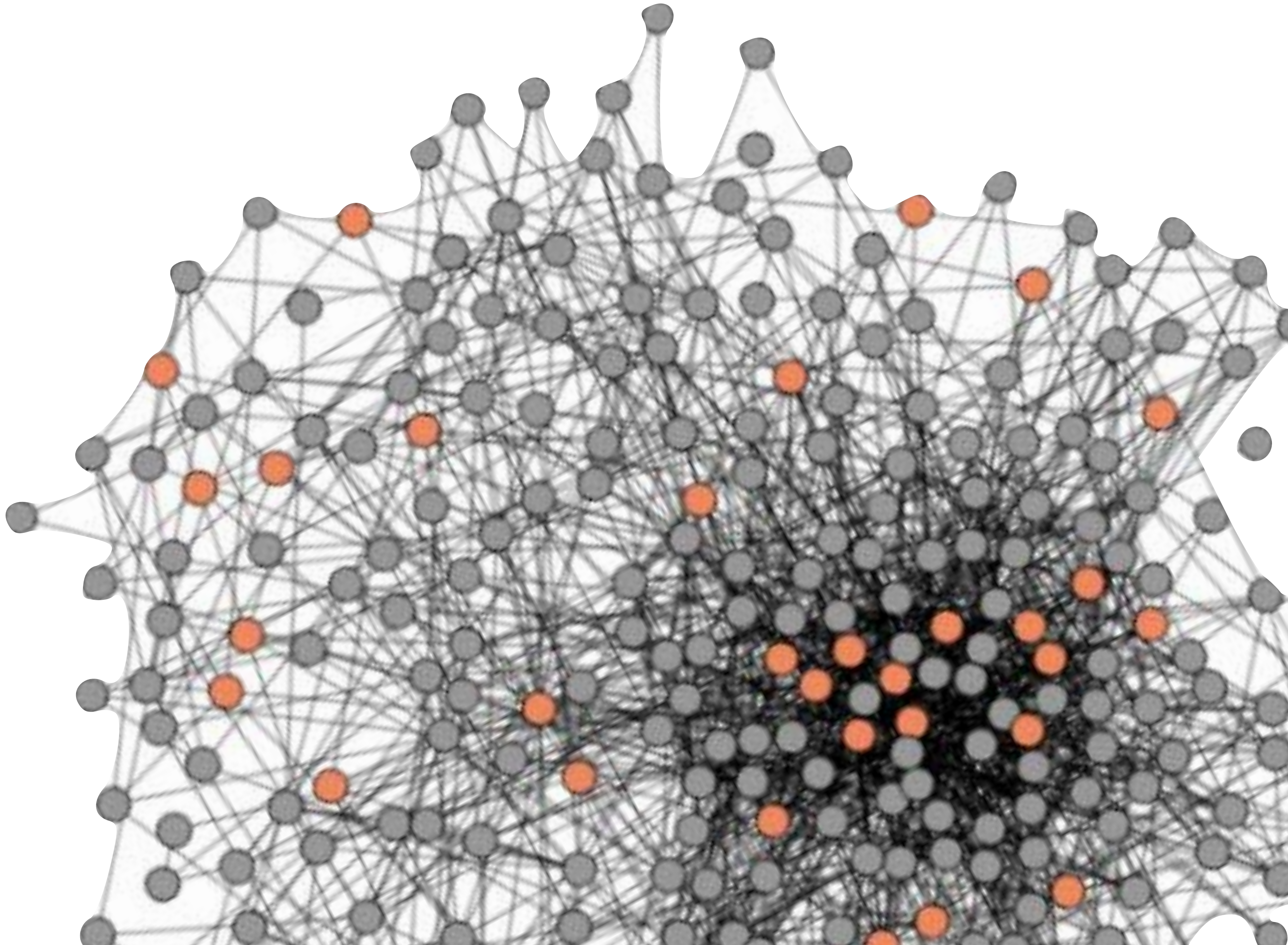
Hyon et al., under review

Brain activity of strangers predicts later friendship



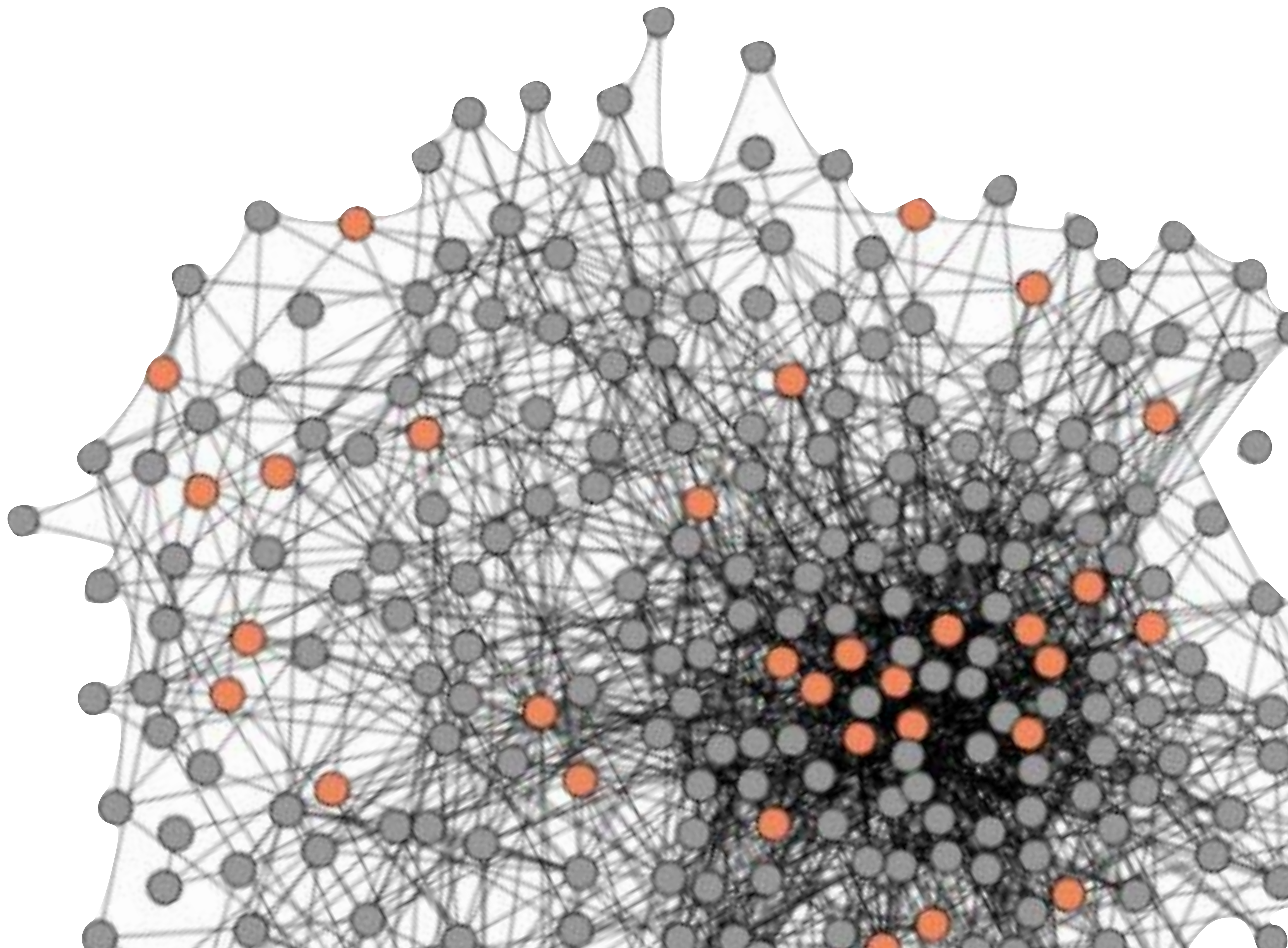
Hyon et al., under review

Do we befriend people who think like us?



Do we befriend people who think like us?

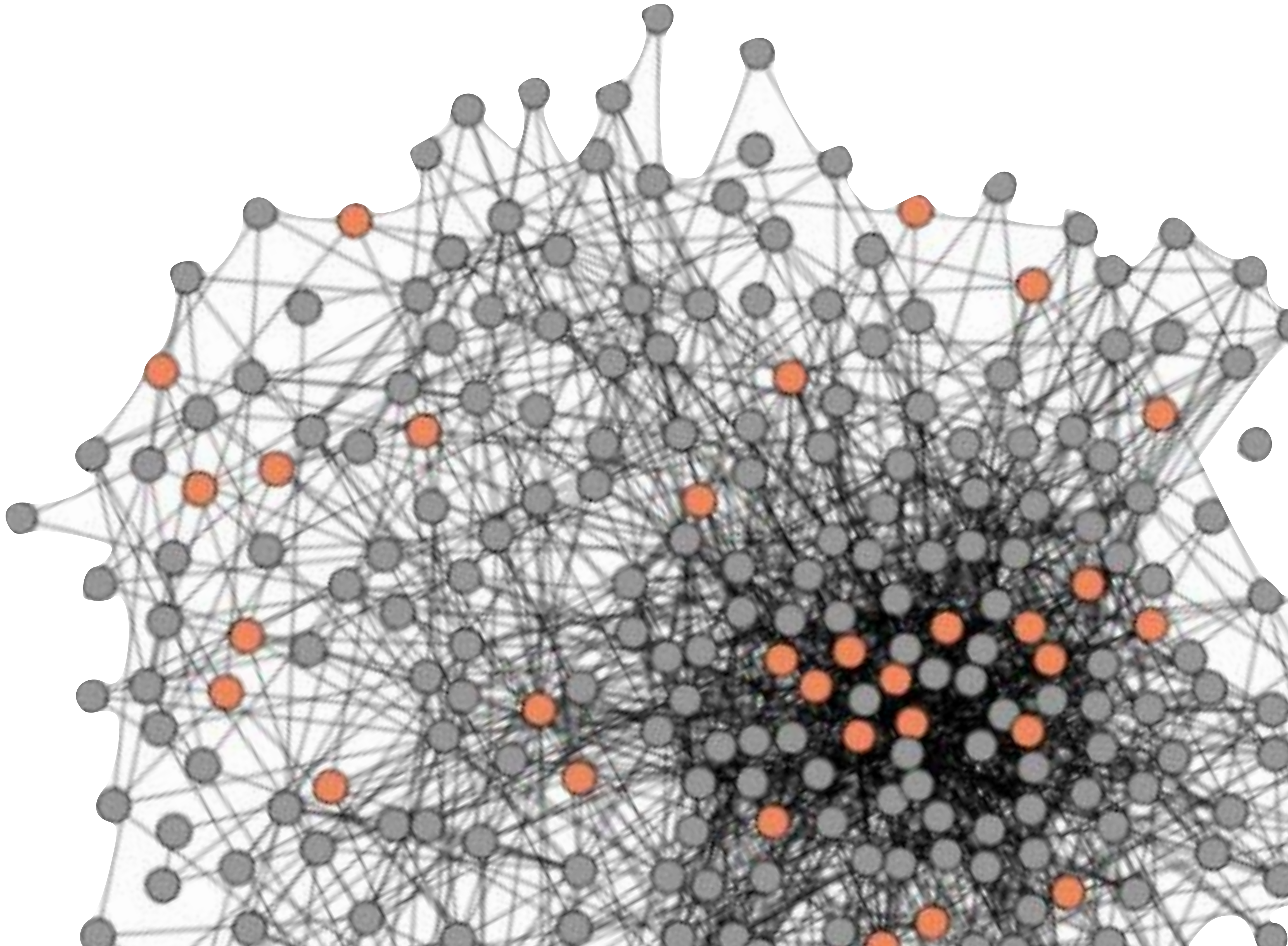
Yes.



Do we befriend people who think like us?

Yes.

(Neural homophily)



We are now *starting* to be able to see
how two brains synchronize
in real time

NEUROSCIENCE

Brain Waves Synchronize when People Interact

The minds of social species are strikingly resonant

By Lydia Denworth on July 1, 2023
Scientific American July 2023 Issue

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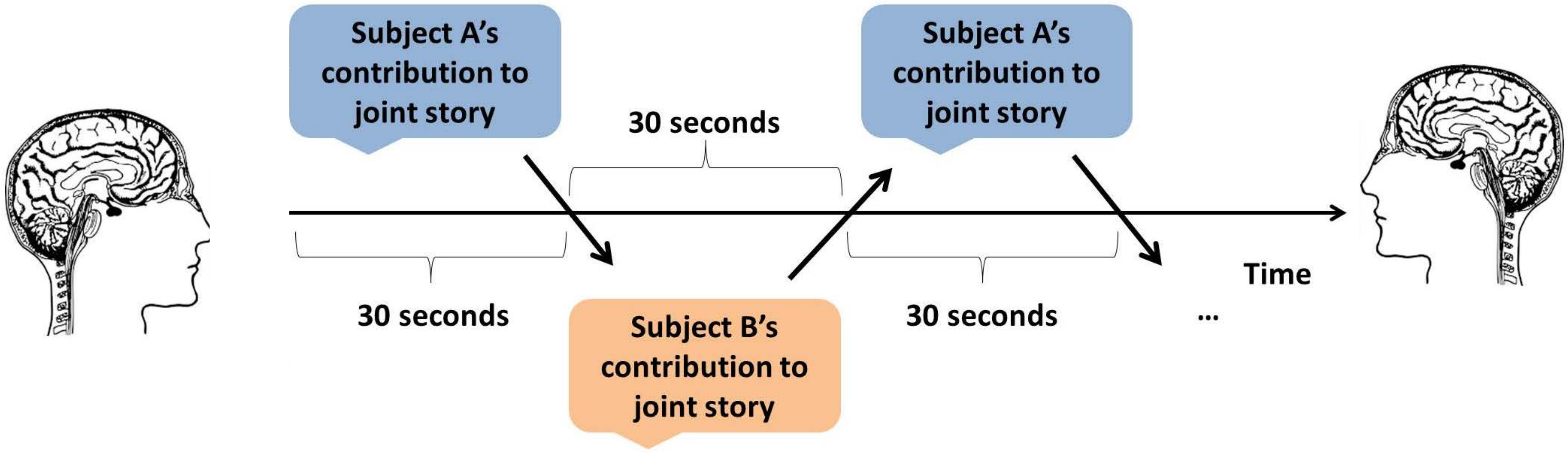
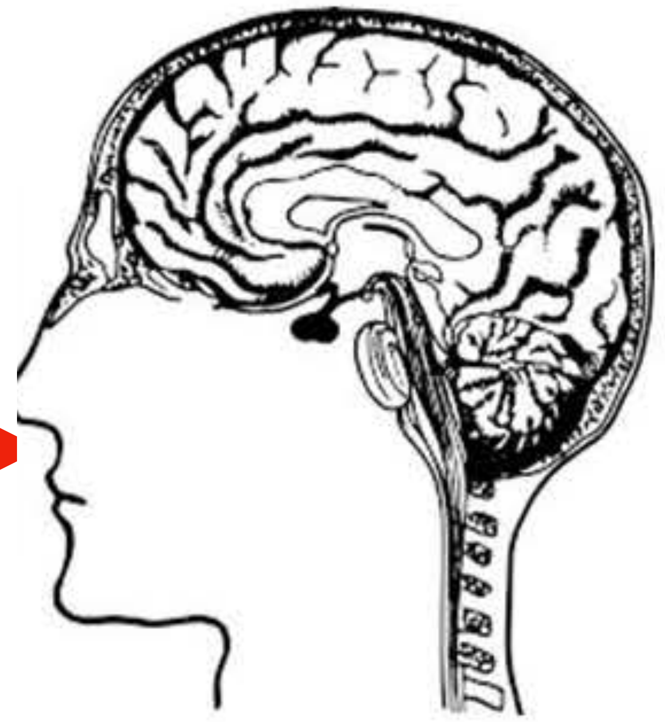
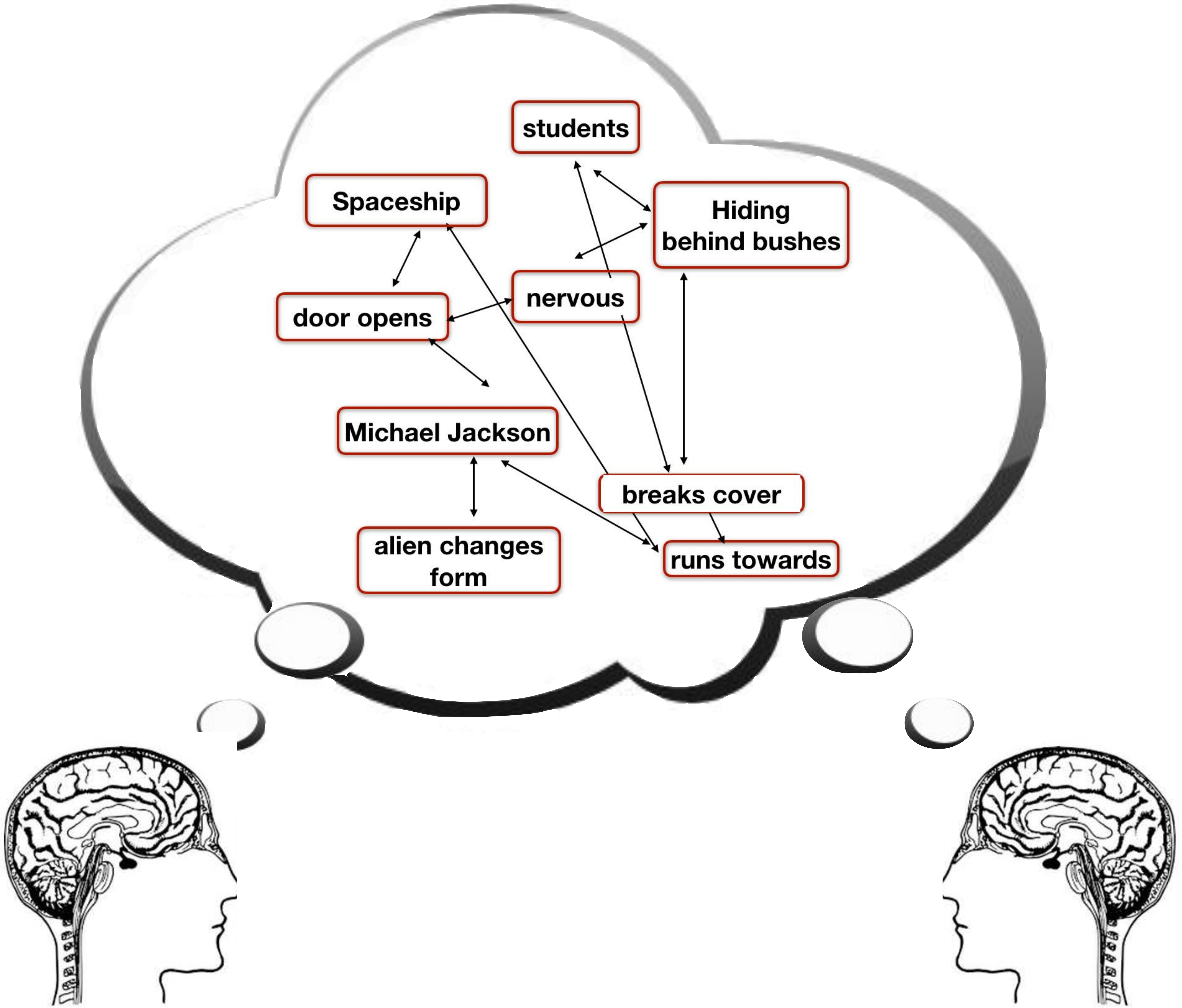
Conversation in fMRI

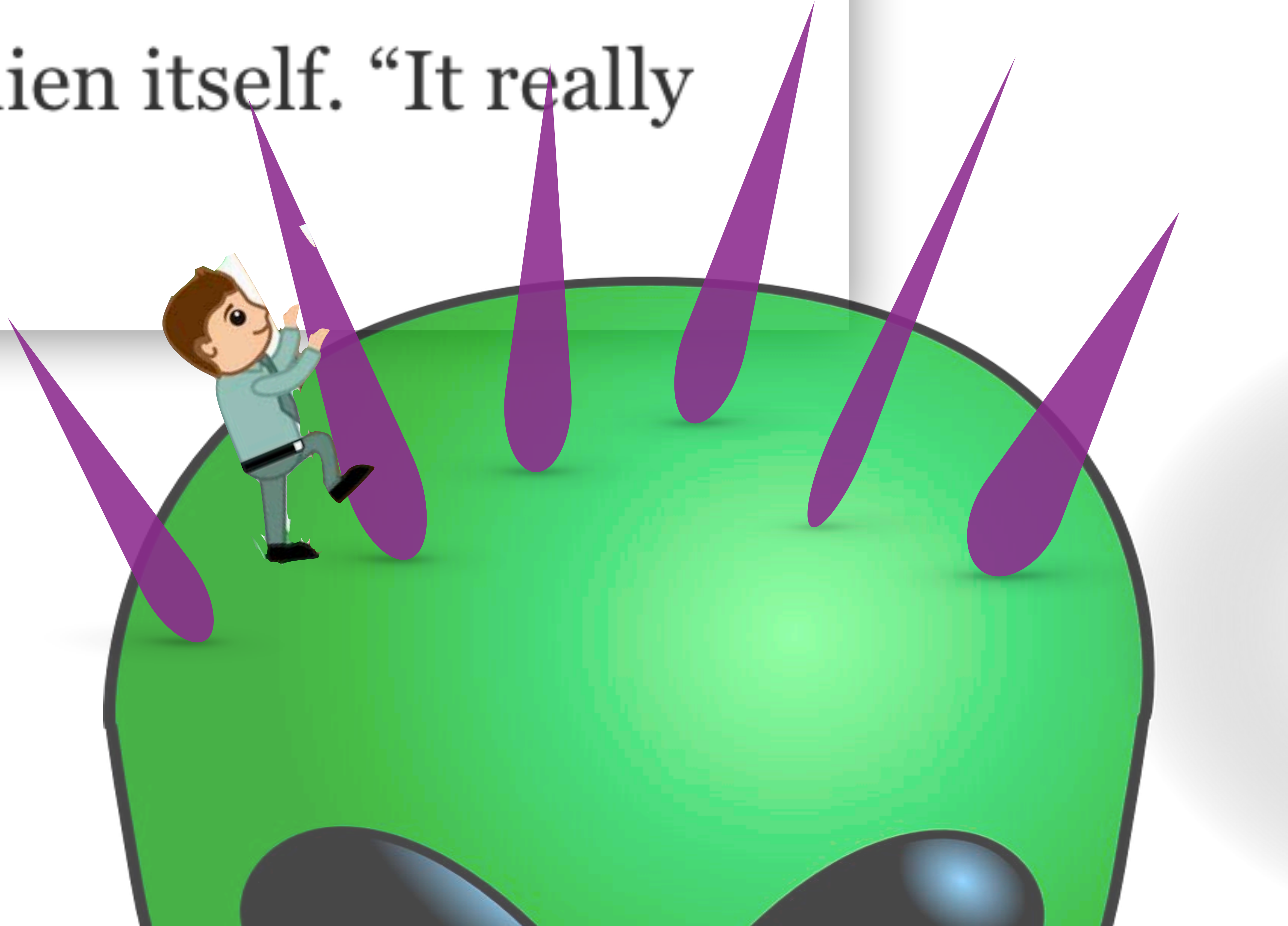





students
Spaceship
Hiding
behind bushes
door opens
nervous
Michael Jackson
breaks cover
alien changes
form
runs towards

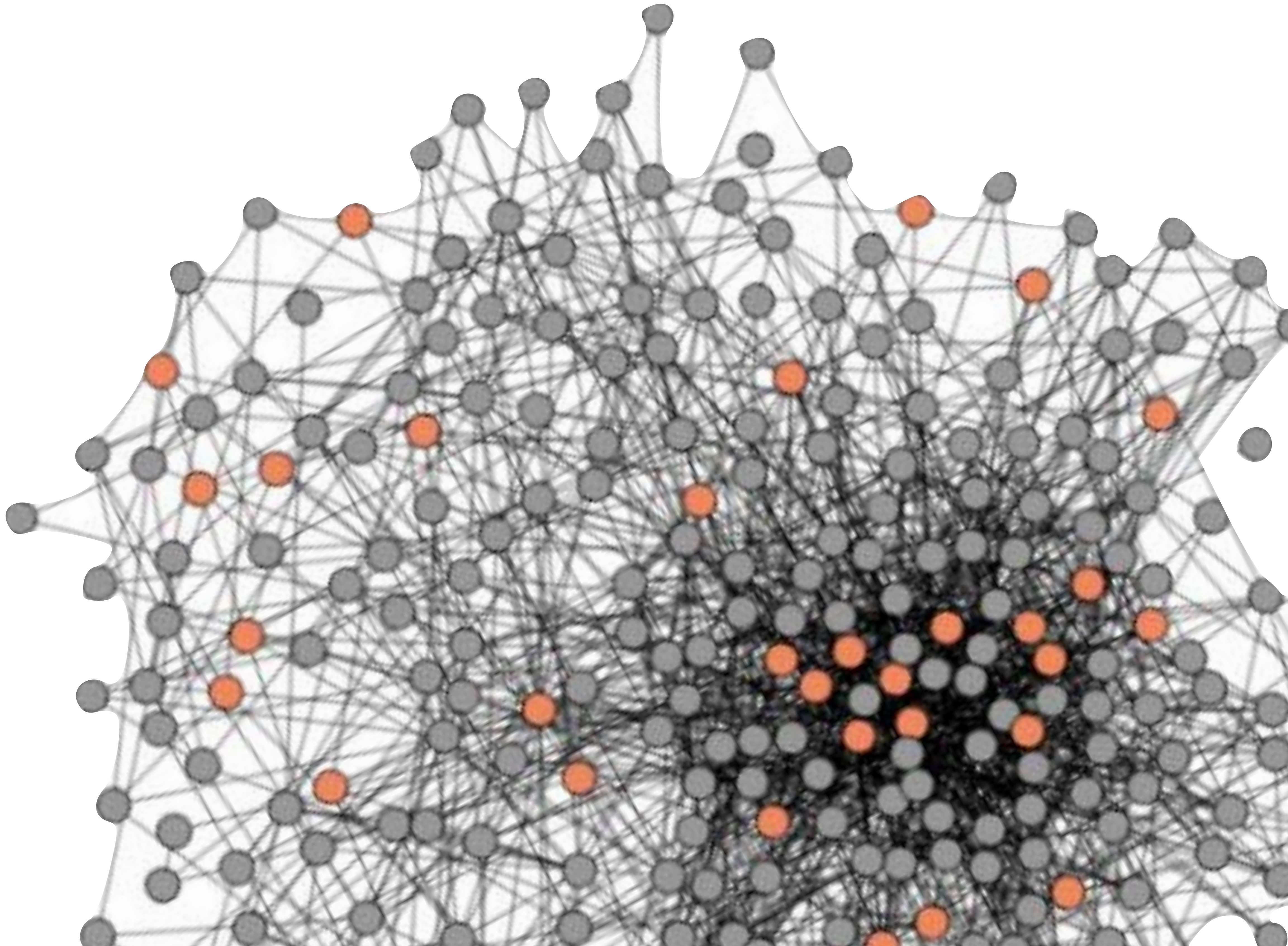
though, was that of the pair who came before us. Caitlyn Lee, a graduate student in Wheatley's lab, was working with Lorie Loeb, a computer science professor at Dartmouth. They set their story not in a park, like ours, but in an unfamiliar landscape. During one of her turns, Lee said, “The trees [the children] were climbing on looked really weird; the ground was starting to rise.” Then her turn cut off, and Loeb picked the story up, though, was that of the pair who came before us. Caitlyn Lee, a graduate student in Wheatley's lab, was working with Lorie Loeb, a computer science professor at Dartmouth. They set their story not in a park, like ours, but in an unfamiliar landscape. During one of her turns, Lee said, “The trees [the children] were climbing on looked really weird; the ground was starting to rise.” Then her turn cut off, and Loeb picked the story up, saying, “It felt like the creature took a breath.” It was exactly what Lee had been thinking: that the children were walking on the alien itself. “It really felt like we were on the same page,” Lee says.

We’ve cov



How do we *adapt* to each other?

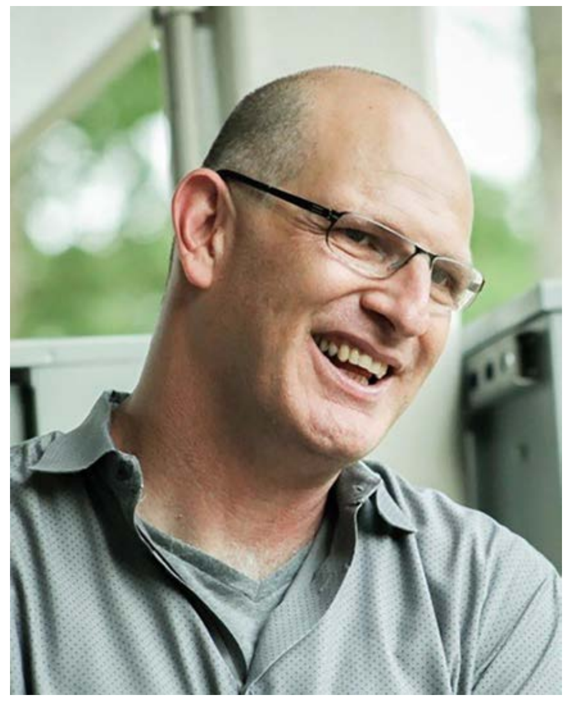
(neural influence)



Beau Sievers, PhD

Chris Welker
Grad student

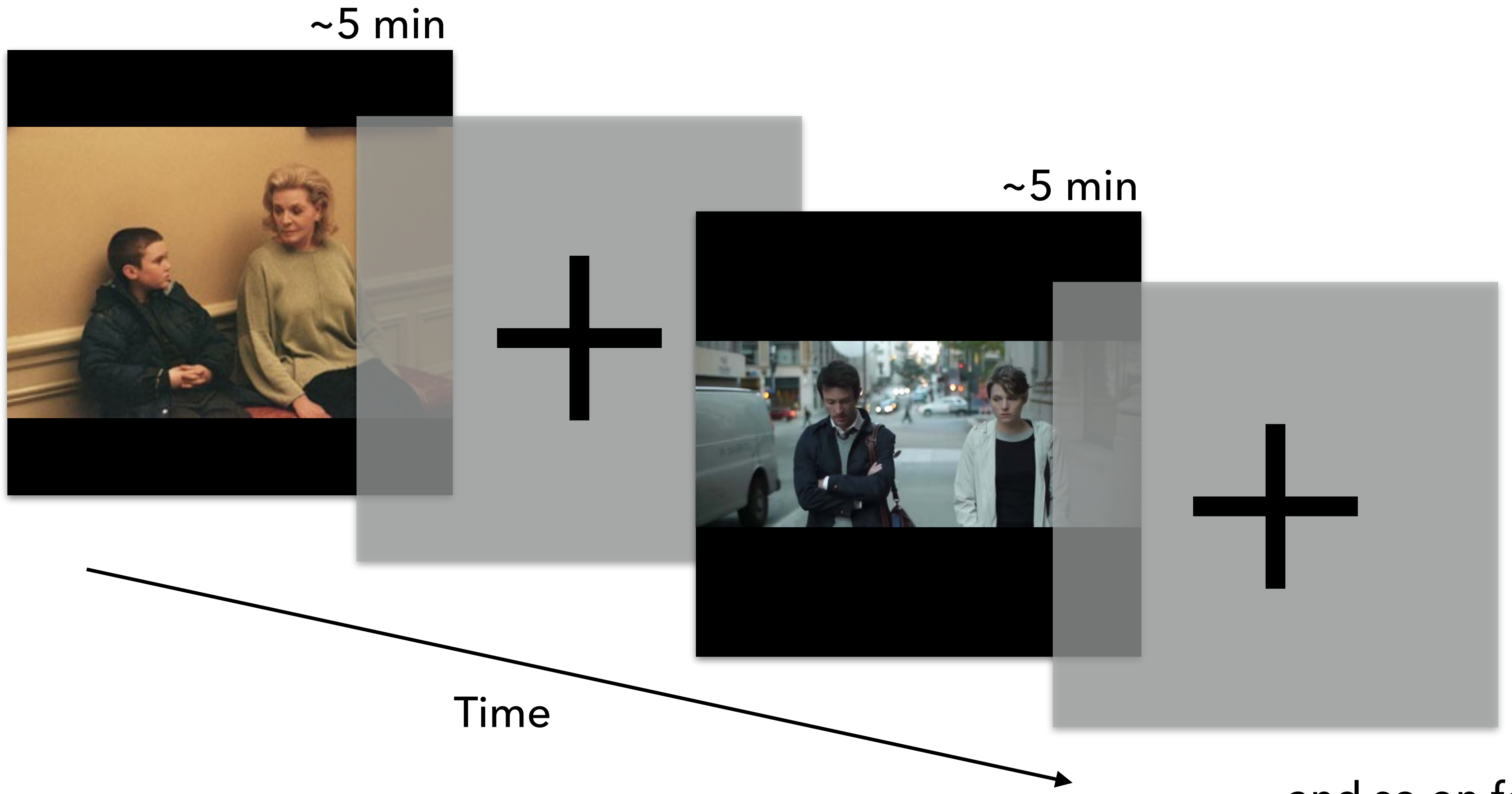
Prof Adam
Kleinbaum
TUCK



Uri Hasson
Princeton

Sievers et al, inv. revision, https://psyarxiv.com/562z7/

Session 1

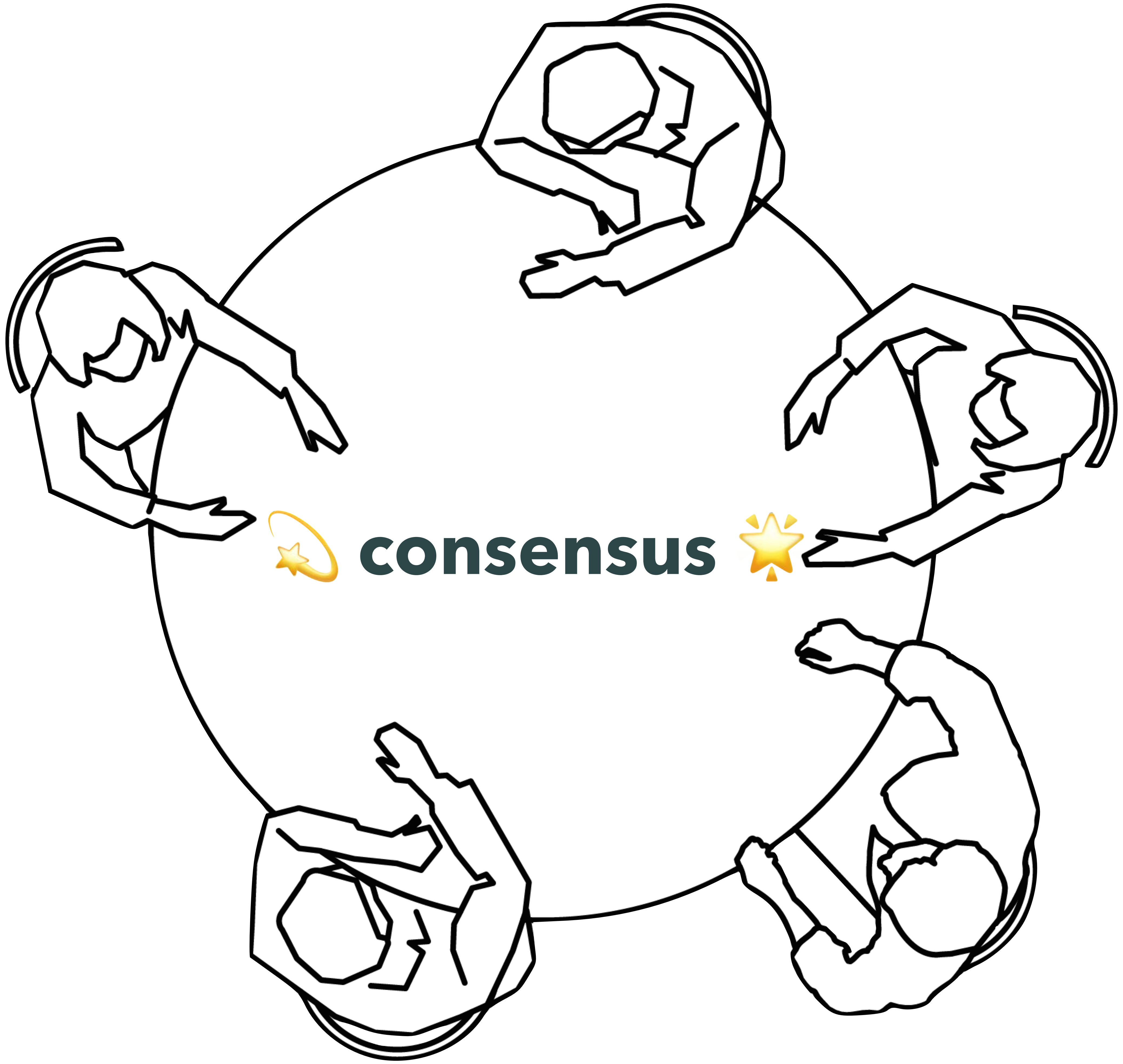


...and so on for 5 movies...

Sievers et al, inv. revision, https://psyarxiv.com/562z7/

Excerpt from *Birth*, dir. Jonathan Glazer

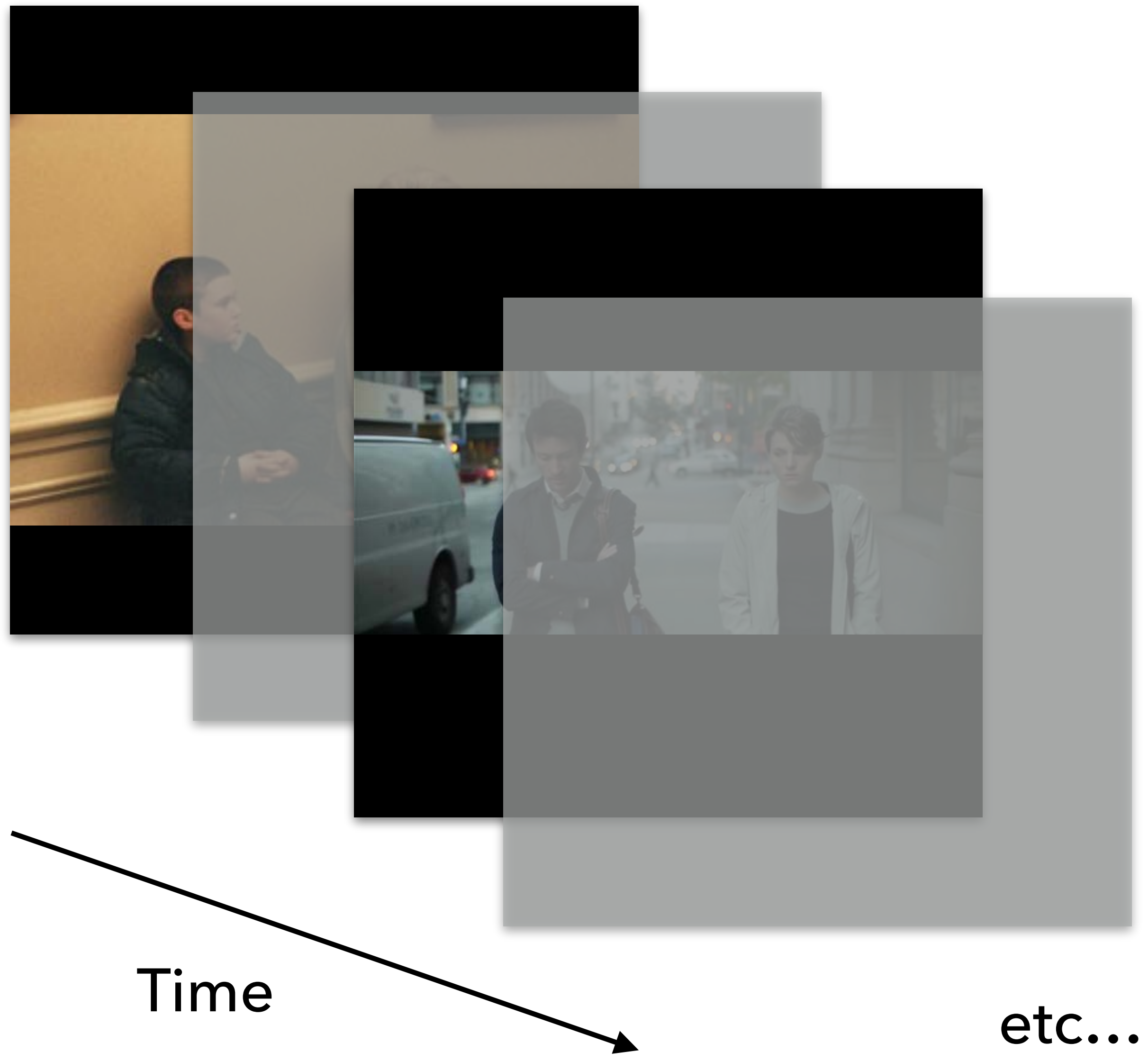
Session 2



Sievers et al, inv. revision, https://psyarxiv.com/562z7/

Session 3

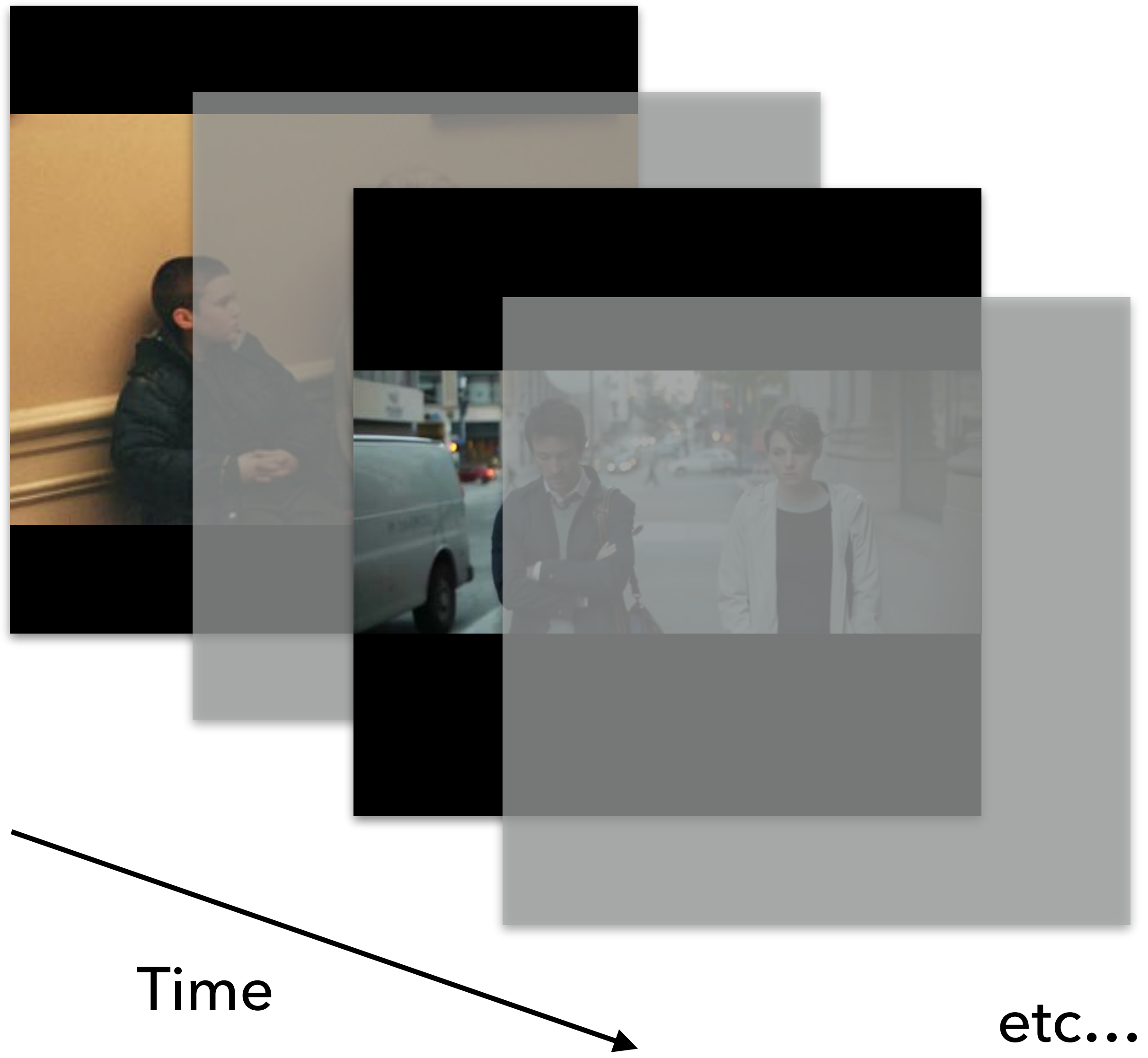
Previously viewed movies...



Sievers et al, inv. revision, https://psyarxiv.com/562z7/

Session 3

Previously viewed movies… …followed by **novel** movie clips with the same characters.

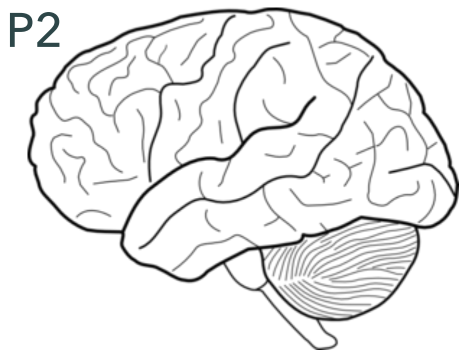
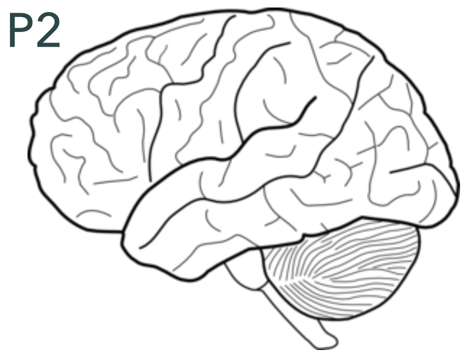


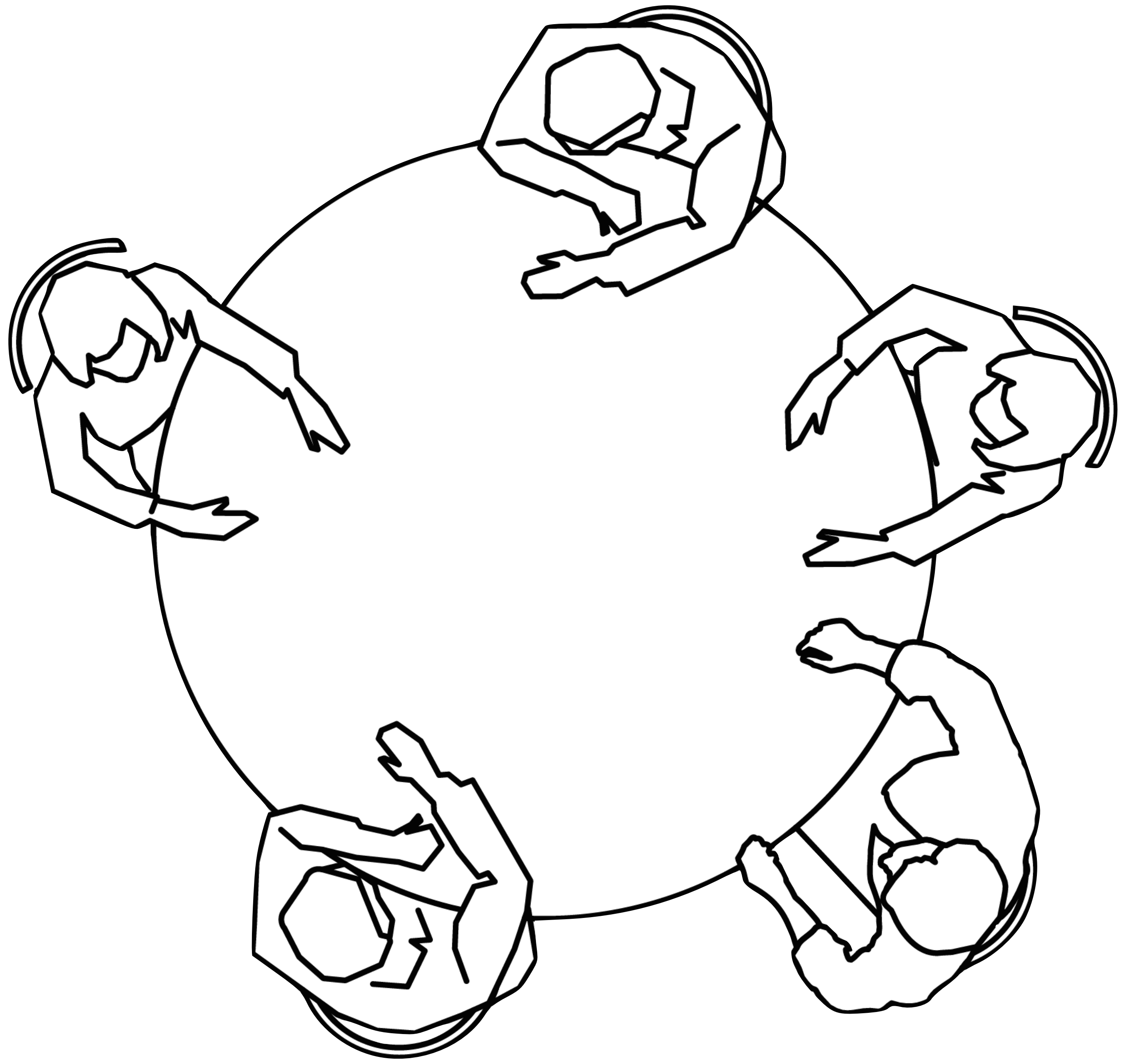
Sievers et al, inv. revision, https://psyarxiv.com/562z7/

Change map =

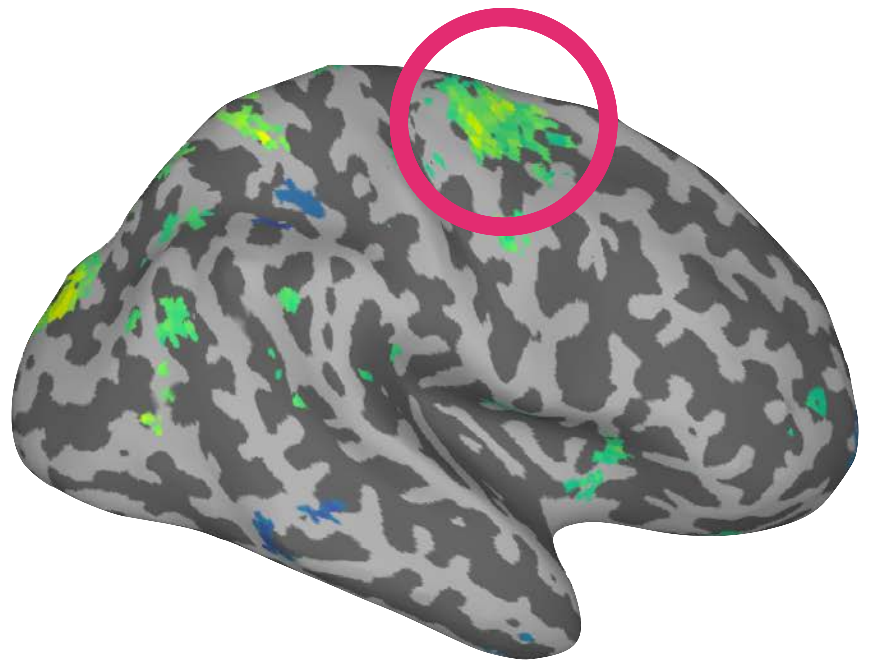
Find changes in synchrony caused by conversation.

After — Before

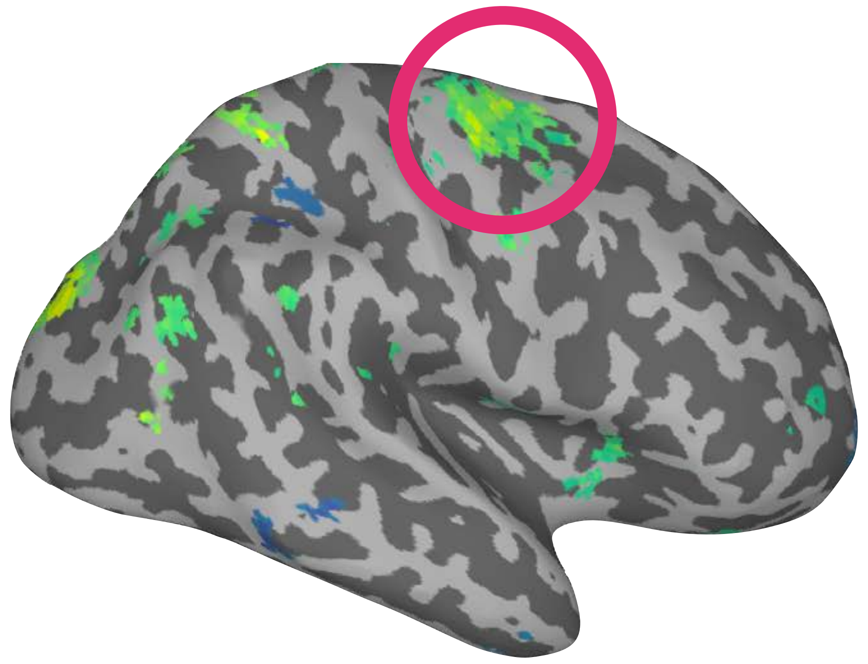
ISC(P1 , P2 ) - ISC(P1 , P2 )

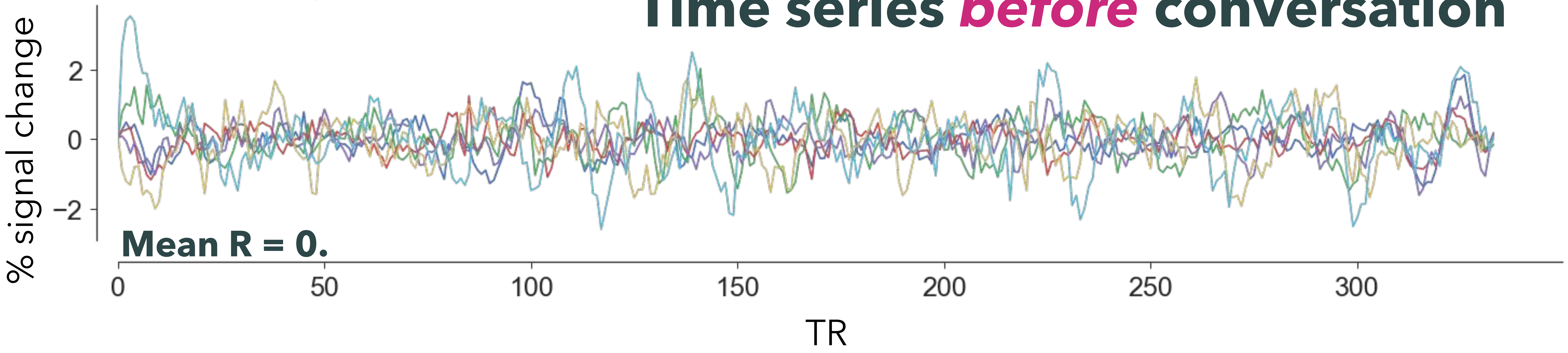


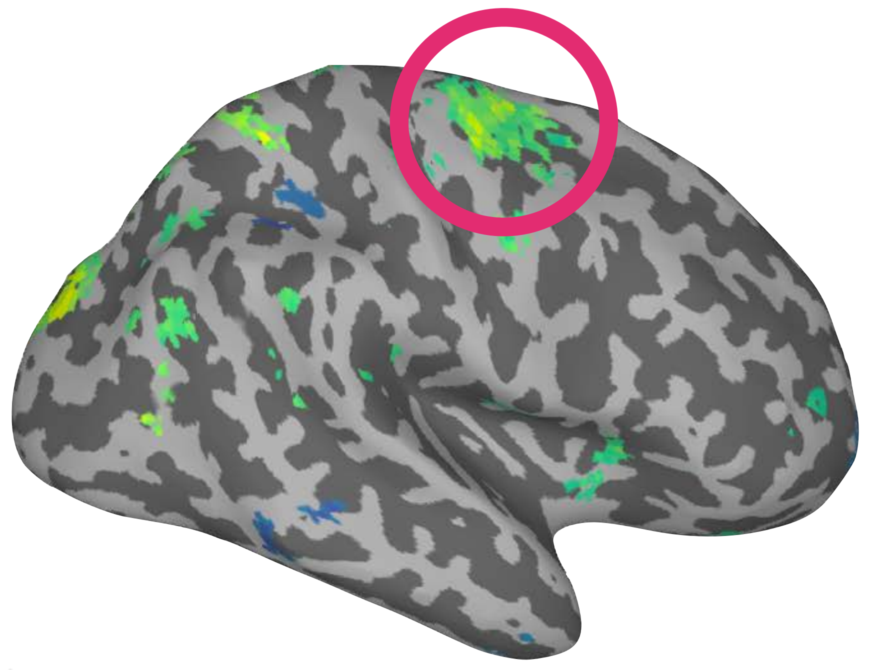
Conversation synchronizes brain activity within groups



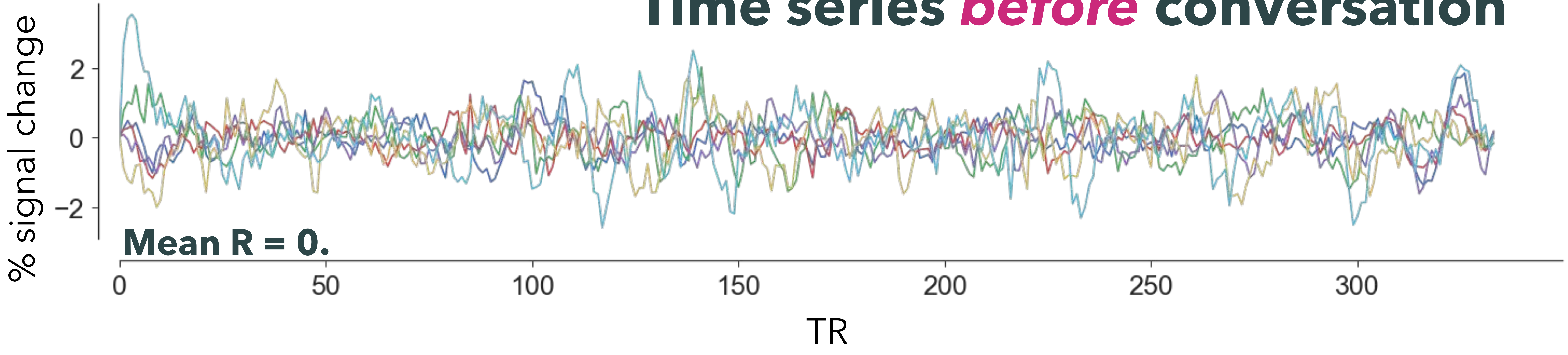
Time series *before* conversation



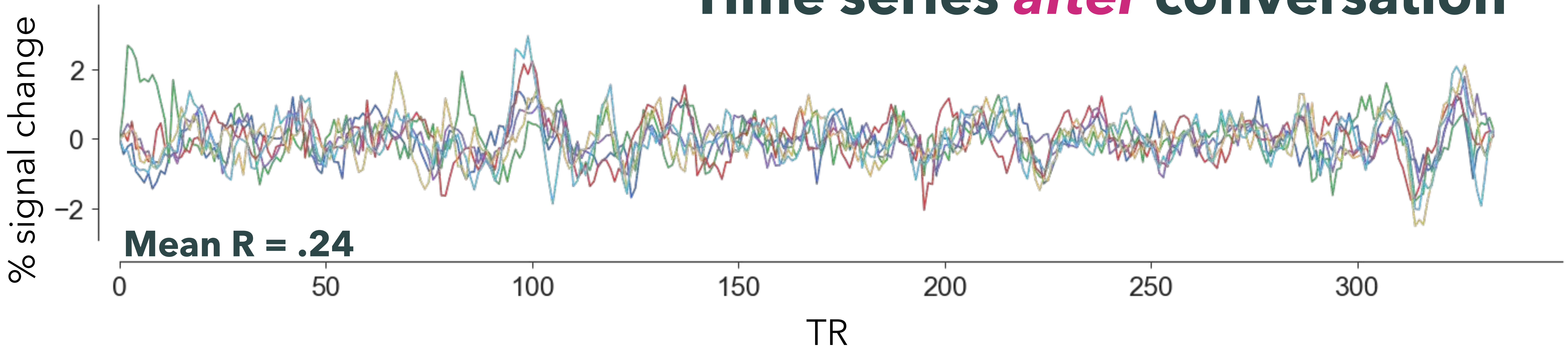


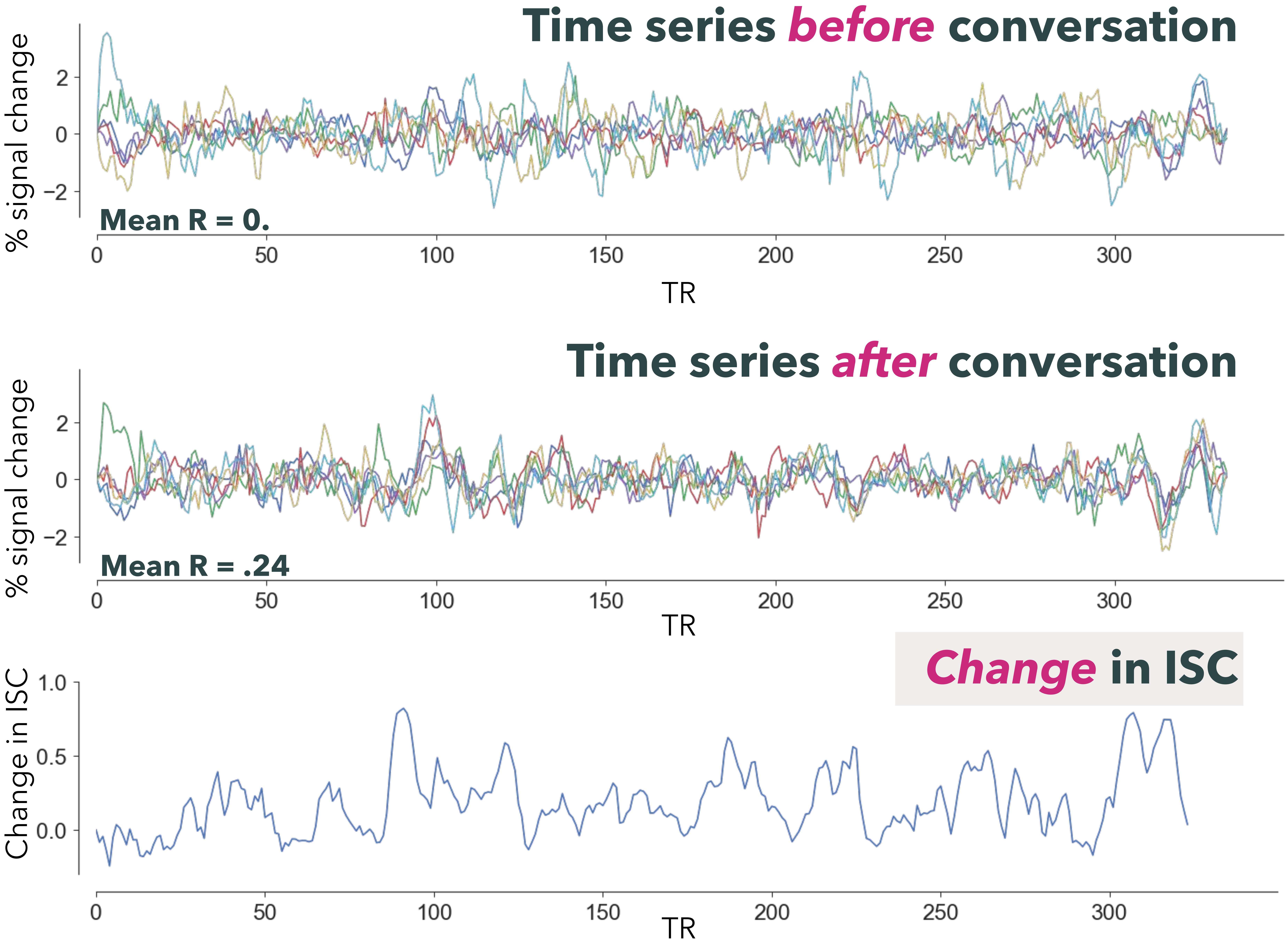


Time series *before* conversation

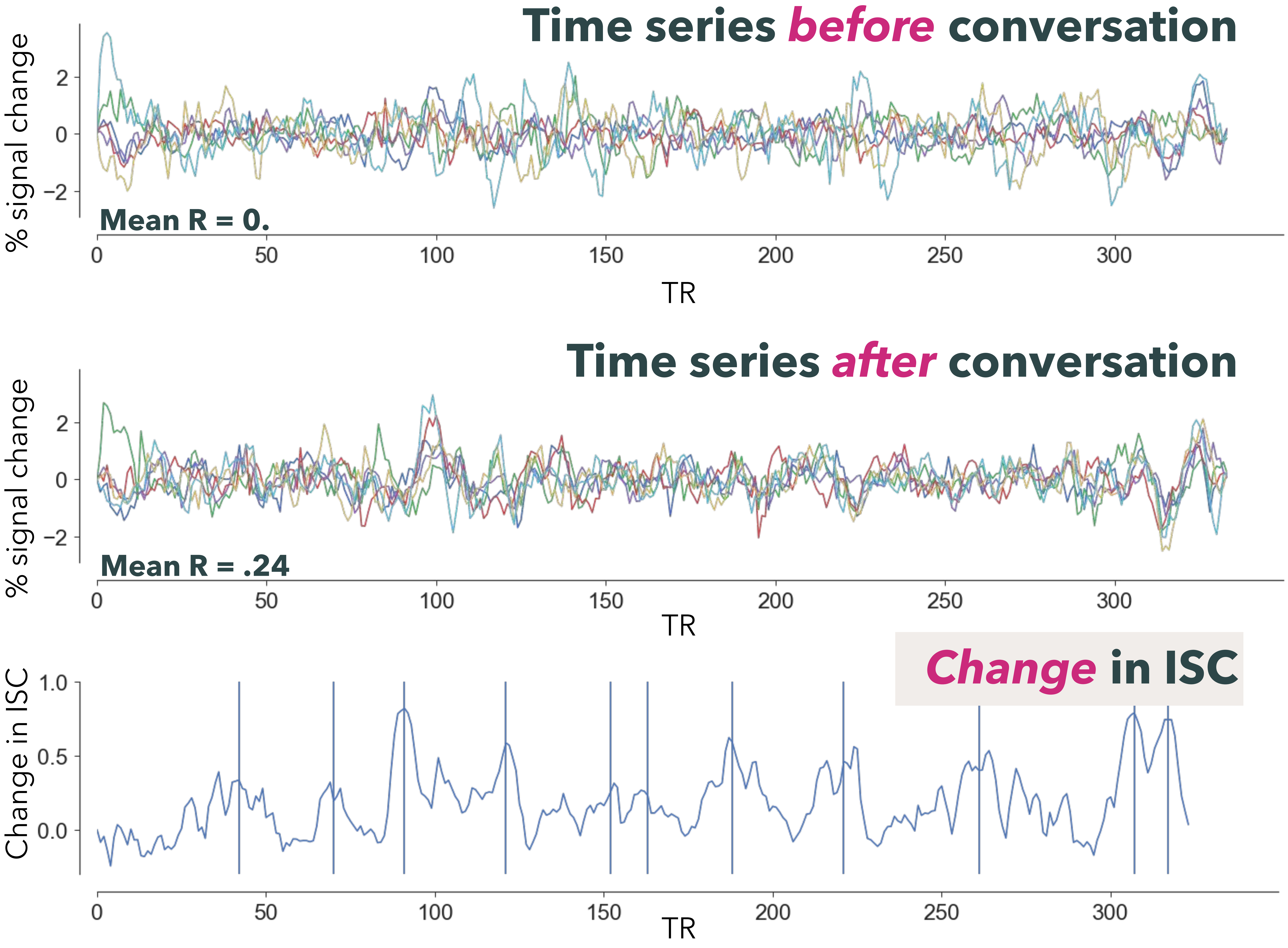


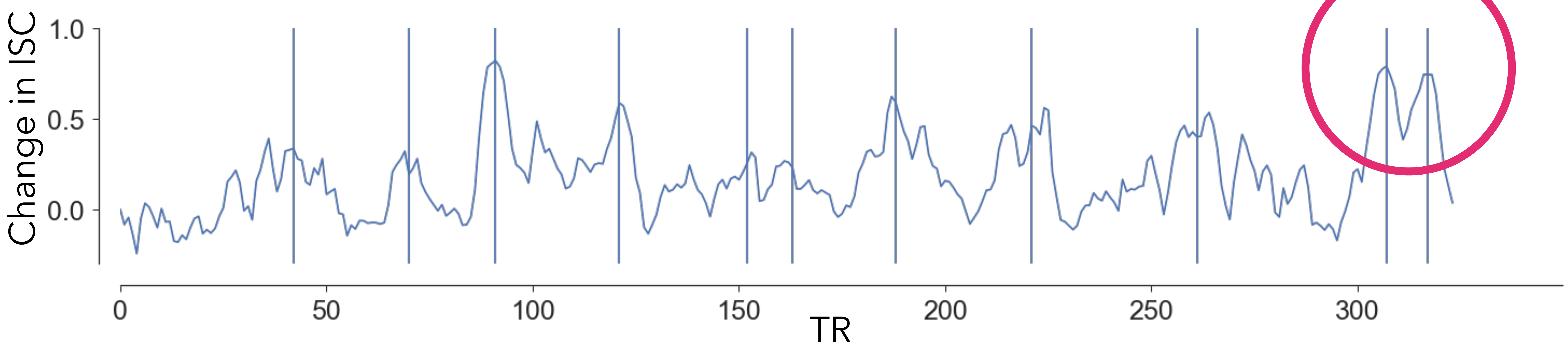
Time series *after* conversation





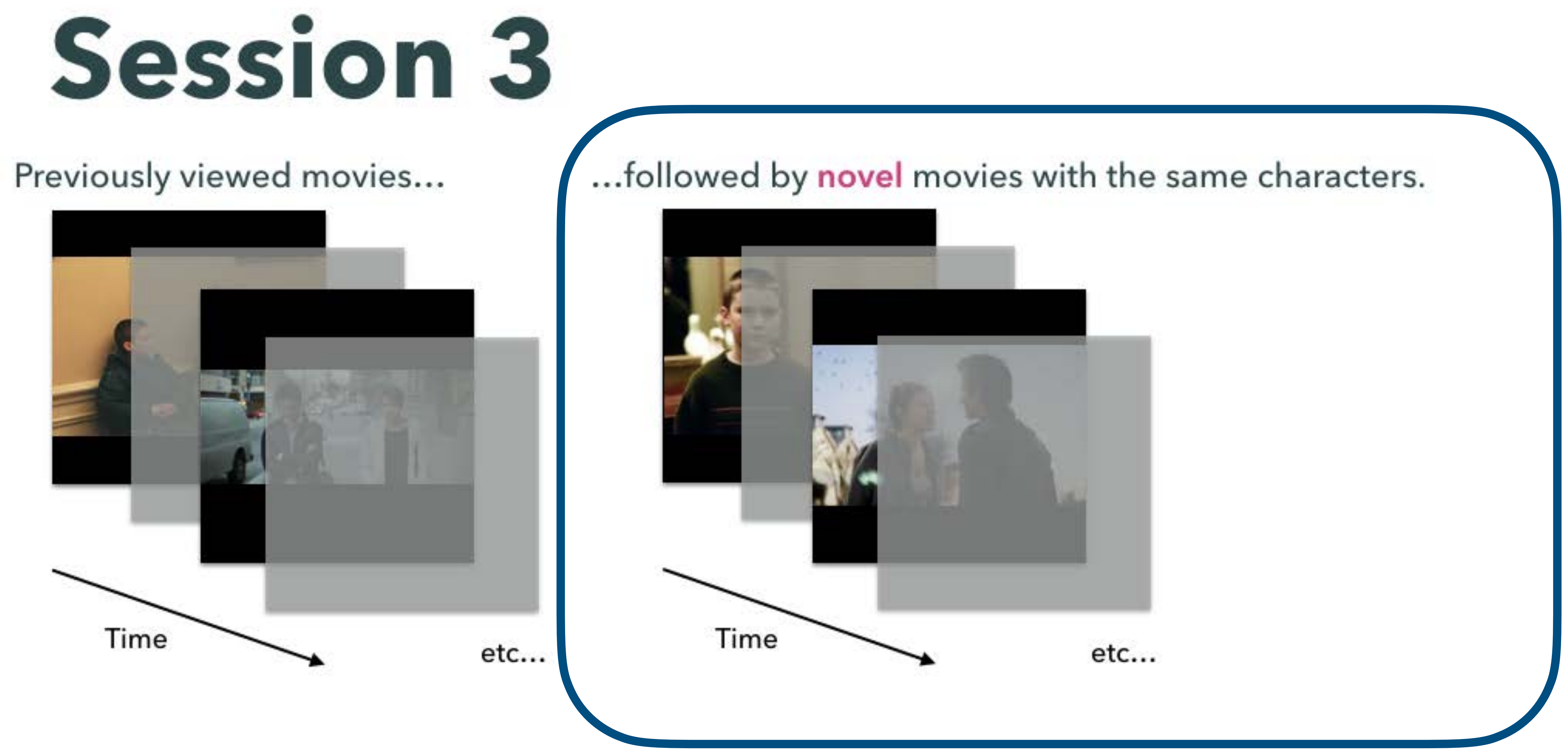
Time series before conversation
% signal change
2
0
−2
Mean R = 0.
0
50
100
150
200
250
300
TR
Time series after conversation
% signal change
2
0
−2
Mean R = .24
0
50
100
150
200
250
300
TR
Change in ISC
Change in ISC
1.0
0.5
0.0
0
50
100
150
200
250
300
TR

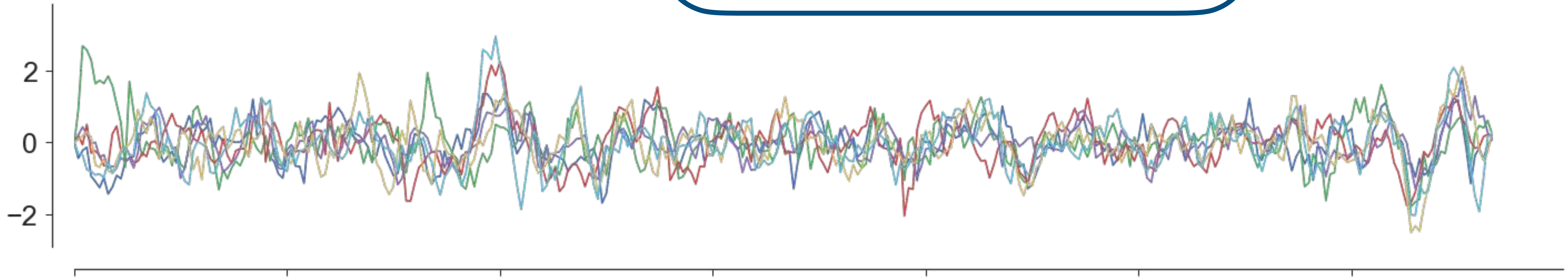

Time series before conversation
% signal change
Mean R = 0.
TR
Time series after conversation
% signal change
Mean R = .24
TR
Change in ISC
Change in ISC
TR



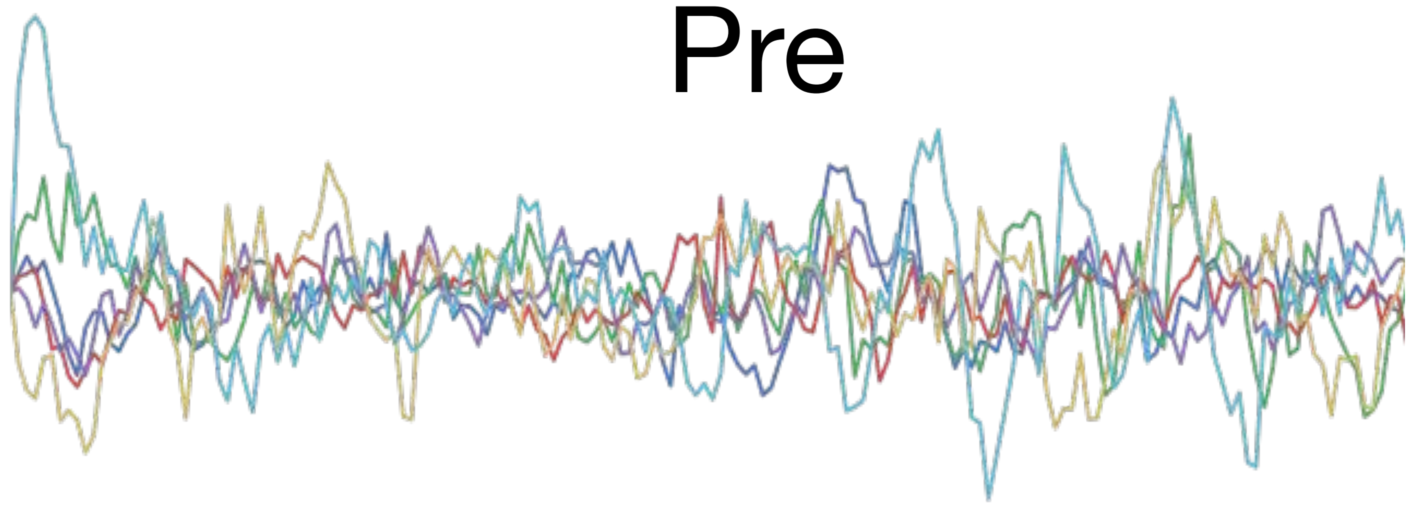
Change in ISC
1.0
0.5
0.0
0
50
100
150
200
250
300
TR

Increased synchrony between group members also persisted for novel clips.

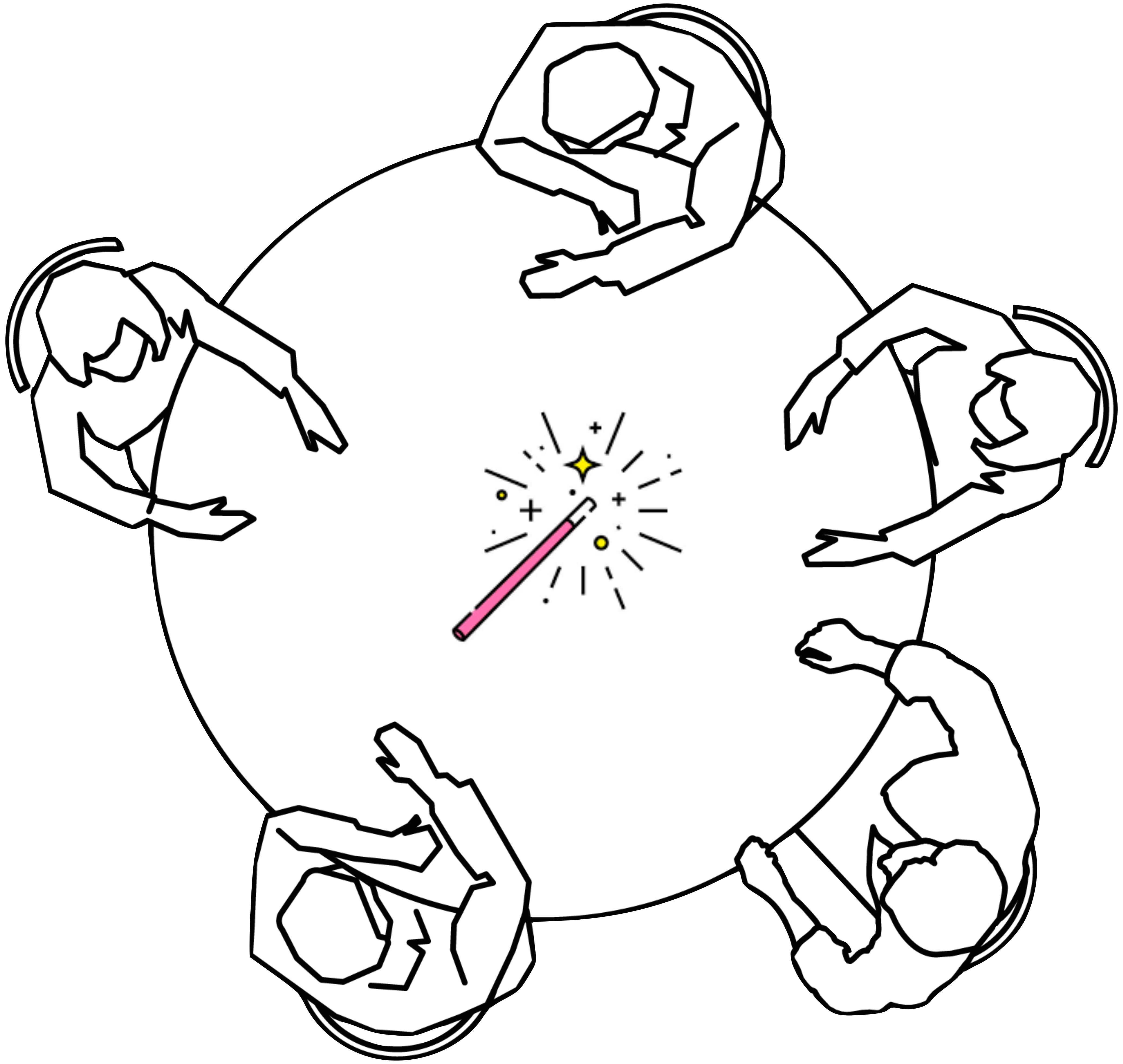




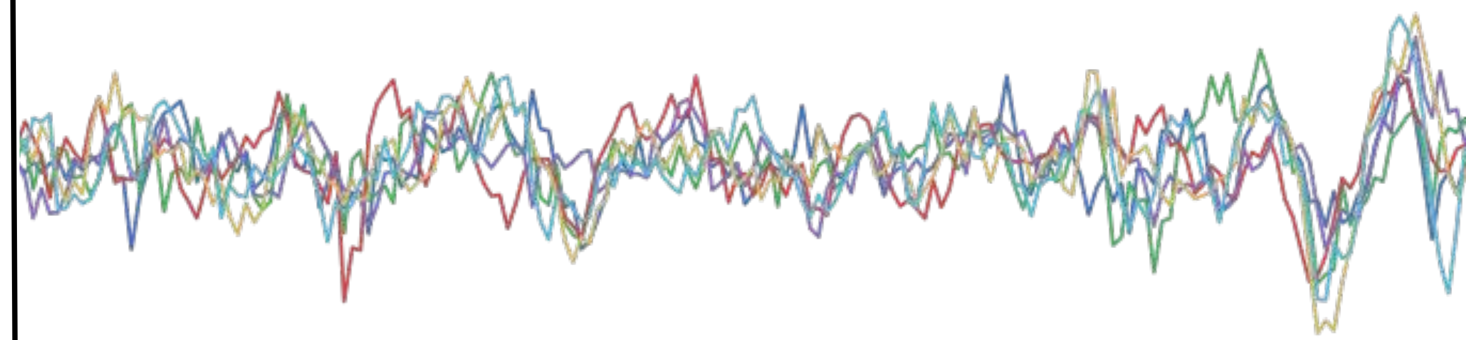
Pre



Where the magic happens

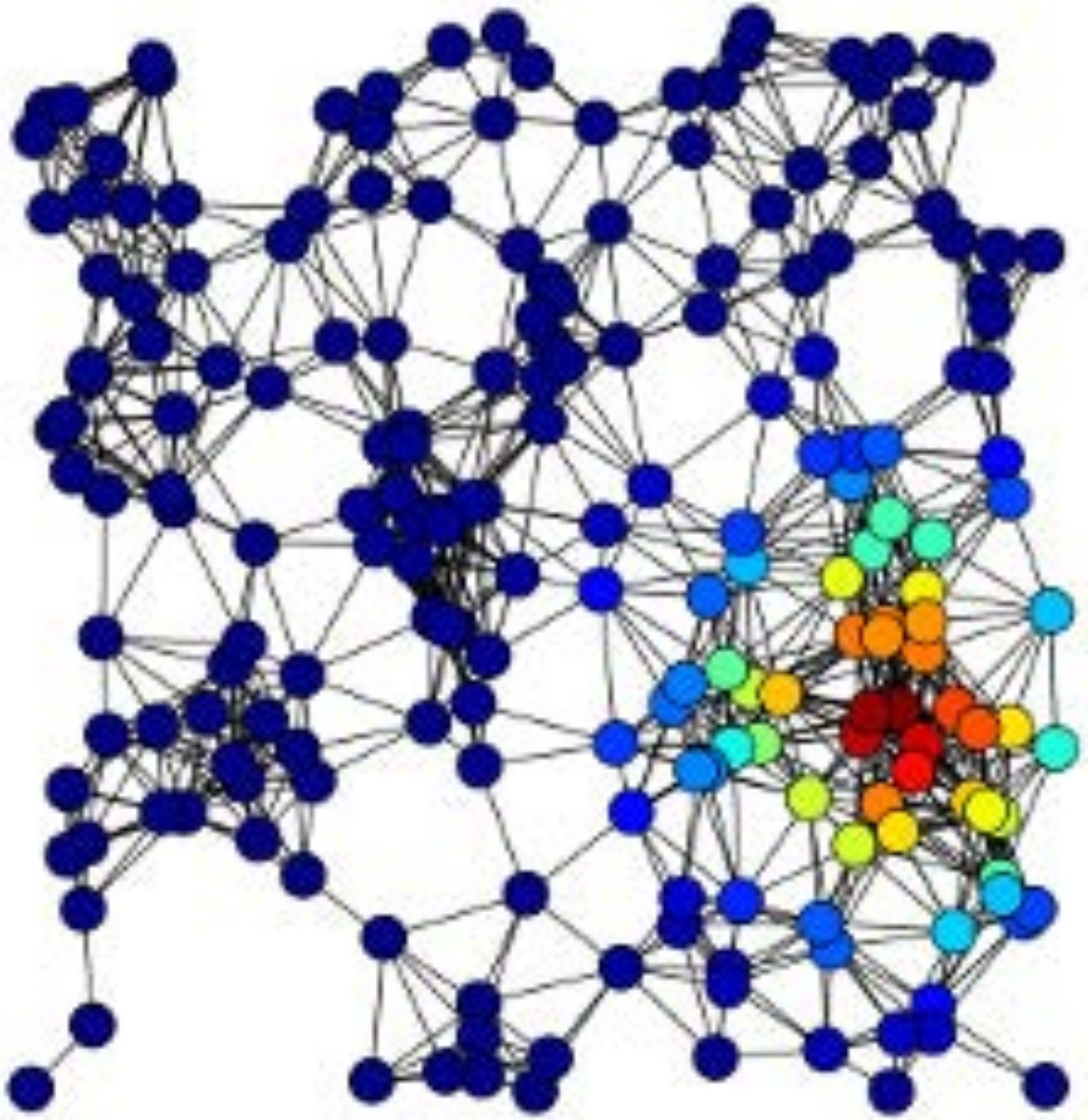


Post

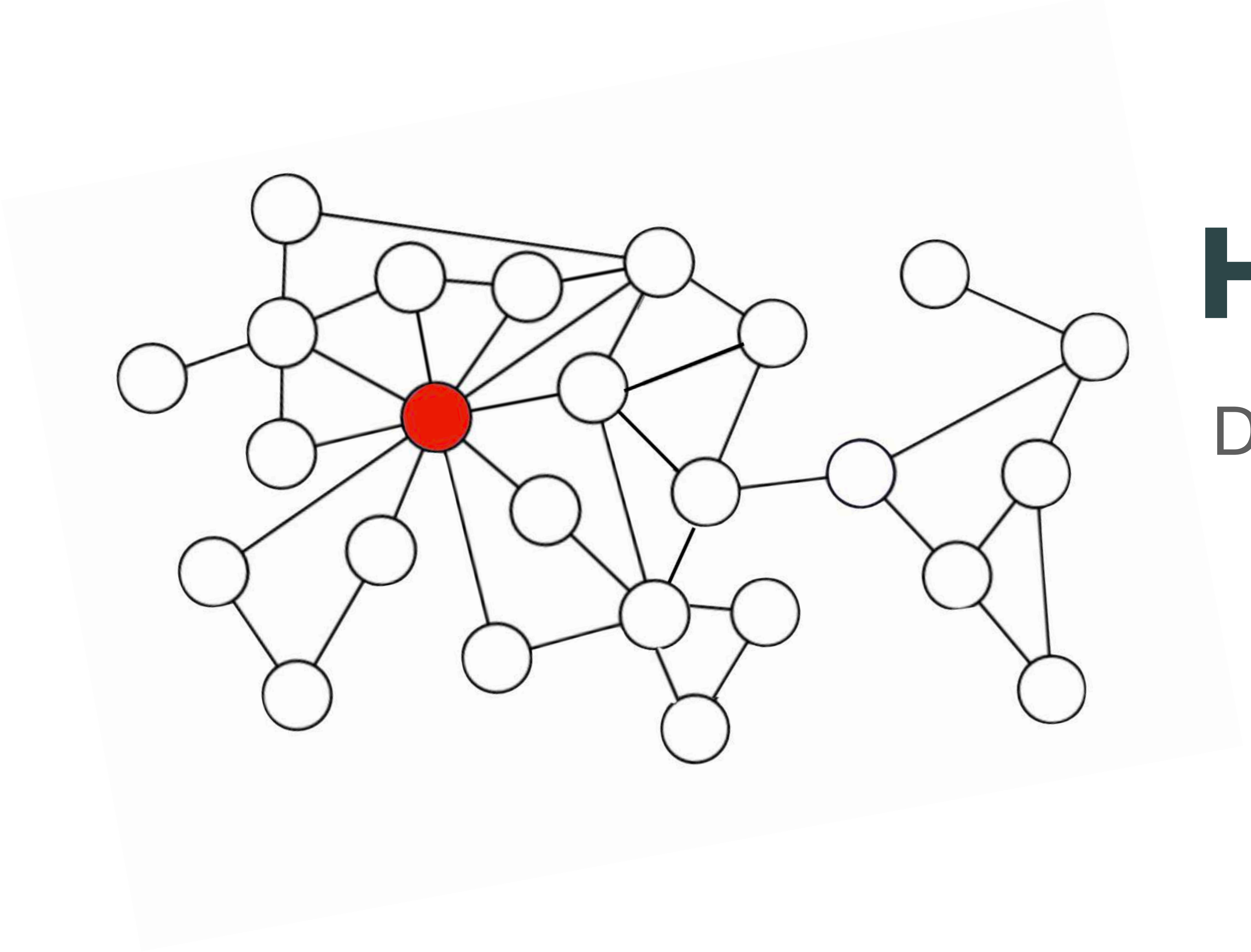



Pre
Where the magic happens
Post


Pre
Where the magic happens
Post

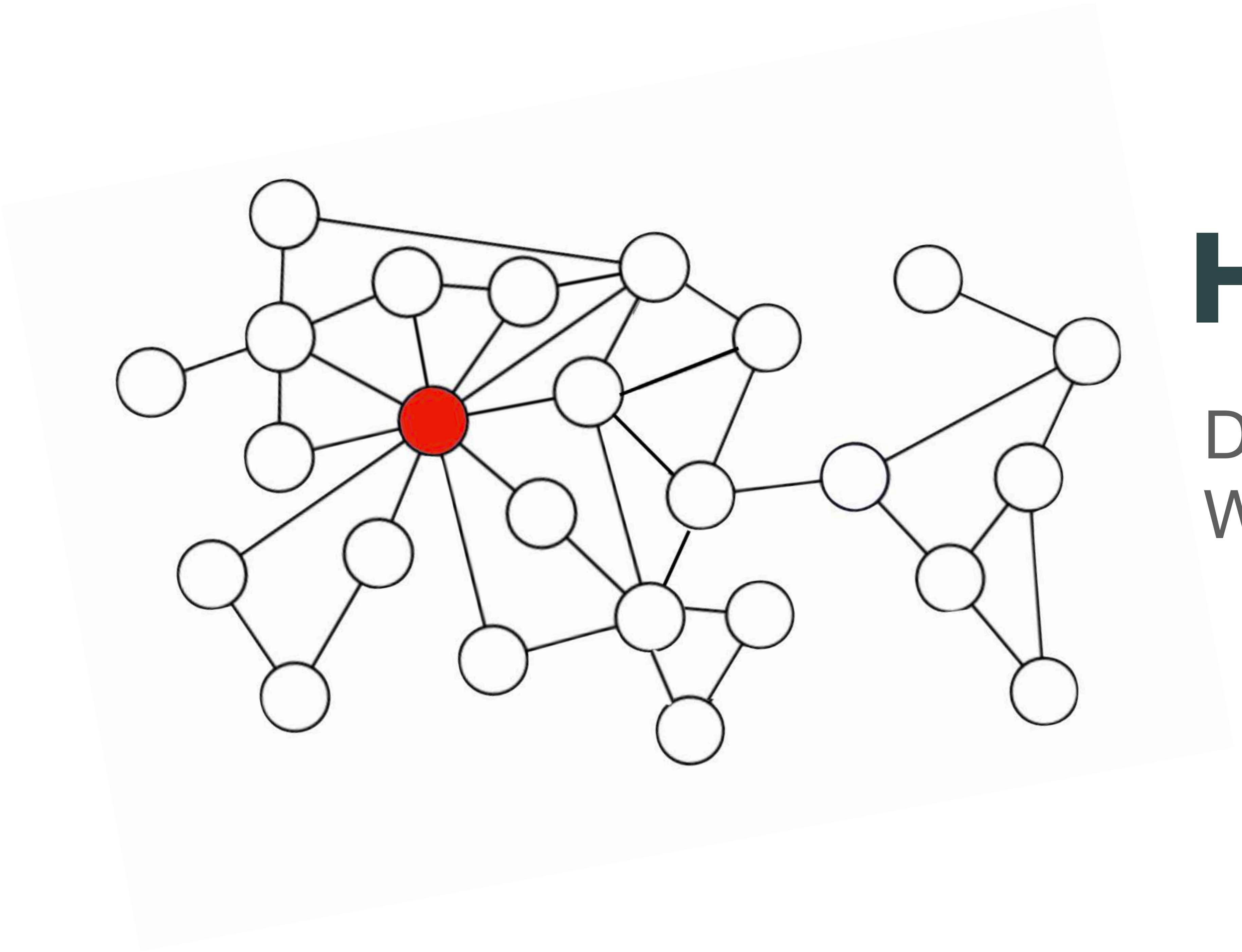


Eigenvector centrality



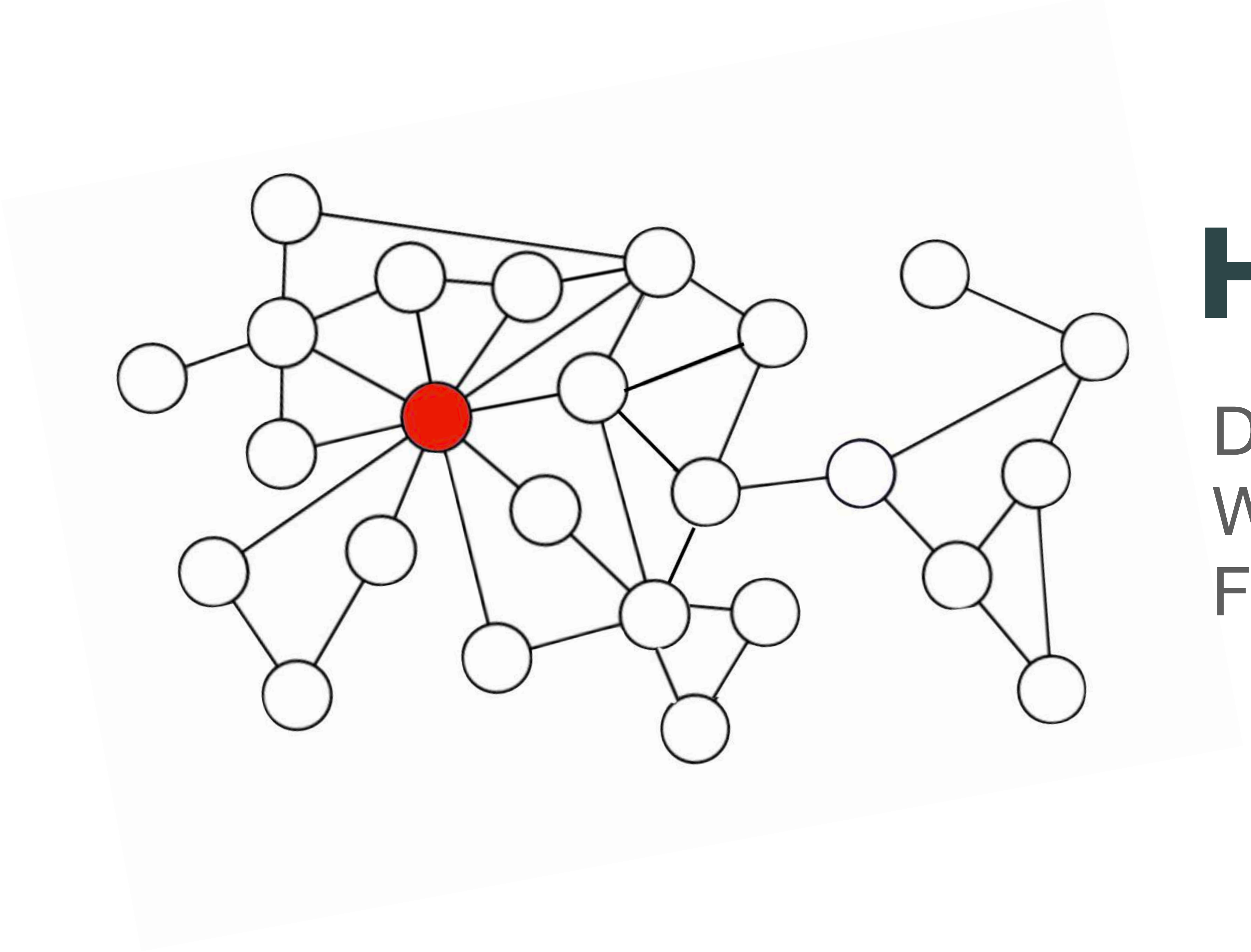
Highly central members

Did not speak more than other members.



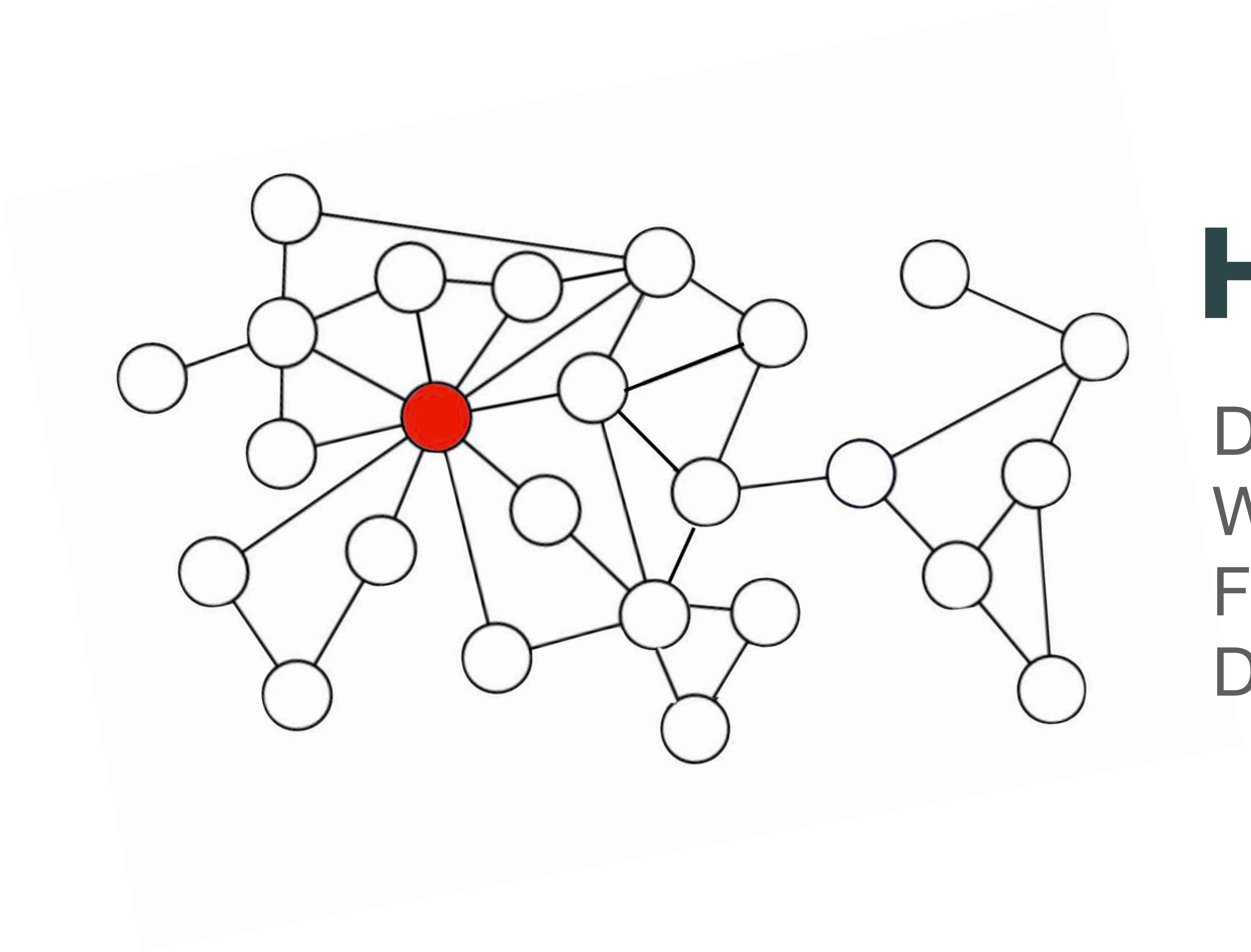
Highly central members

Did not speak more than other members.
Were not rated as more influential by group members nor outside raters



Highly central members

Did not speak more than other members.
Were not rated as more influential by group members or outside raters
For every word they spoke, their groups became more aligned.



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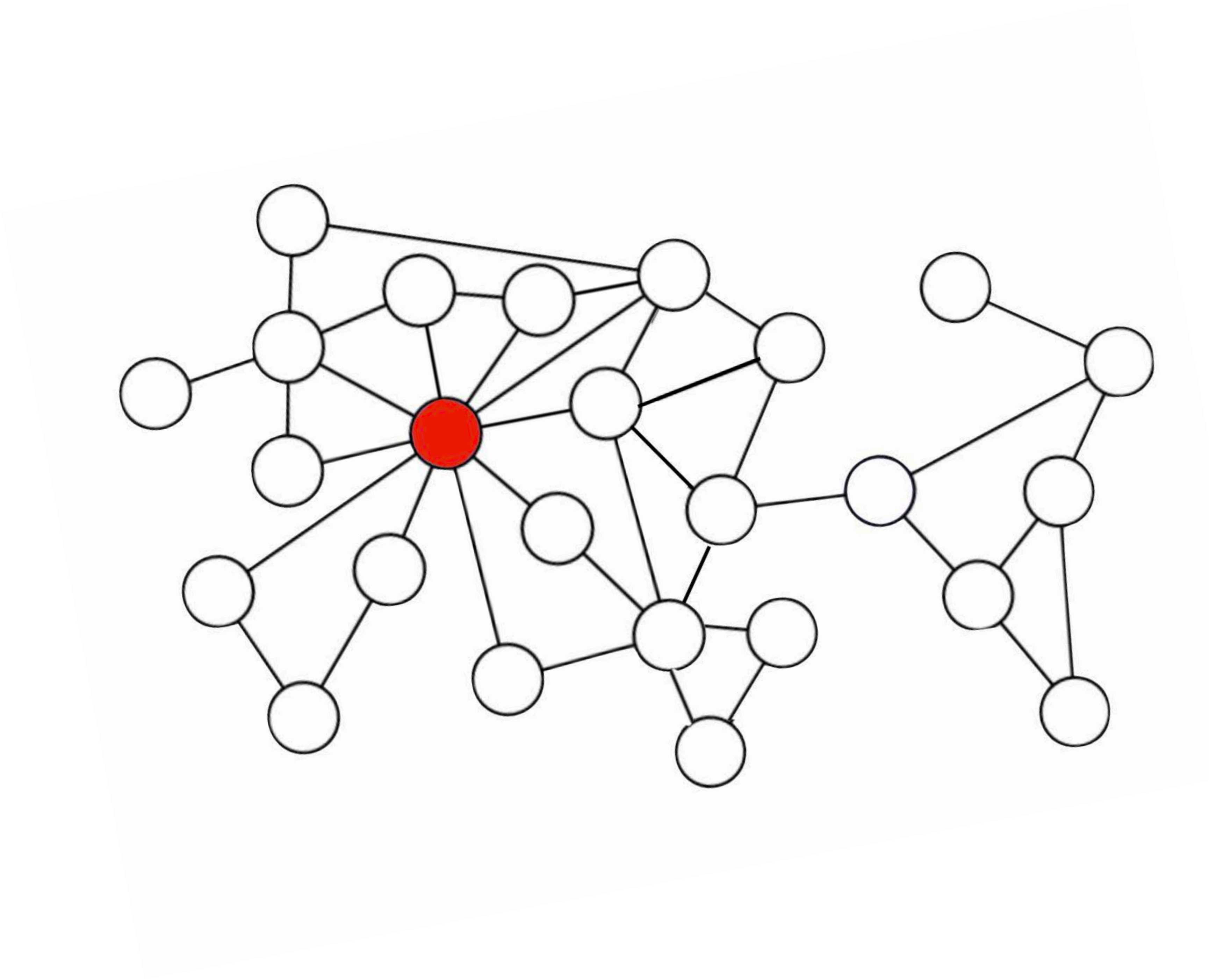
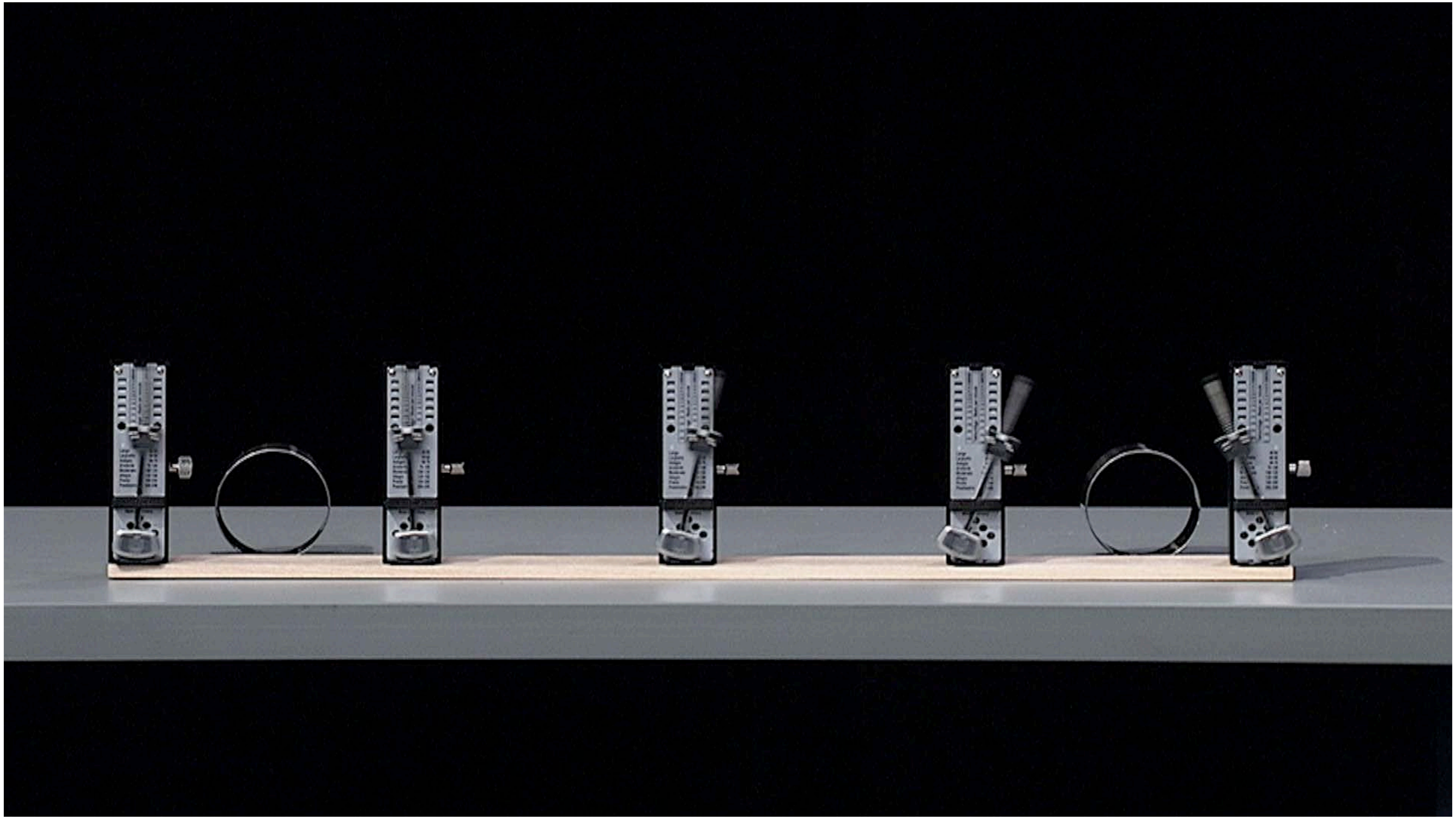
Were not rated as more influential by group members nor outside raters
For every word they spoke, their groups became more aligned.
Directed attention to others, creating equal turn-taking



Highly central members

Did not speak more than other members.
Were not rated as more influential by group members nor outside raters
For every word they spoke, their groups became more aligned.
Directed attention to others, creating equal turn-taking
Adapted their brain activity to the group.

Allowing metronomes to talk to each other



What have we learned so far?

- People befriend likeminded people

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- But conversation also changes minds and aligns brains

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- People befriend likeminded people
- But conversation also changes minds and aligns brains
- High centrality people are good at aligning minds
- High centrality people do this, in part, by getting people to contribute equally and helping to find common ground
- Synchrony is a useful, measure of alignment

Part 2

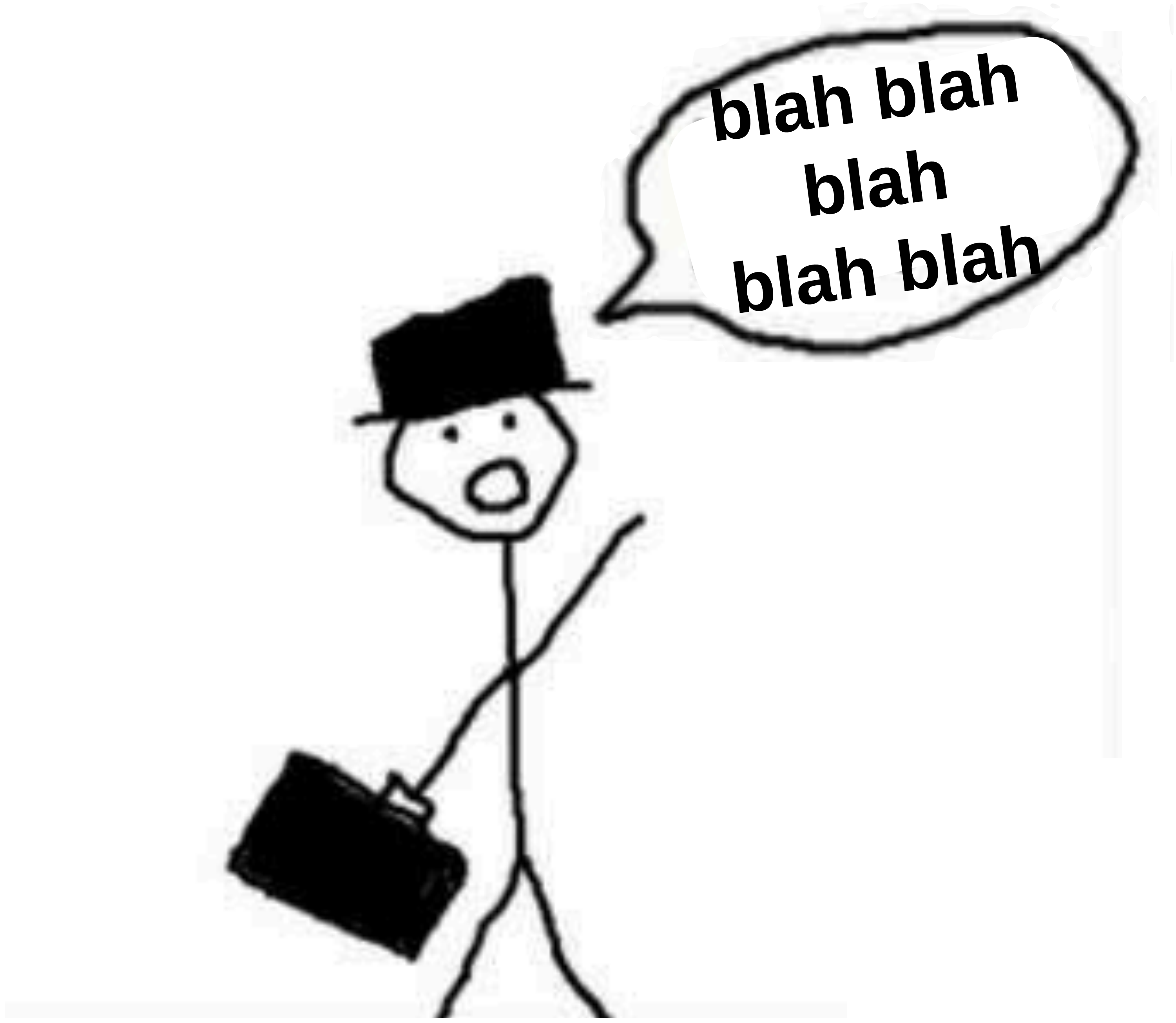
Synchrony and Beyond

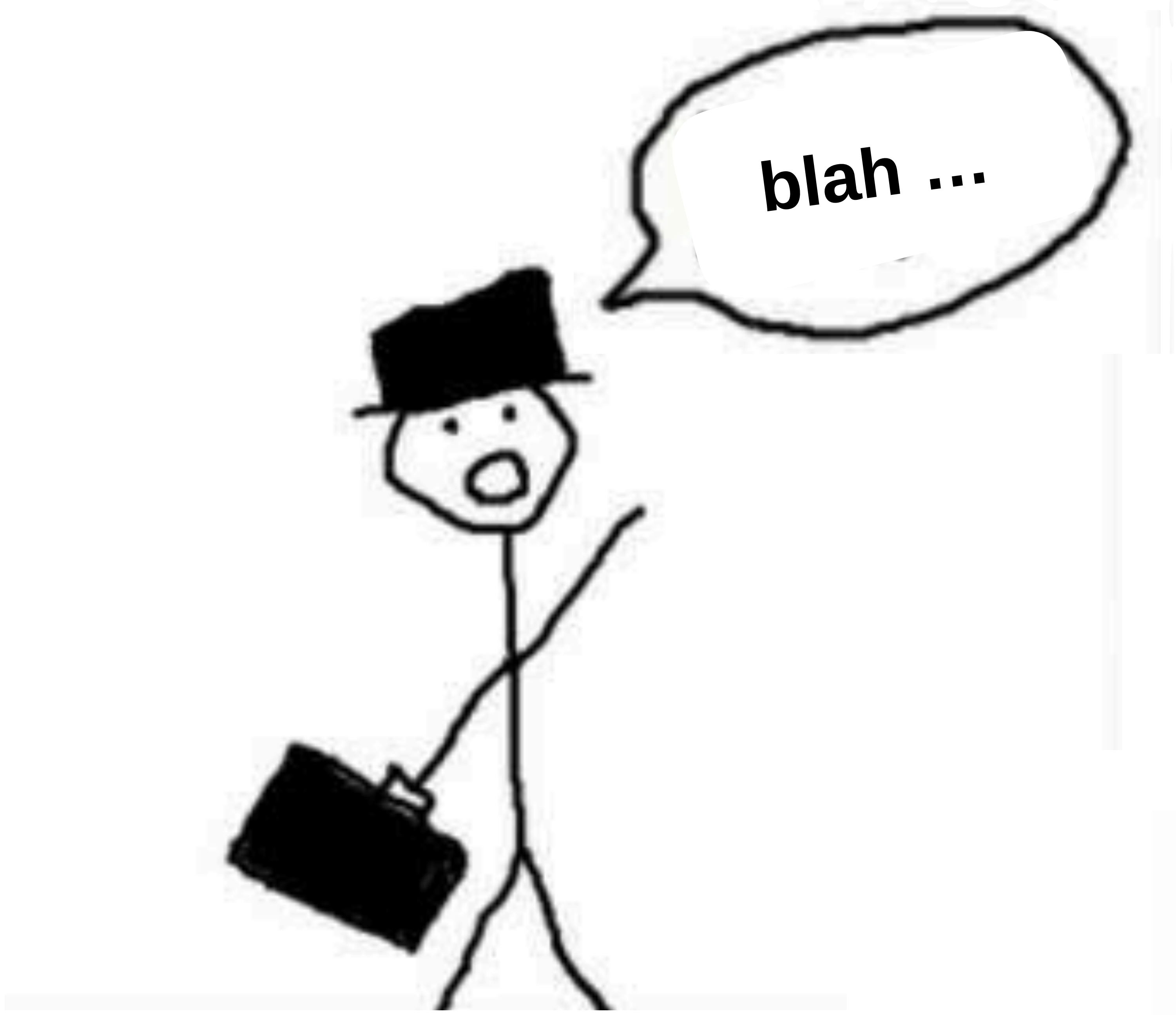
Thalia Wheatley
Dartmouth
Santa Fe Institute

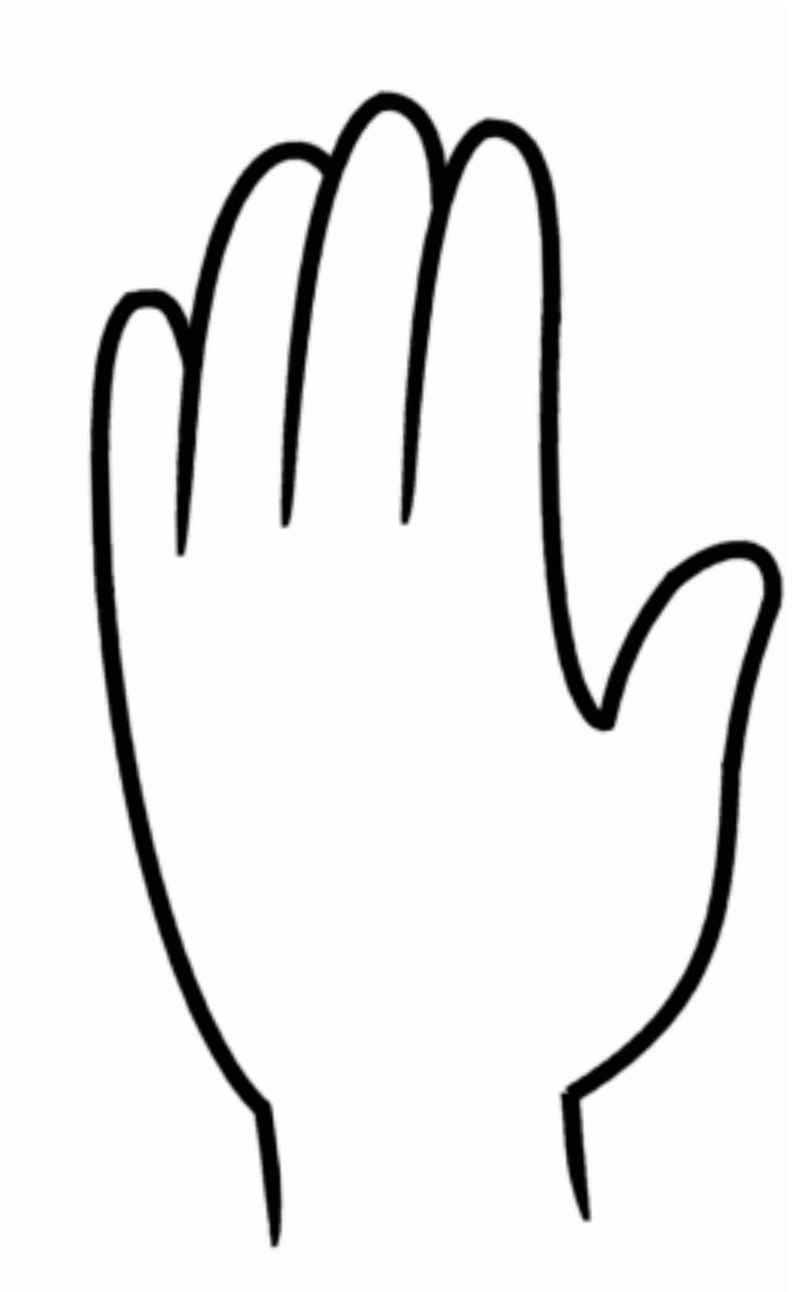
CSSS 2023

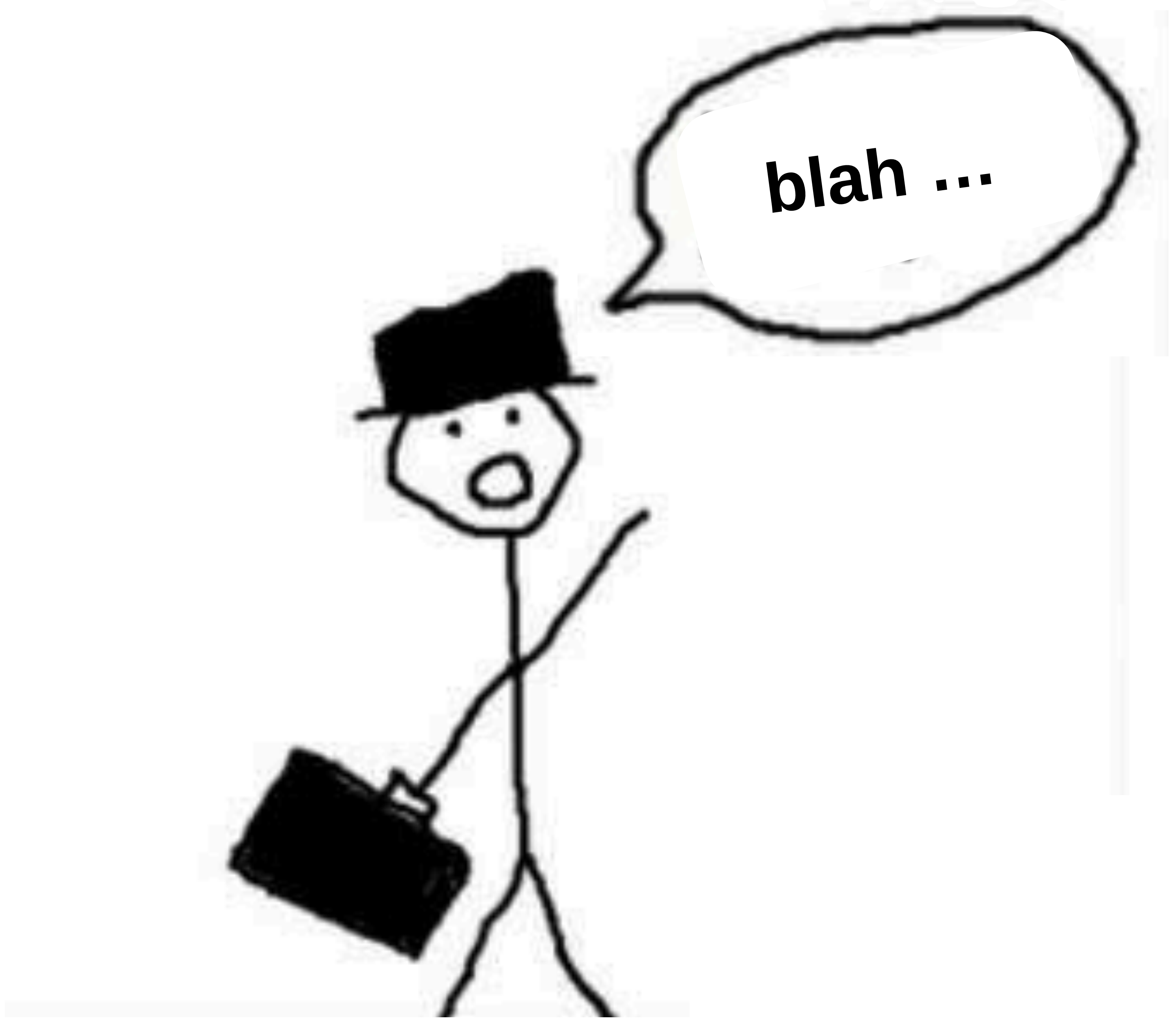

Conversation

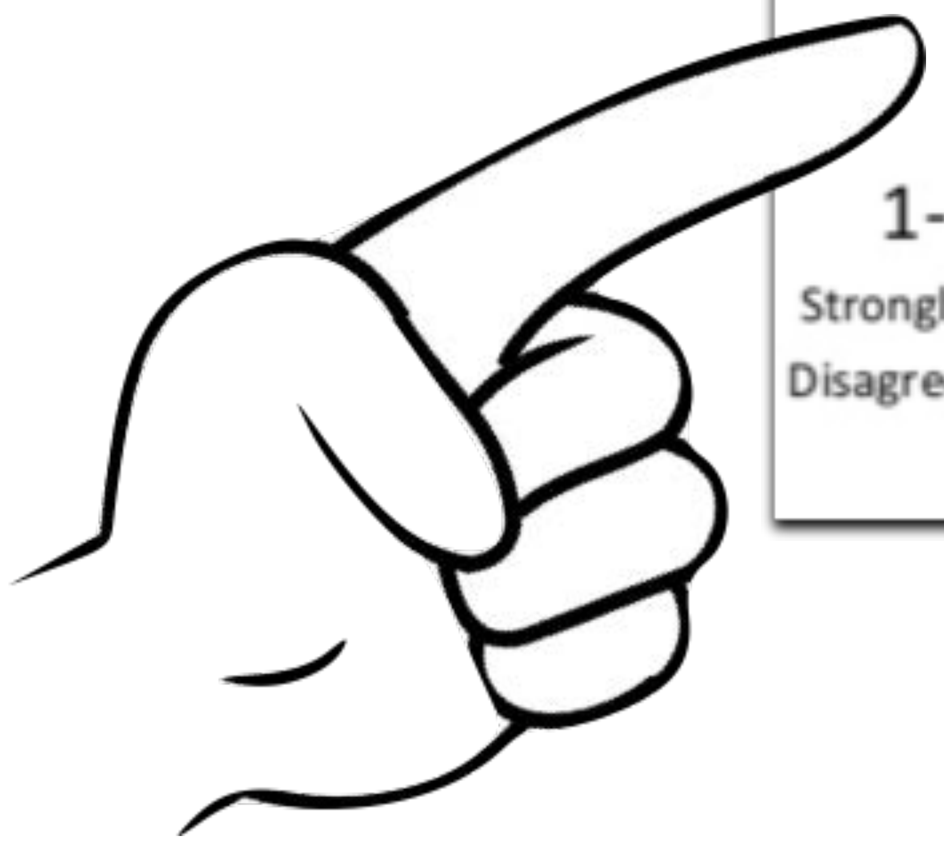
How was your day?


blah blah
blah
blah blah


blah …







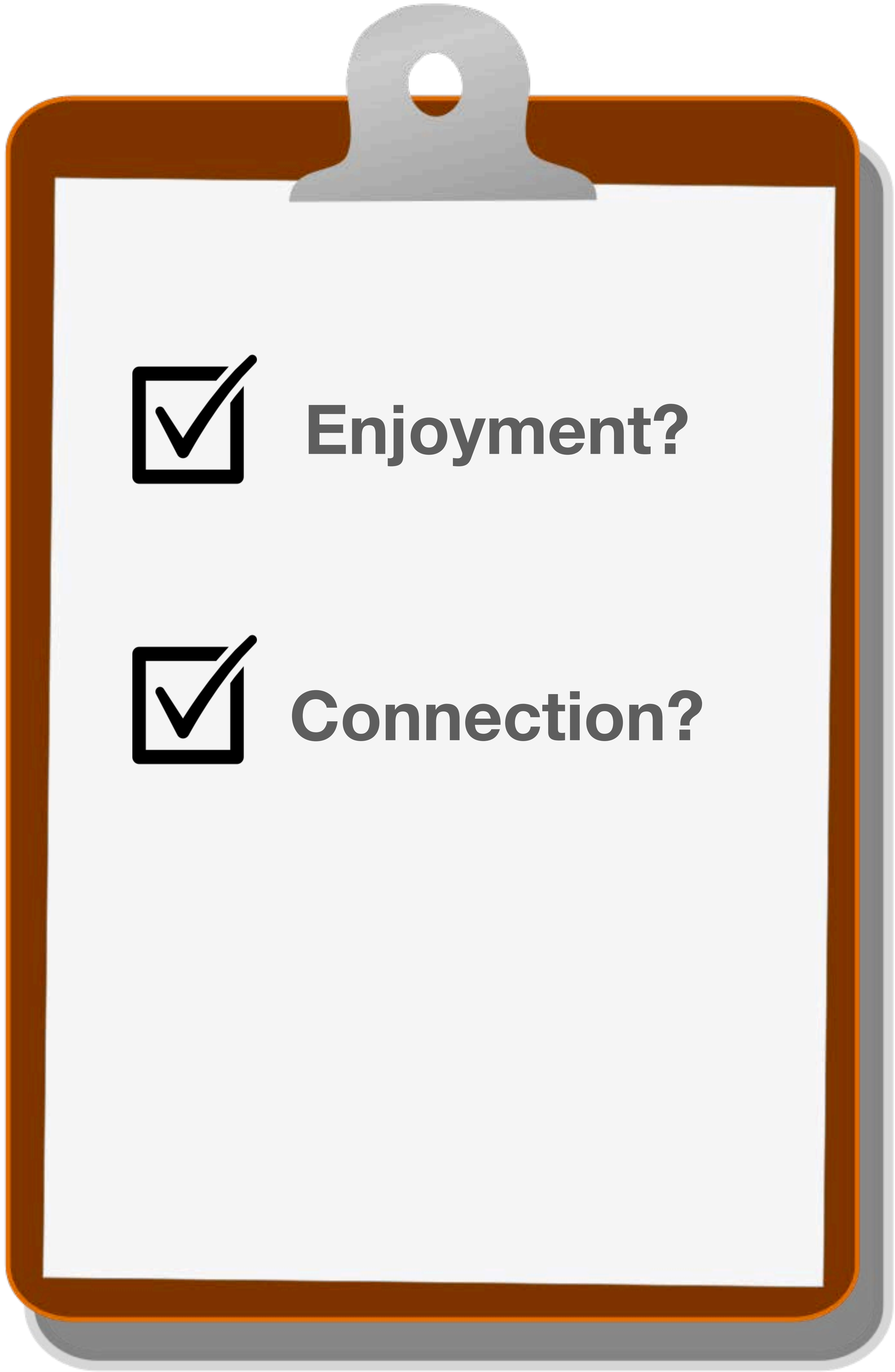
I feel satisfied with my overall well being

1	2	3	4	5	6	7
Strongly Disagree	moderately disagree	slightly disagree	undecided	slightly agree	moderately agree	strongly agree

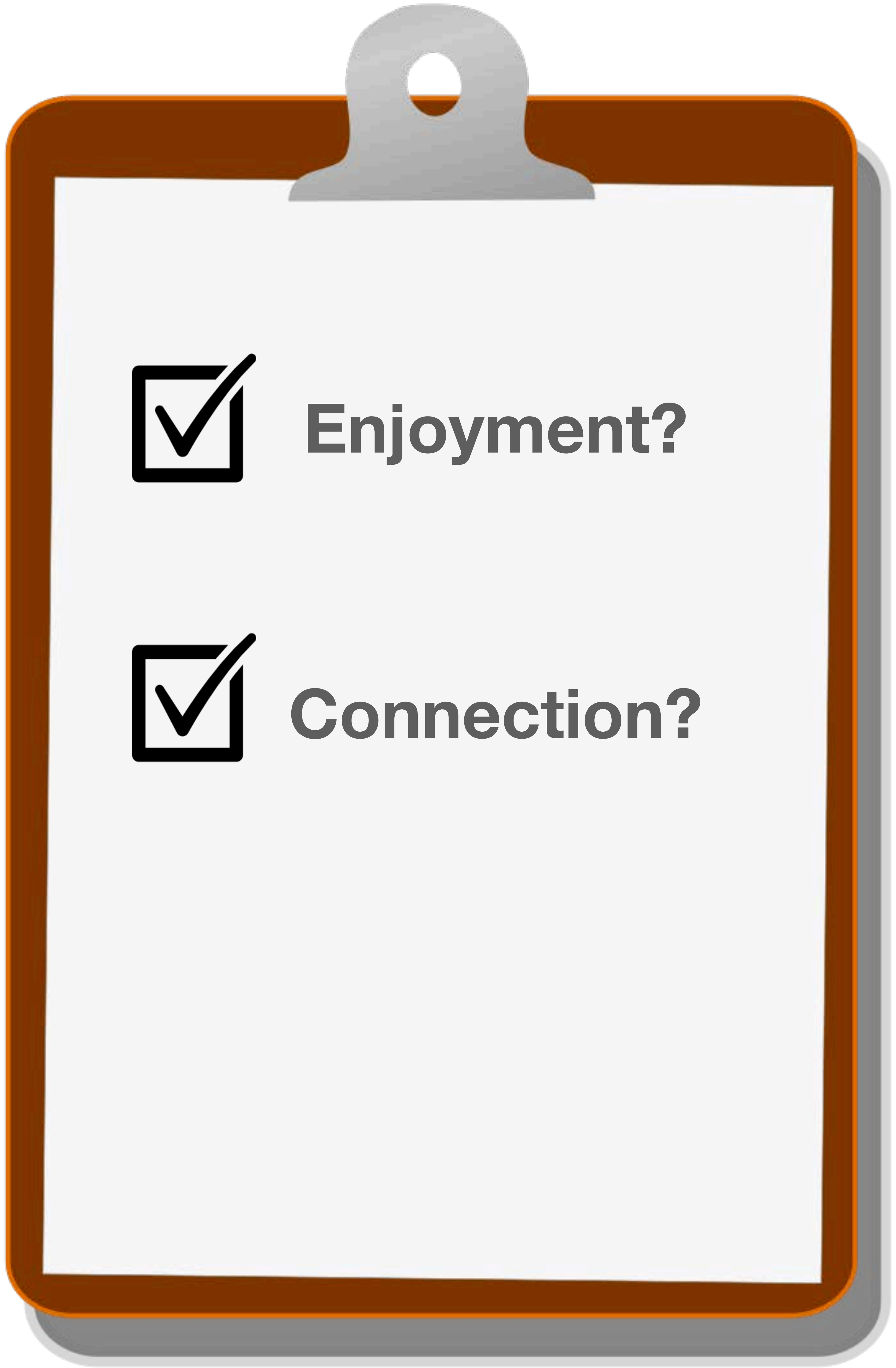
Our Approach

- Keep the conversations as pure as possible
- Use the features that occur naturally in the conversations to guide our hypotheses

Emma Templeton
PhD student


Enjoyment?
Connection?


How connected did you feel at this moment?
None
Very



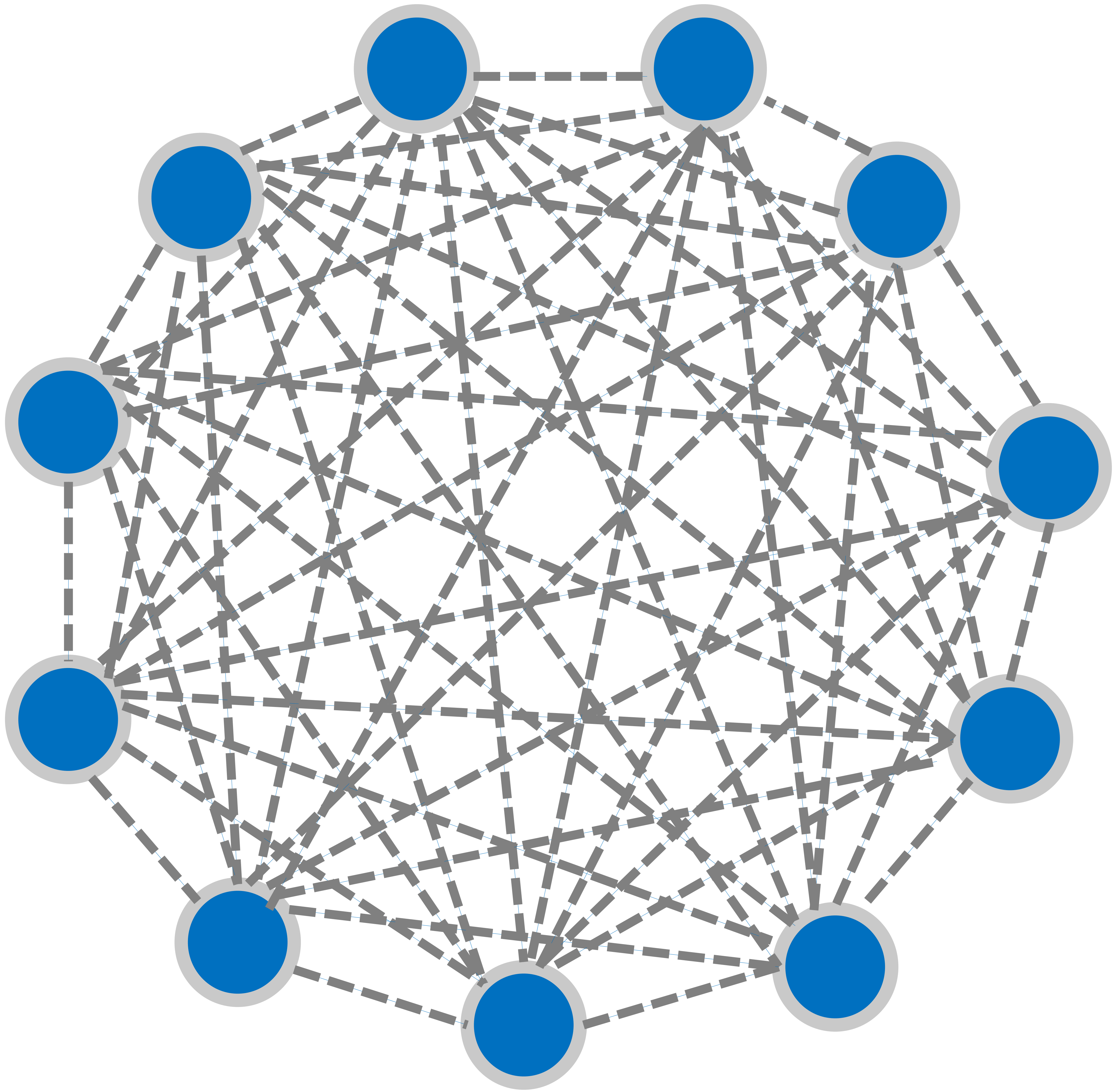




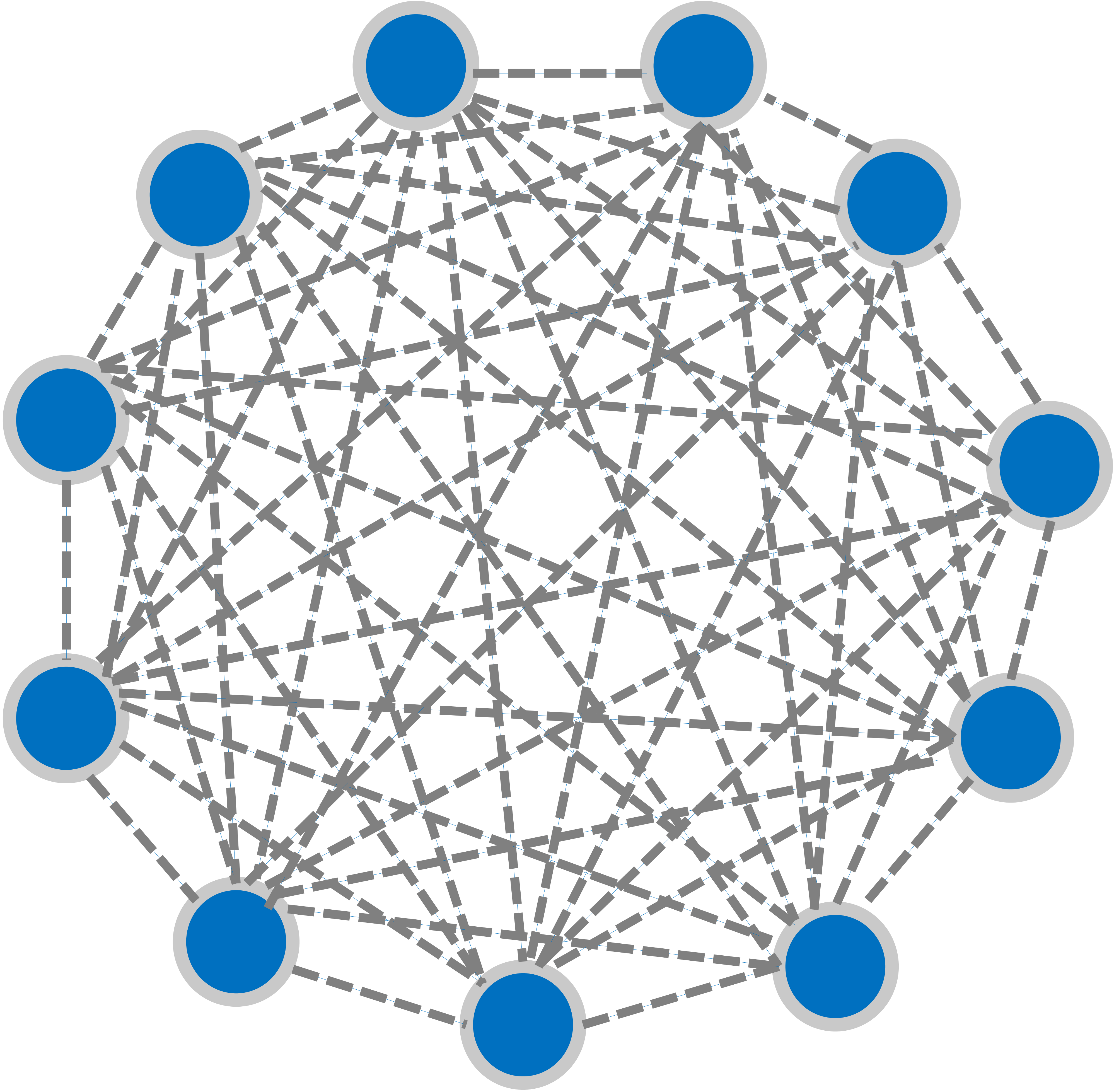
Each participant has
10 conversations



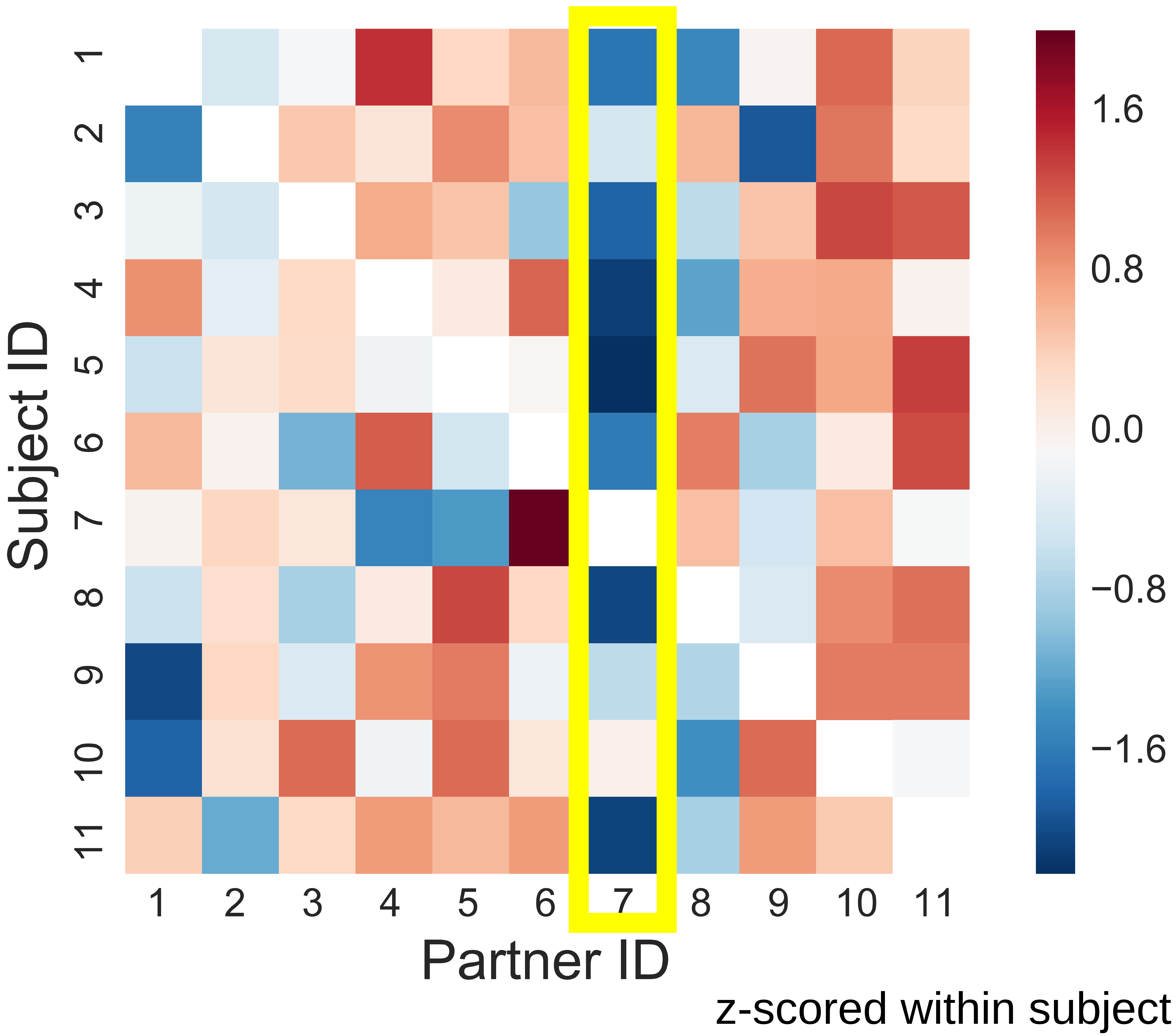


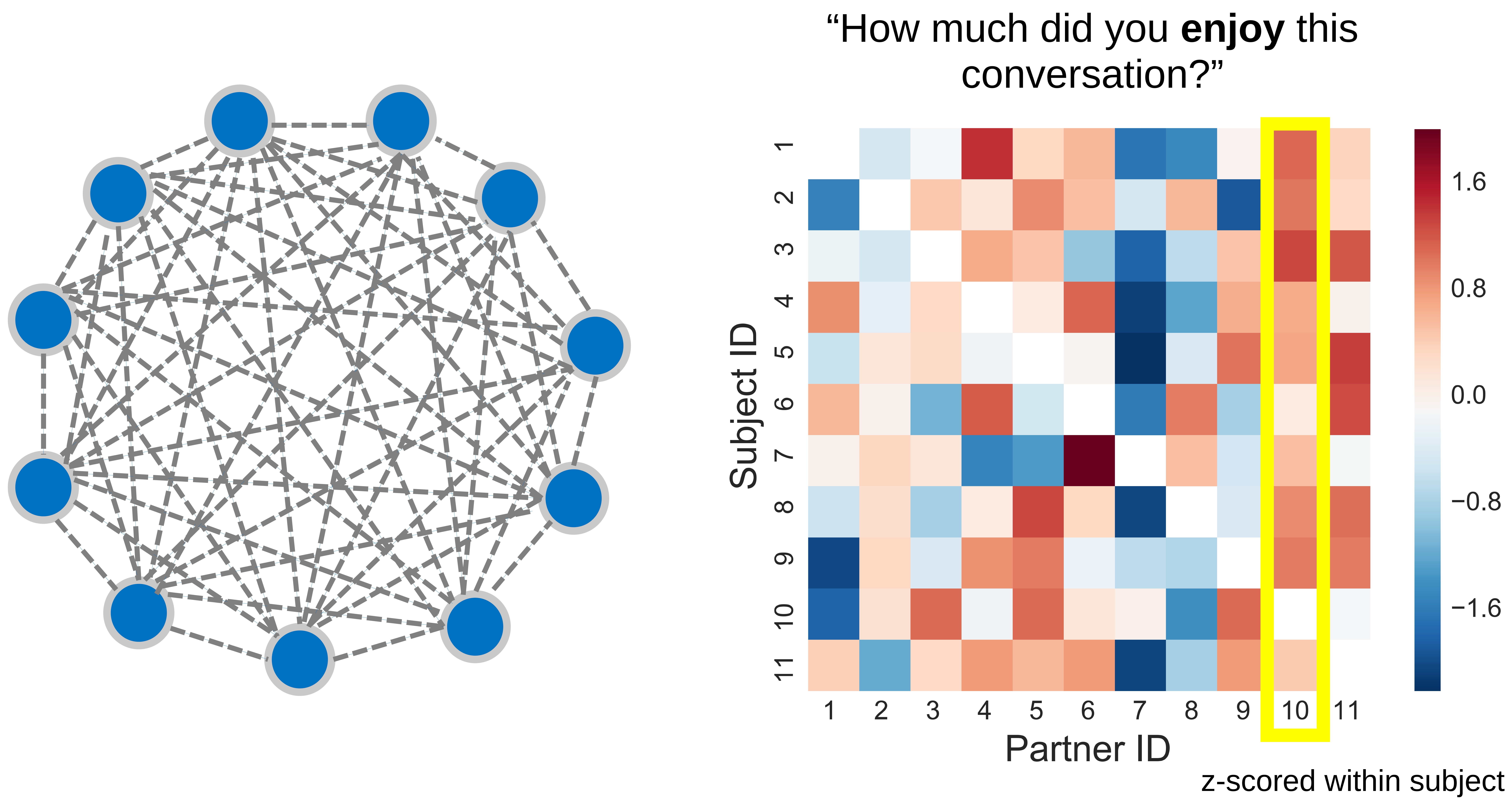


11 participants
55 conversations



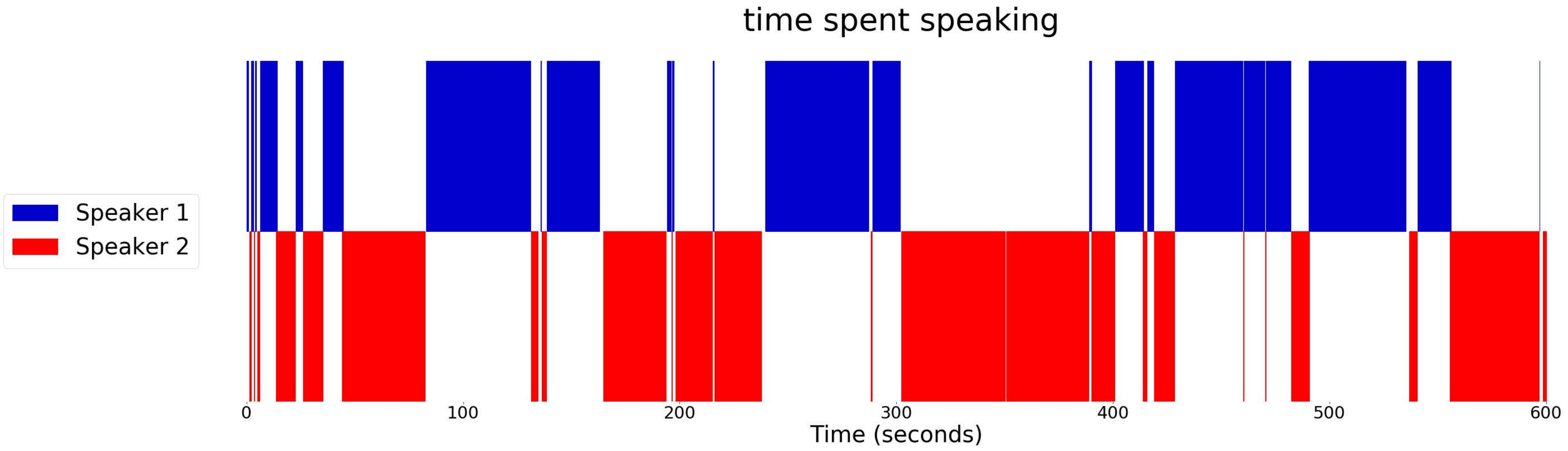
“How much did you **enjoy** this conversation?”



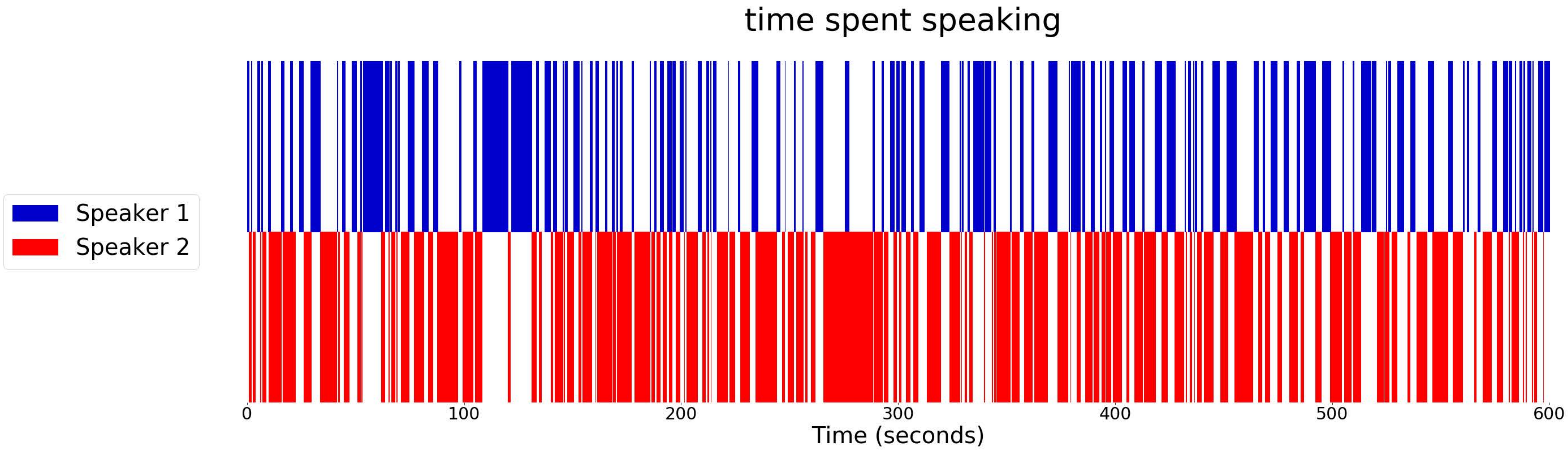


“How much did you **enjoy** this conversation?”
Subject ID
1
2
3
4
5
6
7
8
9
10
11
Partner ID
1
2
3
4
5
6
7
8
9
10
11
1.6
0.8
0.0
−0.8
−1.6
z-scored within subject

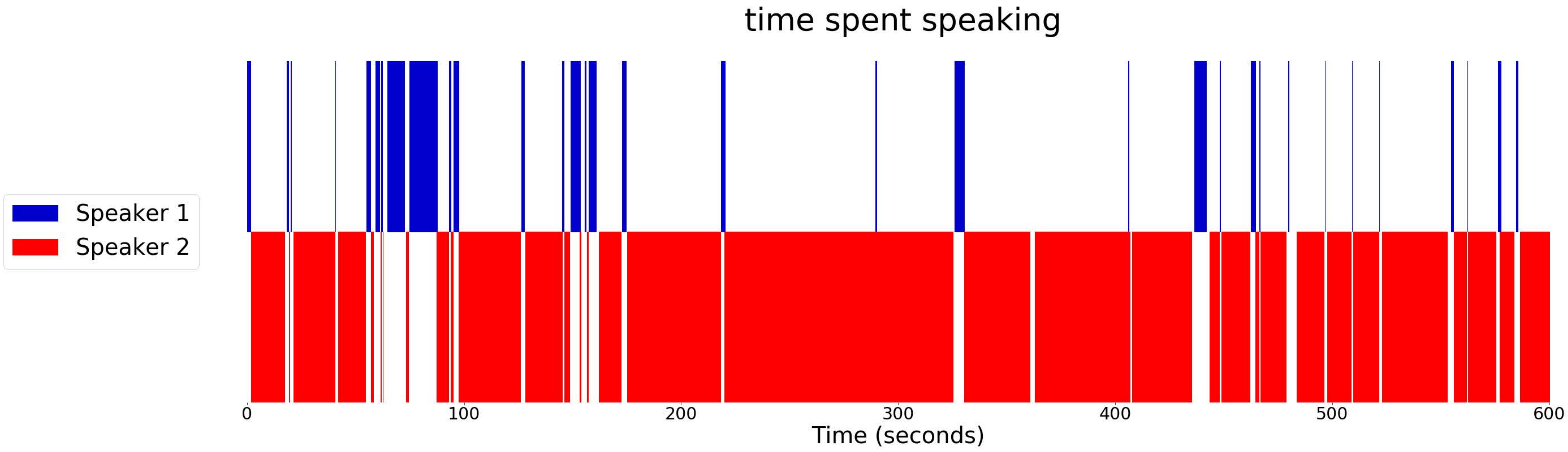
Visualize the conversations

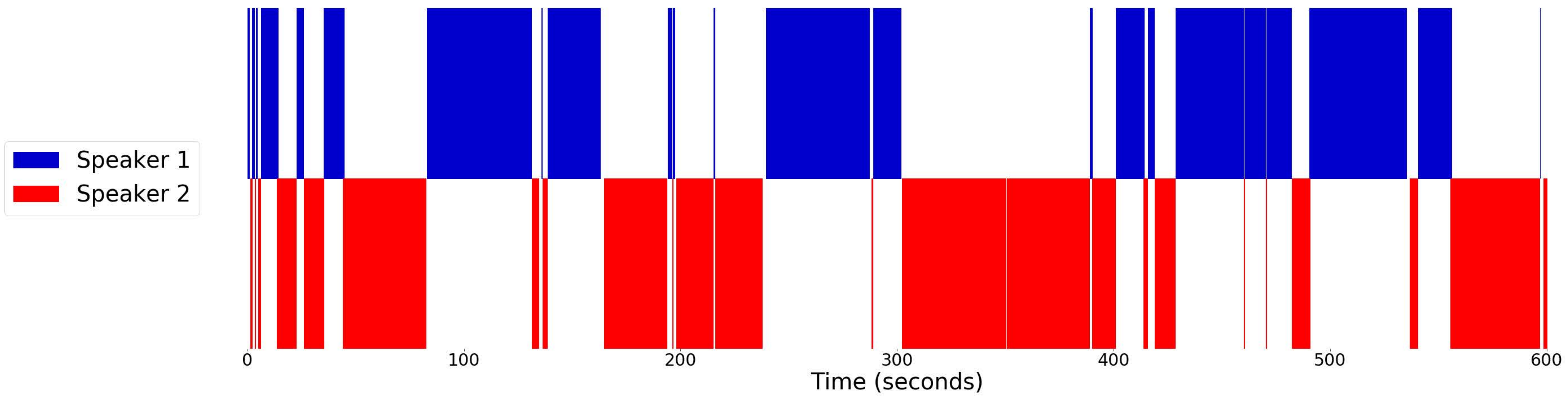


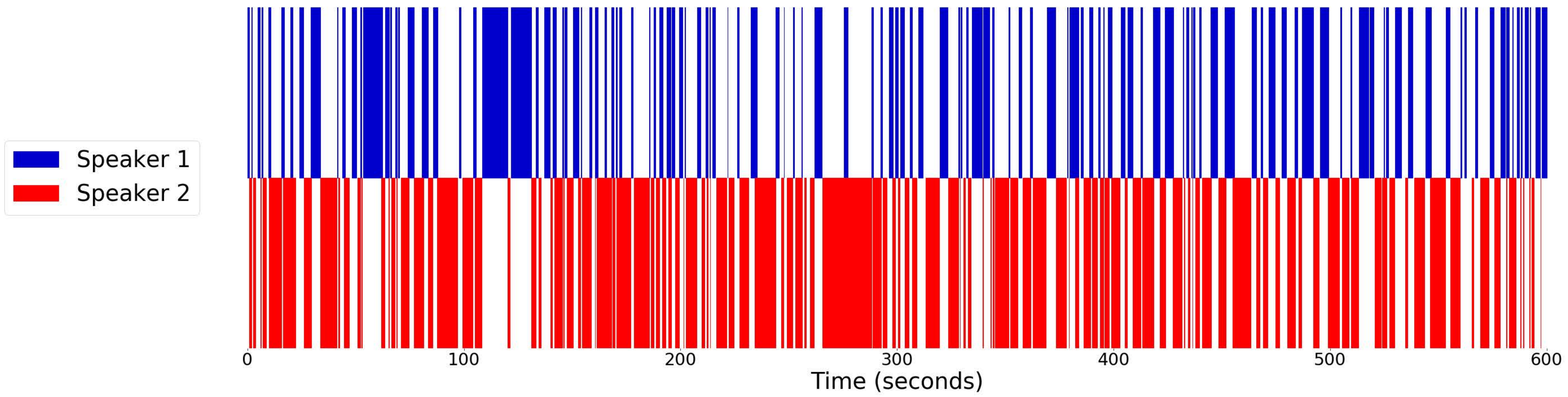
Visualize the conversations

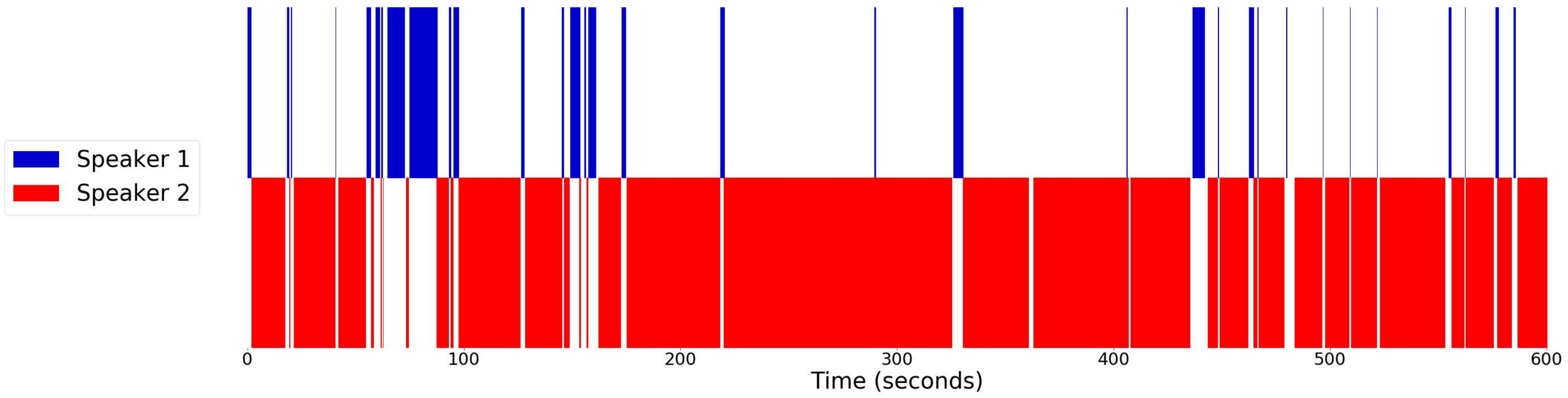


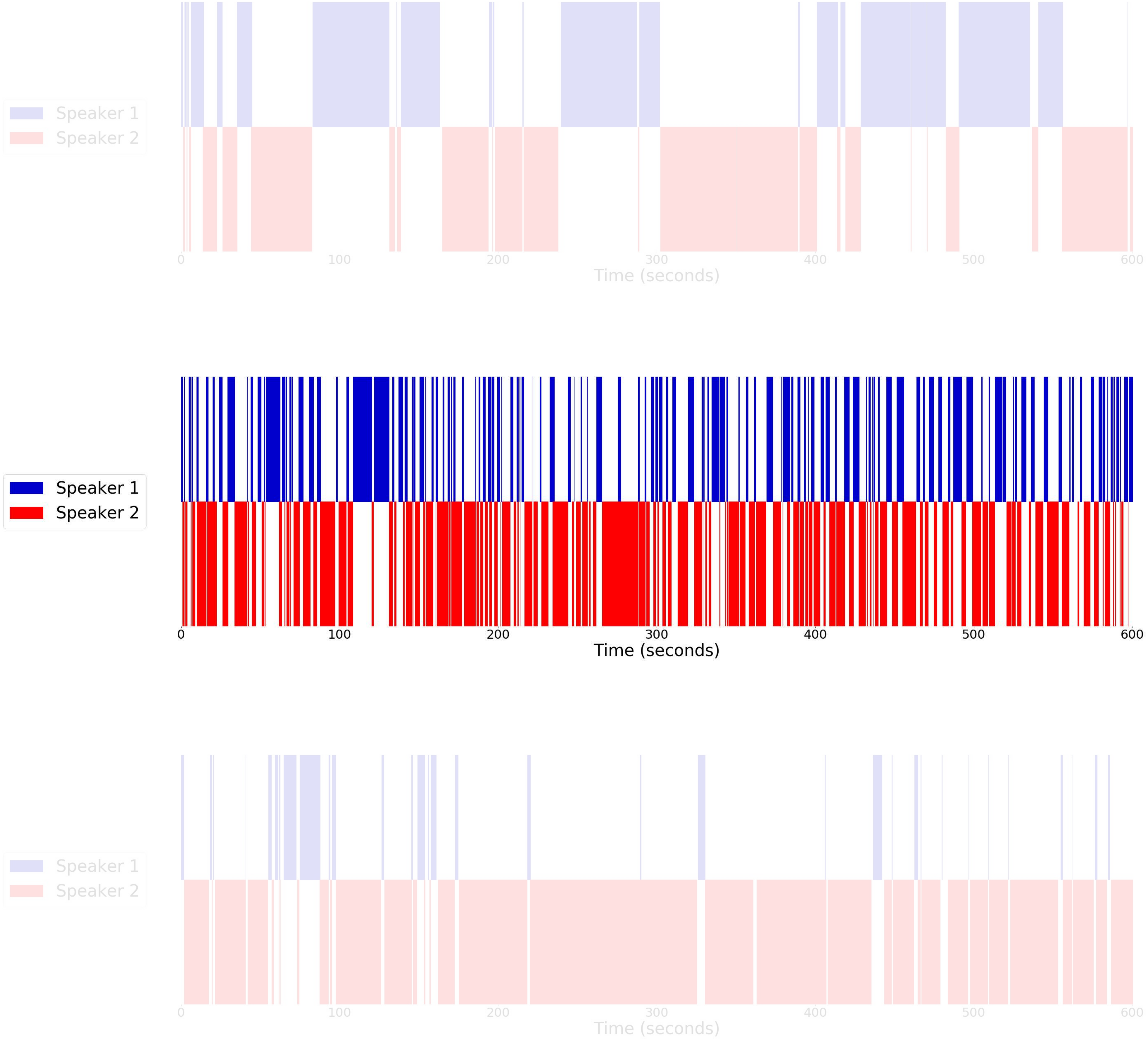
Visualize the conversations




Speaker 1
Speaker 2
0
100
200
300
400
500
600
Time (seconds)

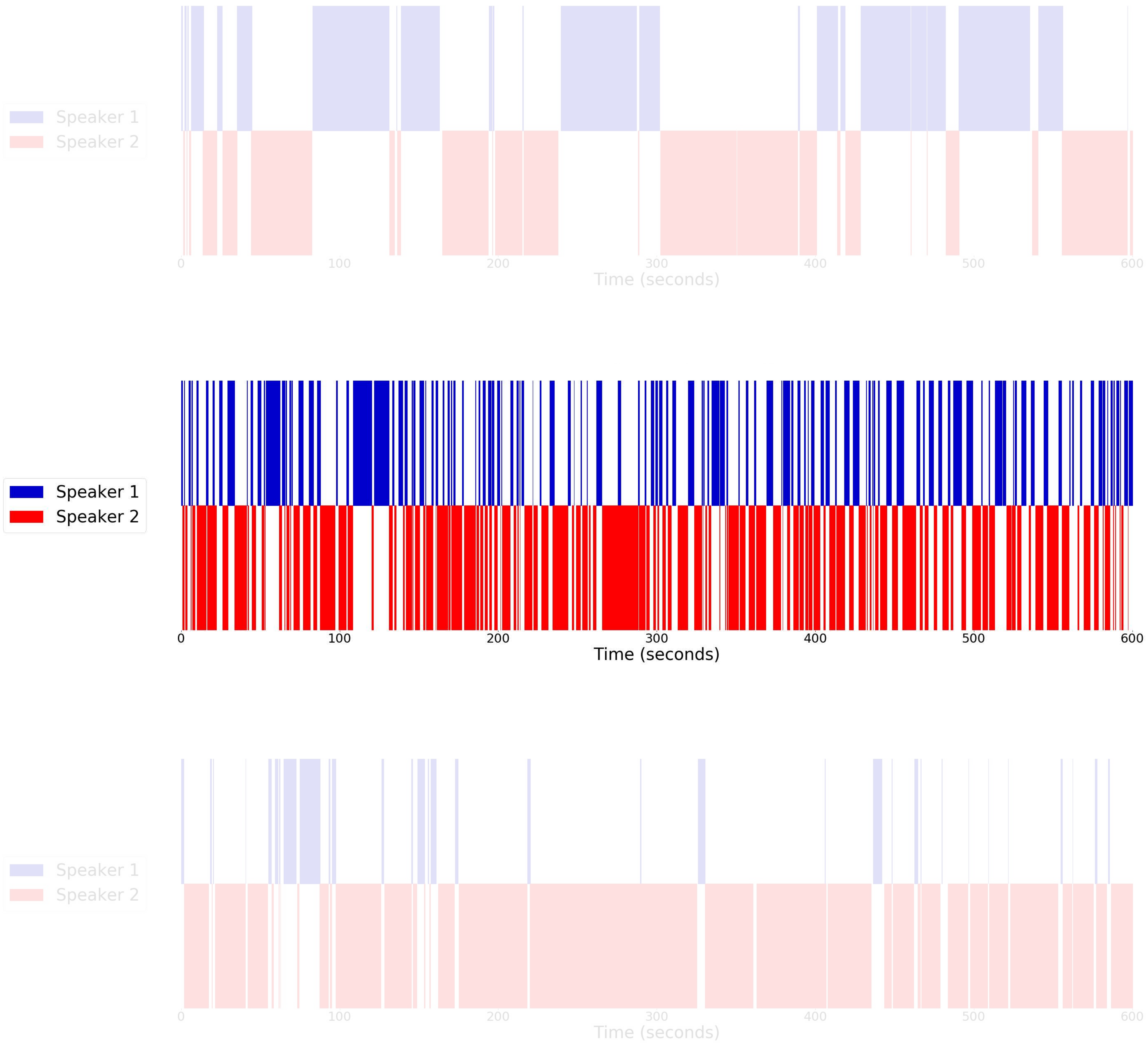

Speaker 1
Speaker 2
0
100
200
300
400
500
600
Time (seconds)


Speaker 1
Speaker 2
0
100
200
300
400
500
600
Time (seconds)



Participants report feeling **more connected** to each other in conversations with **more turn-taking**

(b=0.17, SE=0.04, p<.001)



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(b=0.17, SE=0.04, p<.001)


200 ms

Name this object

Name this object

Name this object

600 ms

Indefrey & Levelt, 2004
Bates *et al.*, 2003
Indefrey, 2011

200 ms

Levinson & Torreira, 2015
Heldner & Edlund, 2010
Stivers *et al.*, 2009

Compute gap lengths from transcripts

```
S1: 00:00:00.000 How's it going? END 00:01.335 END
S2: 00:00:02.236 I'm okay. How are you? END 00:03.215 END
S1: 00:00:03.123 Yeah, I'm good. It's been a busy... END 00:05.599 END
S2: 00:00:05.636 It's been a week. END 00:06.043 END
S1: 00:00:06.397 Yeah, honestly. With rush. Did you rush? END 00:08.880 END
S2: 00:00:08.761 I dropped on Monday. END 00:09.686 END
S1: 00:00:09.582 You dropped? Oh, I'm sorry. END 00:10.731 END
S2: 00:00:10.388 Yeah, I didn't get callbacks. END 00:11.686 END
S1: 00:00:12.067 Oh, okay. END 00:12.432 END
```

Gap length = **901**ms

Compute gap lengths from transcripts

```
S1: 00:00:00.000 How's it going? END 00:01.335 END
S2: 00:00:02.236 I'm okay. How are you? END 00:03.215 END
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```

Gap length = **901**ms

Gap length = **-92**ms

Compute gap lengths from transcripts

```
S1: 00:00:00.000 How's it going? END 00:01.335 END
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```
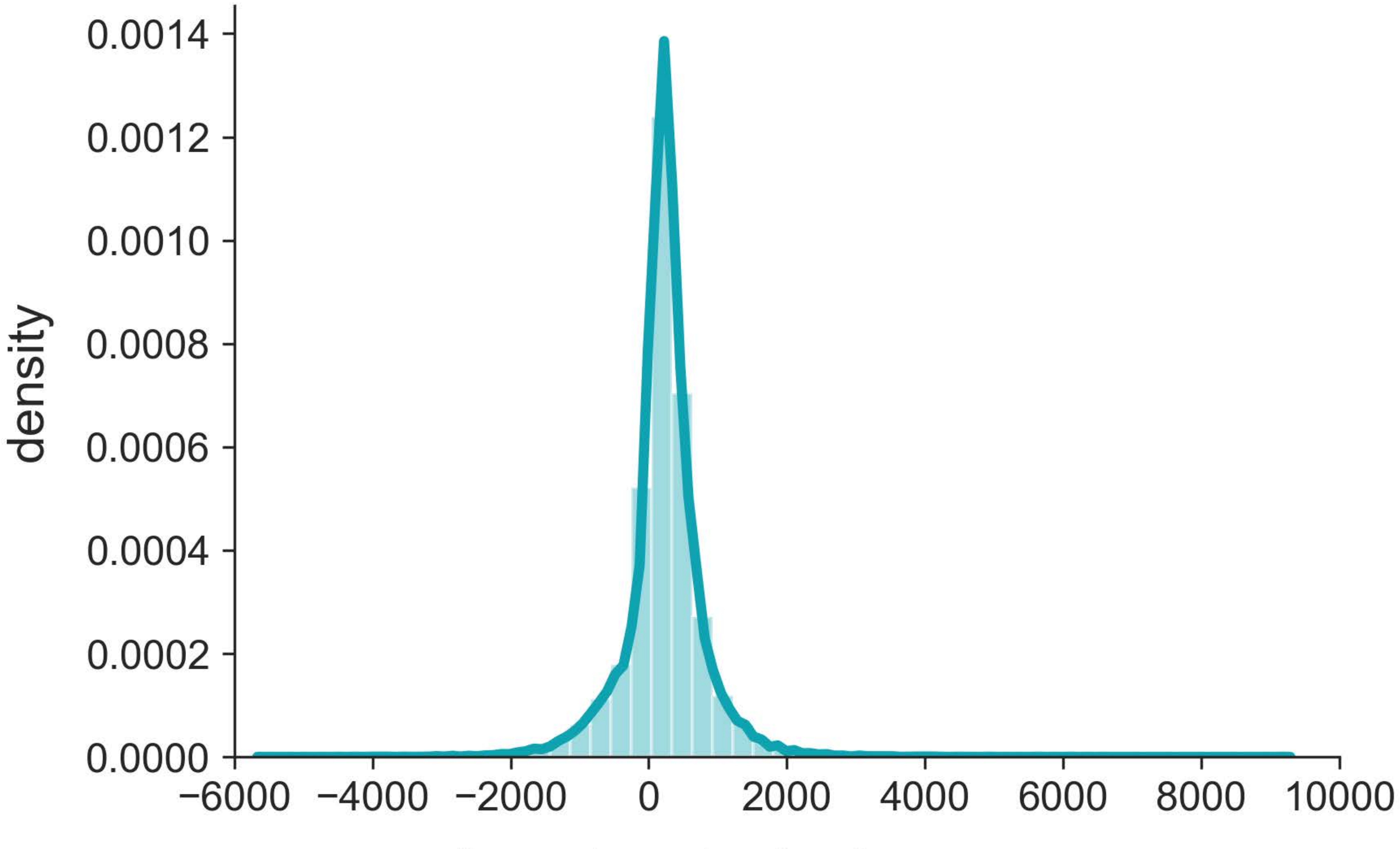

Gap length = **901**ms

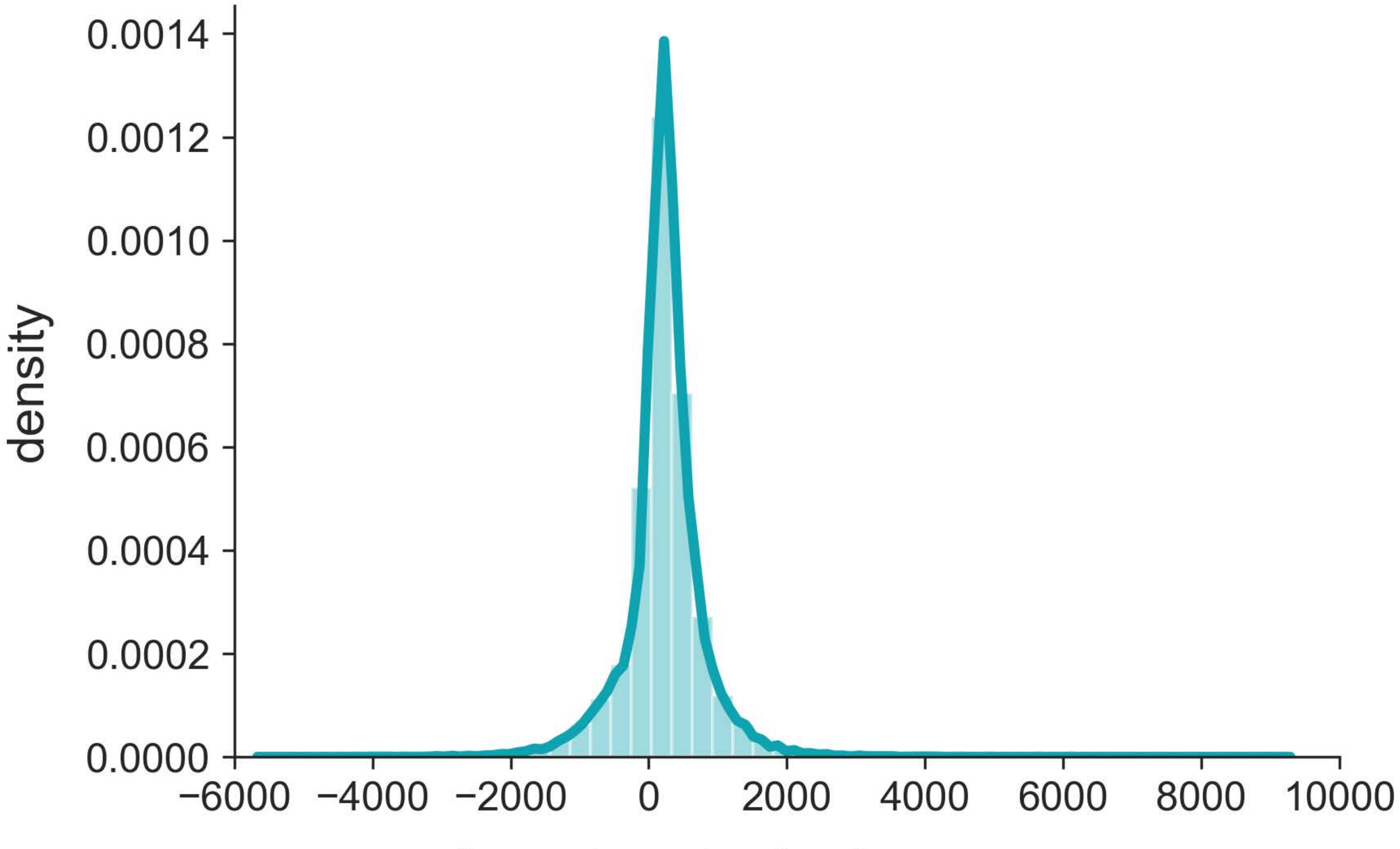
Gap length = **-92**ms

Gap length = **37**ms

Gap lengths in our data



Gap lengths in our data



S1	Yeah, I just... The Philosophy class came out late, so yeah.
S2	What is it? Philosophy of what?
S1	Moral Philosophy.
S2	That seems like a terrible class. [chuckle]
S1	It's so bad. I hate it so much. It's okay...
S2	I just feel like you get some really crazy people in it.
S1	There actually aren't crazy people in it, but the material is really weird.
S2	Why?
S1	I just stopped reading the textbook, which is probably part of the reason why I don't really understand what's going on. But we have papers and then exams, and the exams are just like spitting the textbook out. So you just memorize everything and it's such a pain. But yeah, I didn't fall asleep in class today. That's was a plus.
	That's good. Norton is a small place, with small

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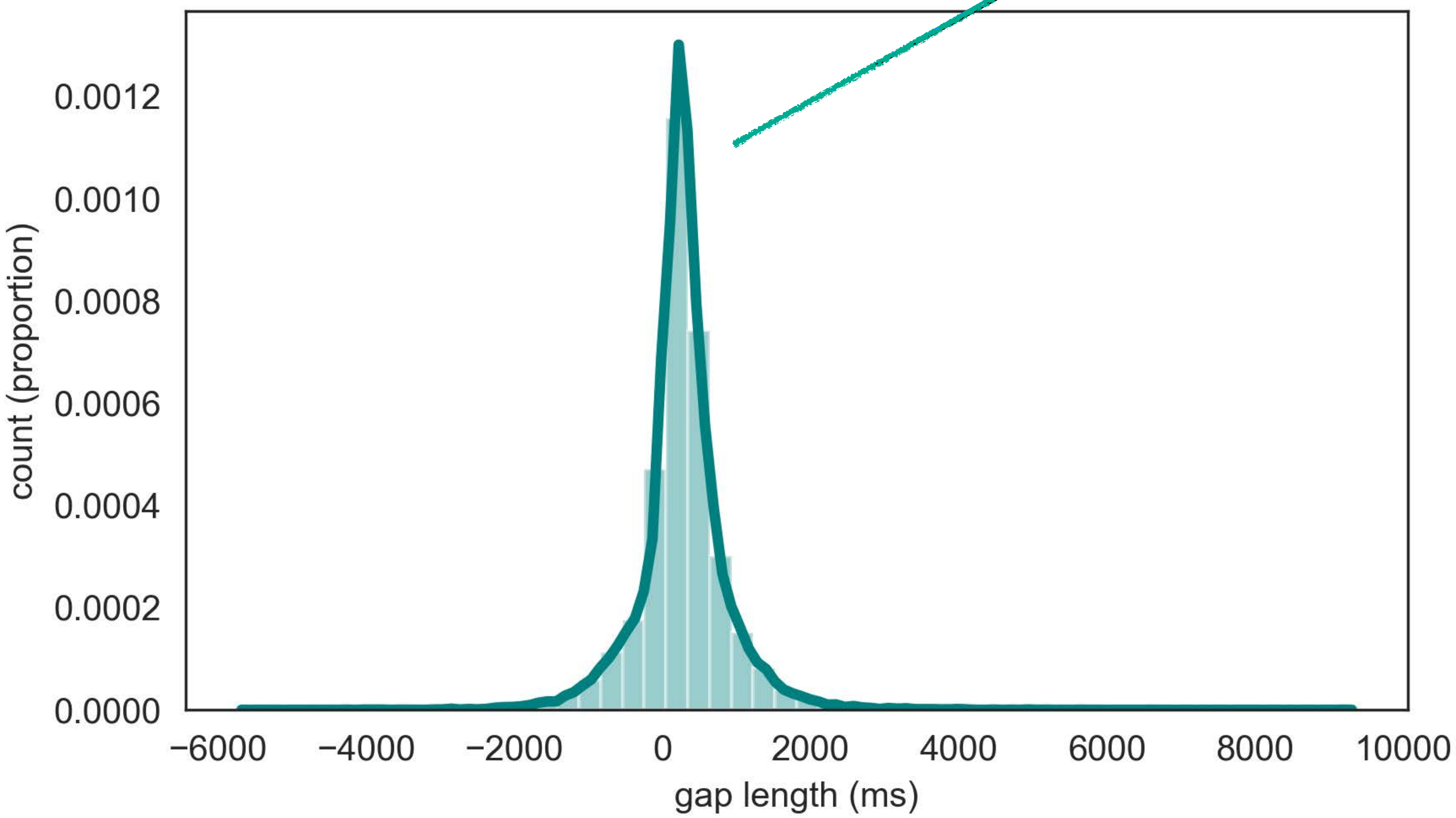

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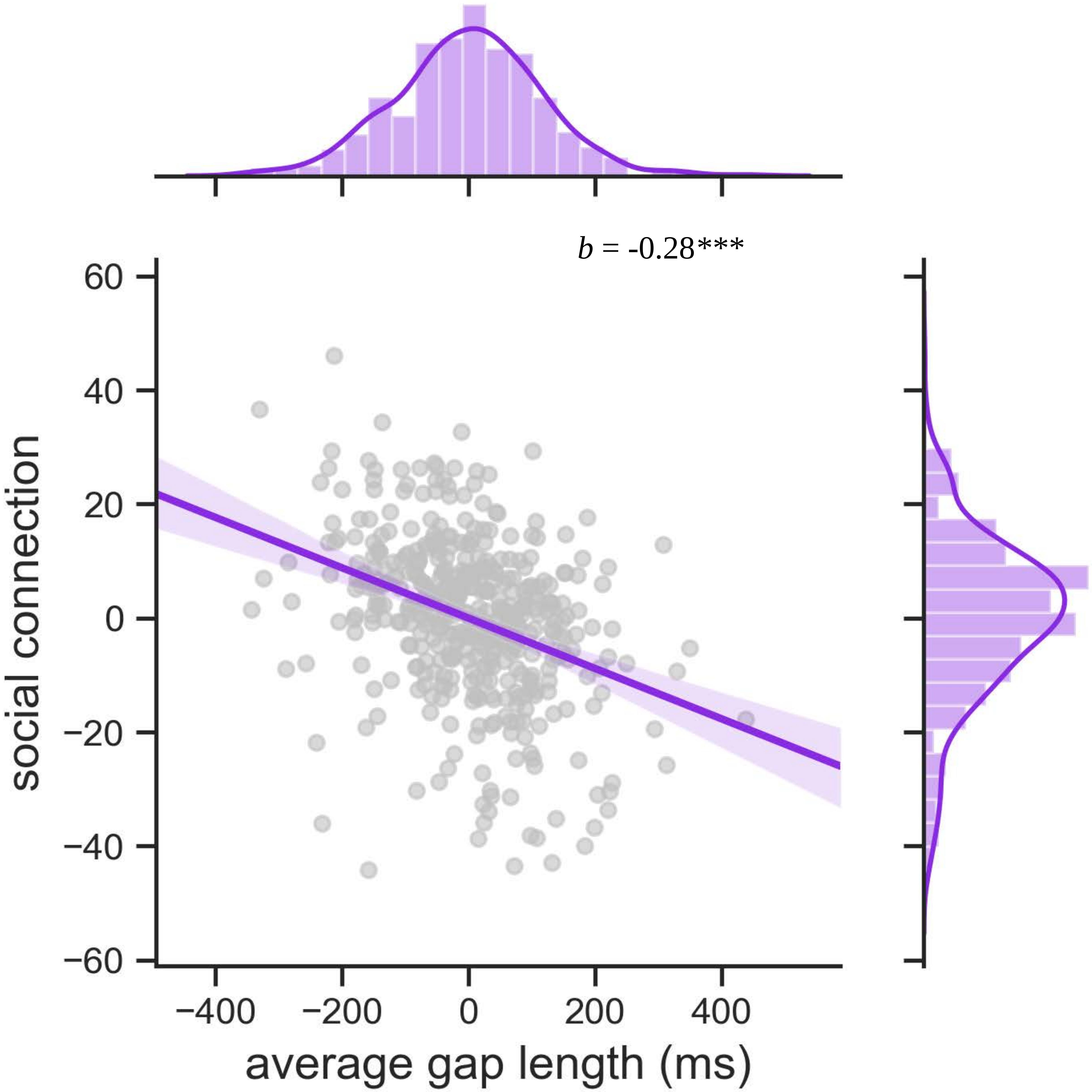
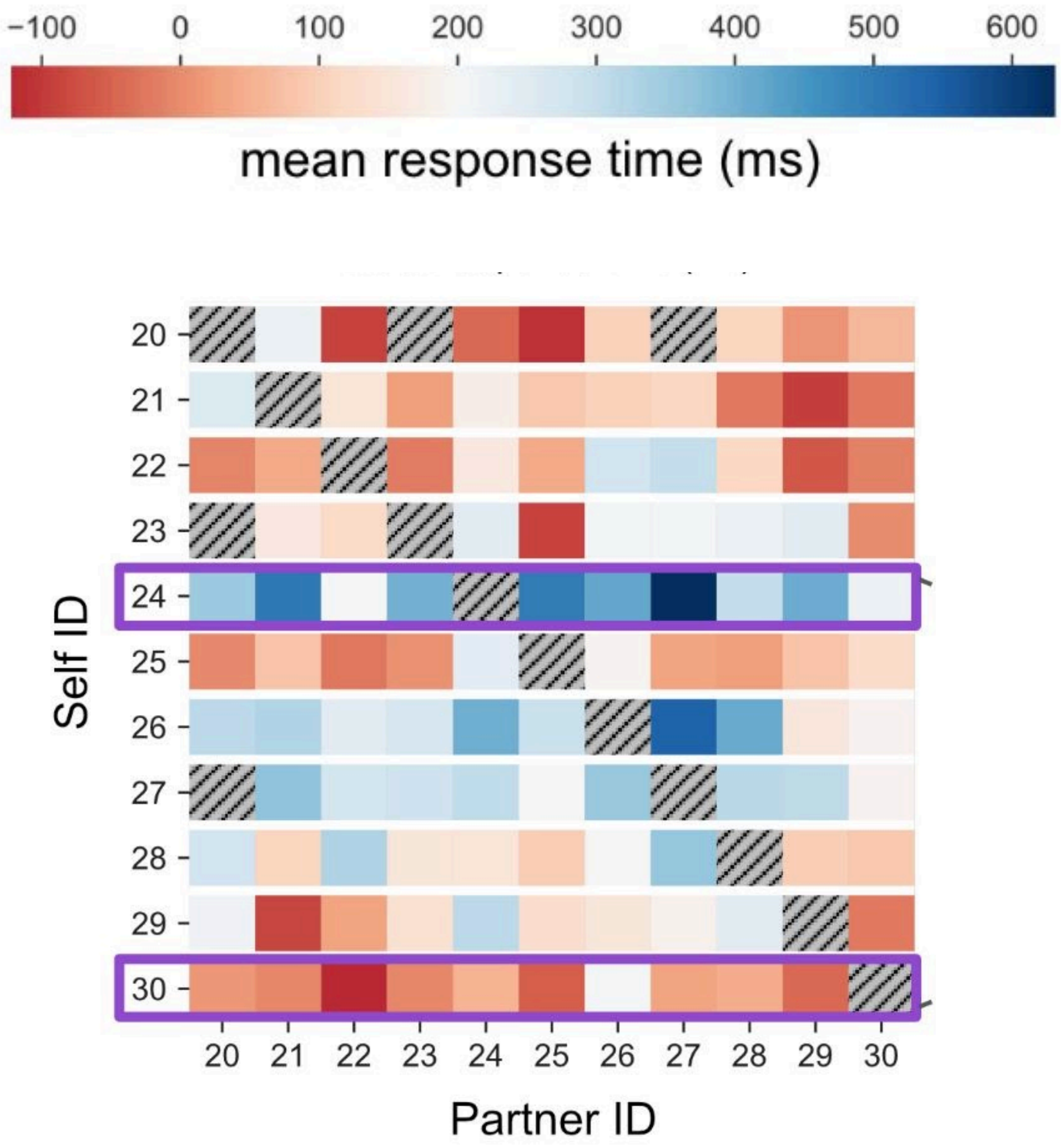
S2	That's good. Norton is a small place, with small classrooms.
S1	I fall asleep in every class. It's so bad.
S2	Why? When do you go to bed?
S1	I get like six hours of sleep every week, which is

Shorter gaps:
More social connection

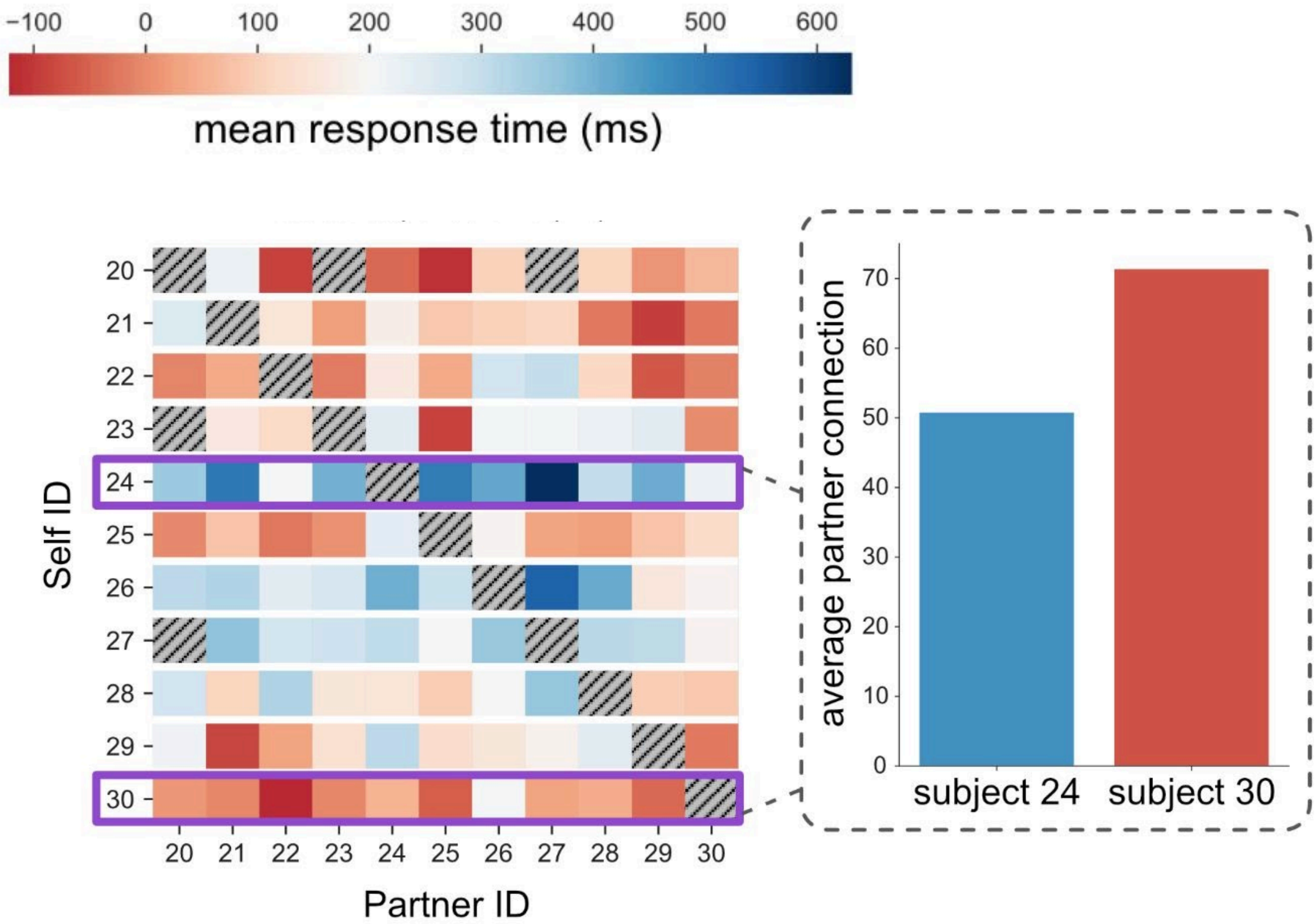


Templeton et al., PNAS, 2022

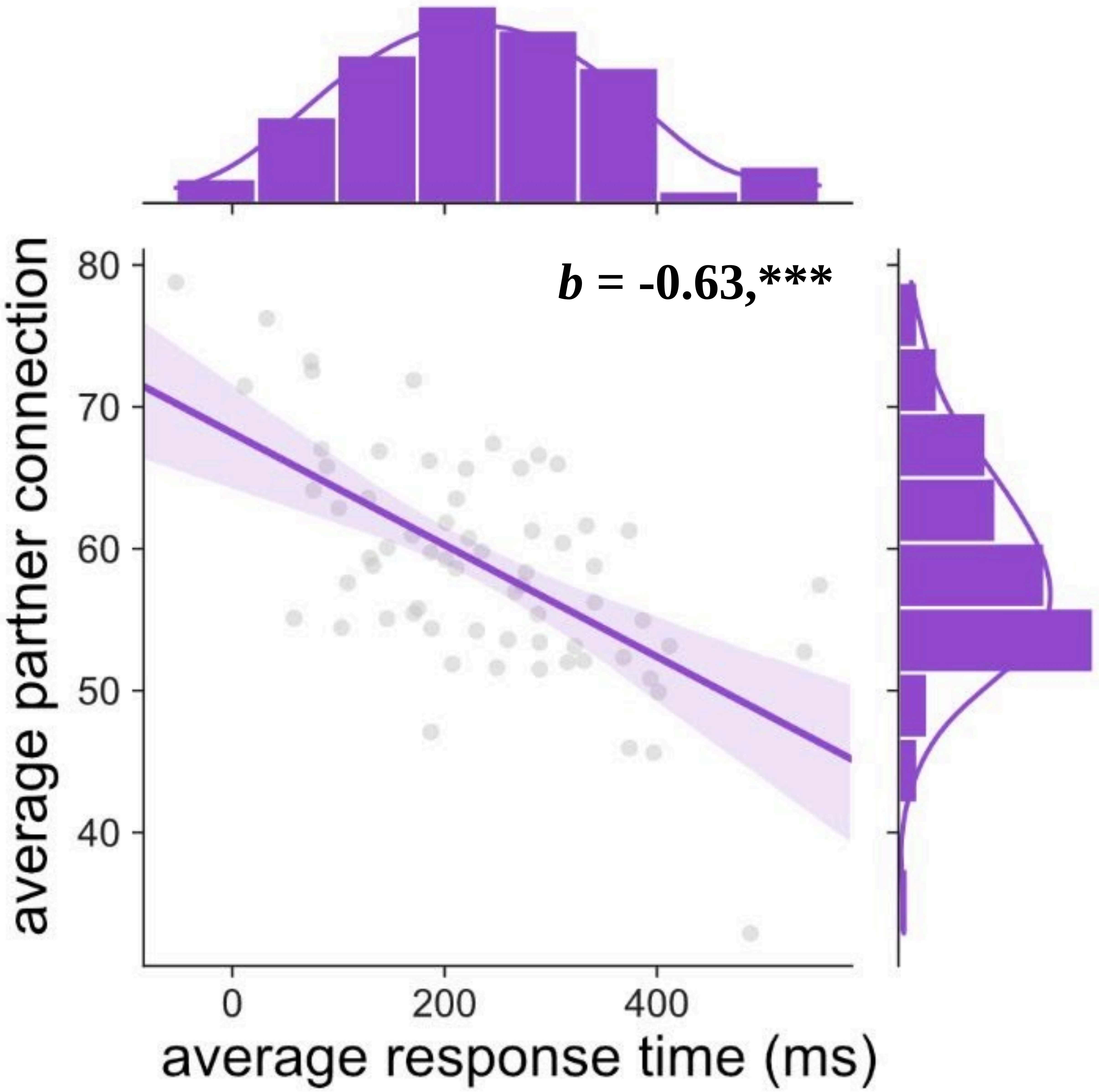

Each participant has
10 conversations



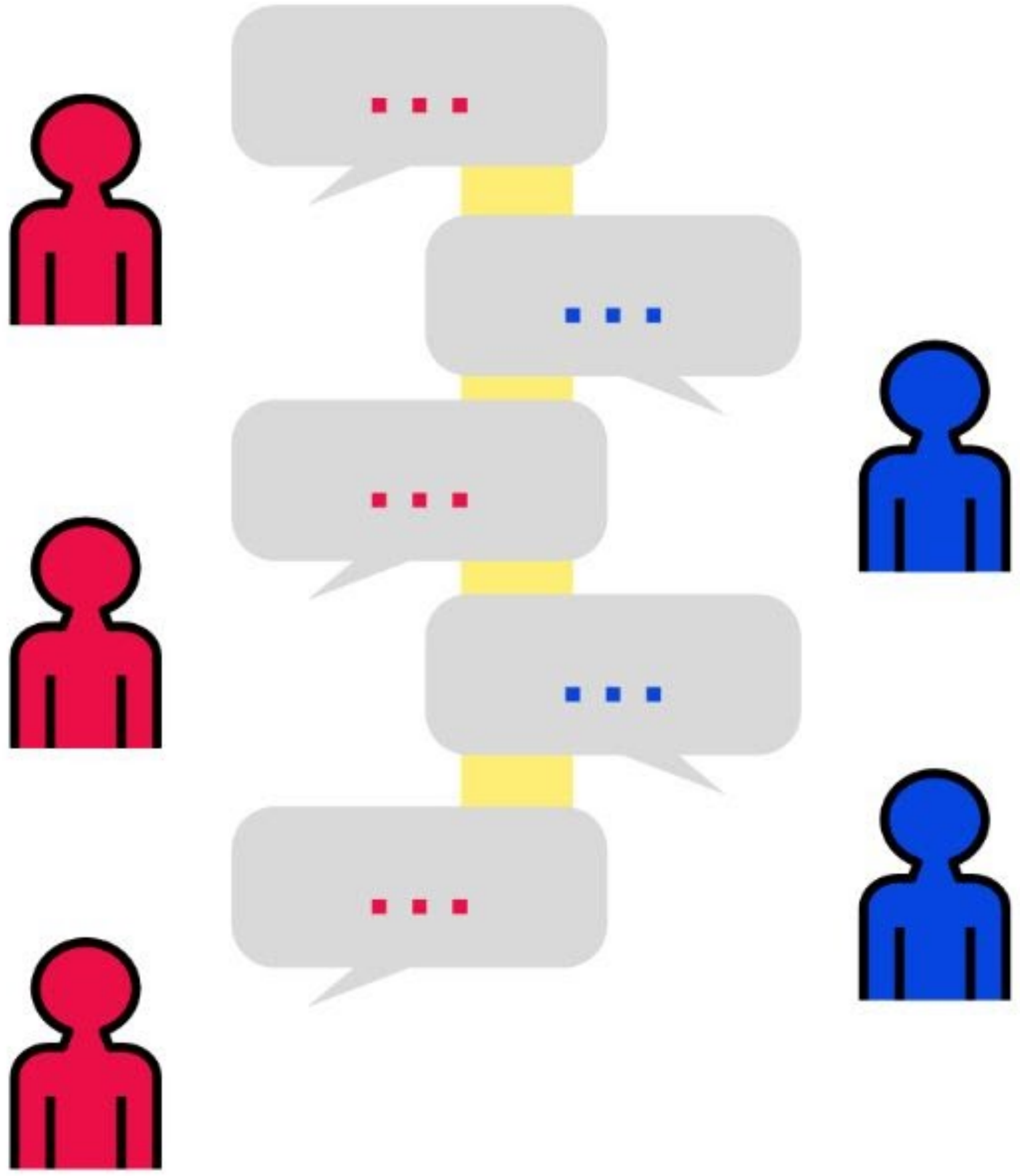
−100
0
100
200
300
400
500
600
mean response time (ms)
Self ID
20
21
22
23
24
25
26
27
28
29
30
Partner ID
20
21
22
23
24
25
26
27
28
29
30



−100 0 100 200 300 400 500 600
mean response time (ms)
Self ID
20
21
22
23
24
25
26
27
28
29
30
20 21 22 23 24 25 26 27 28 29 30
Partner ID
average partner connection
0 10 20 30 40 50 60 70
subject 24
subject 30

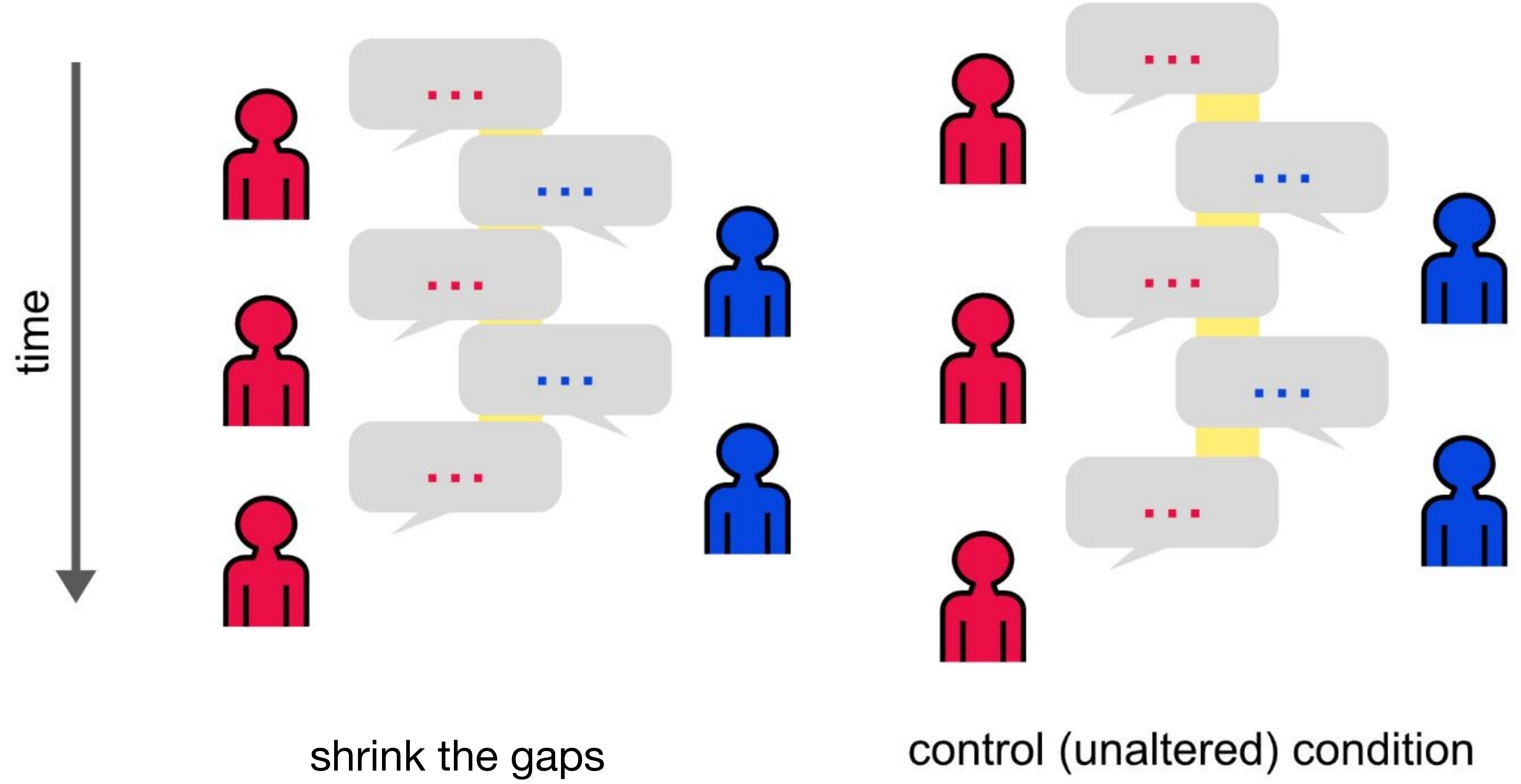


Templeton et al., PNAS, 2022

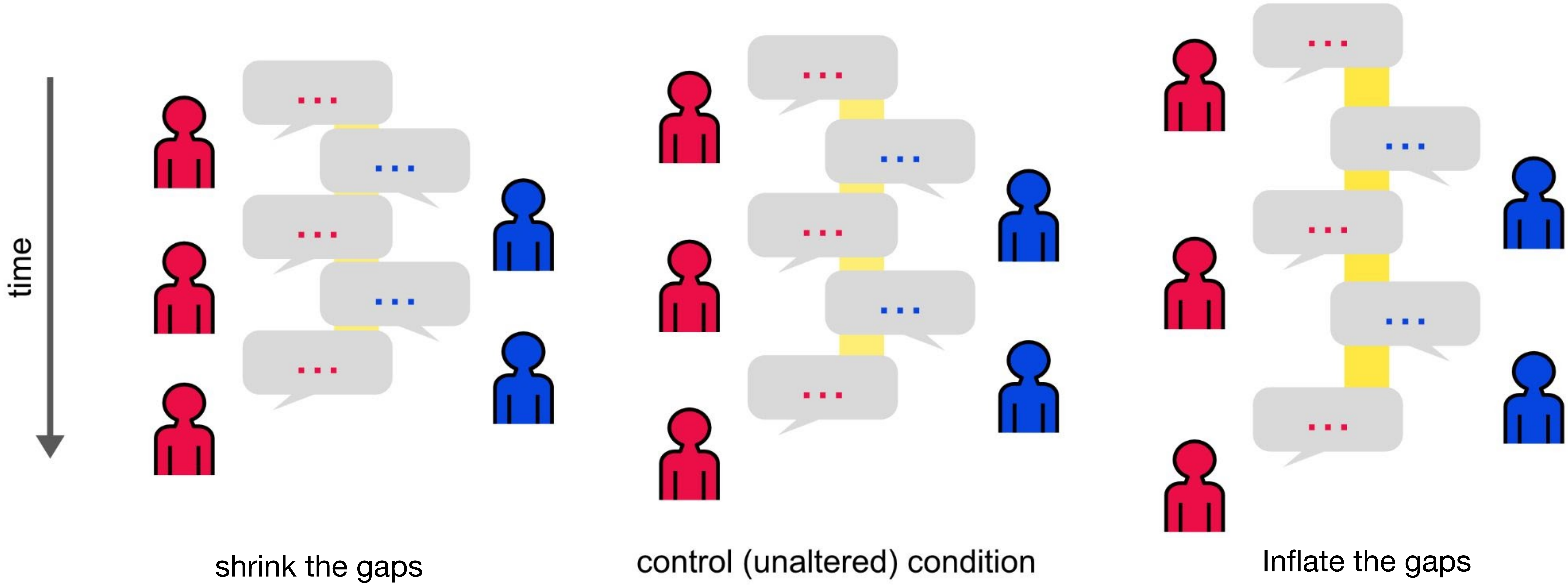


control (unaltered) condition

Templeton et al., PNAS, 2022

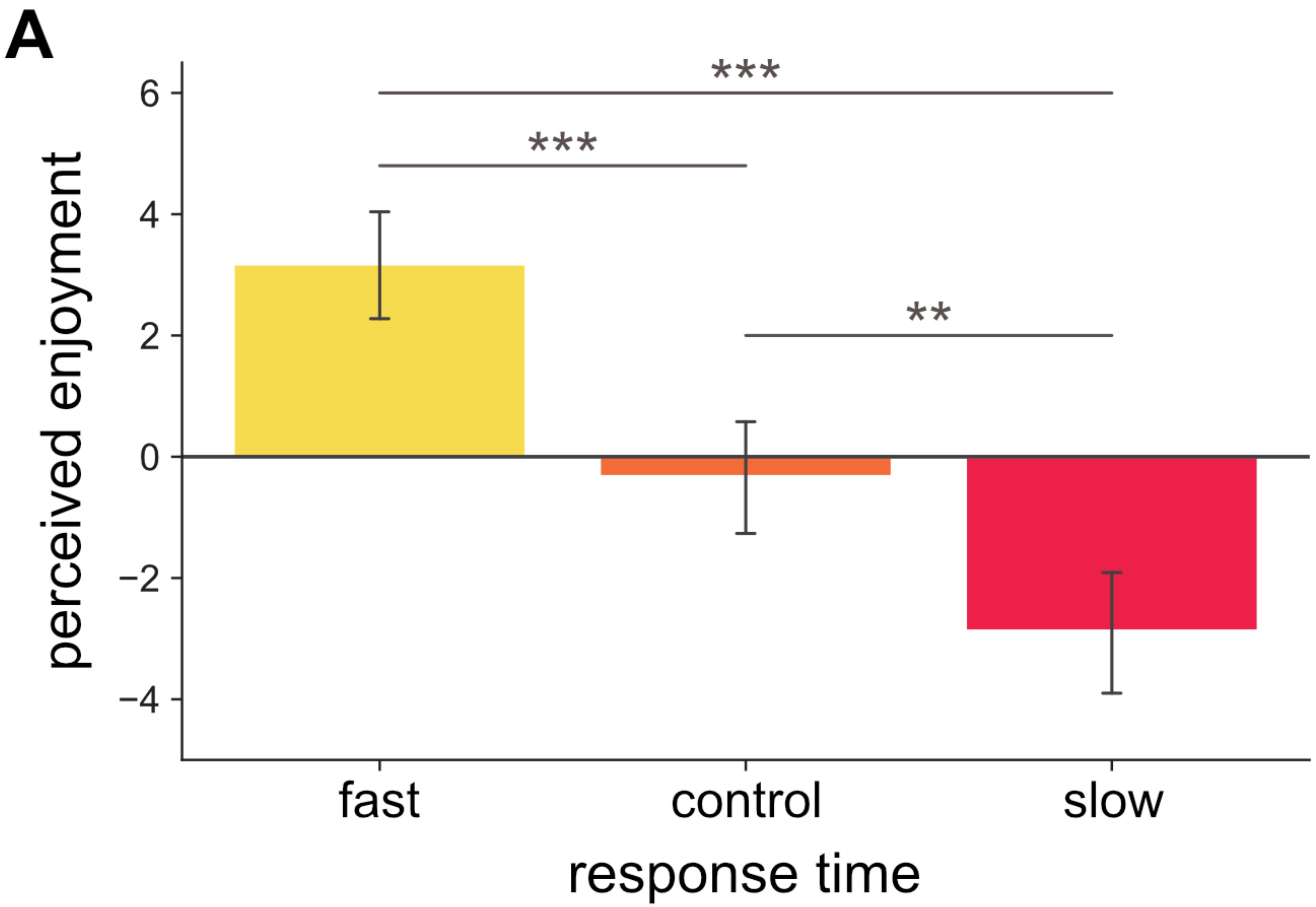


Templeton et al., PNAS, 2022



Templeton et al., PNAS, 2022

Conversations with fast response times are perceived as more enjoyable



Templeton et al., 2022, PNAS

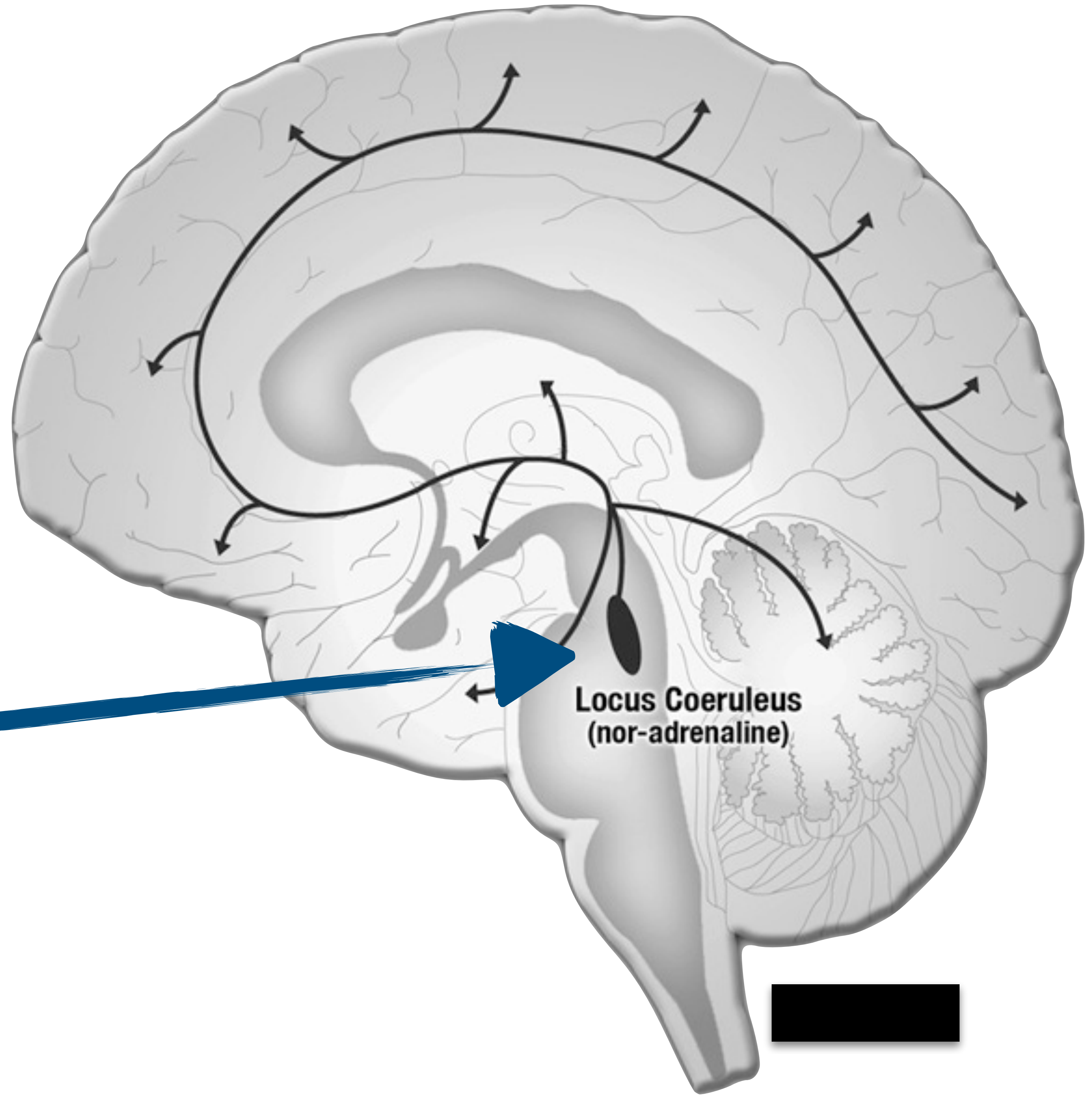
Fast response times are an “honest” signal of being in synch

Fantastic Mr. Fox (2009)

The LC-NE System

Locus Coeruleus

- half the NE neurons in CNS, *Nieuwenhuis et al., 2005*
- sole source of NE to forebrain, *Berridge & Waterhouse, 2003*



[redacted]

Locus Coeruleus

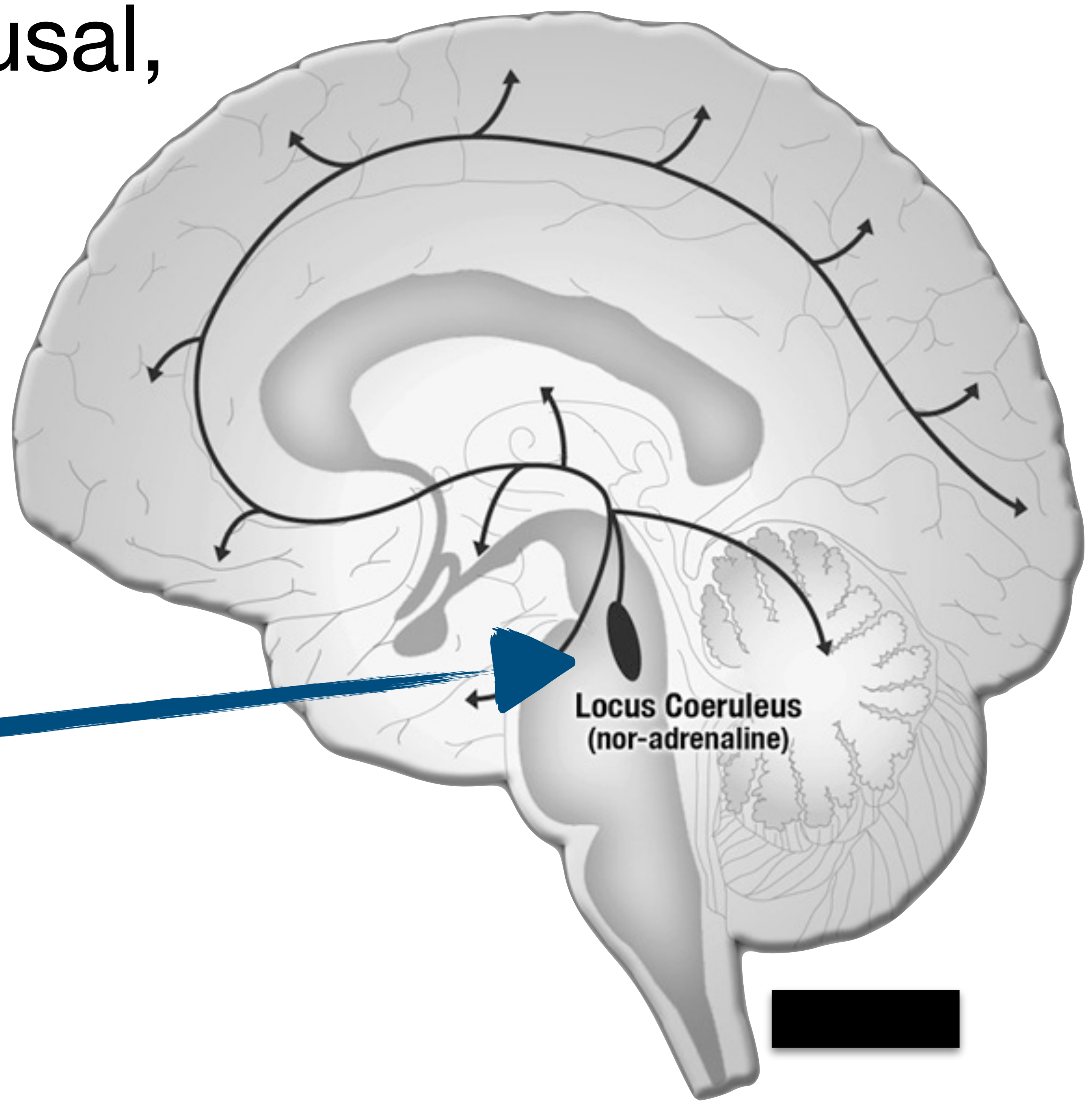
The LC-NE System

Locus Coeruleus

- half the NE neurons in CNS, *Nieuwenhuis et al., 2005*
- sole source of NE to forebrain, *Berridge & Waterhouse, 2003*

Norepinephrine

- causes changes in attention and arousal, *Berridge & Waterhouse, 2003*



[redacted]

Locus Coeruleus

The LC-NE System

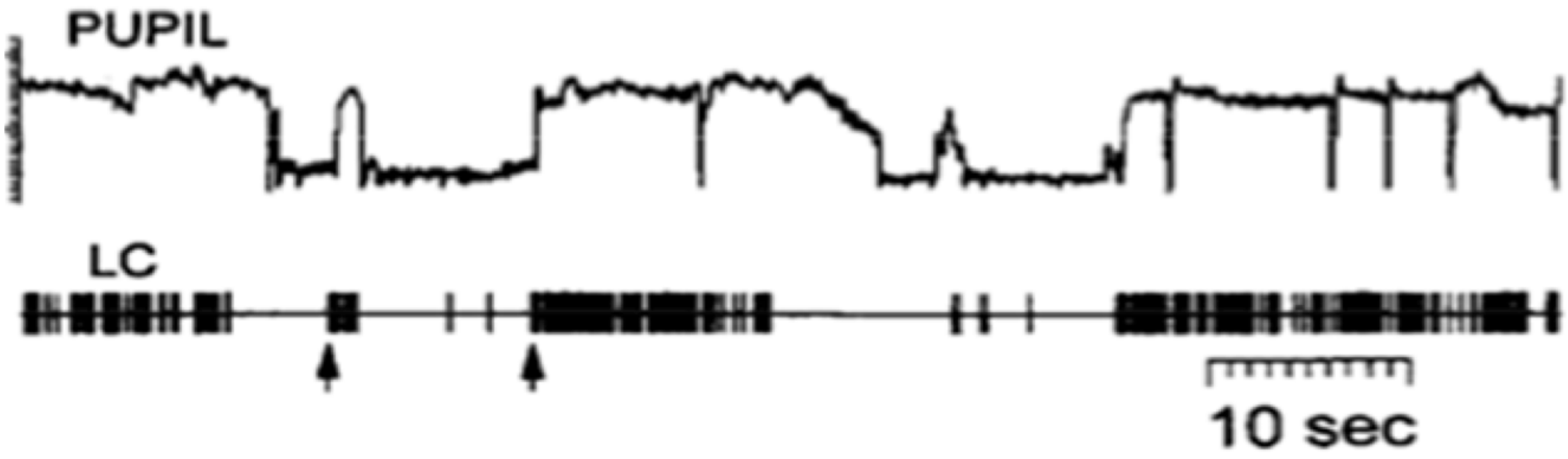
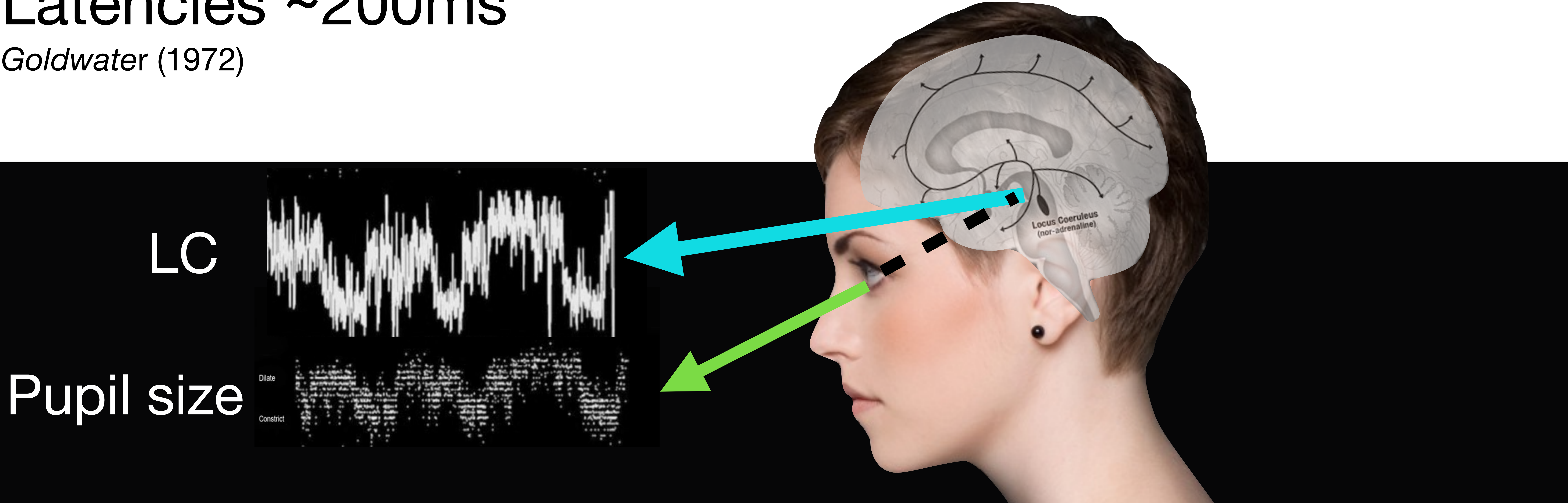


figure adapted from Rajkowski et al. (1994)

Pupil Dilations Track Online Attention

- Close association with LC-NE activity
  Rajkowski et al (1993
- Involuntary "honest signal"
  Beatty & Lucero-Wagoner (2000)
- Latencies ~200ms
  Goldwater (1972)



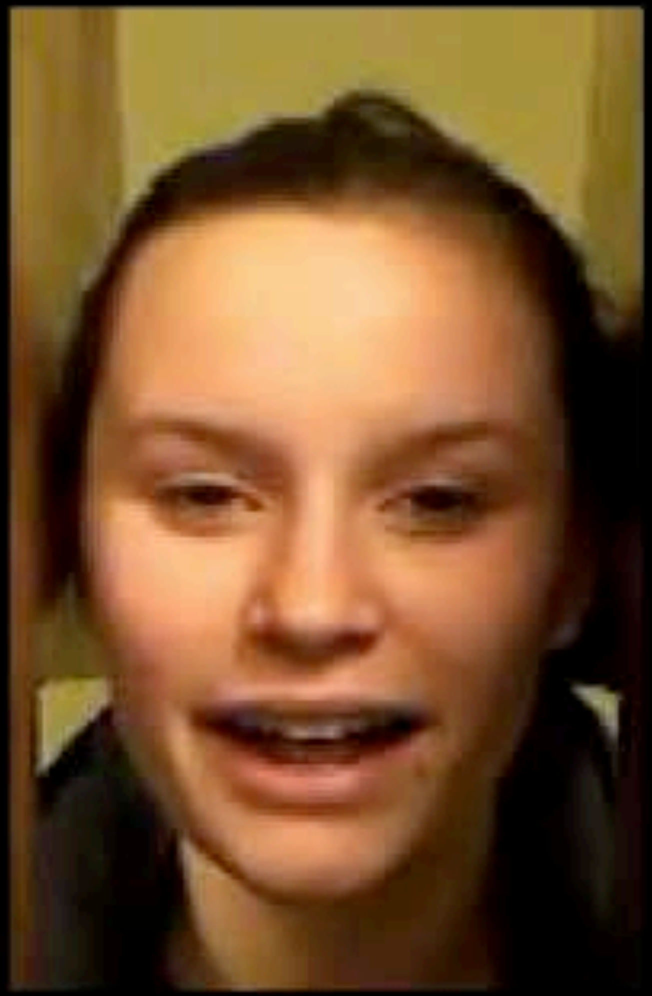
Shared attention

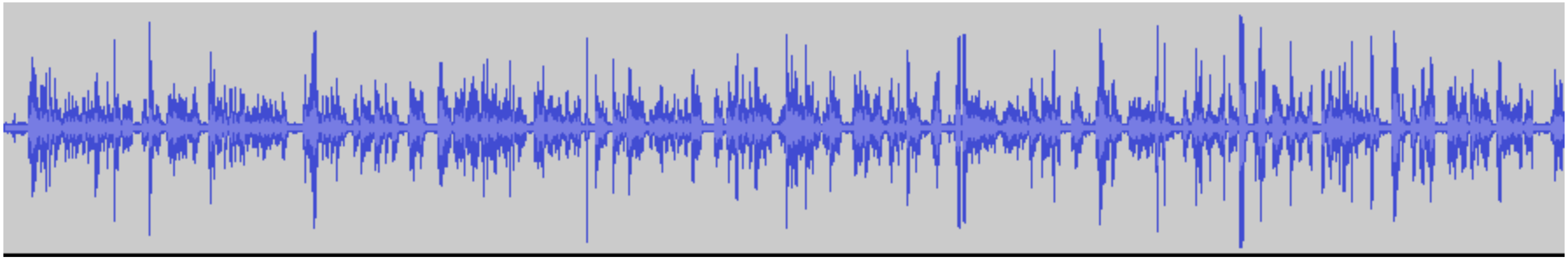
Olivia Kang, PhD
Lucid

Kang & Wheatley (JEP:G, 2017)

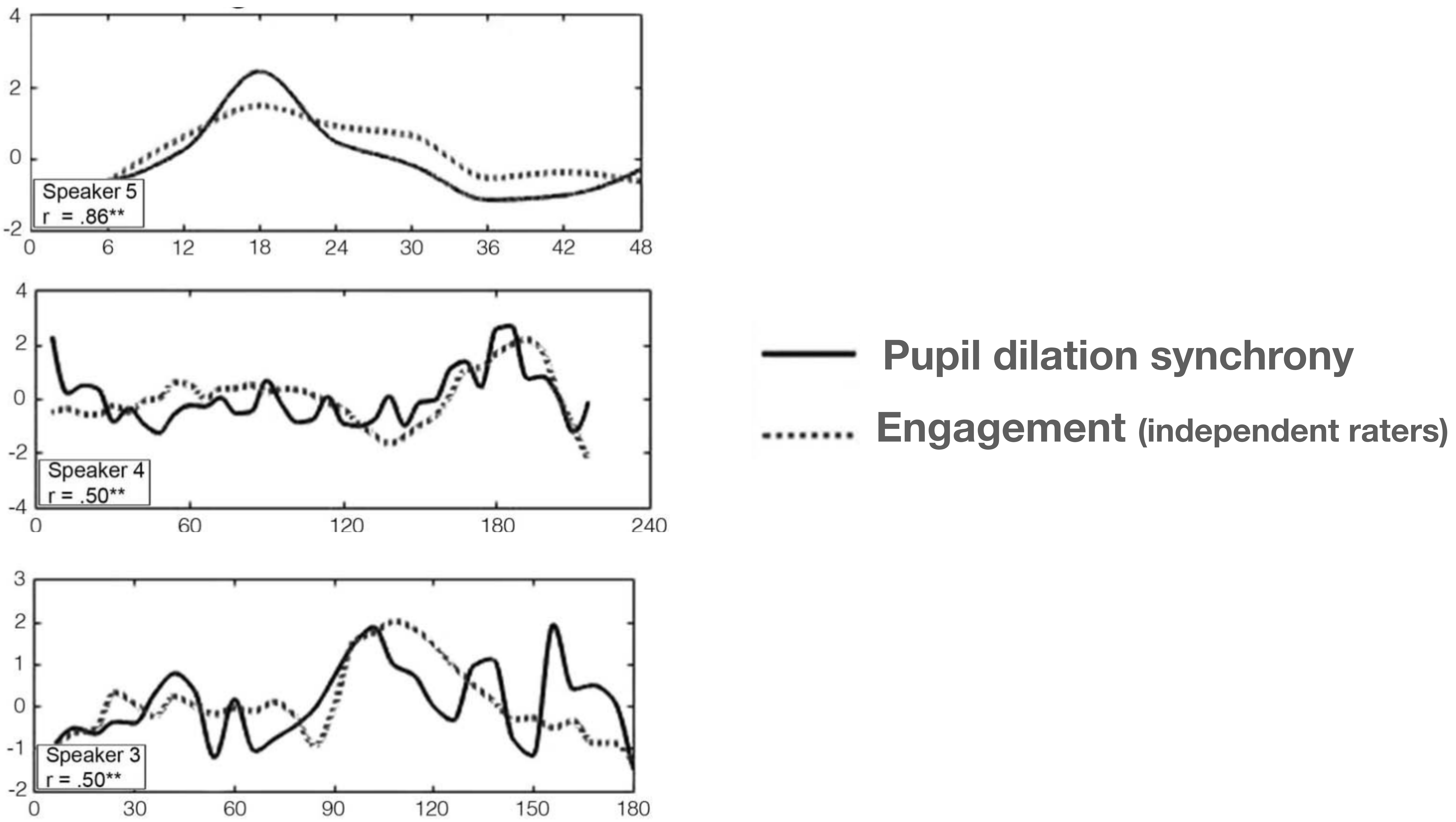
Listener

Speaker





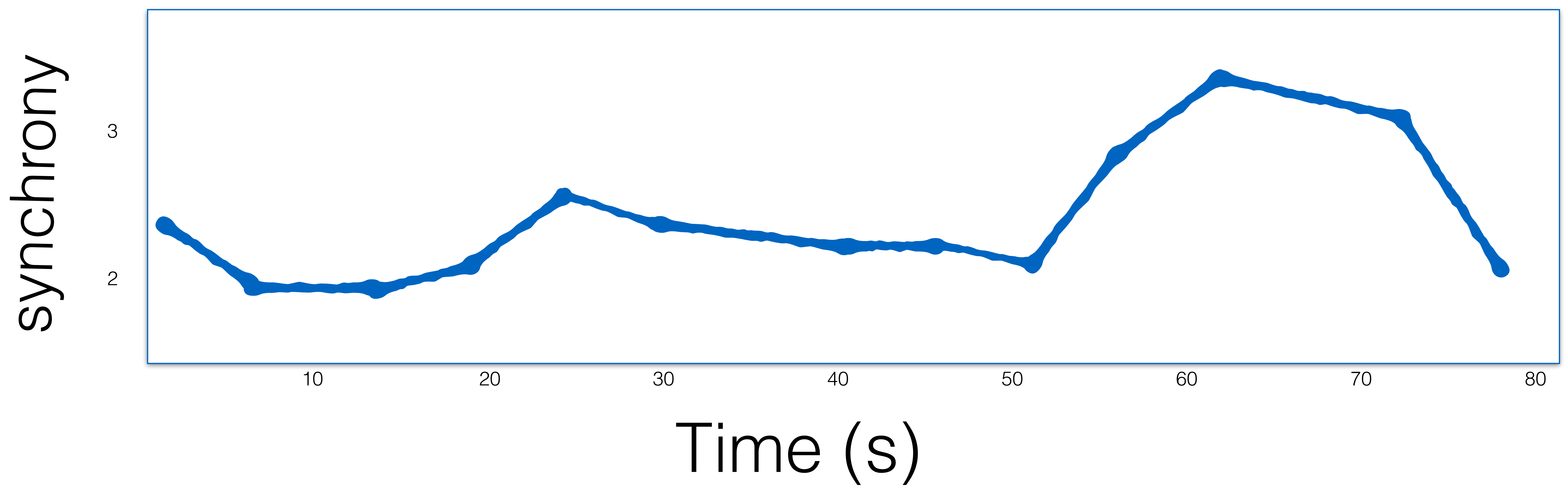
Independent raters listened to each story and rated their engagement, moment by moment.



4
2
0
-2
0
6
12
18
24
30
36
42
48
Speaker 5
r = .86**
4
2
0
-2
-4
0
60
120
180
240
Speaker 4
r = .50**
3
2
1
0
-1
-2
0
30
60
90
120
150
180
Speaker 3
r = .50**
Pupil dilation synchrony
Engagement (independent raters)

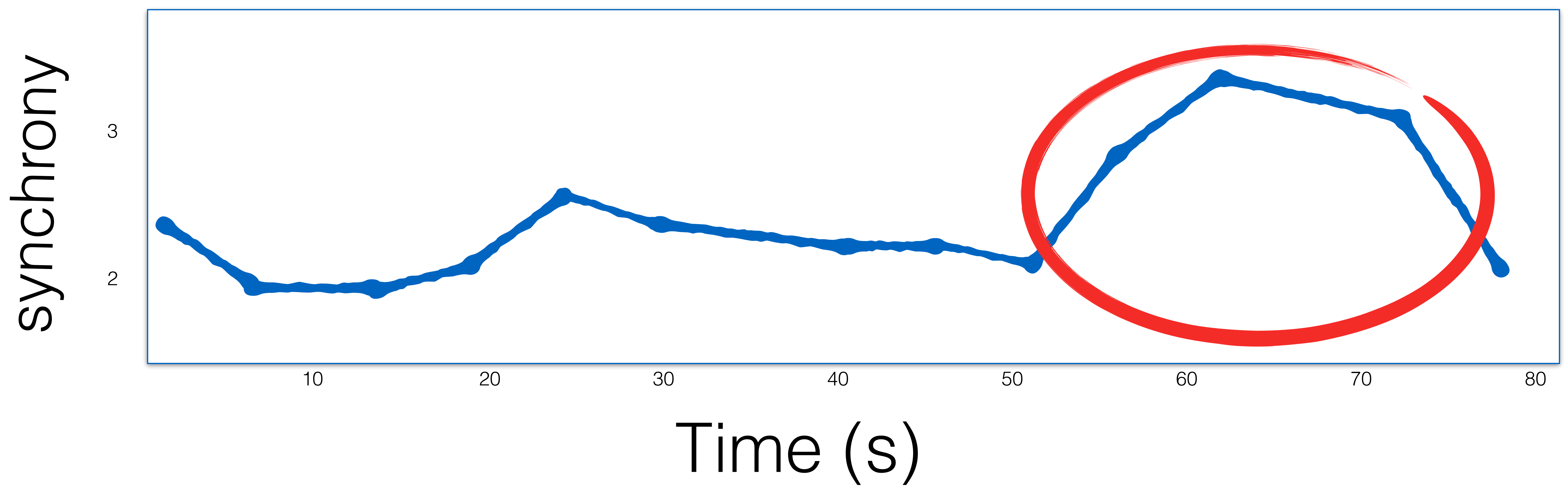
Speaker and listener pupil dilations synchronized during engaging moments of a story.

synchrony between speakers & listeners



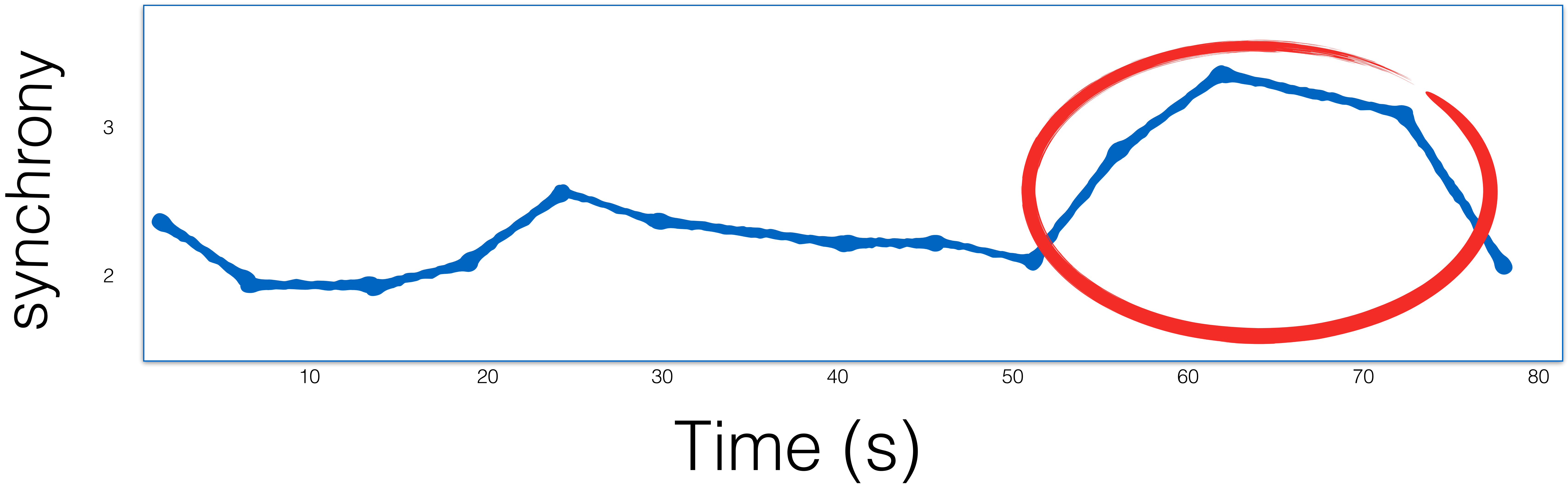
Kang & Wheatley, JEP:G, 2017

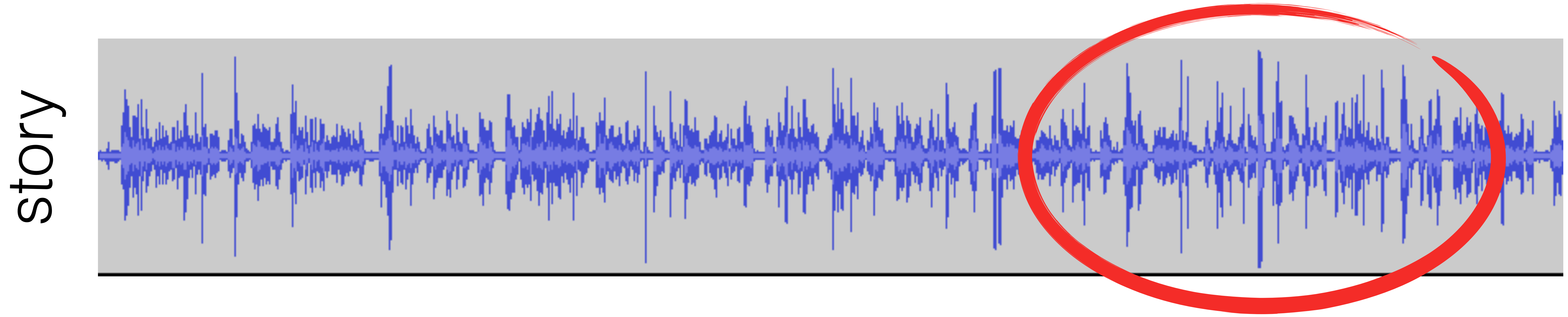
synchrony between speakers & listeners



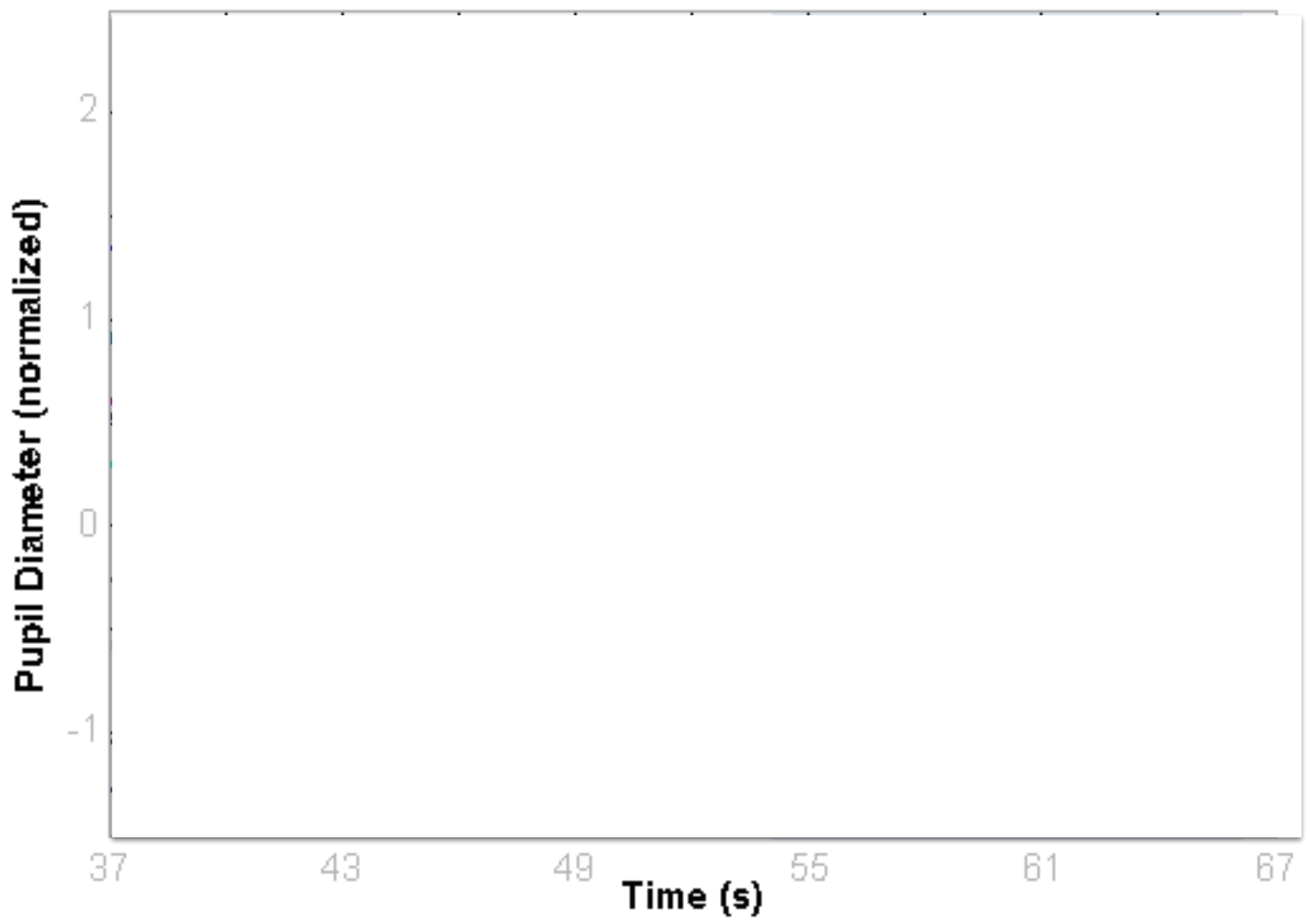
Kang & Wheatley, JEP:G, 2017

synchrony between speakers & listeners

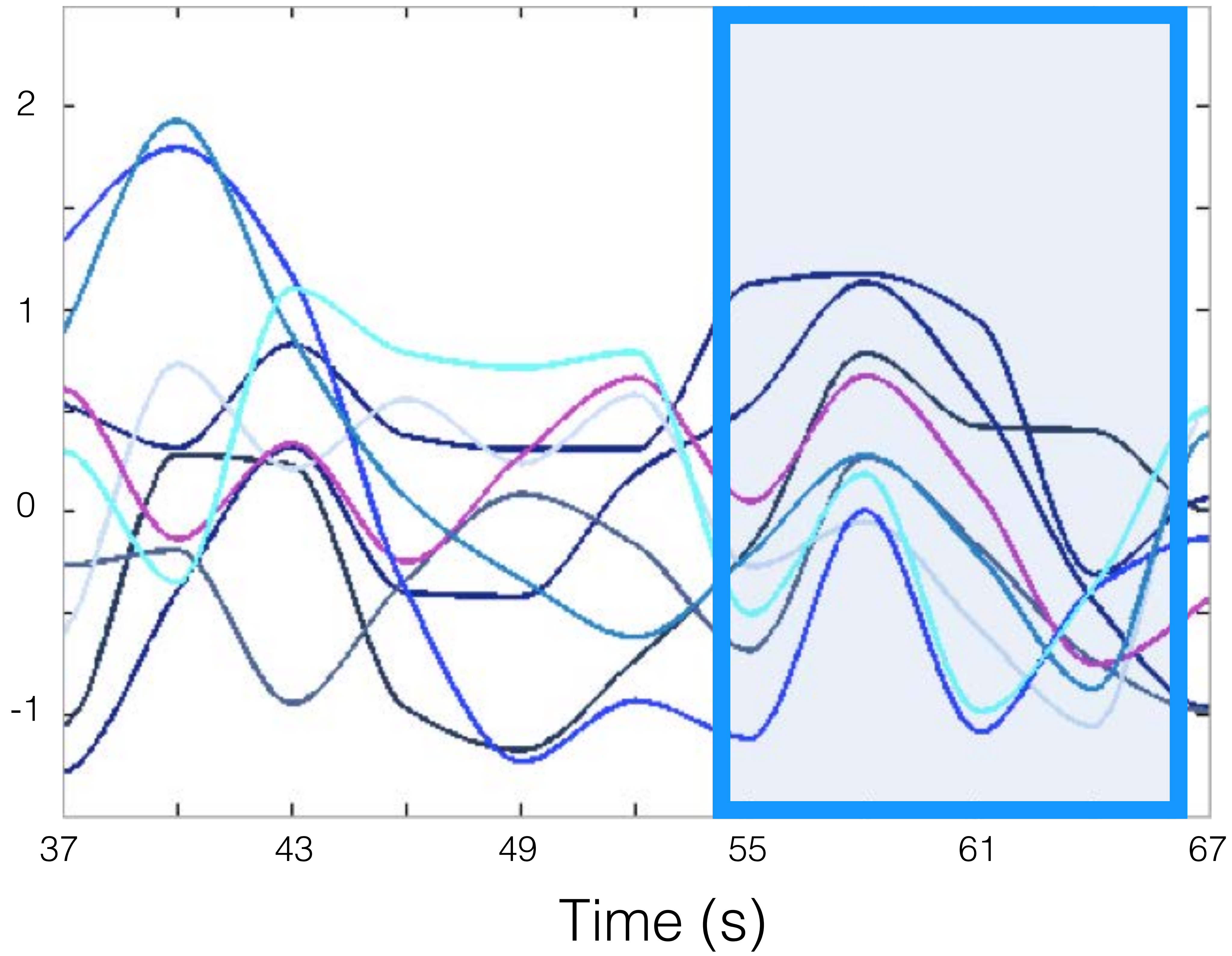




Kang & Wheatley, JEP:G, 2017

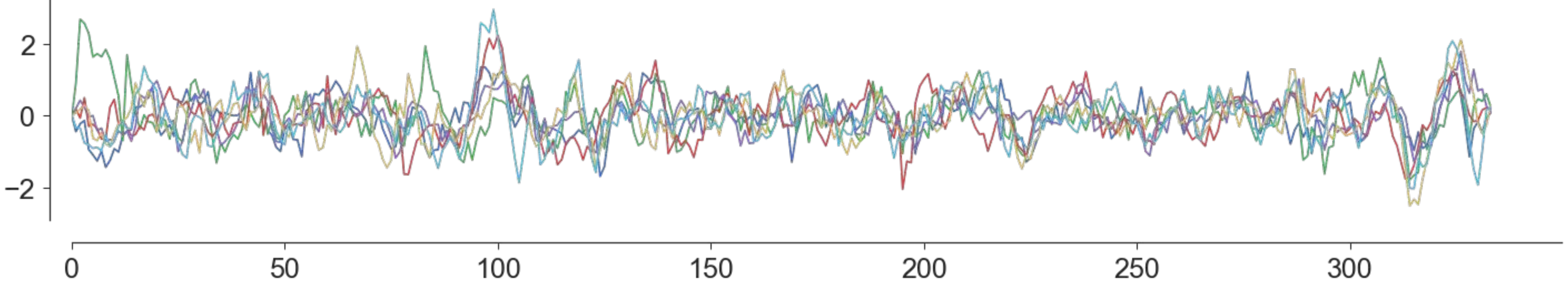


Kang & Wheatley, JEP:G, 2017



“And *all* I wanted him to do was kiss me. And then… it was silent for a few seconds, and he leaned over and actually did kiss me and it was just so amazing because [*clearing throat*] I had really really interested in him [*sic*]” (0:54-1:06)

Kang & Wheatley, JEP:G, 2017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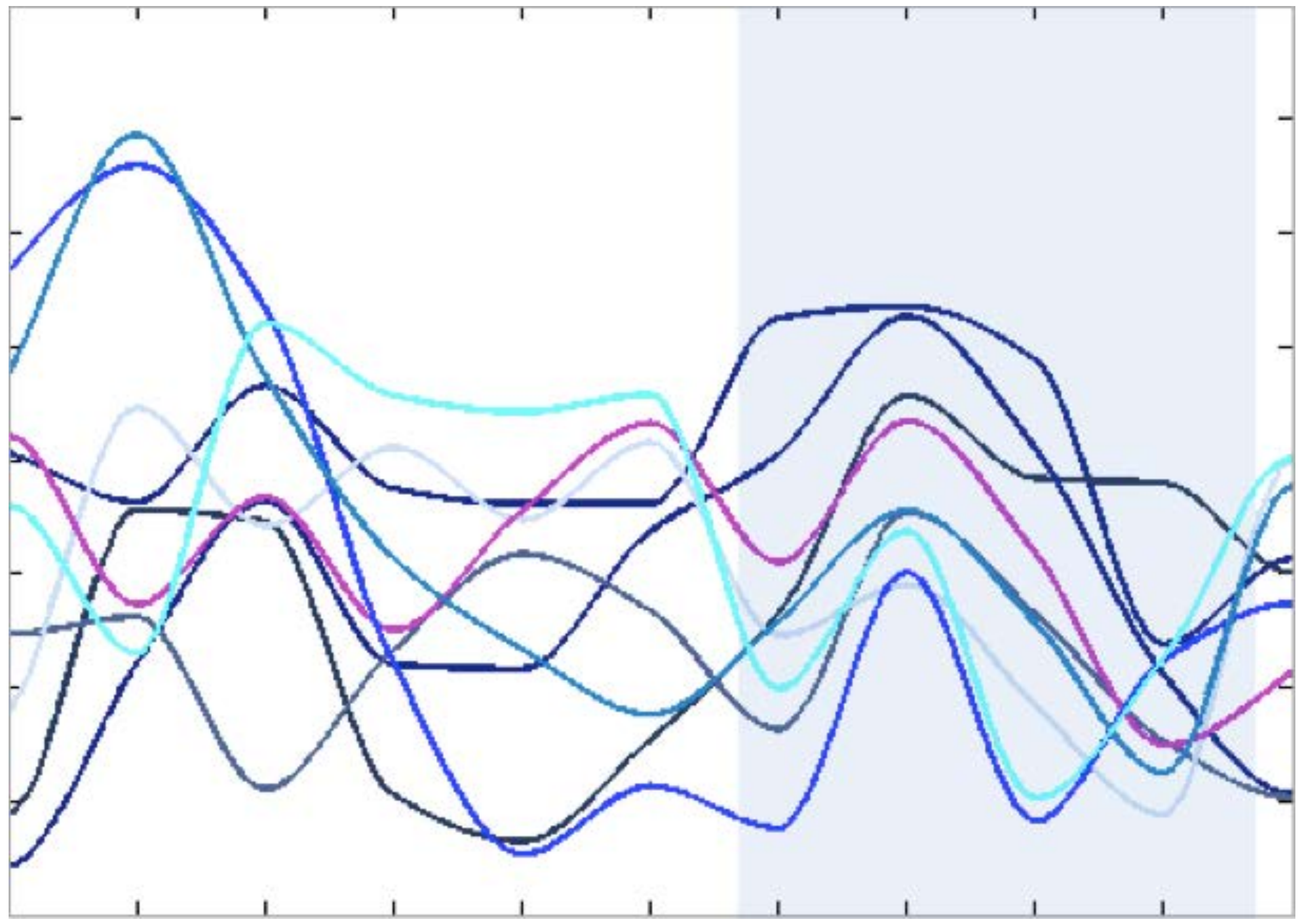
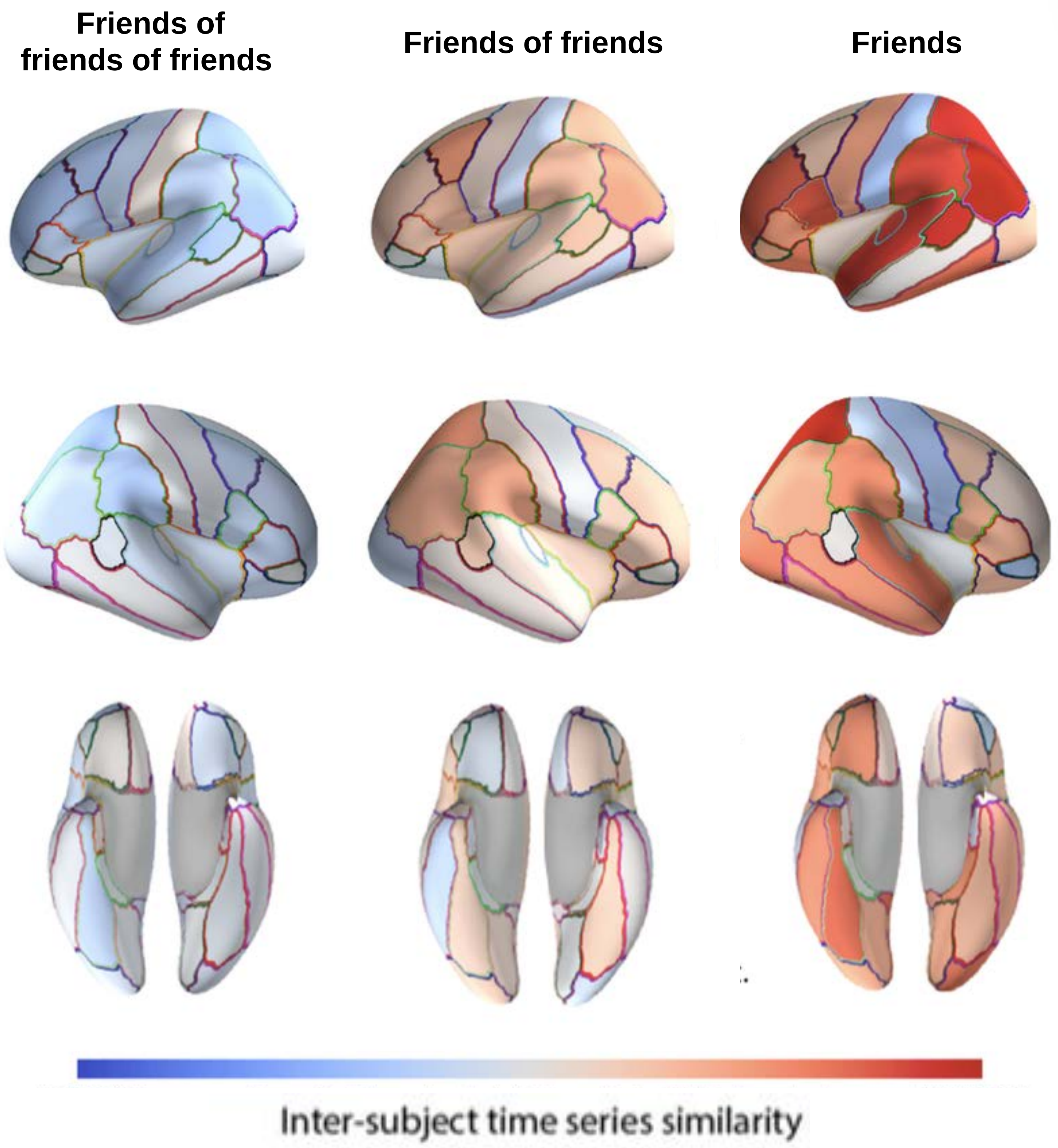
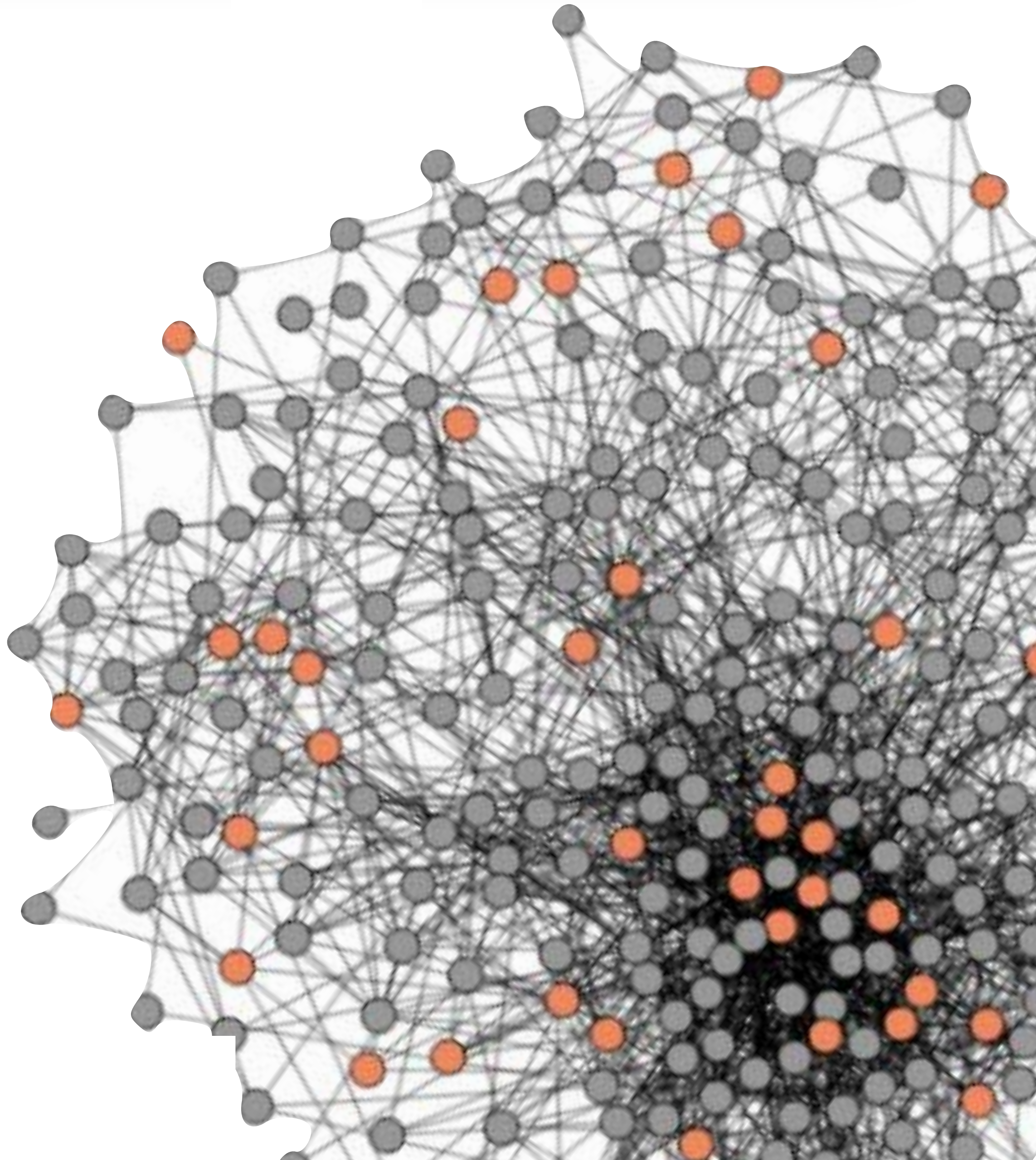
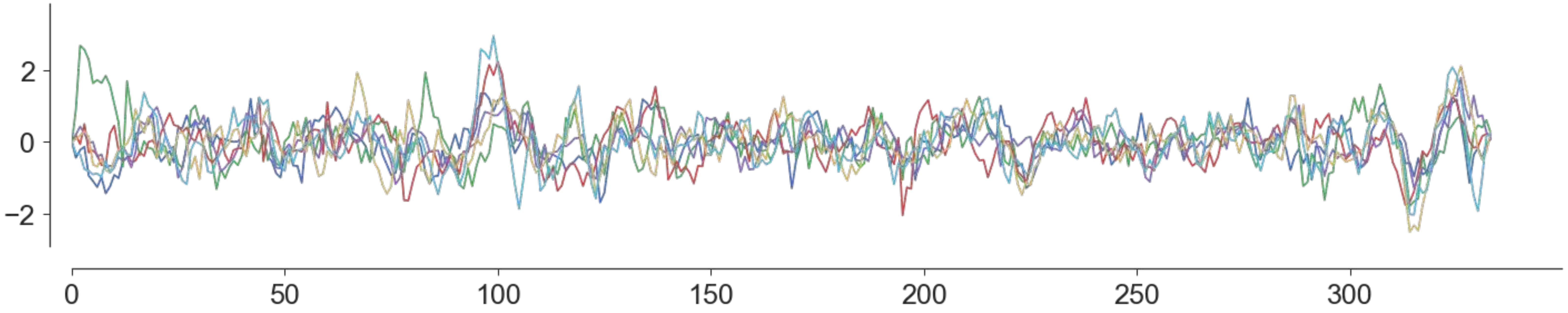



Friends of friends of friends
Friends of friends
Friends
Inter-subject time series similarity

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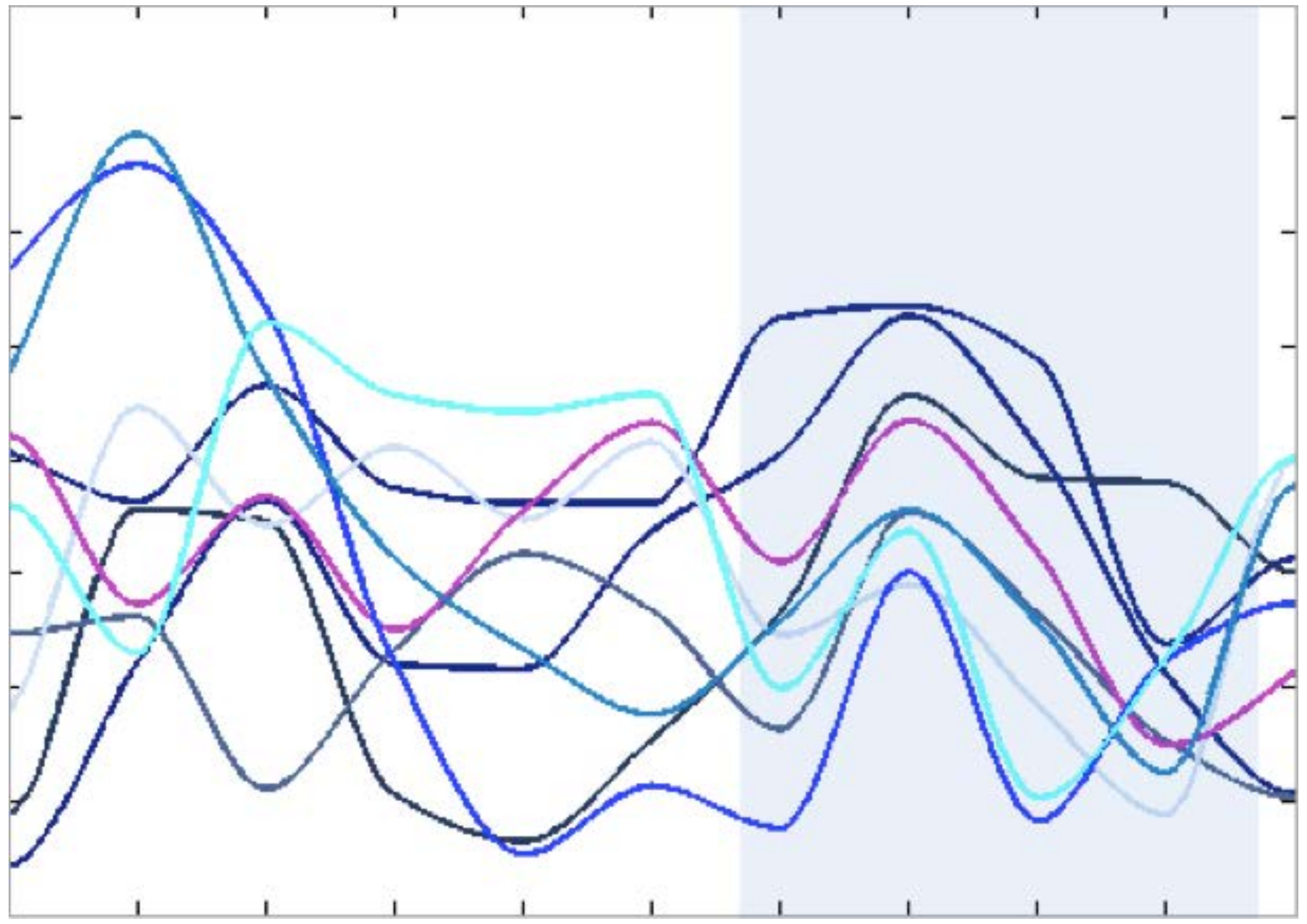
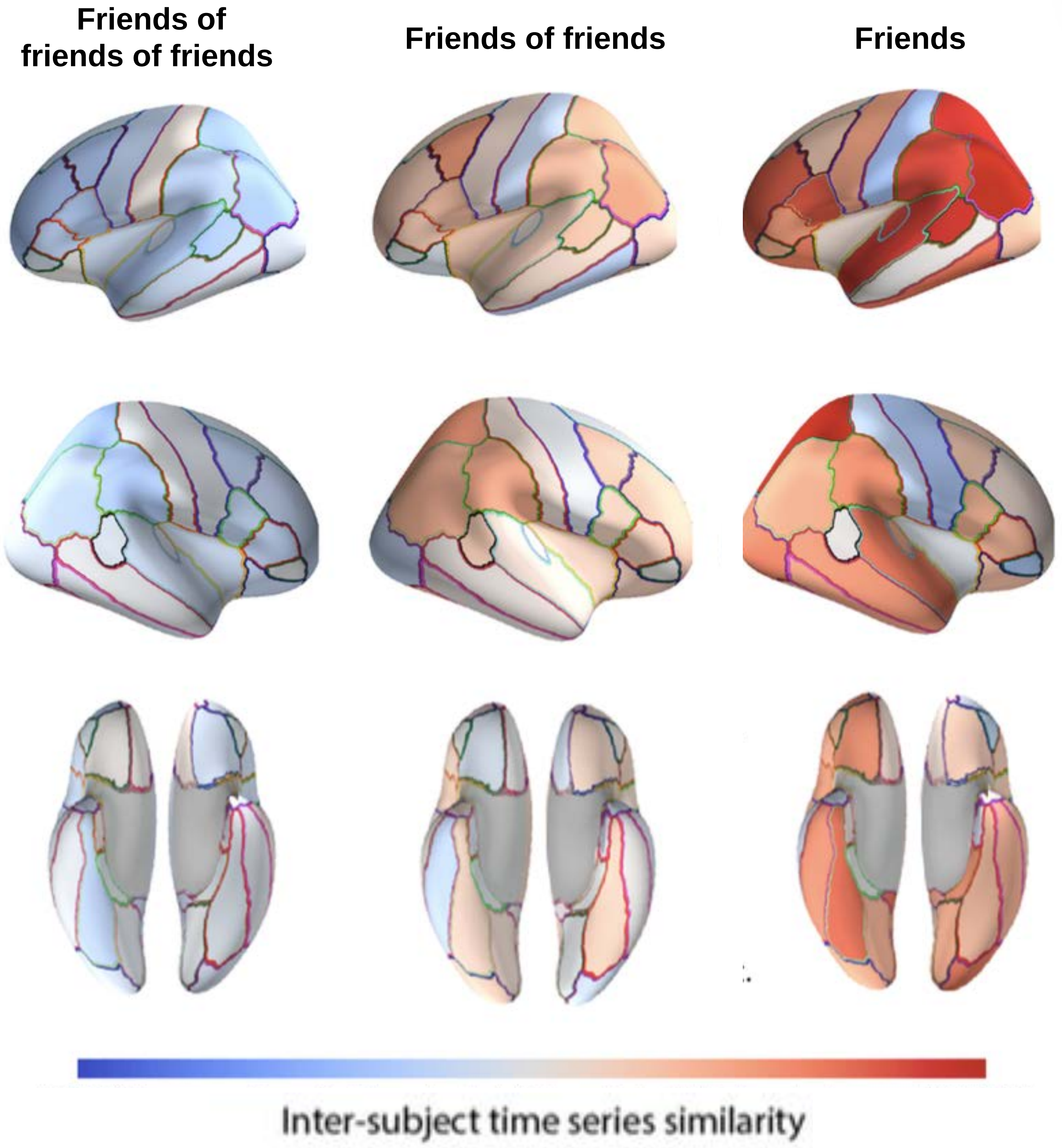
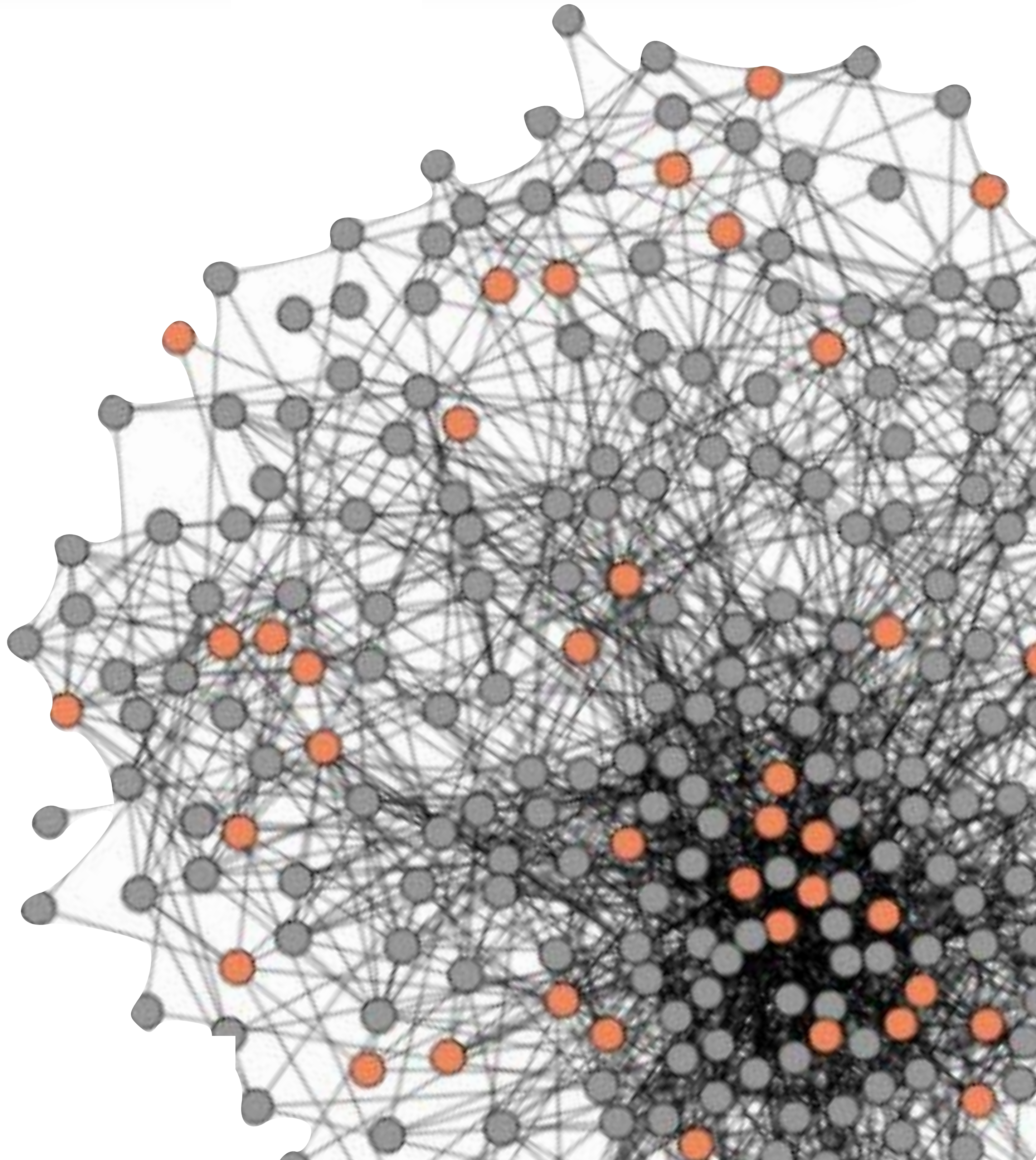
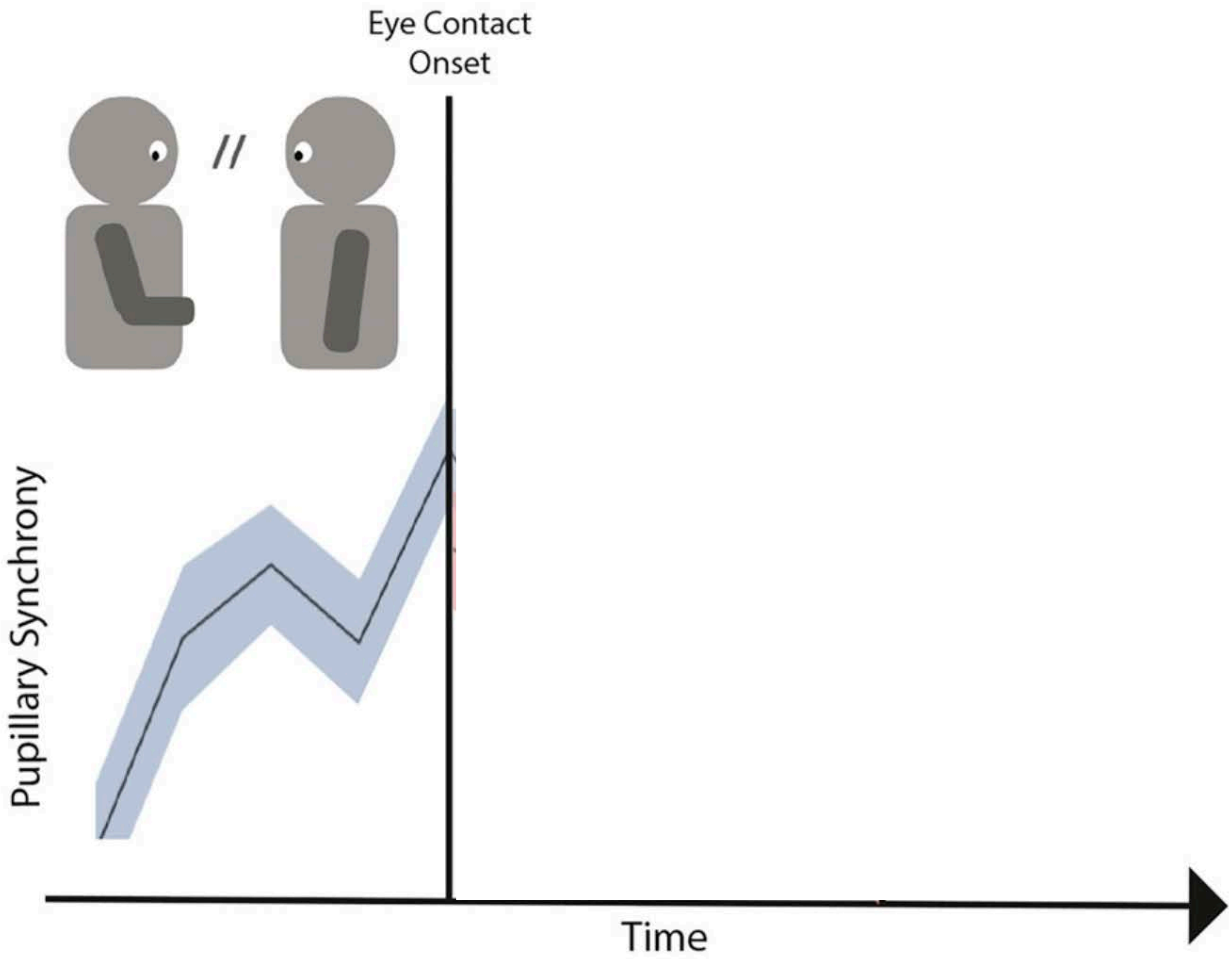


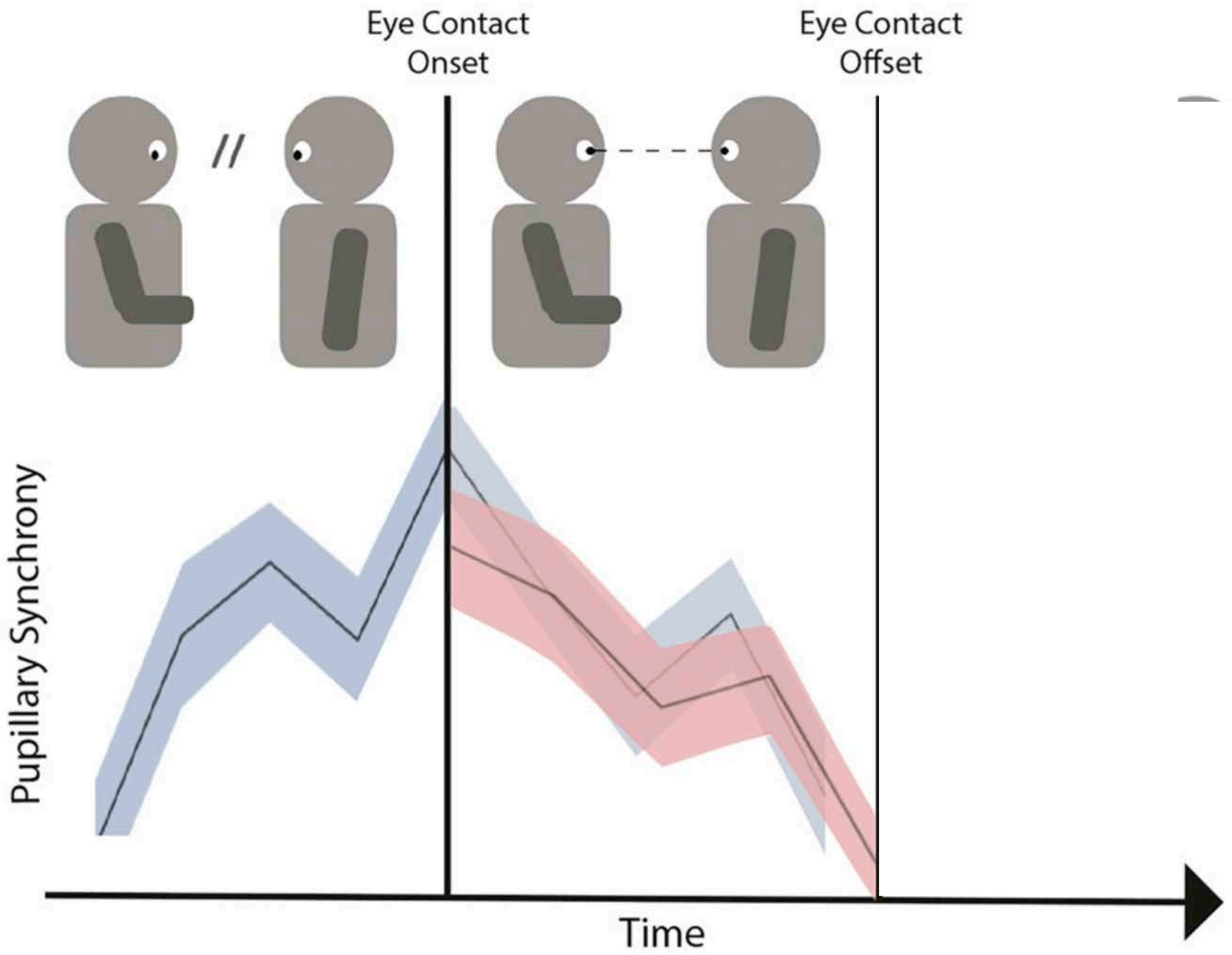

Friends of
friends of friends
Friends of friends
Friends
Inter-subject time series similarity

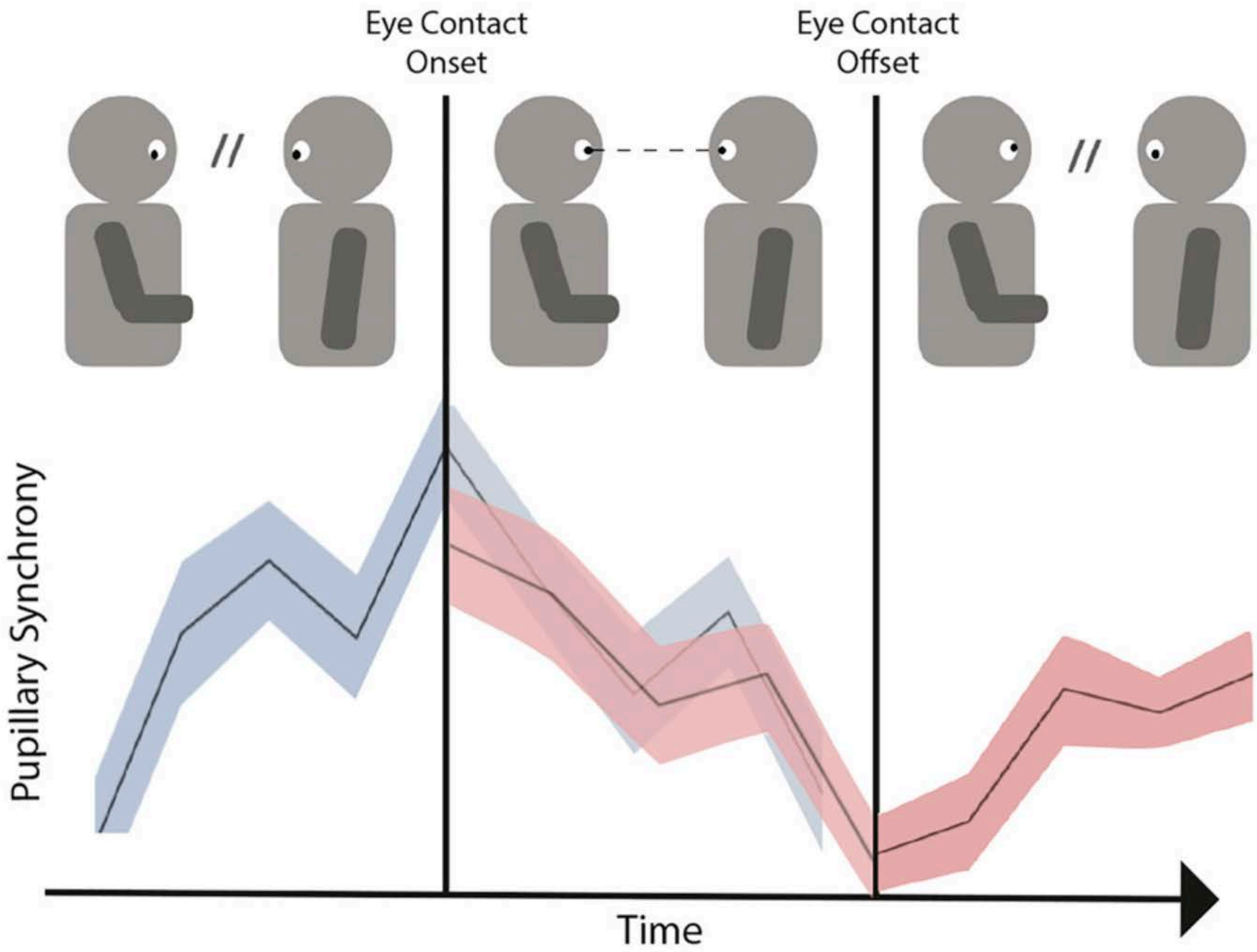


Wohltjen et al, PNAS, 2021

Wohltjen et al, PNAS, 2021


Eye Contact
Onset
//
Pupillary Synchrony
Time


Eye Contact
Onset
Eye Contact
Offset
//
Pupillary Synchrony
Time


Eye Contact
Onset
Eye Contact
Offset
Pupillary Synchrony
Time

Universal Sentence Encoder

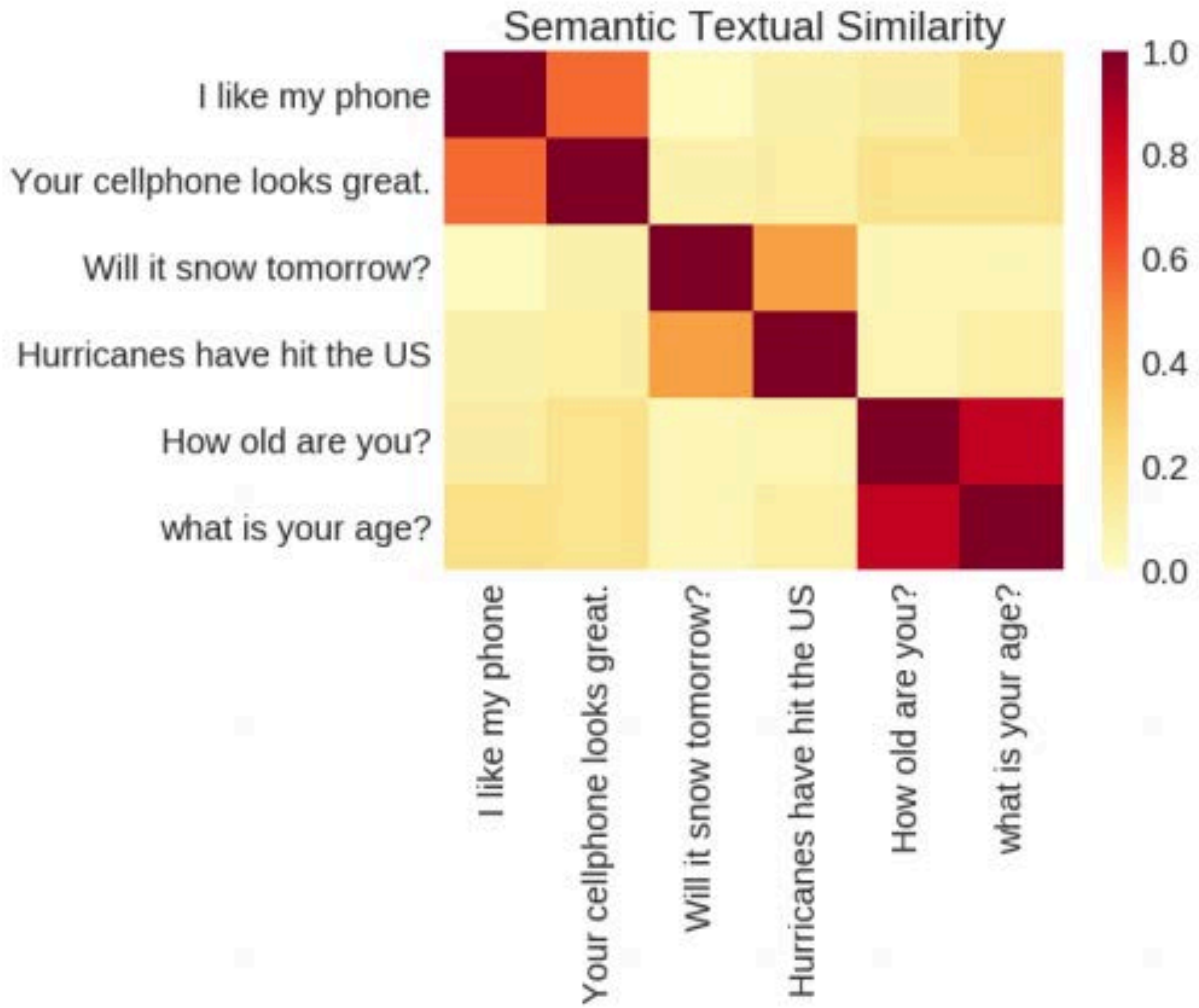
Universal Sentence Encoder

Daniel Cer[a], Yinfei Yang[a], Sheng-yi Kong[a], Nan Hua[a], Nicole Limtiaco[b], Rhomni St. John[a], Noah Constant[a], Mario Guajardo-Céspedes[a], Steve Yuan[c], Chris Tar[a], Yun-Hsuan Sung[a], Brian Strope[a], Ray Kurzweil[a]

[a]Google Research
Mountain View, CA

[b]Google Research
New York, NY

[c]Google
Cambridge, MA



Universal Sentence Encoder

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Daniel Cer[a], Yinfei Yang[a], Sheng-yi Kong[a], Nan Hua[a], Nicole Limtiaco[b], Rhomni St. John[a], Noah Constant[a], Mario Guajardo-Céspedes[a], Steve Yuan[c], Chris Tar[a], Yun-Hsuan Sung[a], Brian Strope[a], Ray Kurzweil[a]

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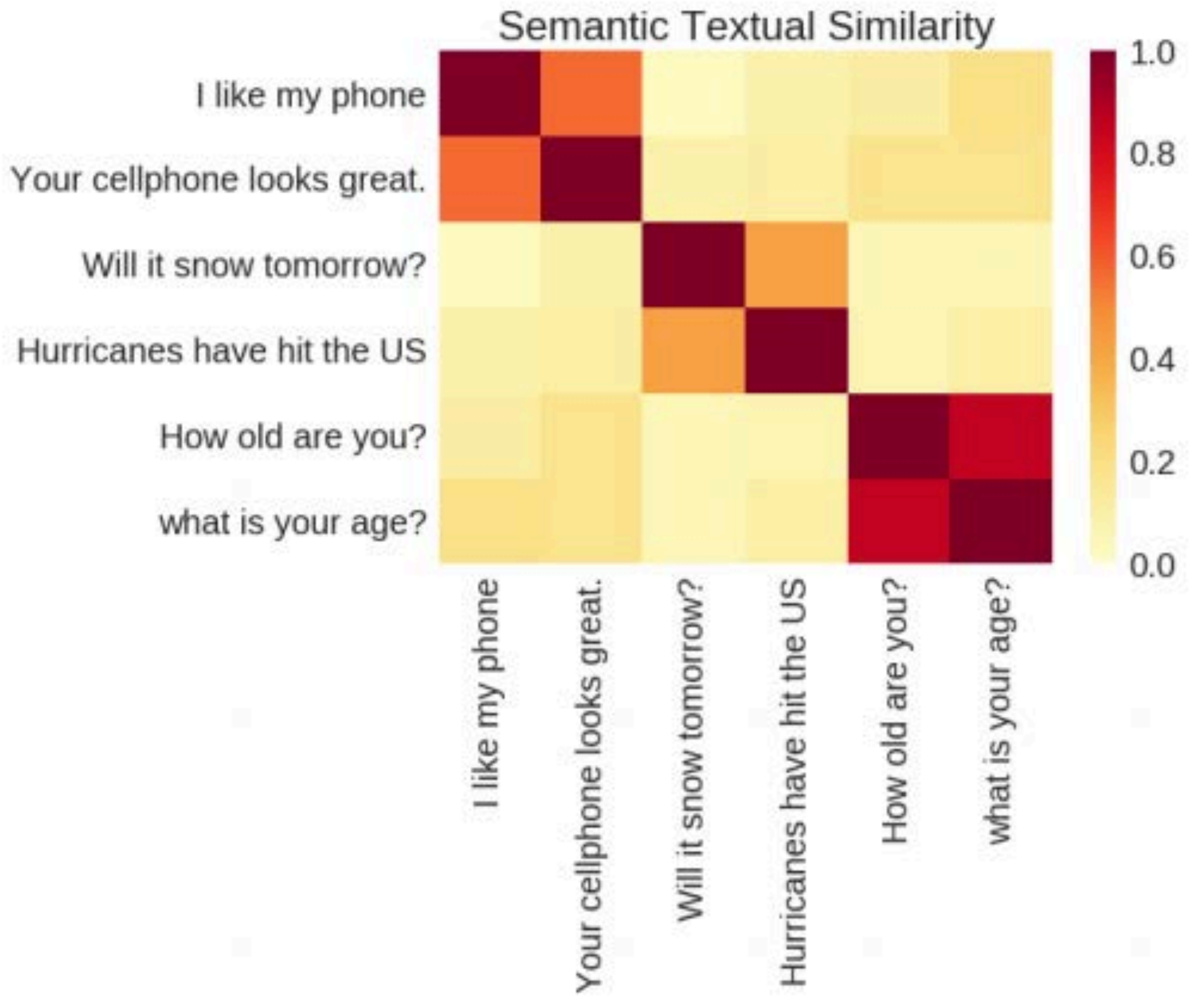

input **How old are you?**

Universal Sentence Encoder

Universal Sentence Encoder

Daniel Cer[a], Yinfei Yang[a], Sheng-yi Kong[a], Nan Hua[a], Nicole Limtiaco[b], Rhomni St. John[a], Noah Constant[a], Mario Guajardo-Céspedes[a], Steve Yuan[c], Chris Tar[a], Yun-Hsuan Sung[a], Brian Strope[a], Ray Kurzweil[a]

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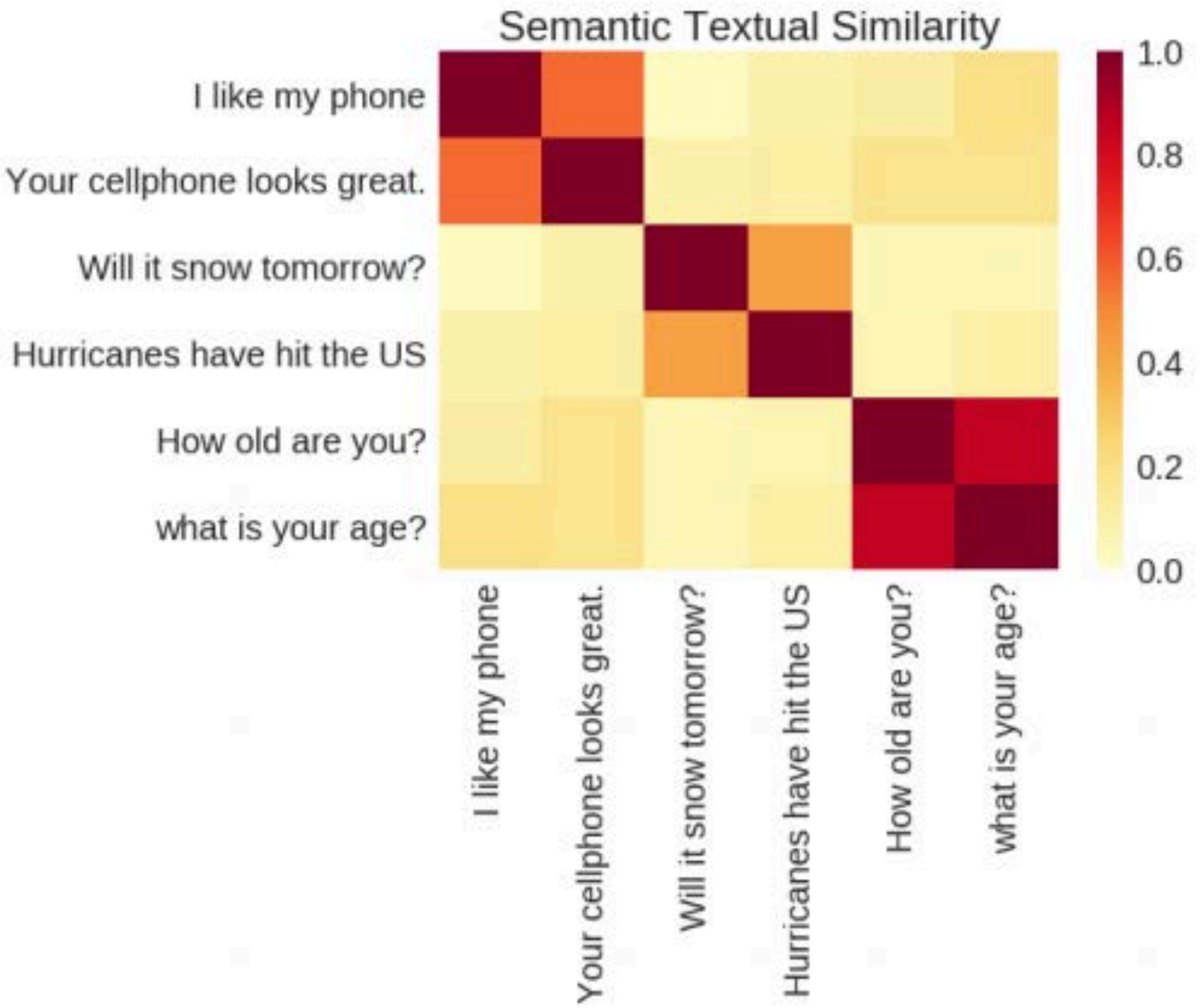

input **How old are you?**

output **[.12, .00, .26, .41, … .17]**

Universal Sentence Encoder

Universal Sentence Encoder

Daniel Cer[a], Yinfei Yang[a], Sheng-yi Kong[a], Nan Hua[a], Nicole Limtiaco[b], Rhomni St. John[a], Noah Constant[a], Mario Guajardo-Céspedes[a], Steve Yuan[c], Chris Tar[a], Yun-Hsuan Sung[a], Brian Strope[a], Ray Kurzweil[a]

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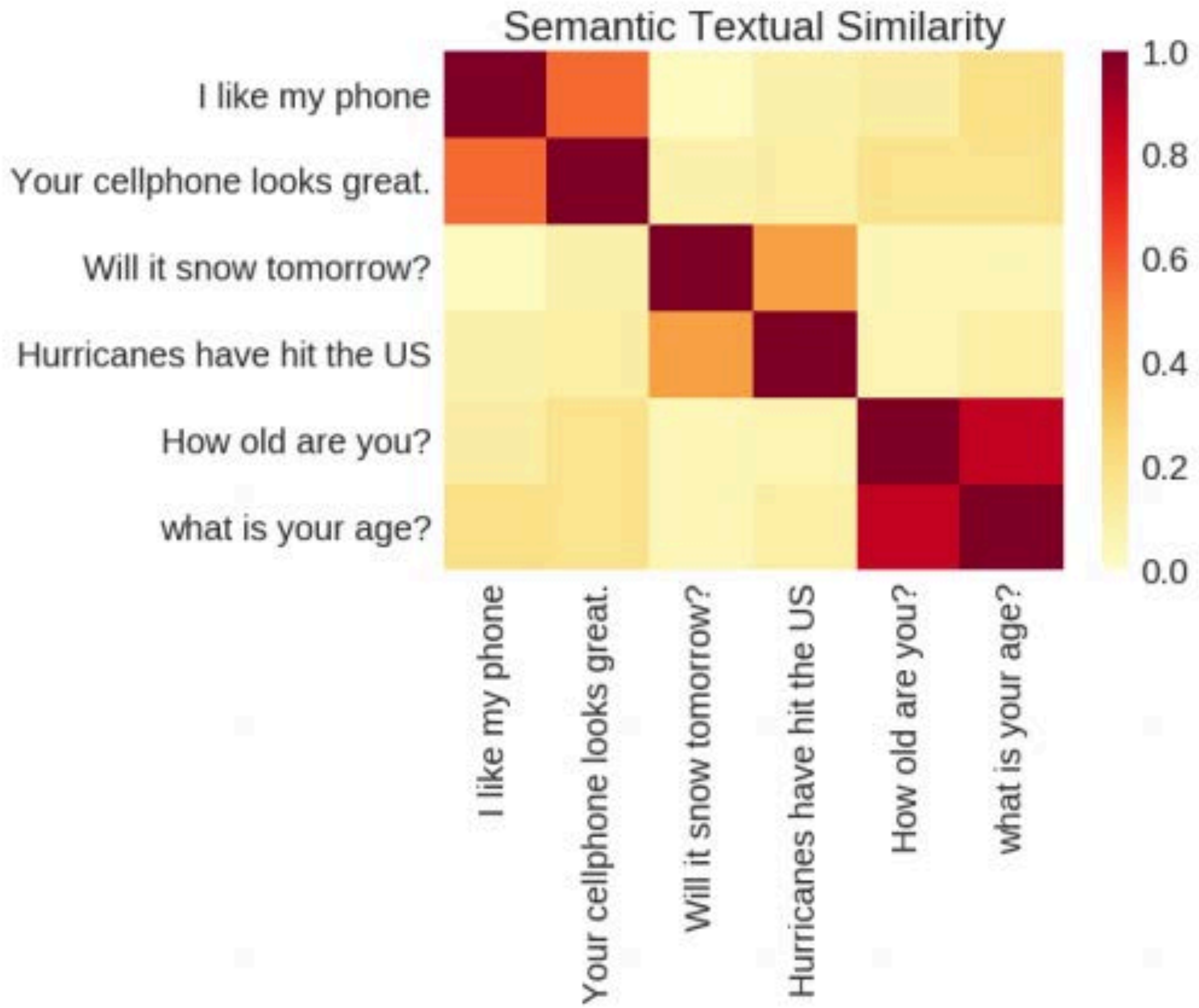

input **How old are you?**

output **[.12, .00, .26, .41, … .17]**

1 2 3 4 … 512

0:00:00	S1	Yeah, I just... The Philosophy class came out late, so yeah.
0:00:05	S2	What is it? Philosophy of what?
0:00:07	S1	Moral Philosophy.
0:00:08	S2	That seems like a terrible class. [chuckle]
0:00:11	S1	It's so bad. I hate it so much. It's okay...
0:00:14	S2	I just feel like you get some really crazy people in it.
0:00:19	S1	There actually aren't crazy people in it, but the material is really weird.
0:00:23	S2	Why?
0:00:26	S1	I just stopped reading the textbook, which is probably part of the reason why I don't really understand what's going on. But we have papers and then exams, and the exams are just like spitting the textbook out. So you just memorize everything and it's such a pain. But yeah, I didn't fall asleep in class today. That's was a plus.
0:00:43	S2	That's good. Norton is a small place, with small classrooms.
0:00:48	S1	I fall asleep in every class. It's so bad.
0:00:52	S2	Why? When do you go to bed?
0:00:54	S1	I get like six hours of sleep every week, which is...
0:00:58	S2	Week?
0:01:00	S1	Yeah, like average.
0:01:02	S2	Per night?
0:01:03	S1	Yeah.
0:01:03	S2	Okay. You said six hours of sleep per week. I was like, "Oh my God!"
0:01:08	S1	Oh yeah, that came out wrong.
0:01:08	S2	Yeah, yeah, I know what you mean.
0:01:11	S1	But yeah. How was your week? [chuckle] Last week?
0:01:15	S2	The weekend was great. I did no work though, and so now I'm like, "Ah!" I have so much work to do.
0:01:23	S1	Do you have any midterms this week?

0:00:00	S1	Yeah, I just... The Philosophy class came out late, so yeah.
0:00:05	S2	What is it? Philosophy of what?
0:00:07	S1	Moral Philosophy.
0:00:08	S2	That seems like a terrible class. [chuckle]
0:00:11	S1	It's so bad. I hate it so much. It's okay...
0:00:14	S2	I just feel like you get some really crazy people in it.
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0:01:15	S2	The weekend was great. I did no work though, and so now I'm like, "Ah!" I have so much work to do.
0:01:23	S1	Do you have any midterms this week?

input **Yeah, I just… The Philosophy class came out late, so yeah.**

output **[.00, .41, .16, .17, … .03]**

0:00:00	S1	Yeah, I just... The Philosophy class came out late, so yeah.
0:00:05	S2	What is it? Philosophy of what?
0:00:07	S1	Moral Philosophy.
0:00:08	S2	That seems like a terrible class. [chuckle]
0:00:11	S1	It's so bad. I hate it so much. It's okay...
0:00:14	S2	I just feel like you get some really crazy people in it.
0:00:19	S1	There actually aren't crazy people in it, but the material is really weird.
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0:00:52	S2	Why? When do you go to bed?
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0:01:00	S1	Yeah, like average.
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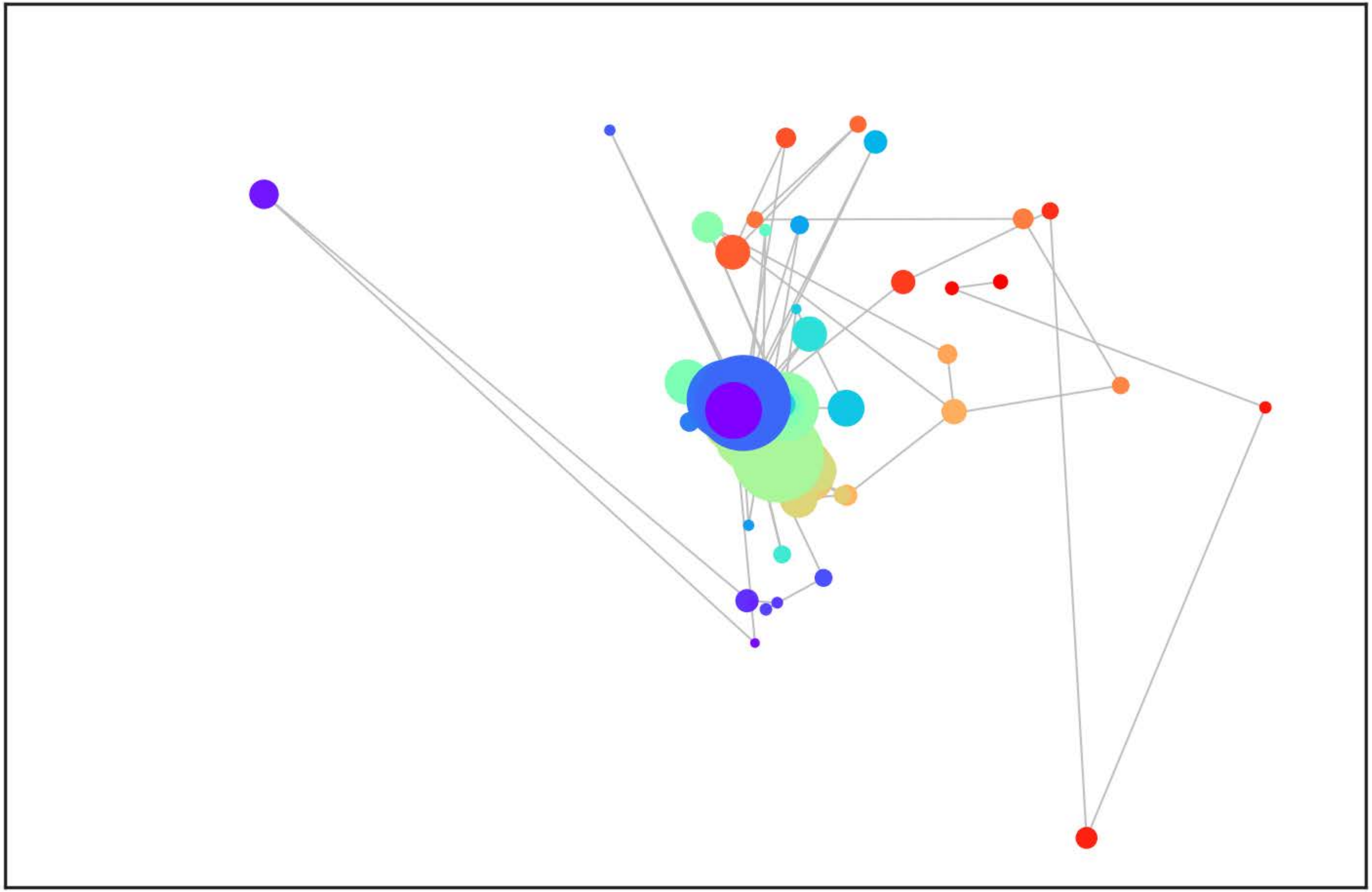
0:01:11	S1	But yeah. How was your week? [chuckle] Last week?
0:01:15	S2	The weekend was great. I did no work though, and so now I'm like, "Ah!" I have so much work to do.
0:01:23	S1	Do you have any midterms this week?

input **What is it? Philosophy of what?**

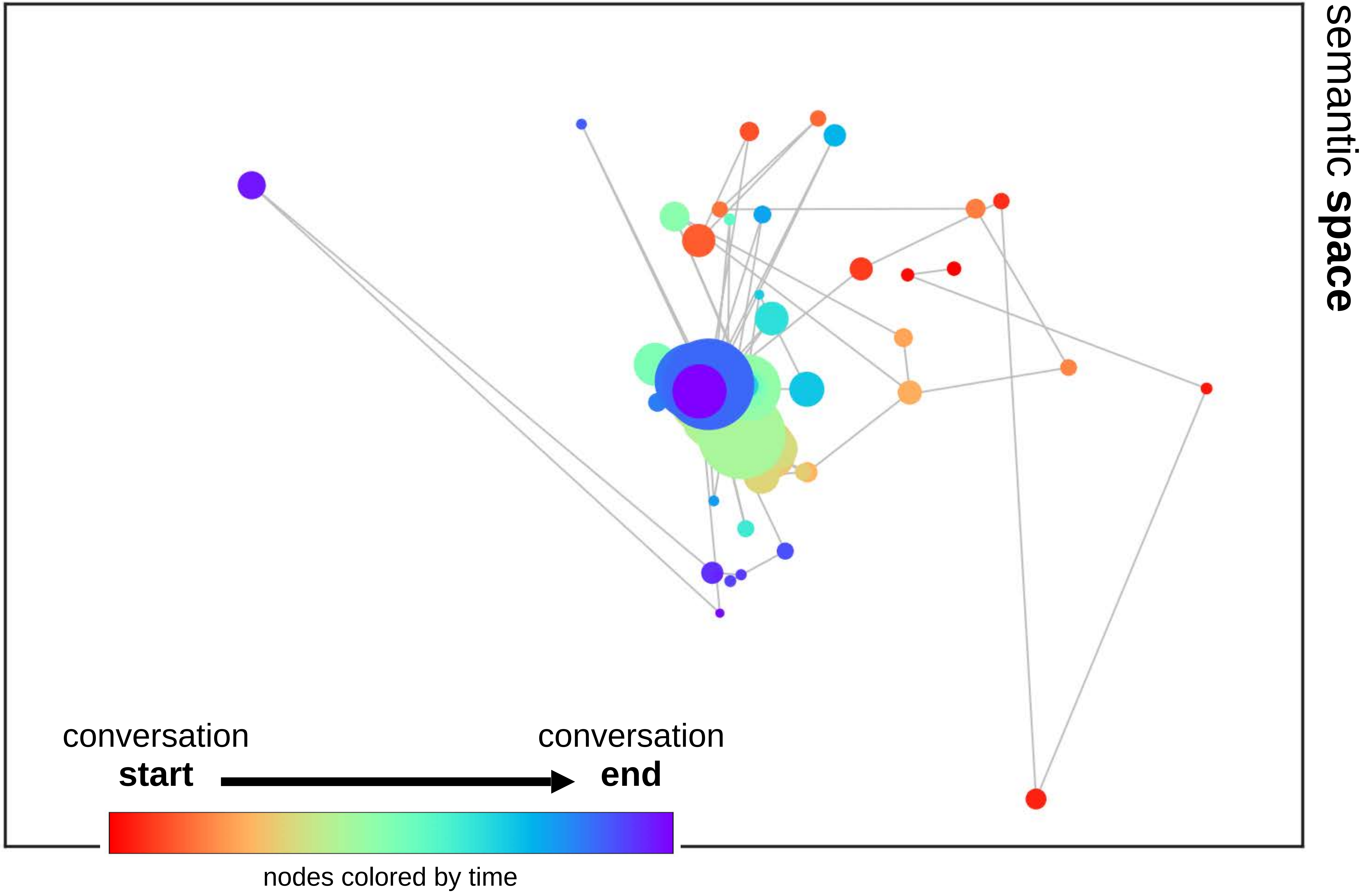
output **[.06, .14, .22, .22, … .50]**

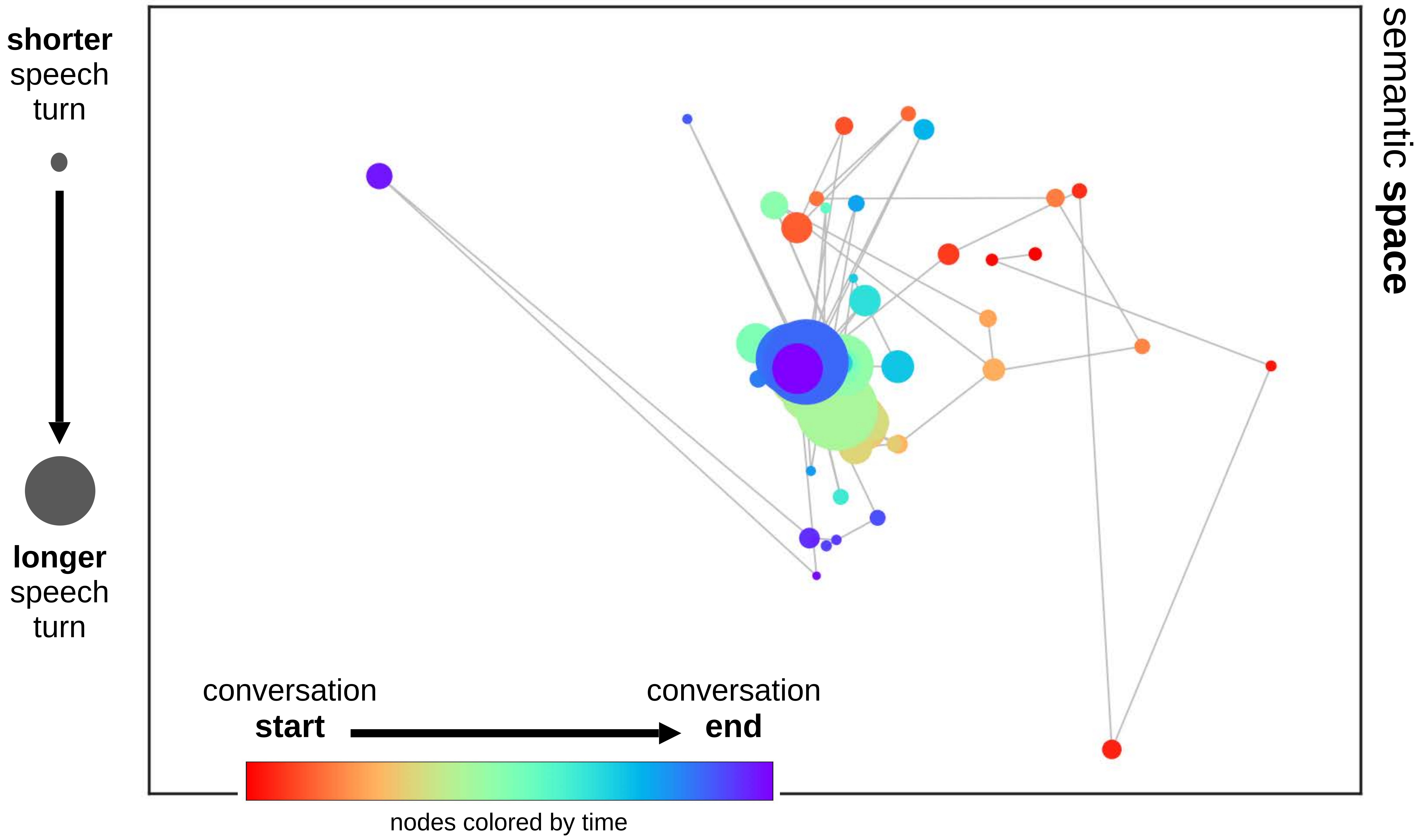
(repeat)

semantic **space**

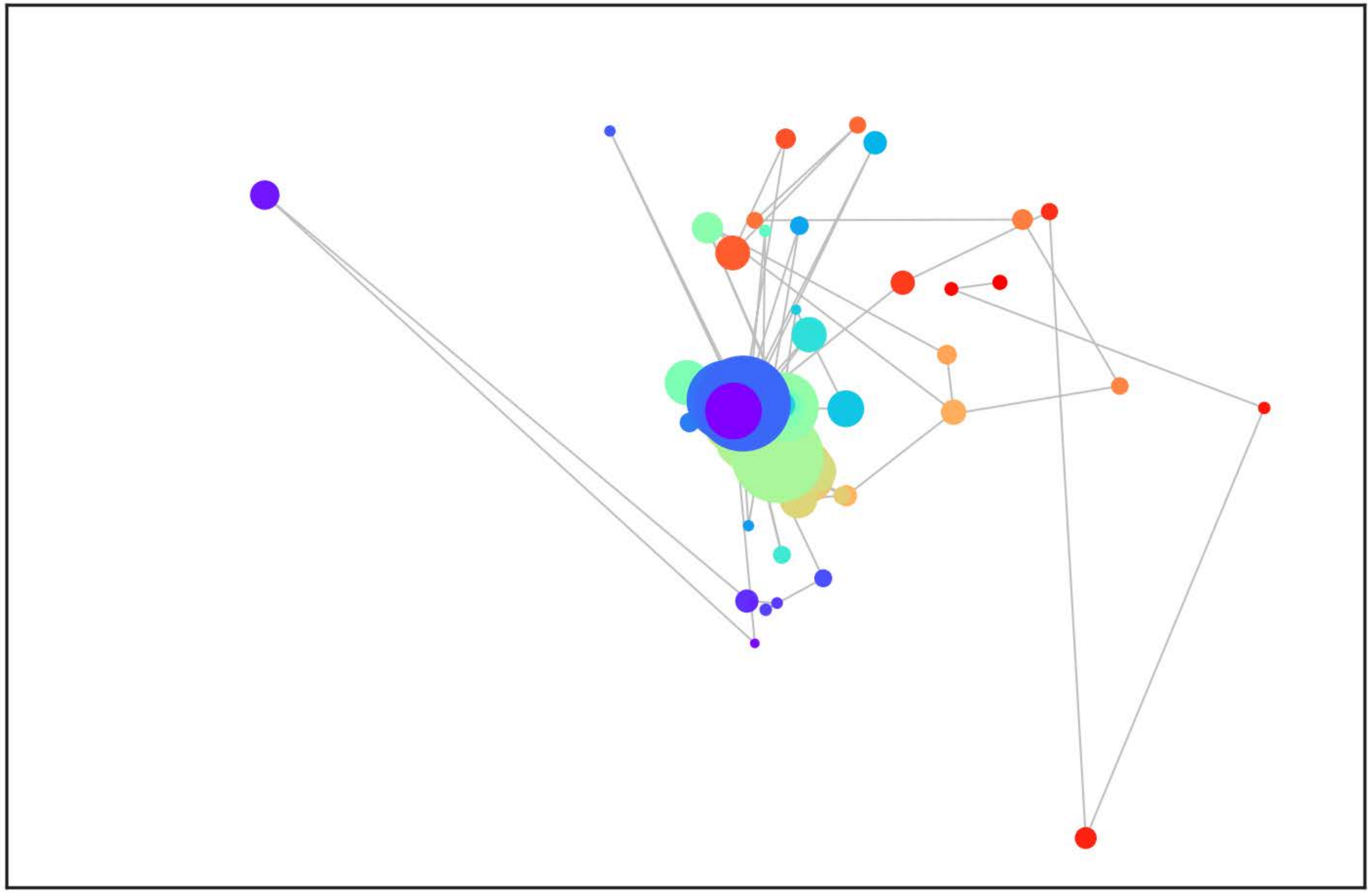


semantic **space**


semantic space
conversation start
conversation end
nodes colored by time

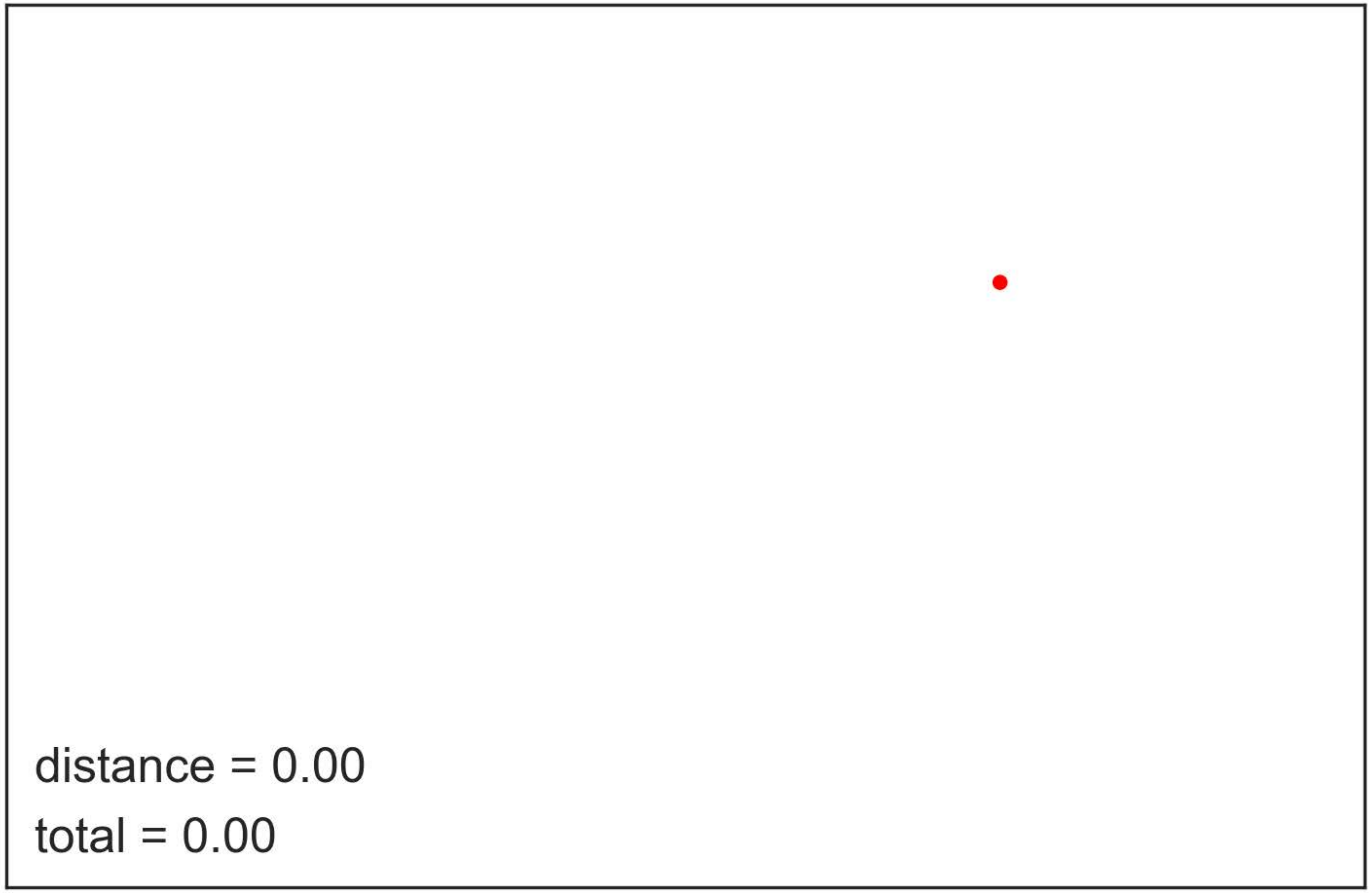

shorter speech turn
longer speech turn
semantic space
conversation start
conversation end
nodes colored by time

Quantify the trajectories



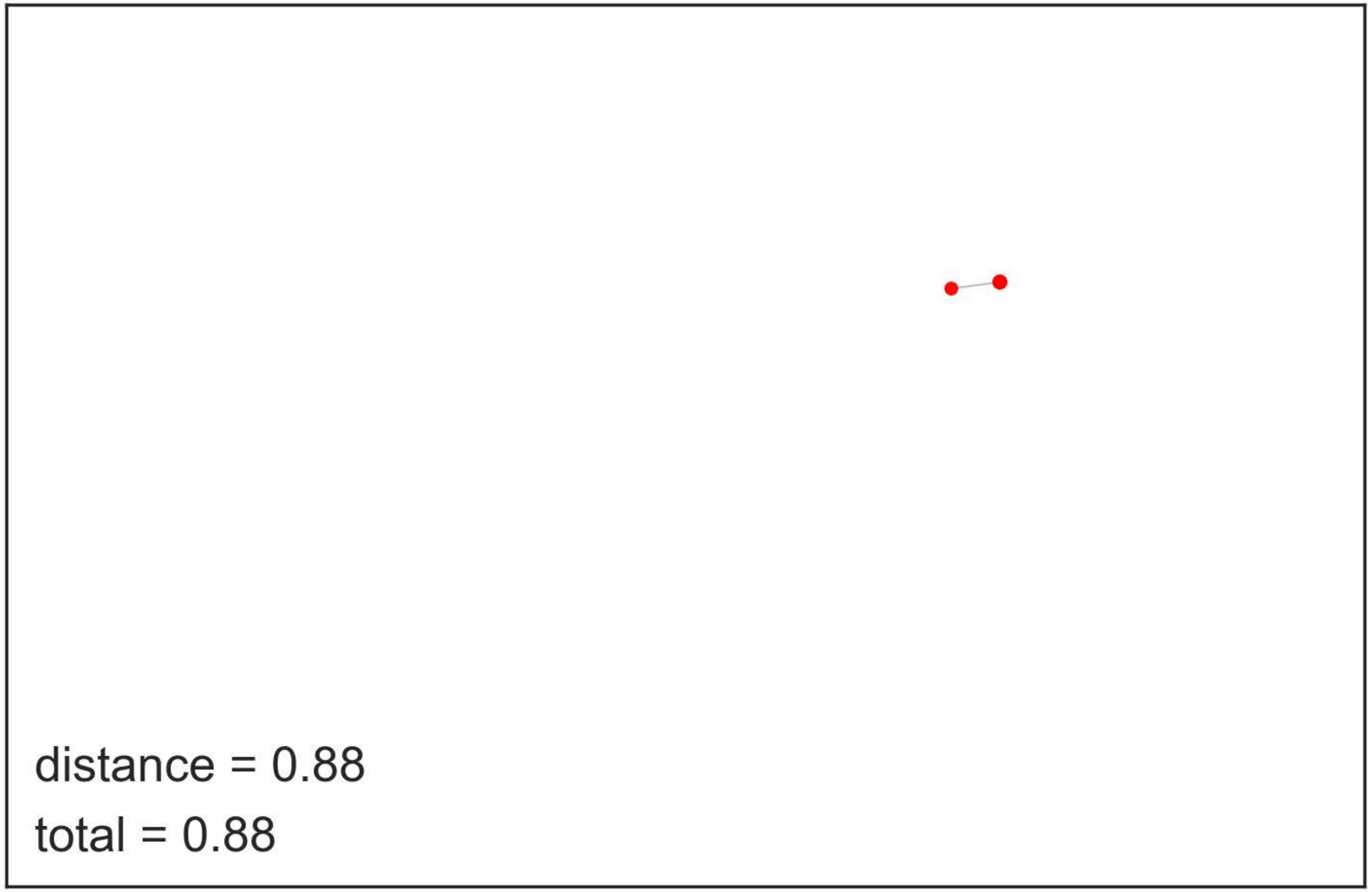
- Extract features to describe the shape of the trajectories
- Do this in the original, high-dimensional space
- Example: **Euclidean distance**

Quantify the trajectories



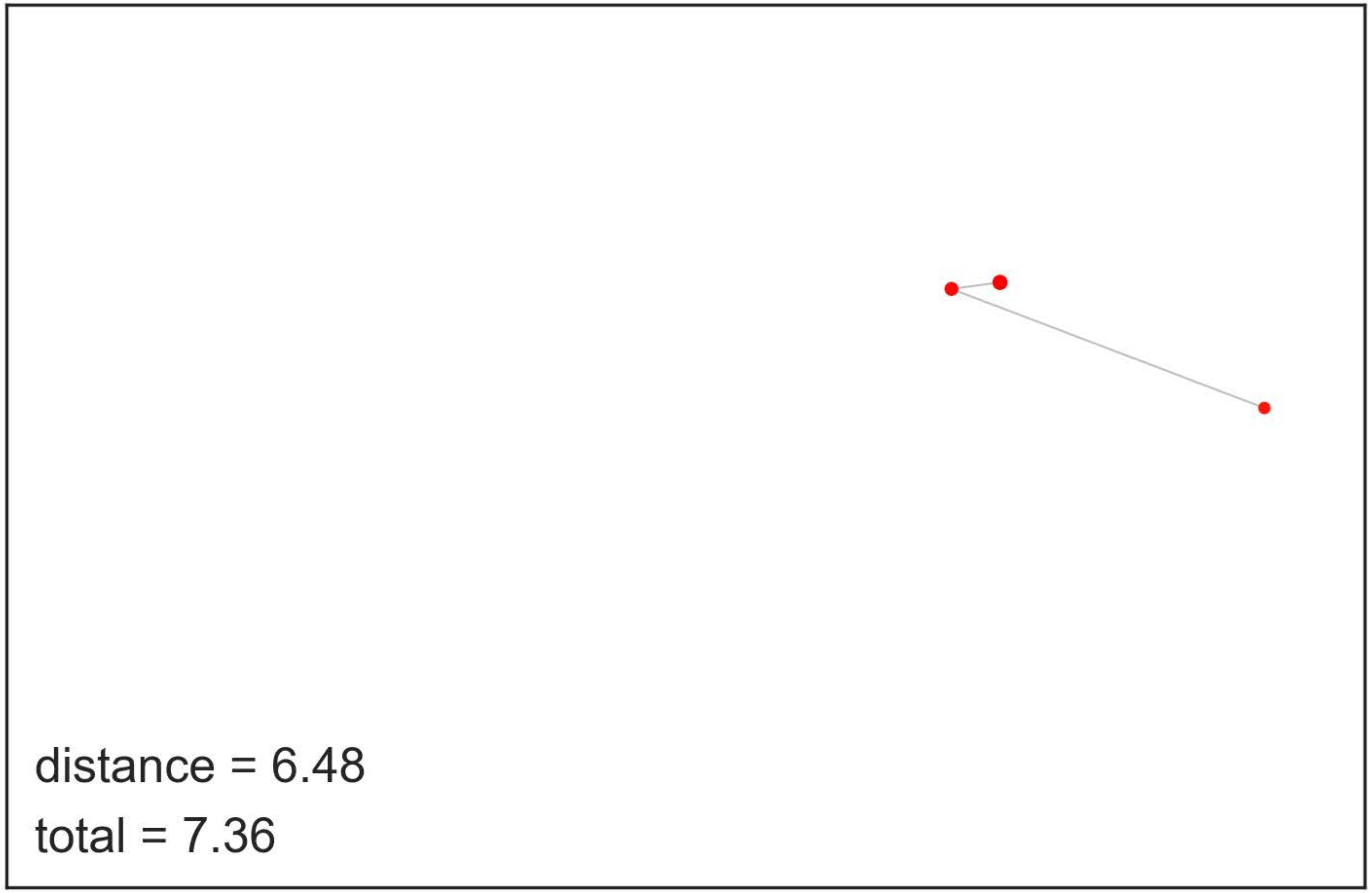
- Extract features to describe the shape of the trajectories
- Do this in the original, high-dimensional space
- Example: **Euclidean distance**

Quantify the trajectories



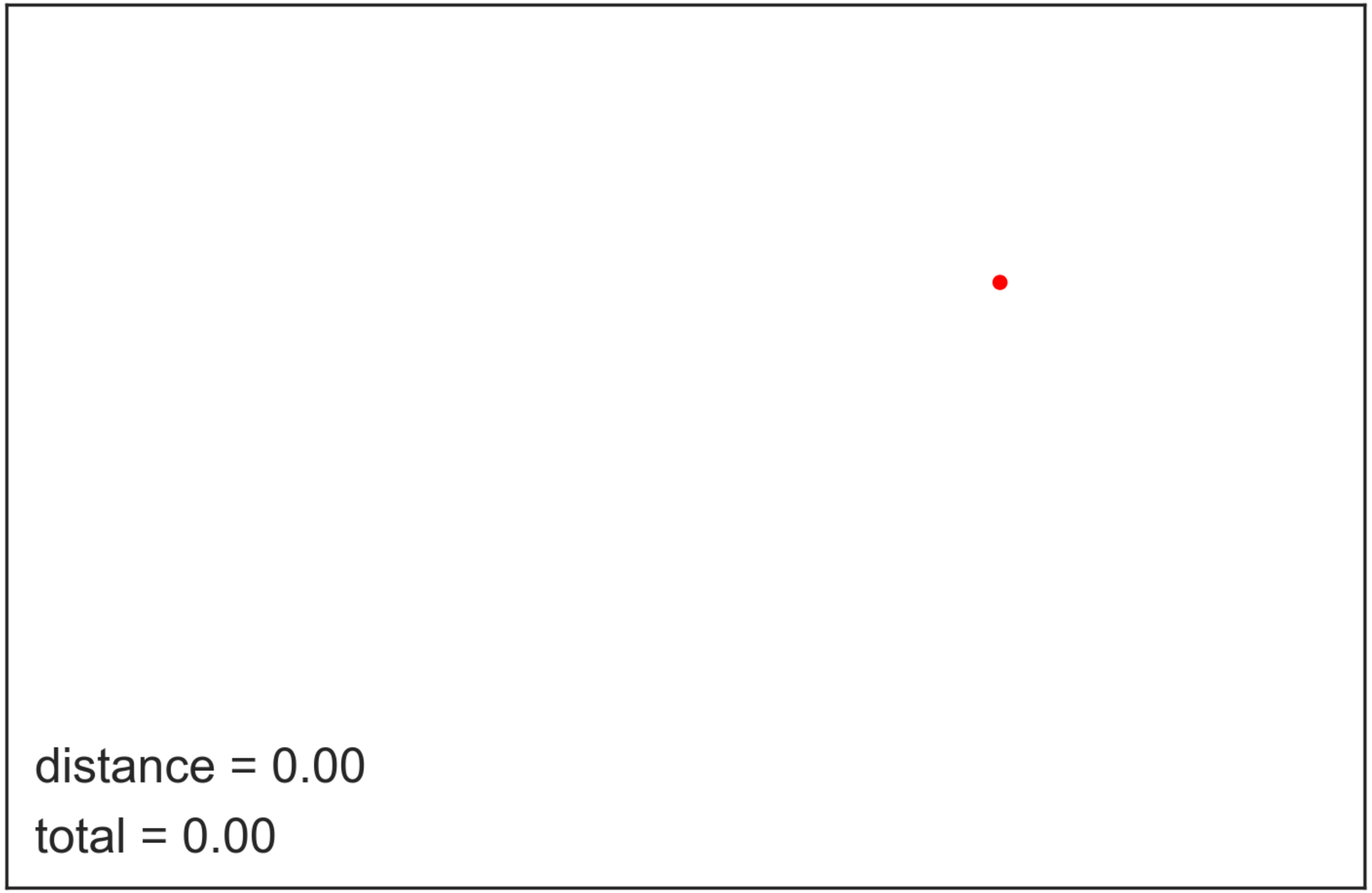
- Extract features to describe the shape of the trajectories
- Do this in the original, high-dimensional space
- Example: **Euclidean distance**

Quantify the trajectories



- Extract features to describe the shape of the trajectories
- Do this in the original, high-dimensional space
- Example: **Euclidean distance**

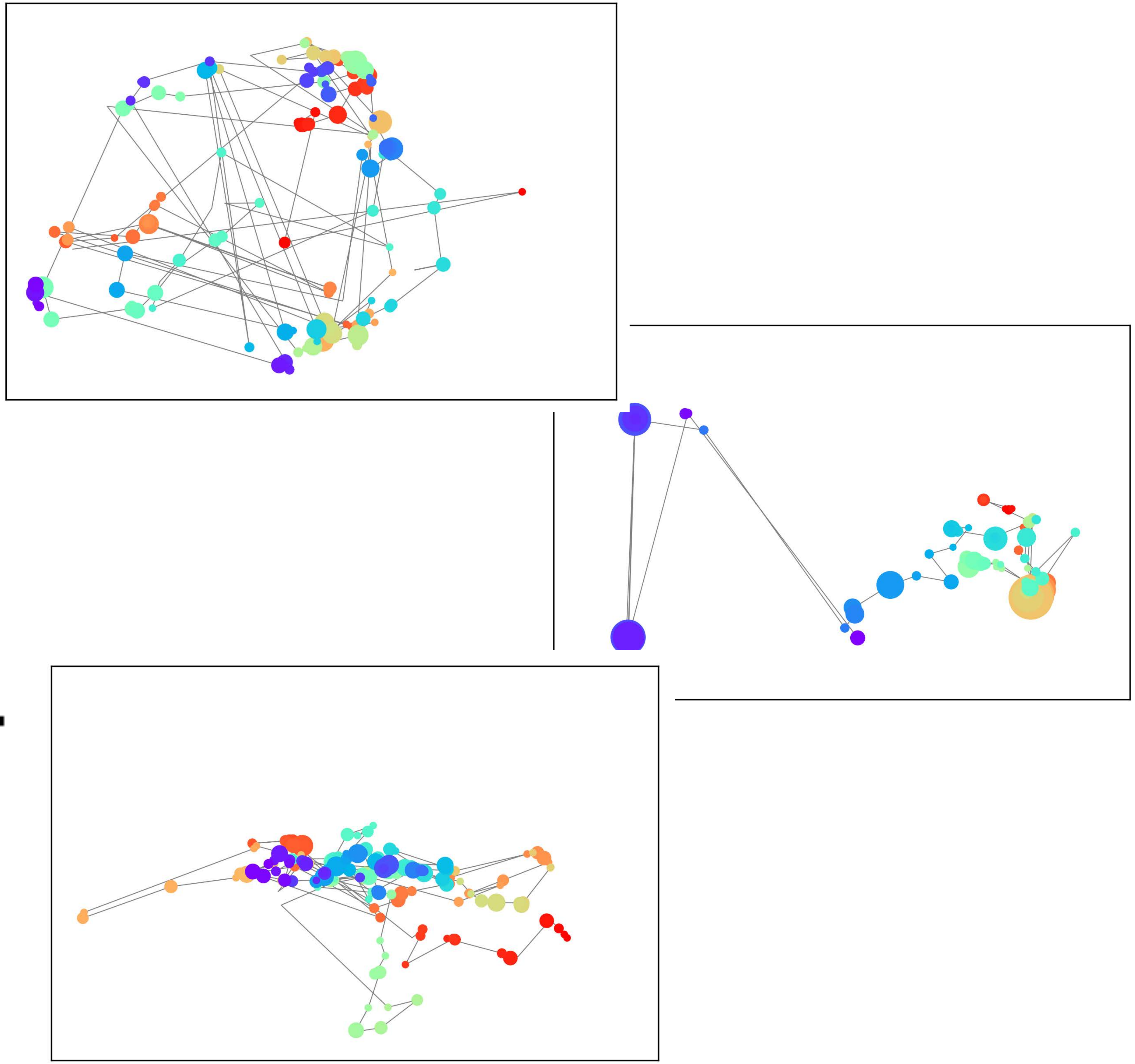
Quantify the trajectories



Divide by number of turns

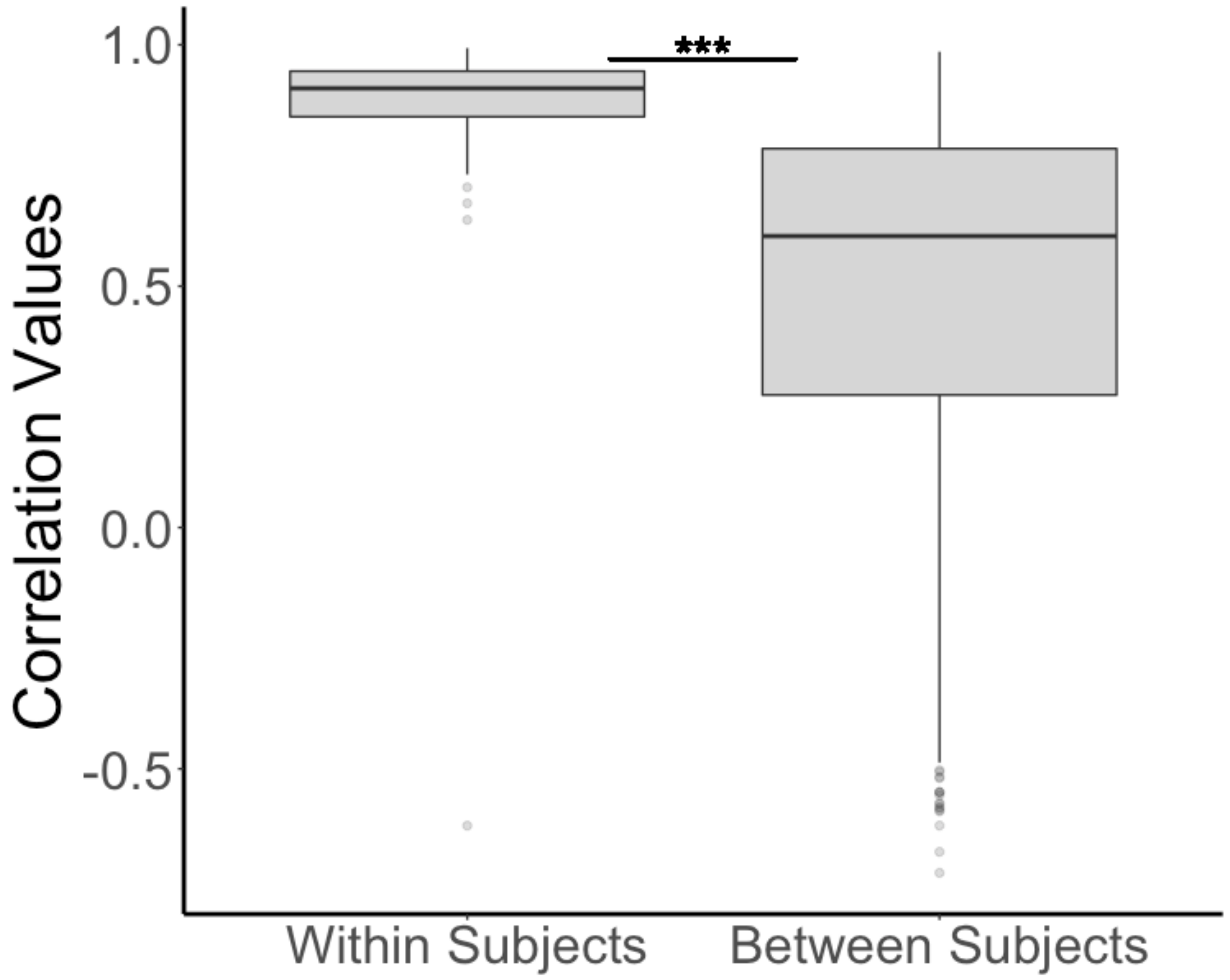
Average semantic distance traveled between turns

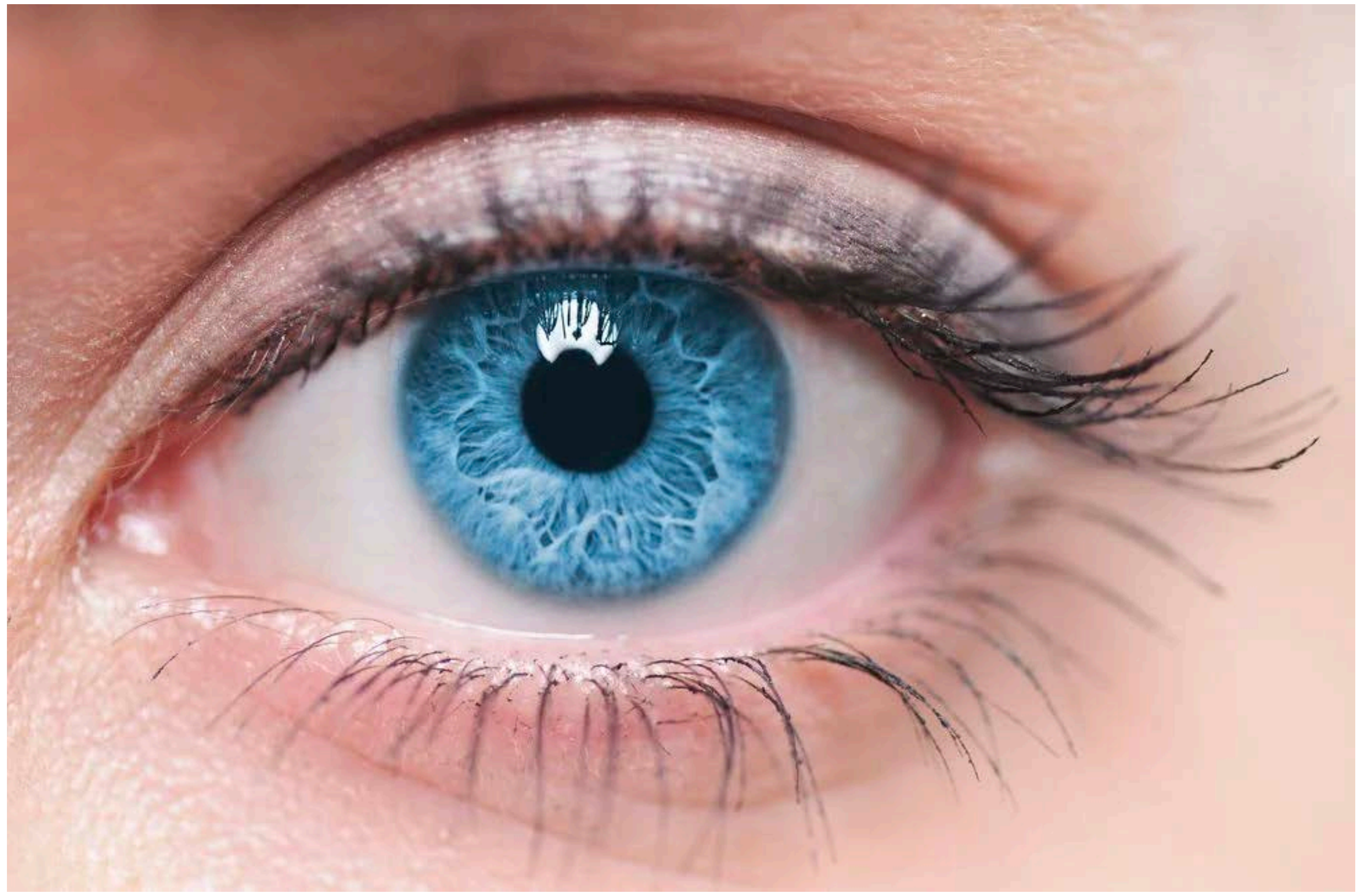
- Extract features to describe the shape of the trajectories
- Do this in the original, high-dimensional space
- Example: **Euclidean distance**



Reliable individual differences in entrainment

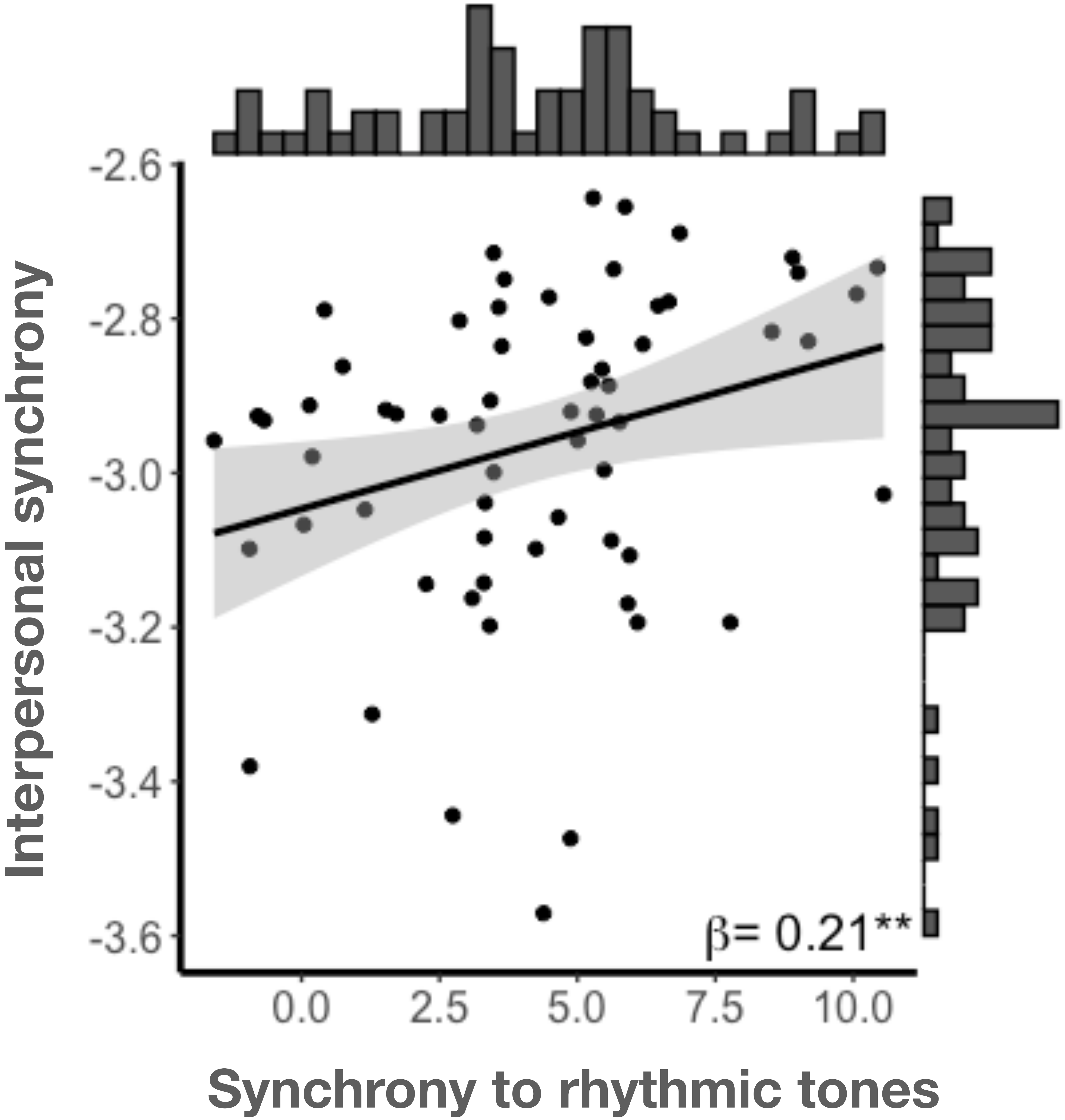
(pupillary entrainment to periodic tones)



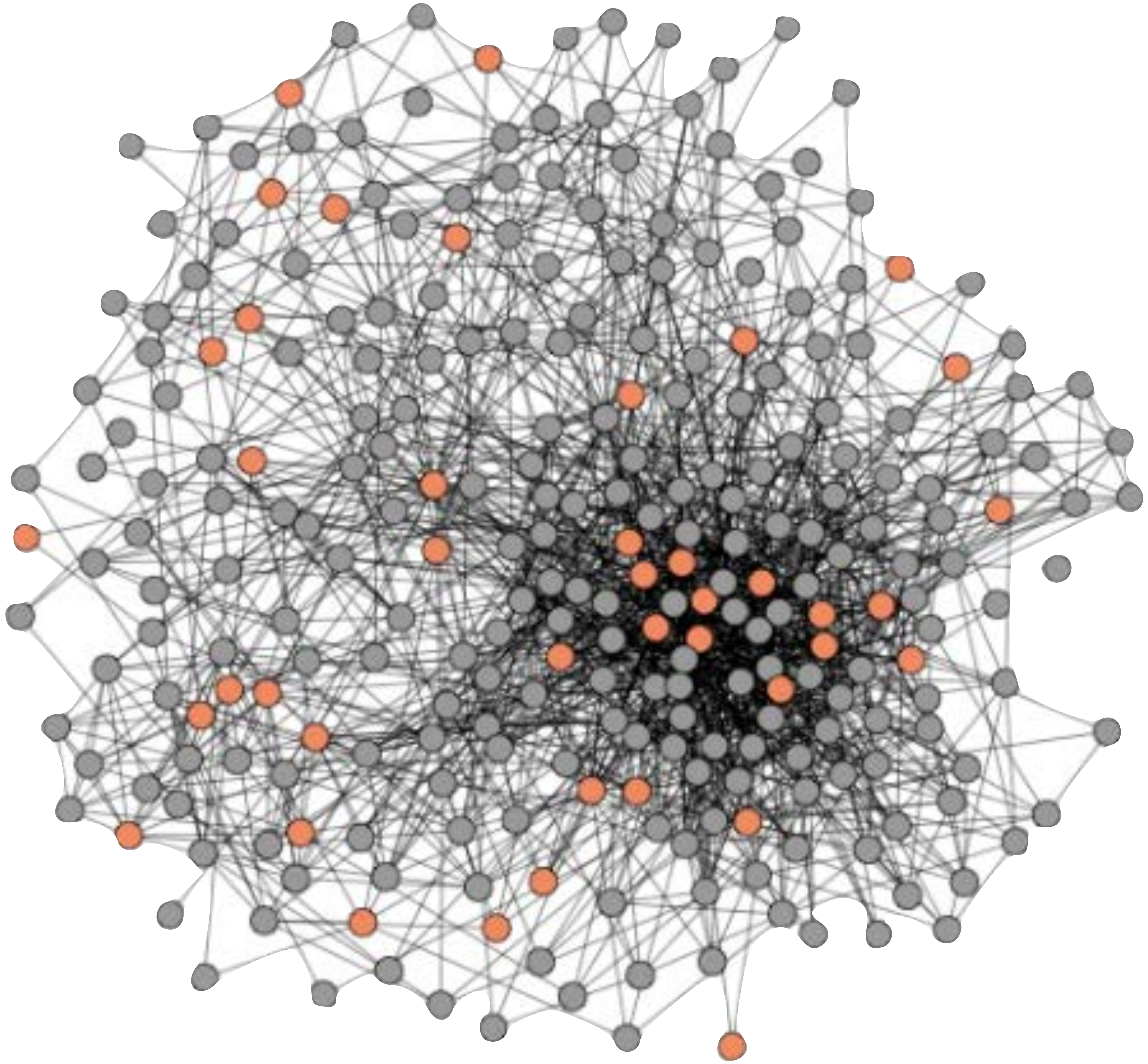


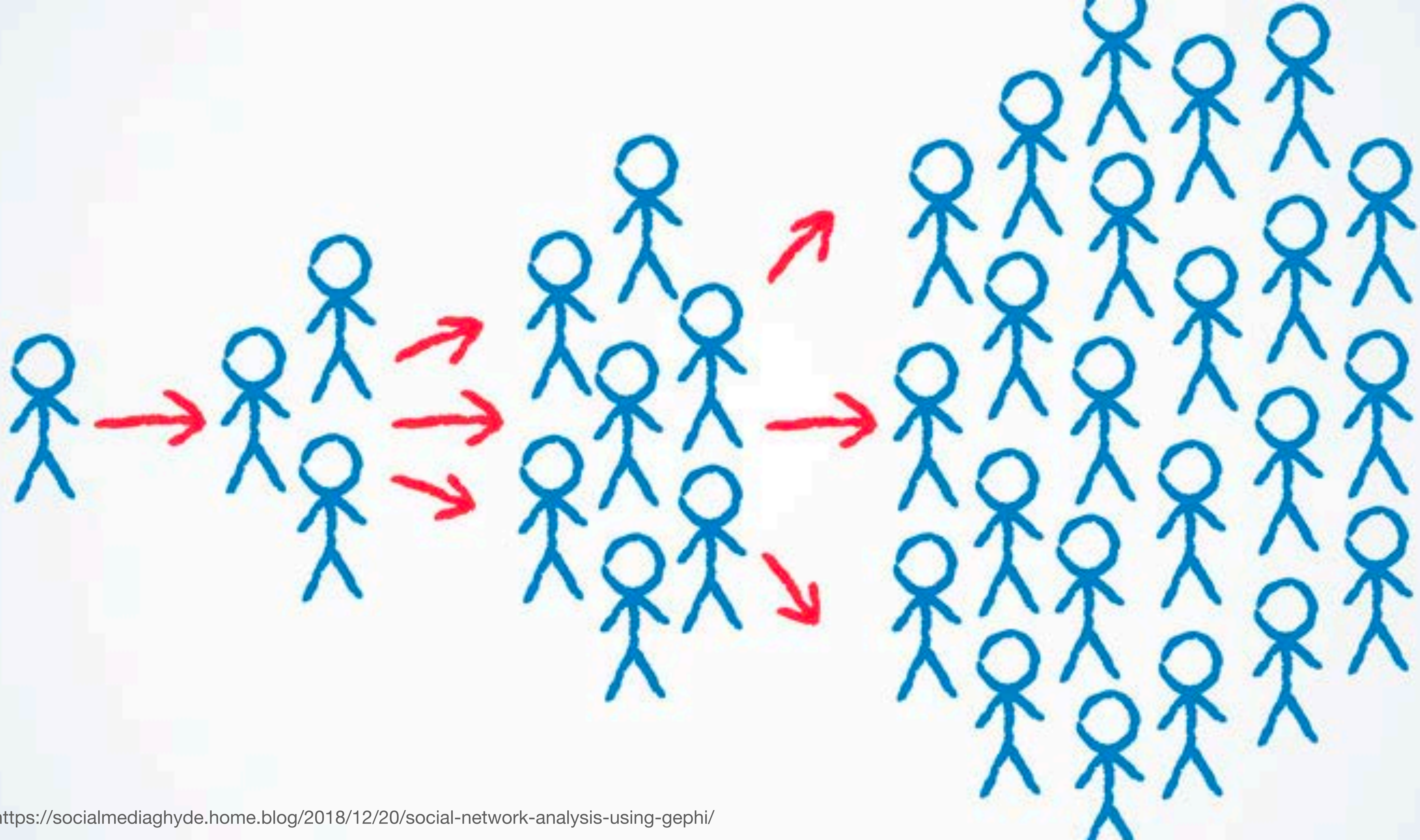
Wohltjen et al,
Scientific Reports, 2023

People who synchronize to tones tend to synchronize with other minds

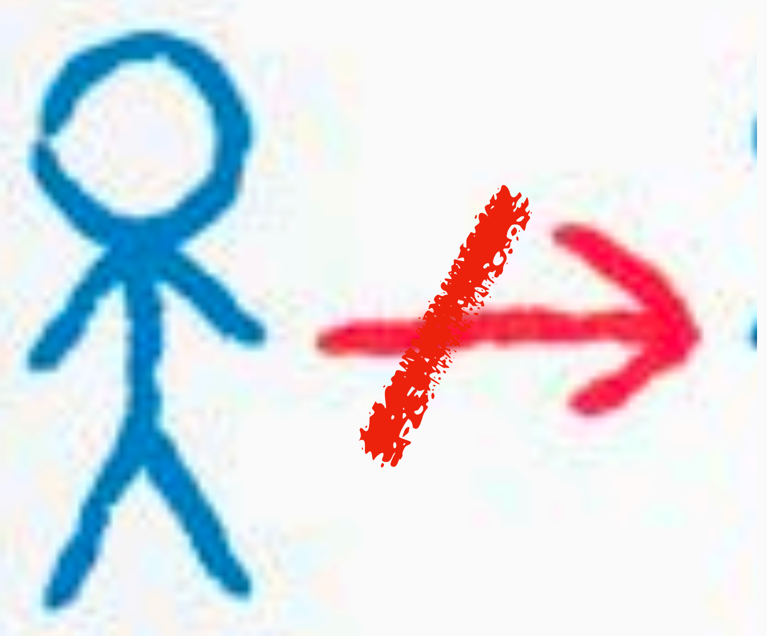


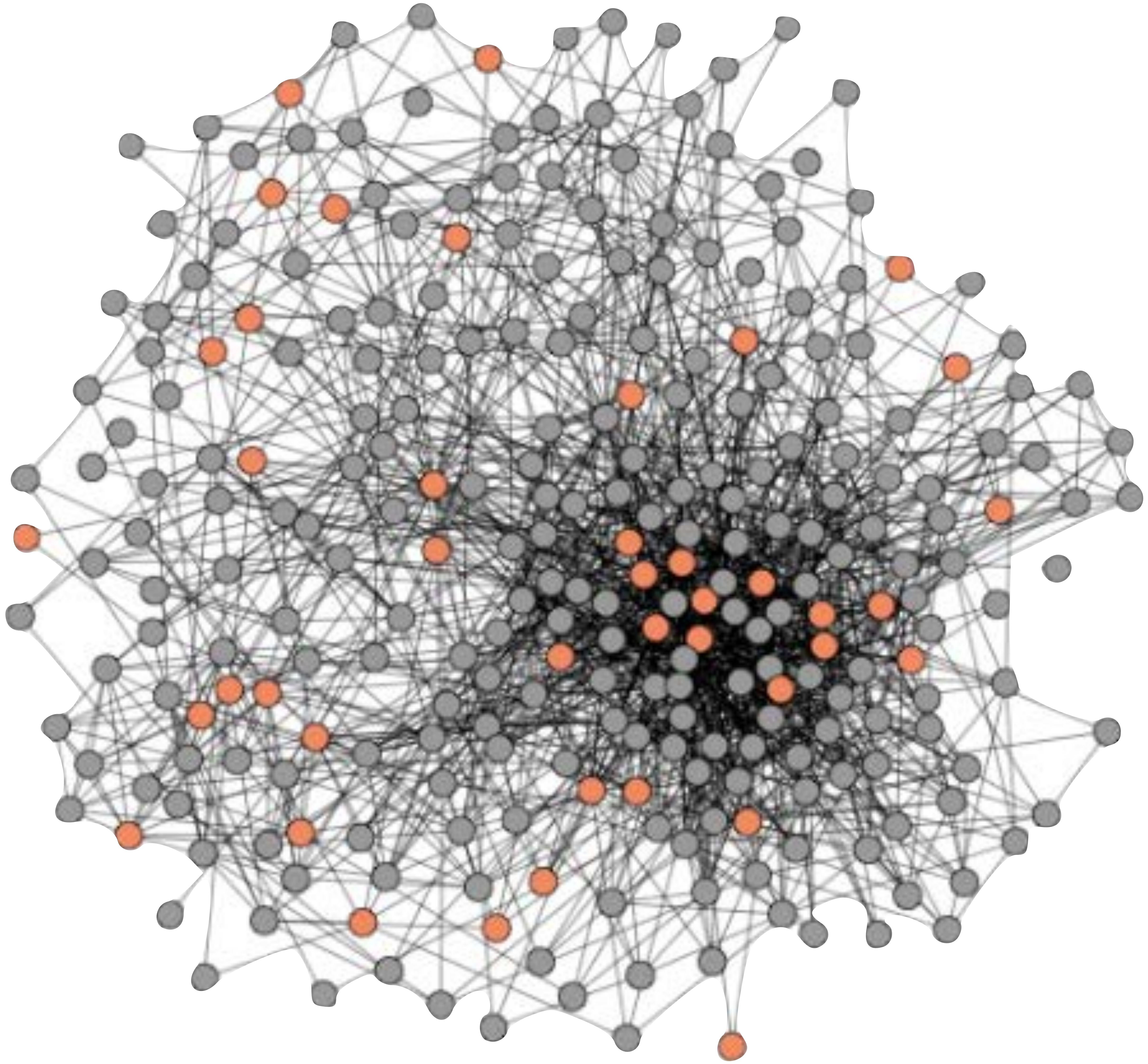
Wohltjen et al,
Scientific Reports, 2023

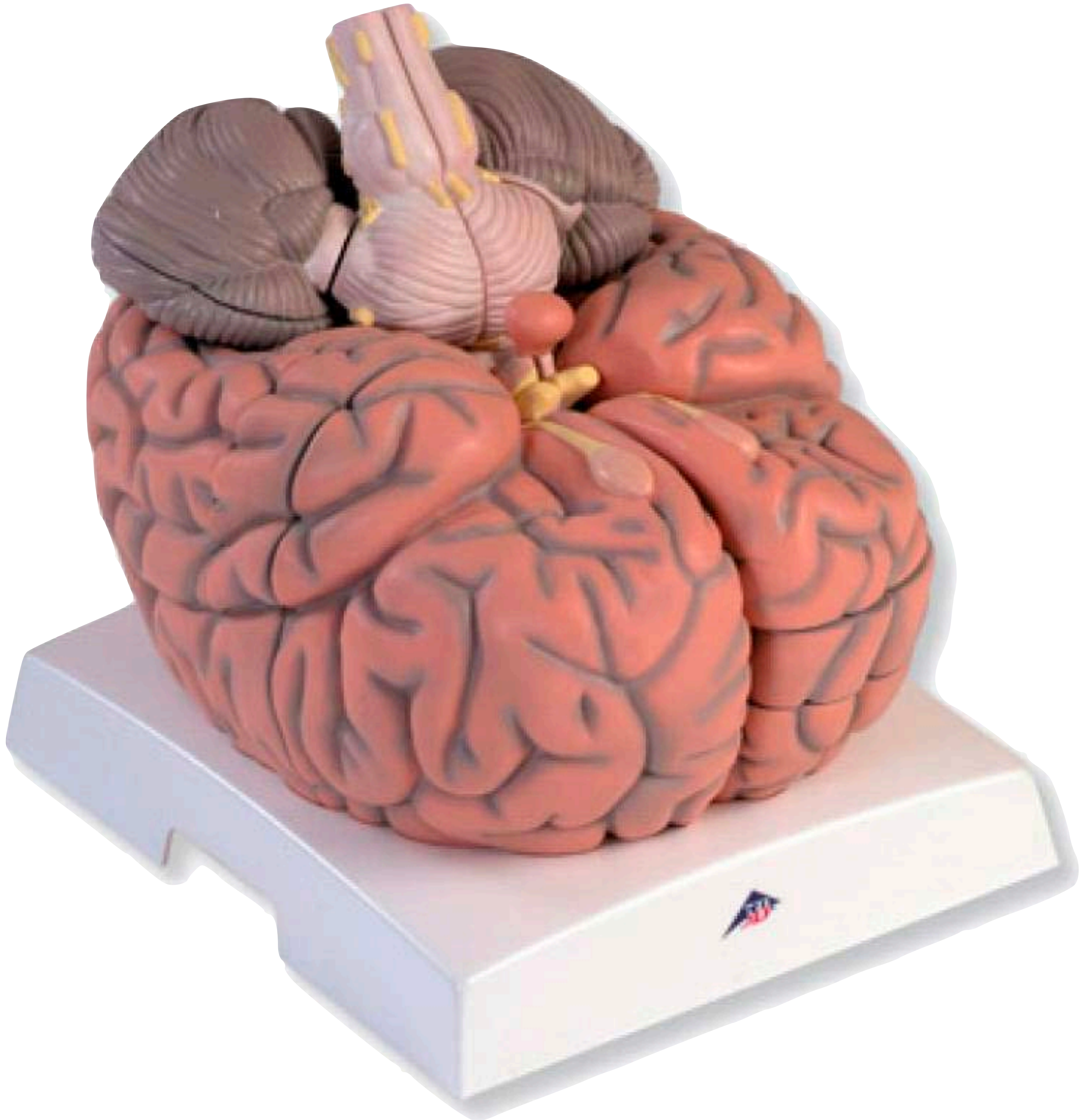


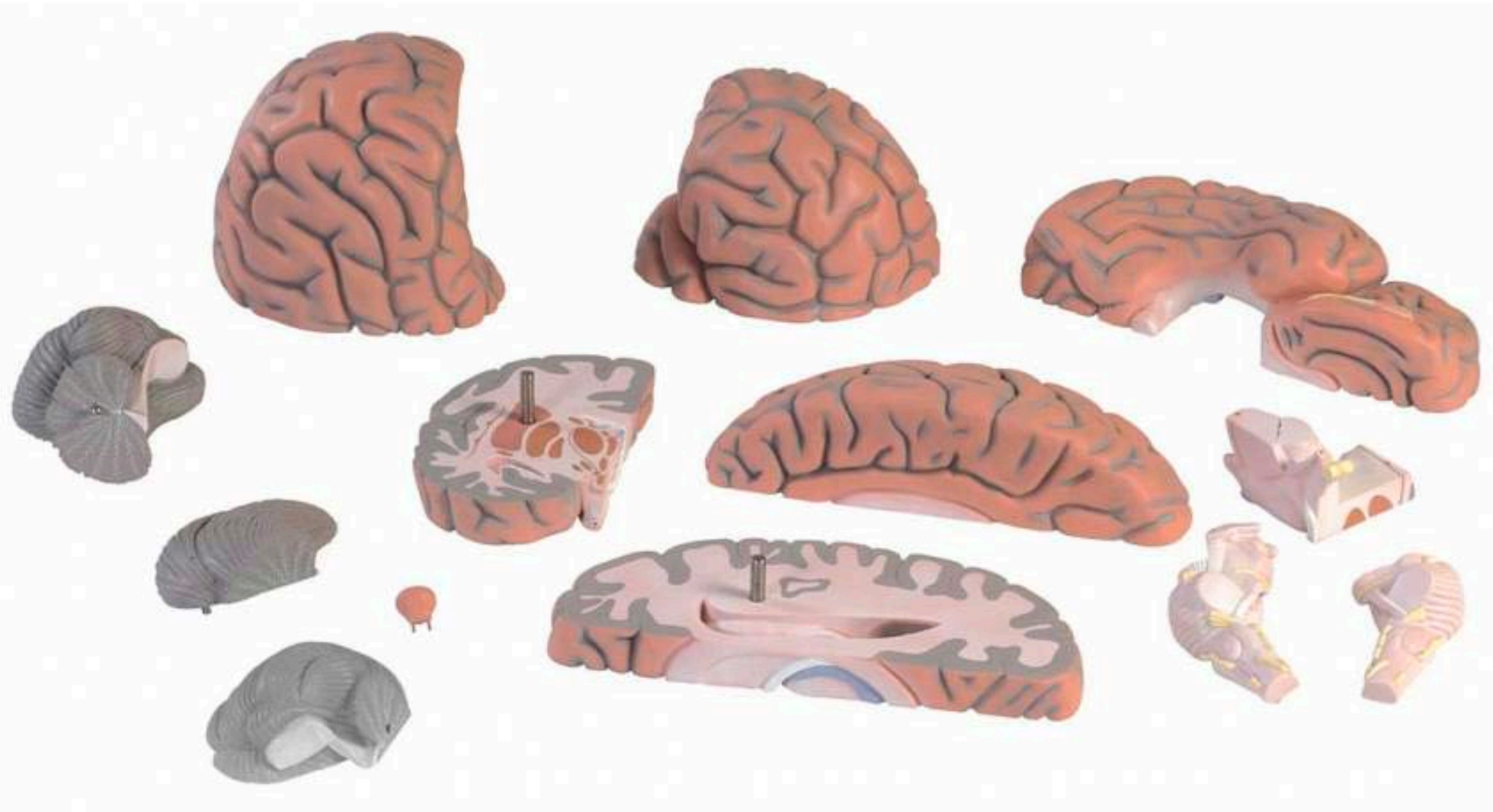


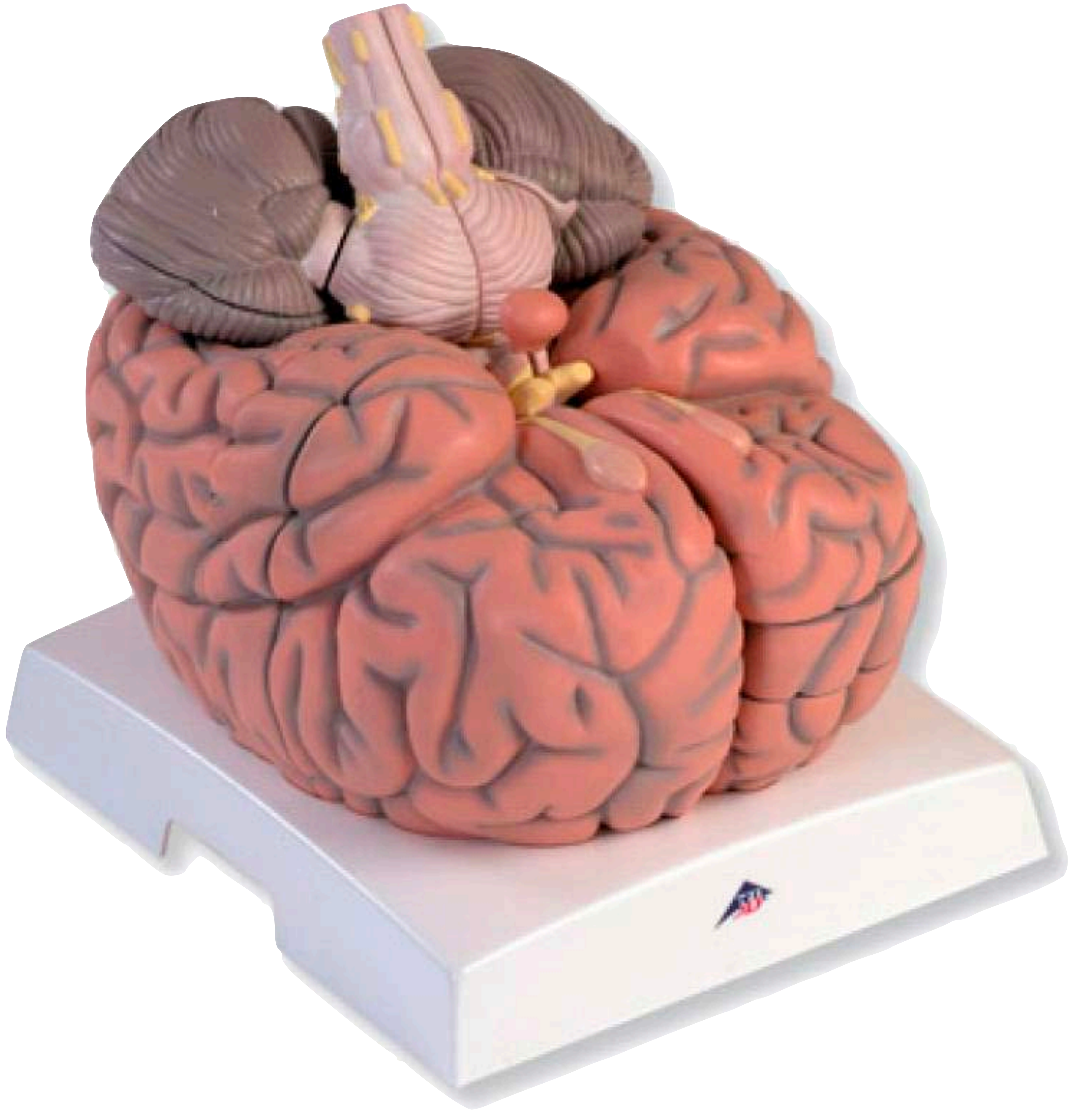
https://socialmediaghyde.home.blog/2018/12/20/social-network-analysis-using-gephi/

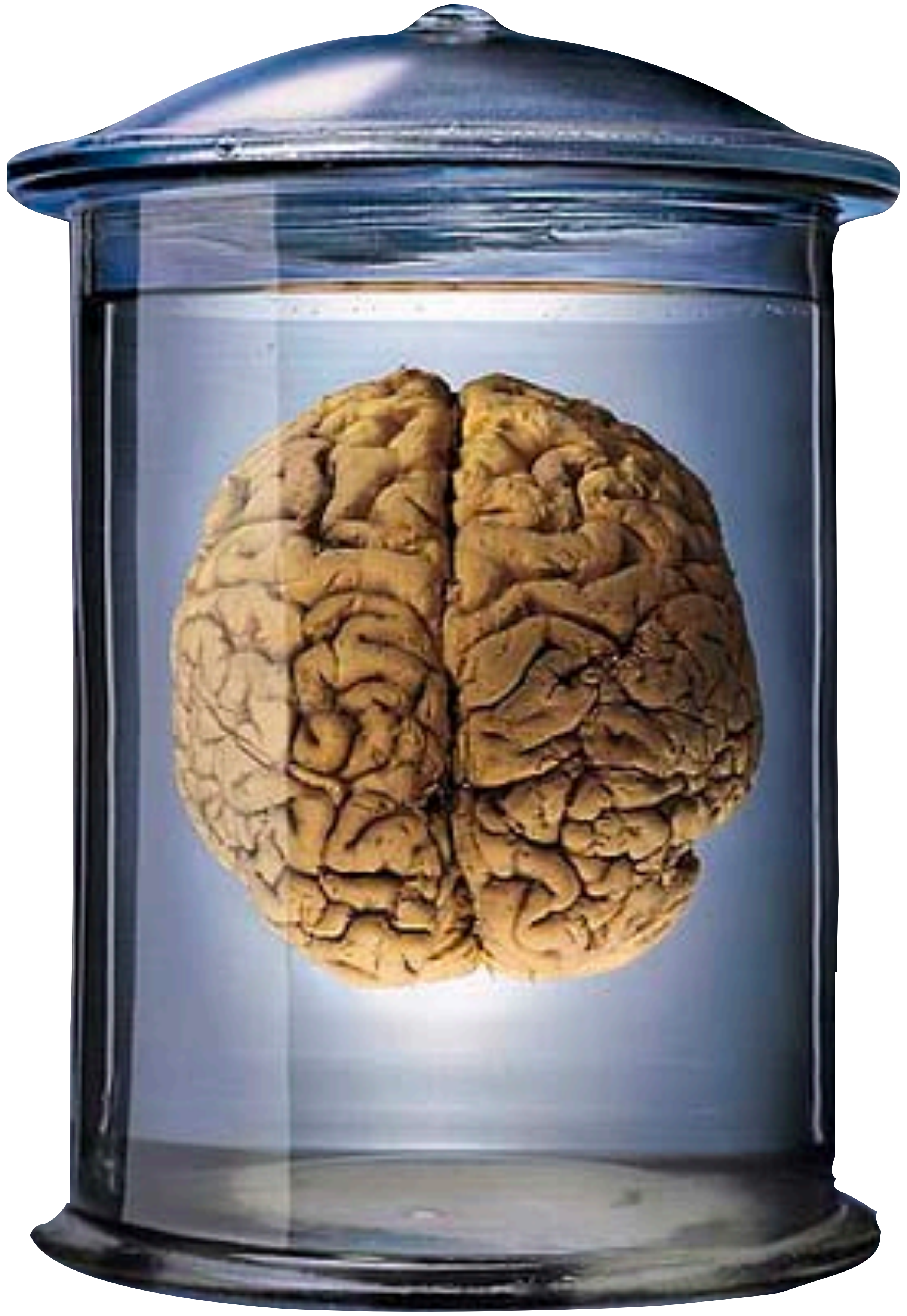










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