# Discovering Temporal Dependencies and Directional Influences in Multimodal Time Series with Granger Causality

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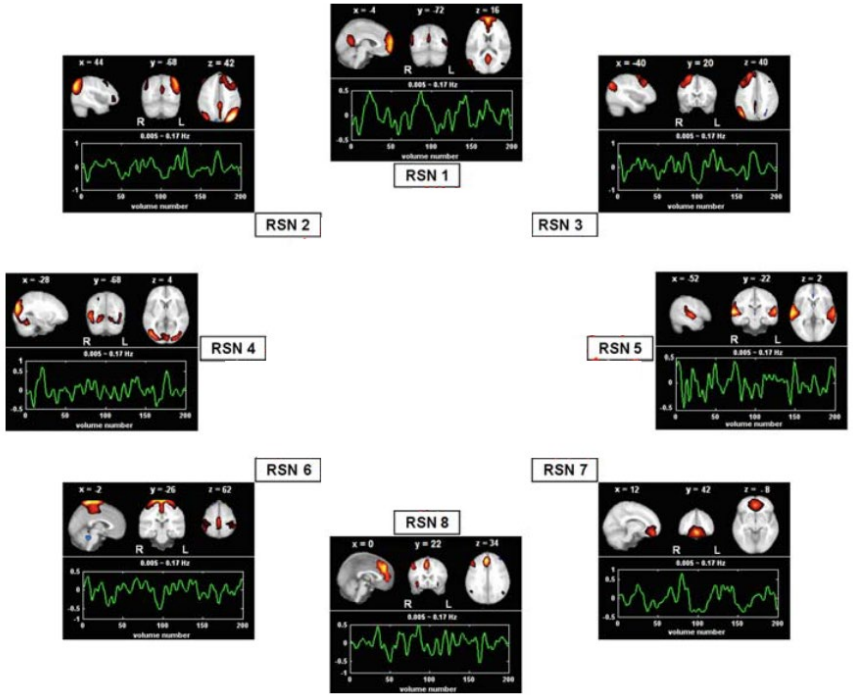
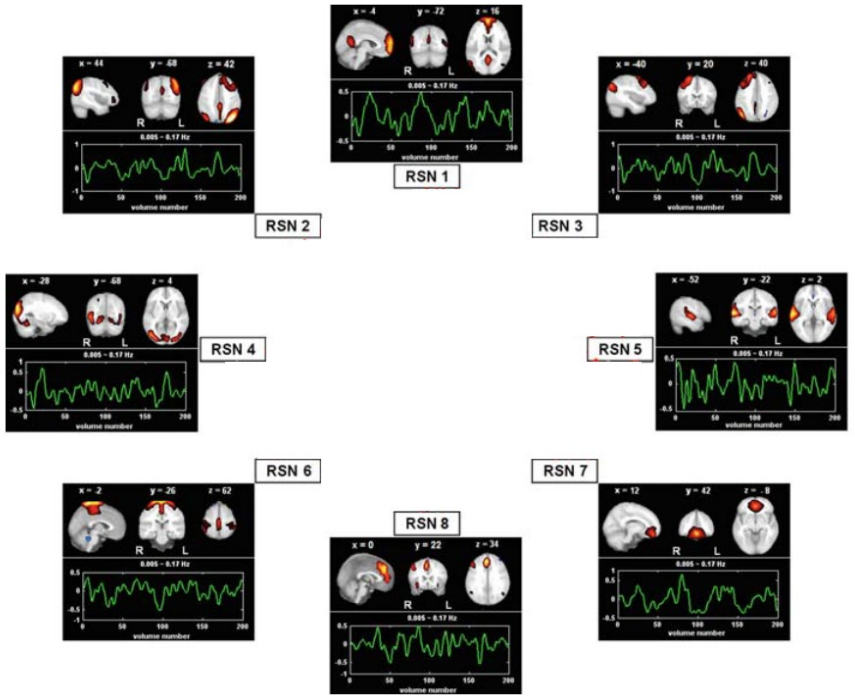



Liao et al., 2010

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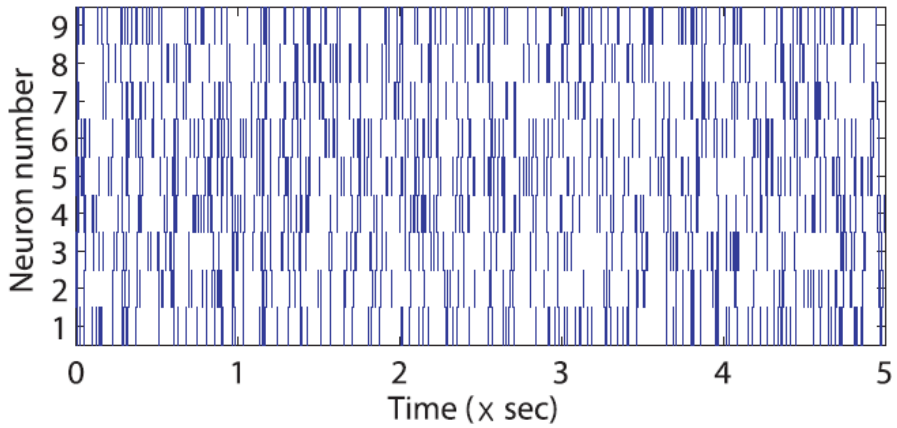


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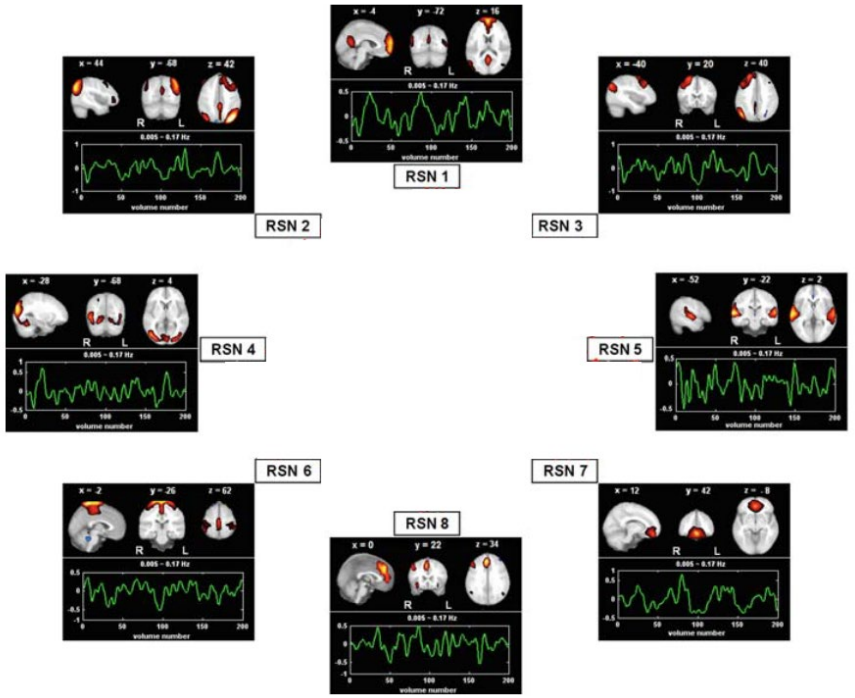


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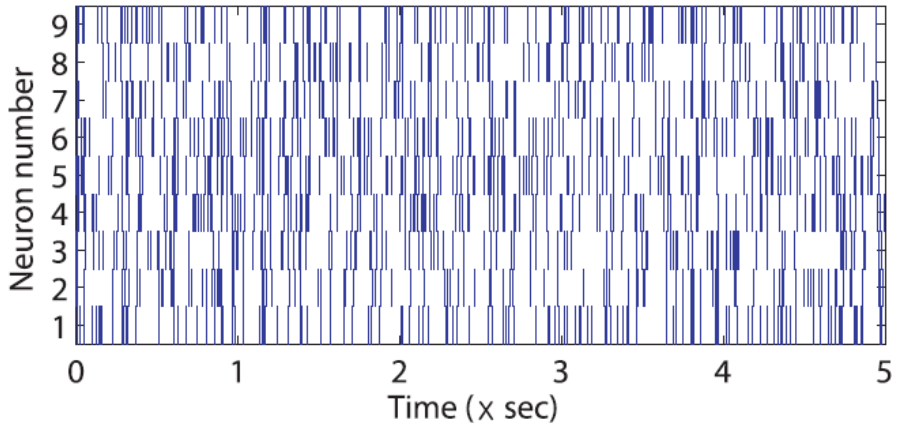


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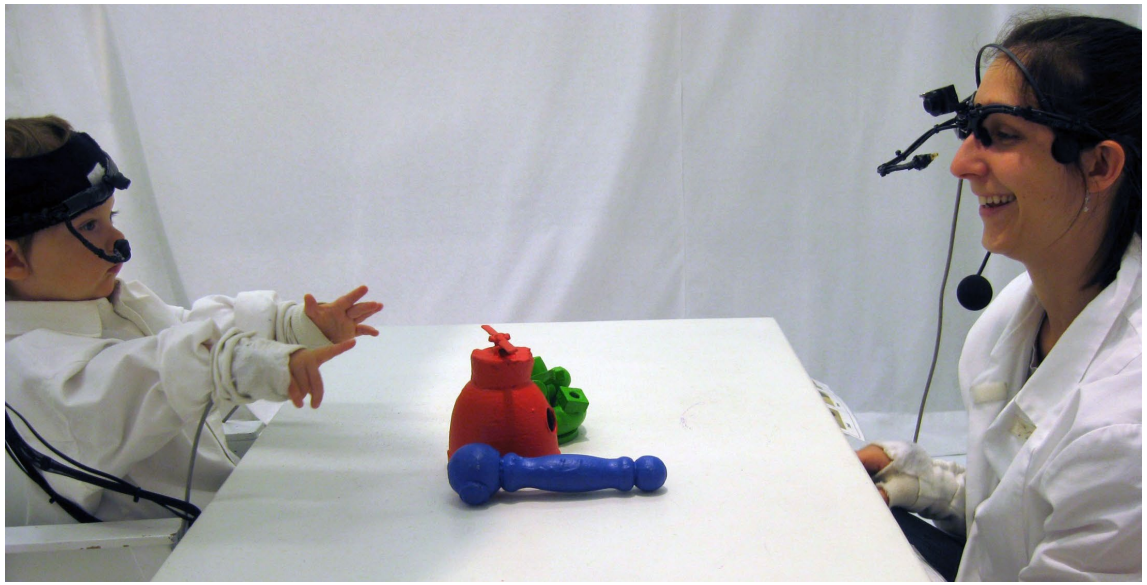

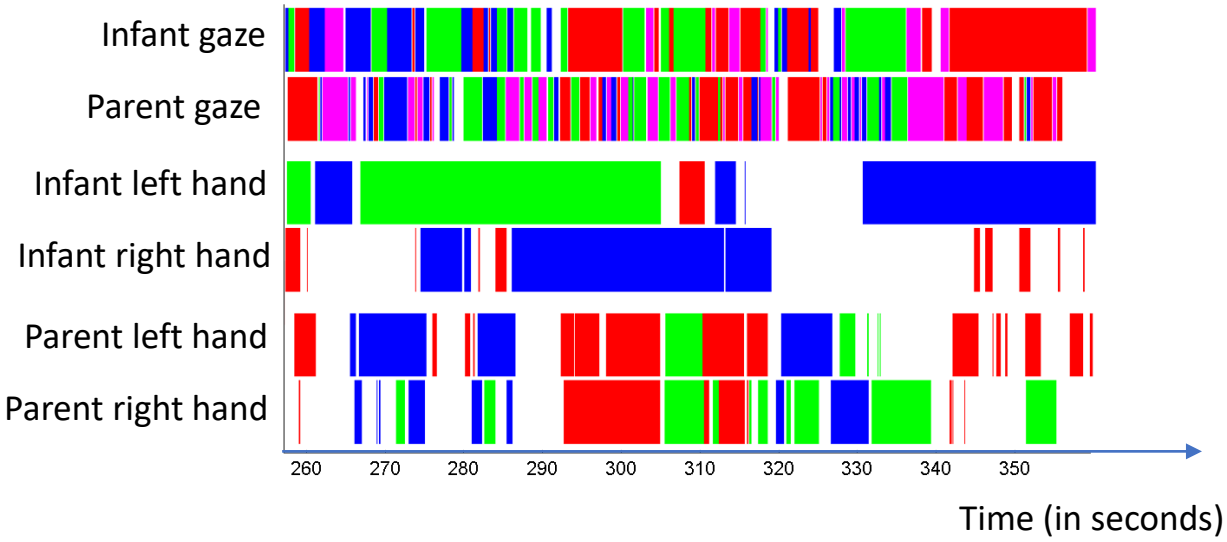


Xu, Abney & Yu, 2017; Xu, Abney, Foster, Smith & Yu, in prep

# How to quantify the directional influences when time series data were continuously influencing each other in real-time?

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# Granger Causality

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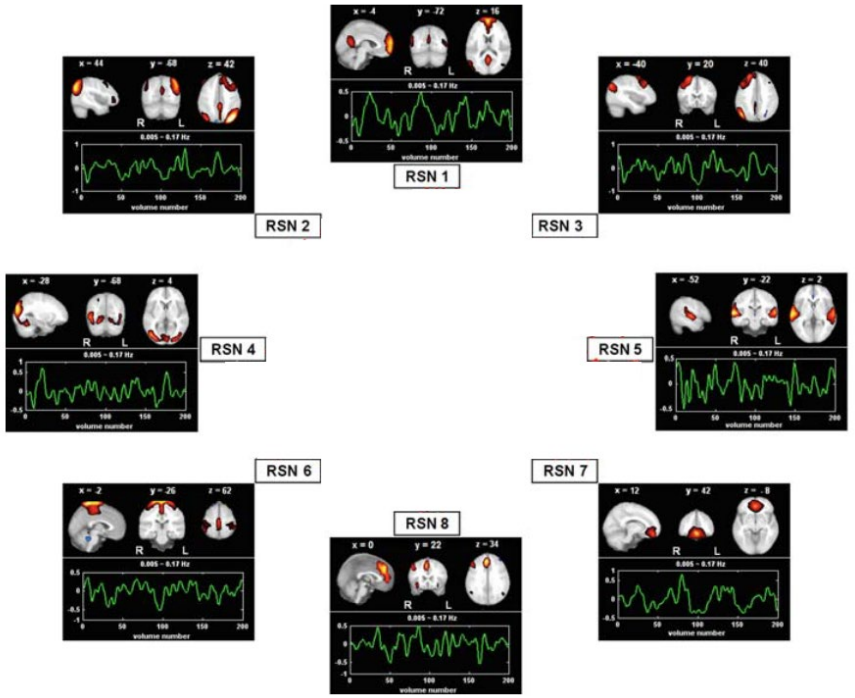


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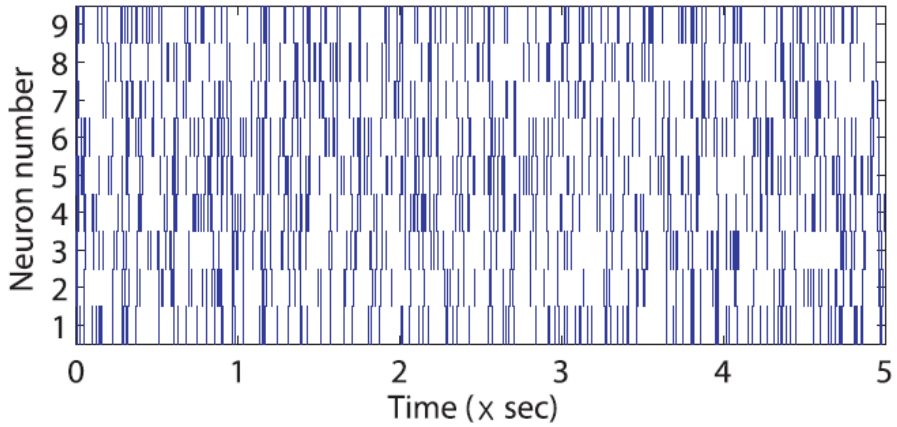


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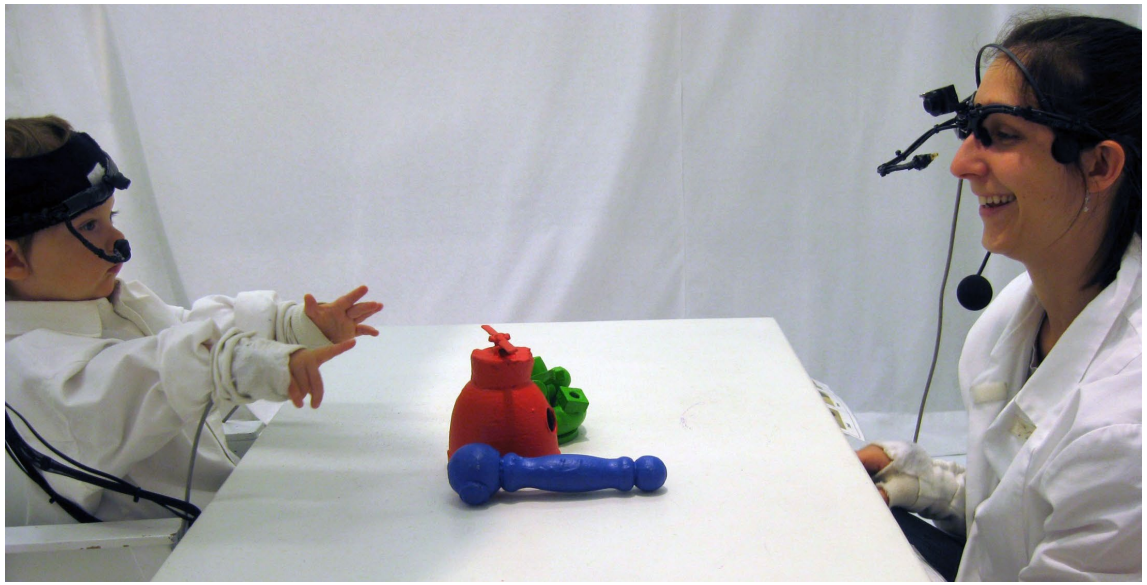

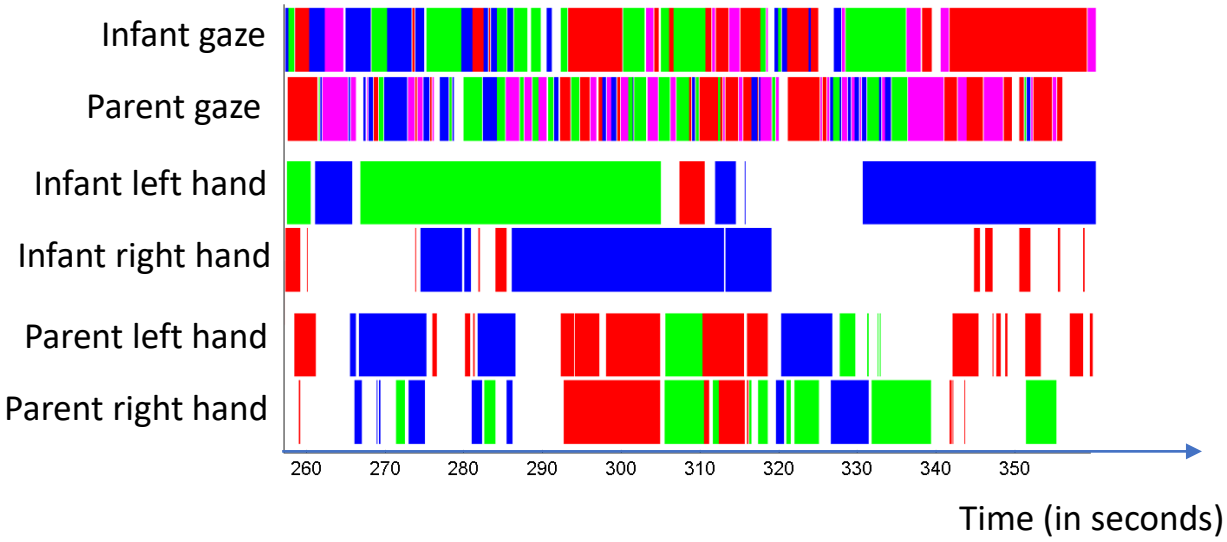


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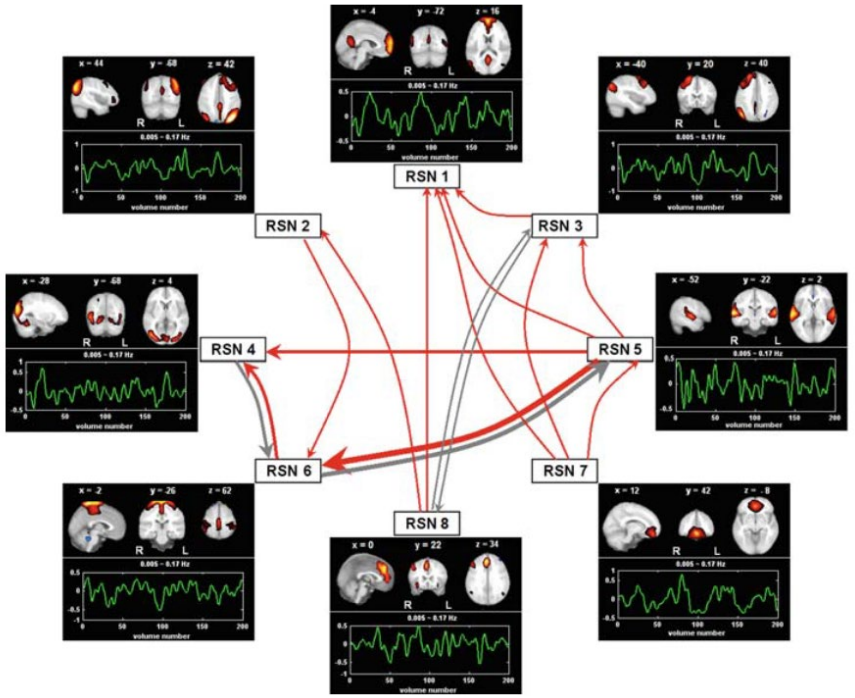


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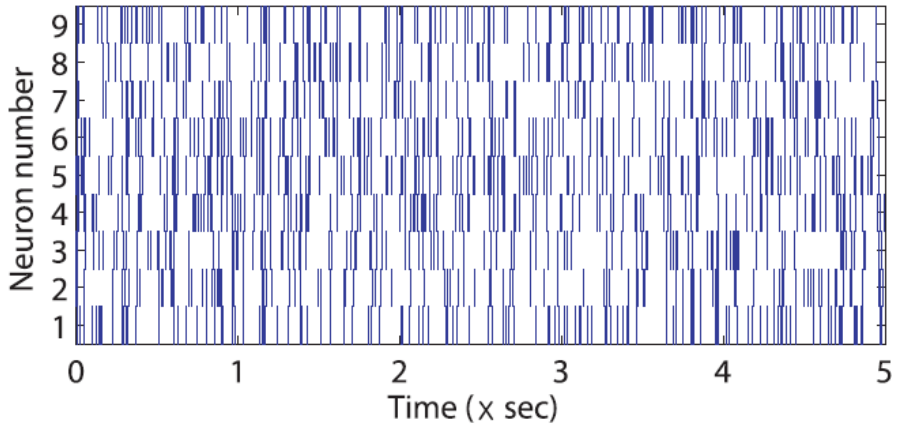


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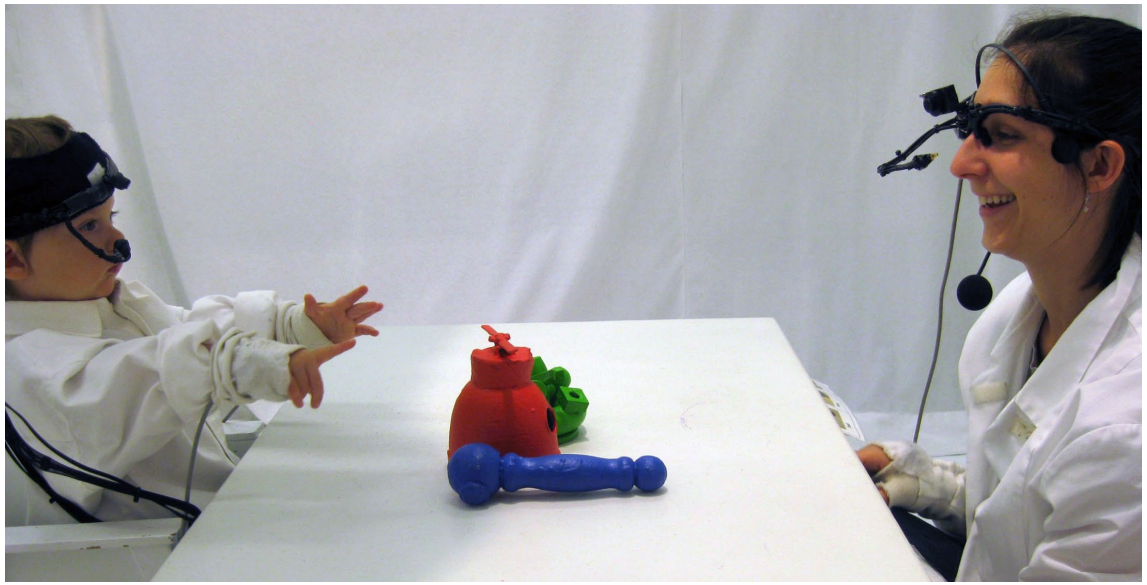

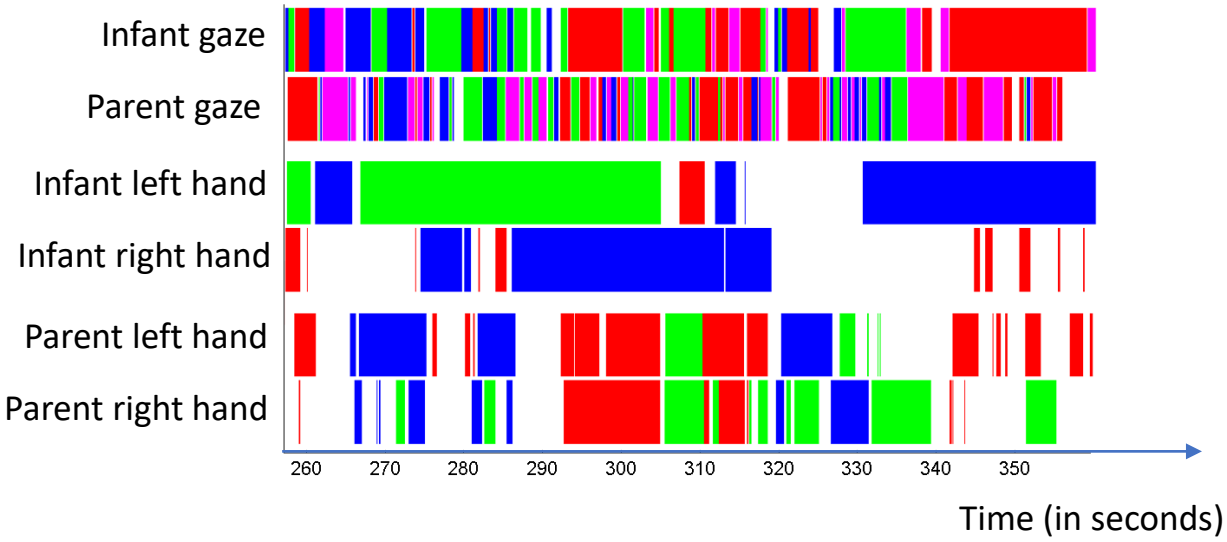


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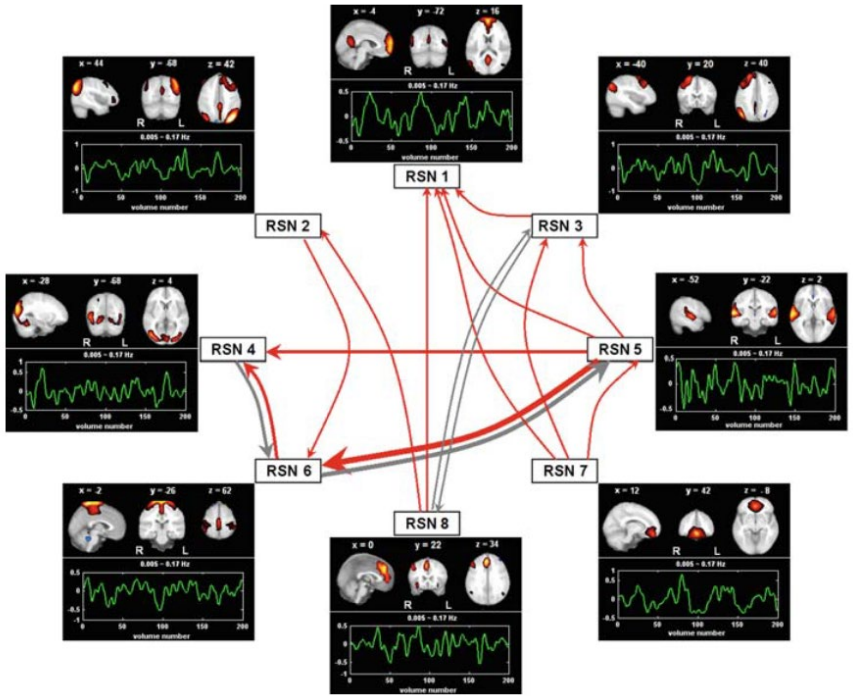


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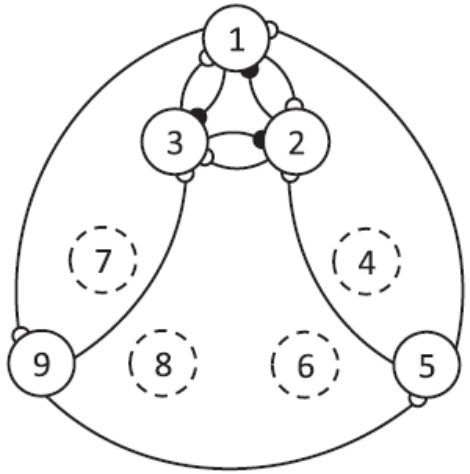


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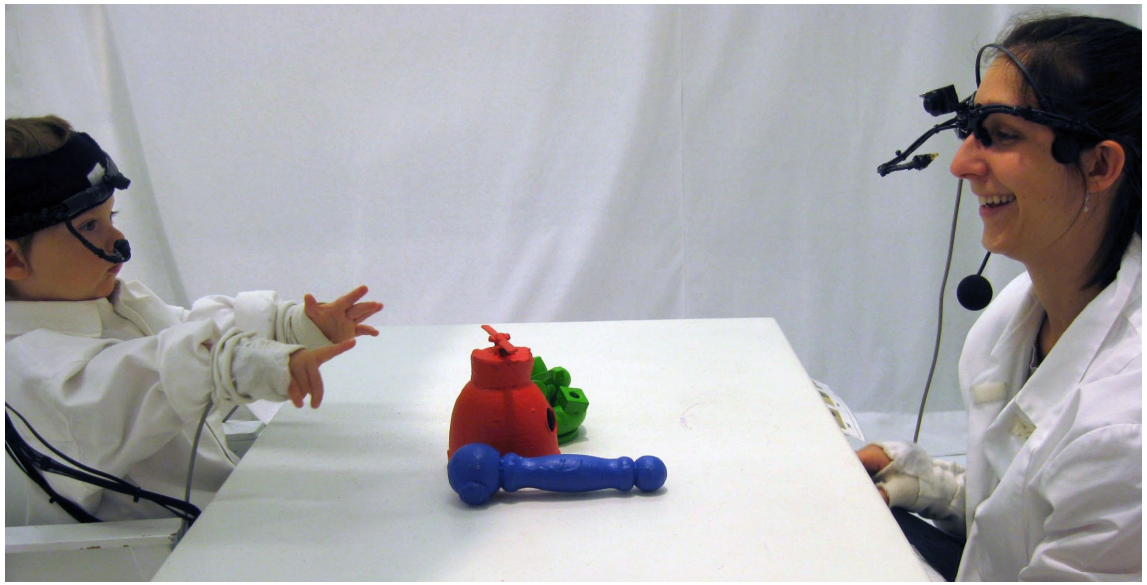

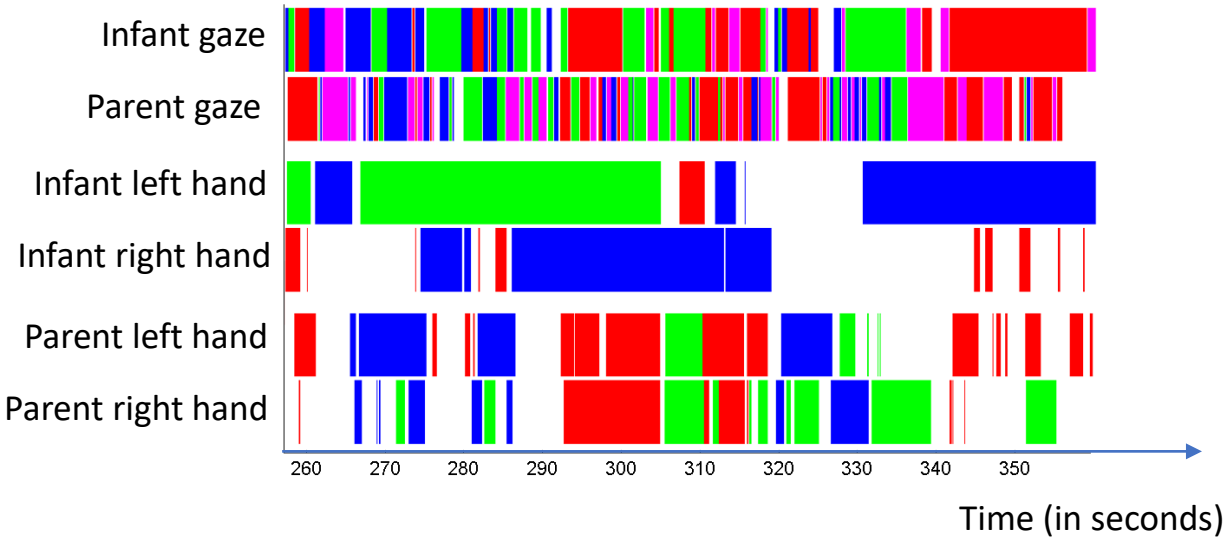


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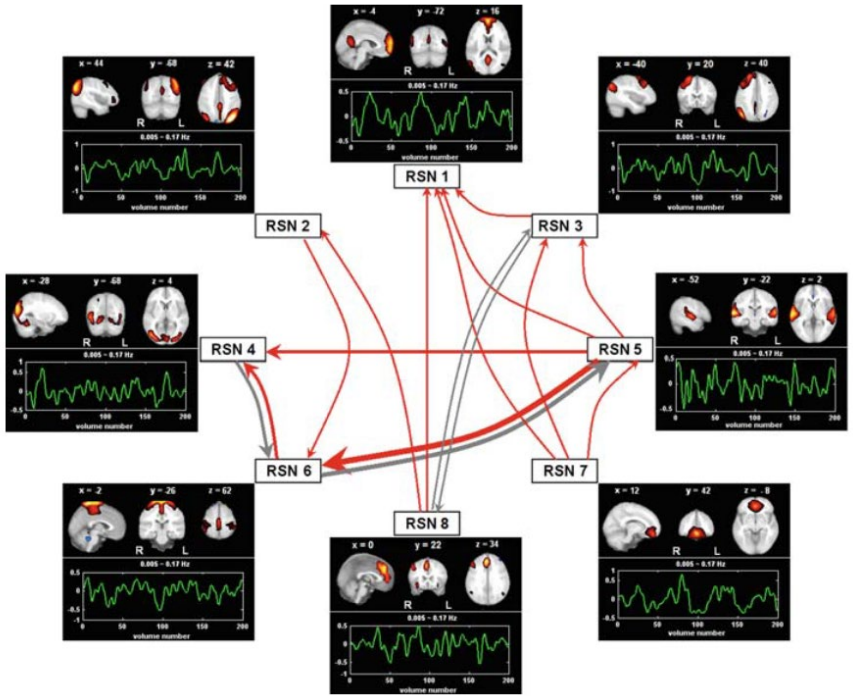


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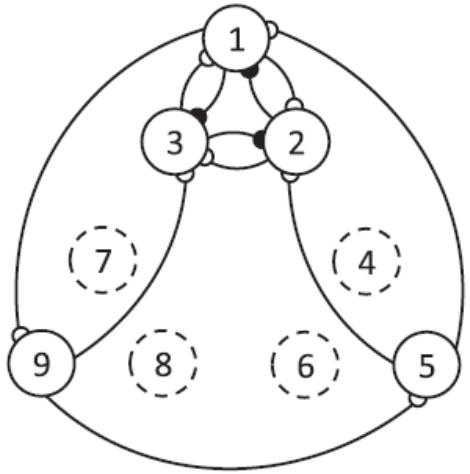


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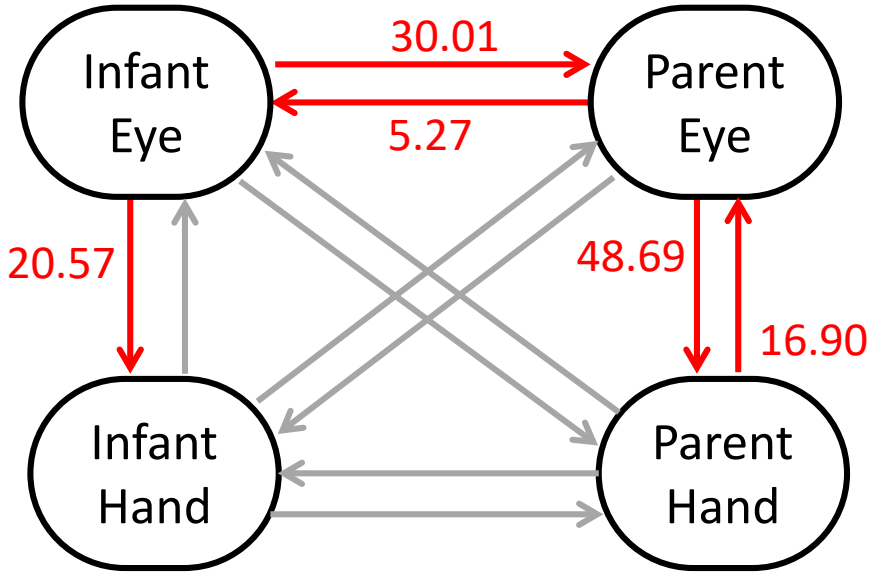


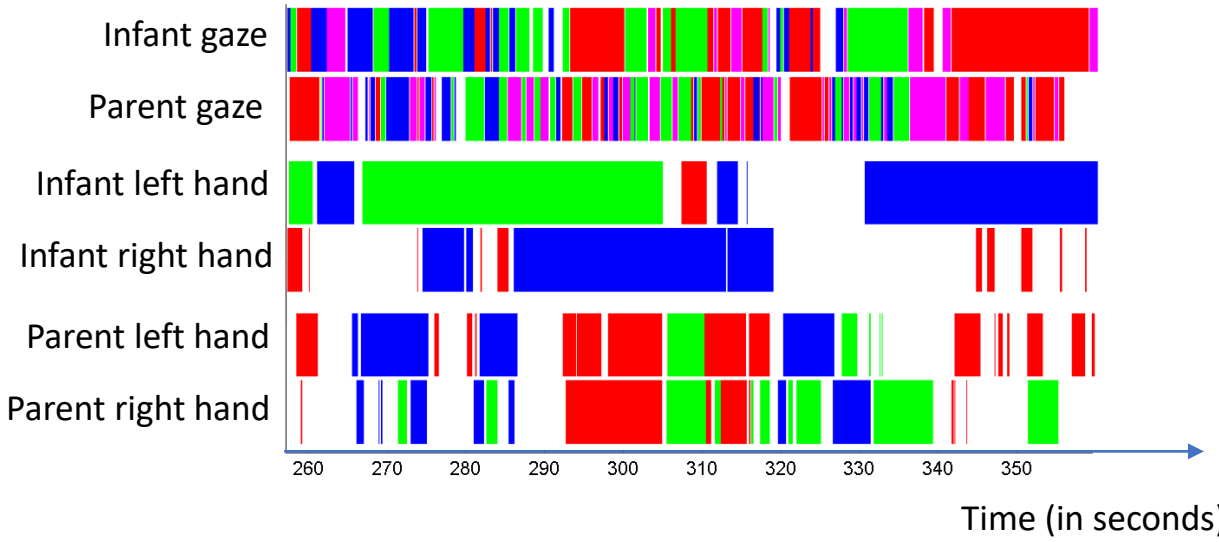


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# Outline

- What is Granger Causality?
- How to calculate it?
  - Using Granger Causality to quantify the directional influences in infant-parent coordinated behaviors (Xu, Abney & Yu, 2017)
- Run Granger Causality on simulated data sets to understand Granger Causality measures
  - What factors does this measurement reflect on?

# Granger causality

- Wiener-Granger causality is a statistical notion of causality applicable to time series data, originally developed in the context of econometric theory.

- In 2003, Clive Granger was awarded the Nobel Memorial Prize in Economic Sciences, in recognition that he and his co-winner, Robert F. Engle, had made contributions to the analysis of time series data that had changed fundamentally the way in which economists analyze financial and macroeconomic data.

(Bressler & Seth, 2011; Granger, 1969)

# Granger causality

- Granger (1969) formalized the basic idea of causality between signals introduced by Wiener (1956) based on multivariate autoregressive (MVAR) models.

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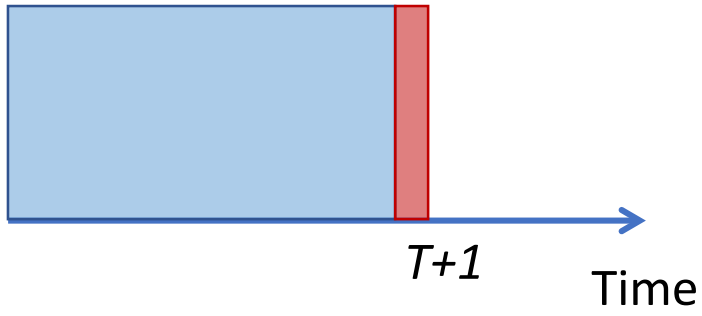


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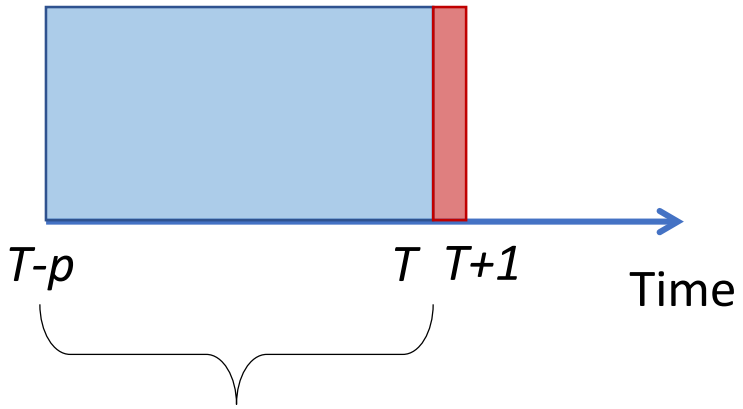


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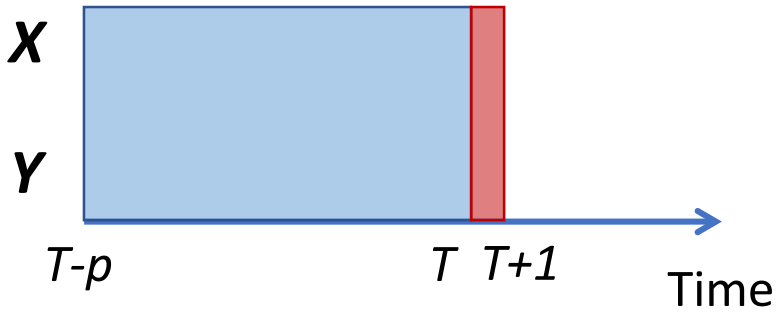


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  If past values of ***Y*** contains **unique** information that helps to predict ***X*** **above and beyond** the information contained in the past history of all other variables, then ***Y*** is said to Granger-cause ***X***.

(Bressler & Seth, 2011; Granger, 1969)

# Applications in Neuroscience

- G-causality has been used as a well established method in neuroscience to make Time Series Inference, that does not require intervention in the nervous system.
  - electroencephalographic (EEG)
  - magnetoencephalographic (MEG)
  - functional Magnetic Resonance (fMRI) data
  - neural spike trains from multiple electrode recordings

(Brown et al., 2004; David et al., 2008; Chang et al., 2008; Vakorin et al., 2007; Roebroeck et al., 2005)

# Applications in Psychology

- The early development of vocal turn-taking between marmoset monkey infants and parents (Takahashi, Fenley & Ghazanfar, 2016)
- Leader and follower dynamics in joint music performance (Chang, Livingstone, Bosnyak & Trainor, 2017)
- The development of coordinated behaviors in infant-parent interaction (Xu, Abney & Yu, 2017)

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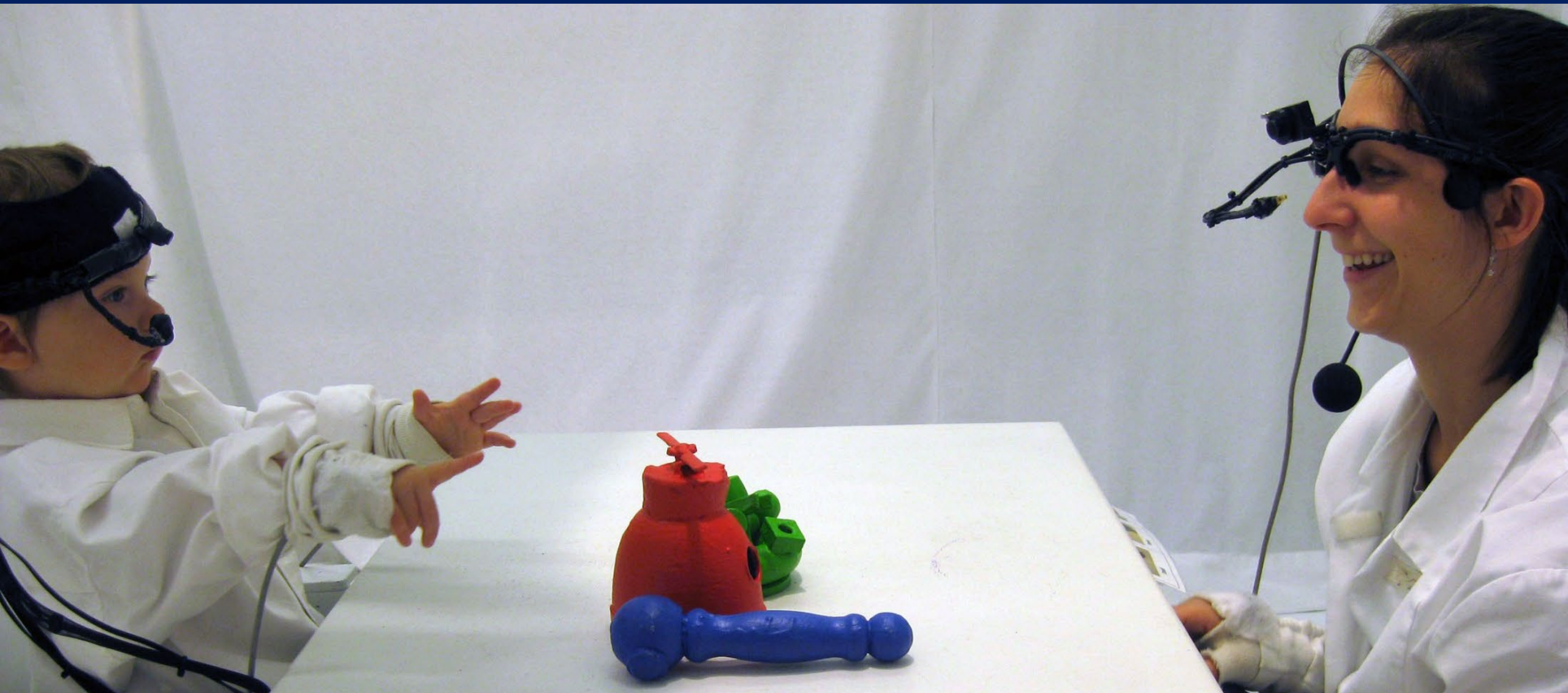
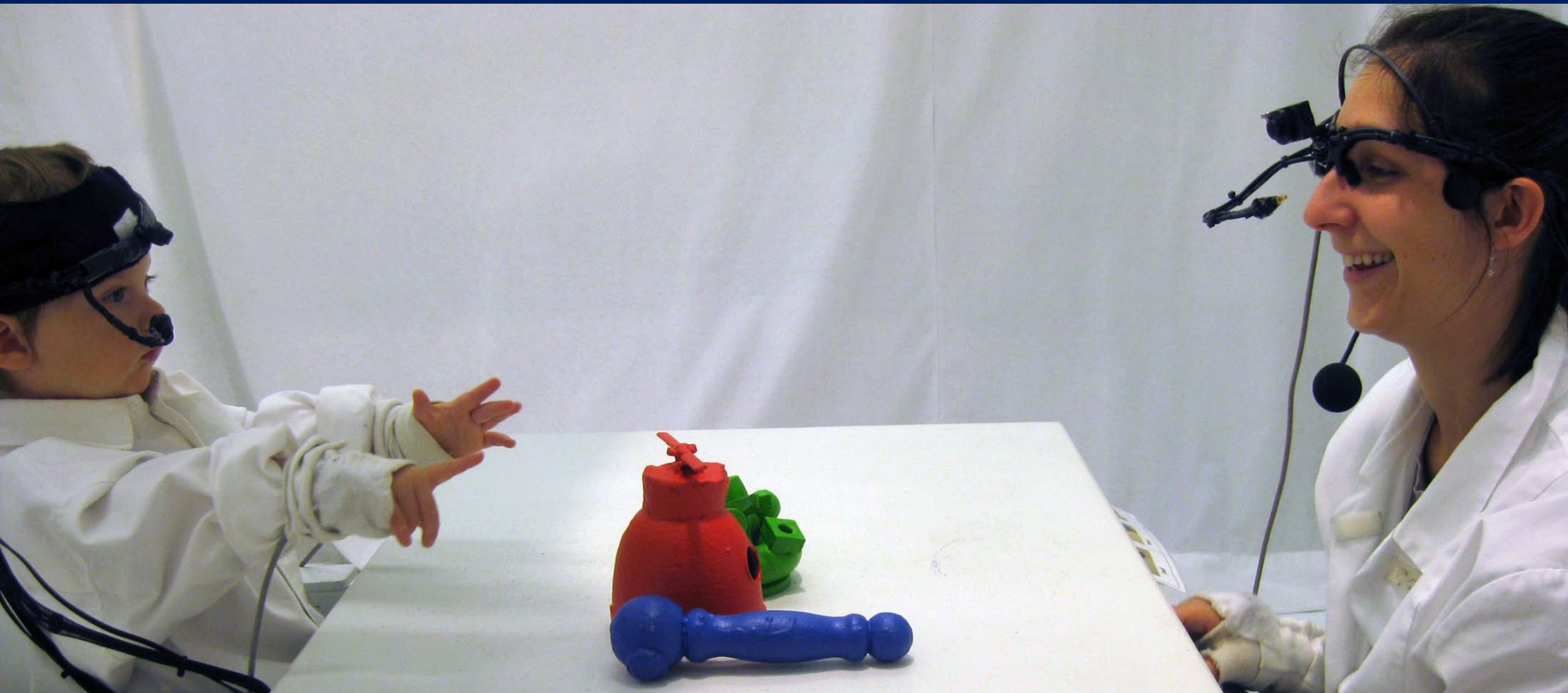
# Infant-Parent Toy Play Experiment



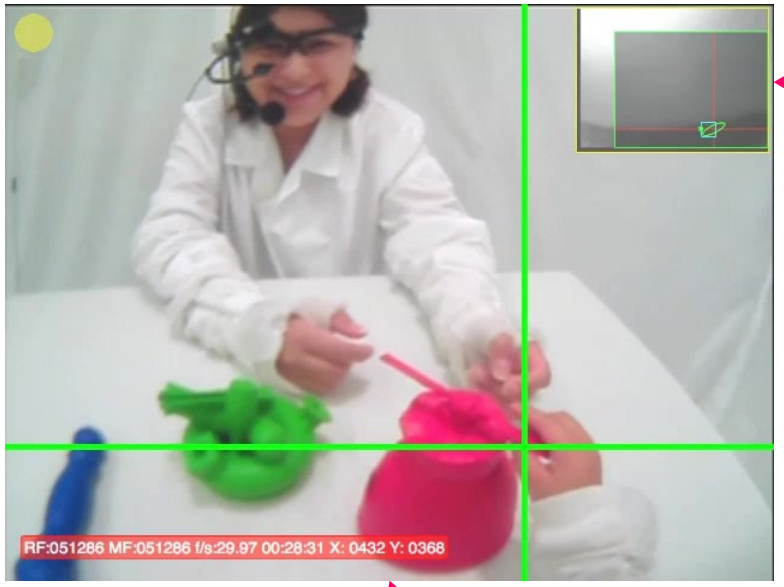
**Participants**. 21 infant-parent dyads participated in toy play experiment when the infant was 9 and 12 month old.



Infant’s eye tracker

Parent’s eye tracker

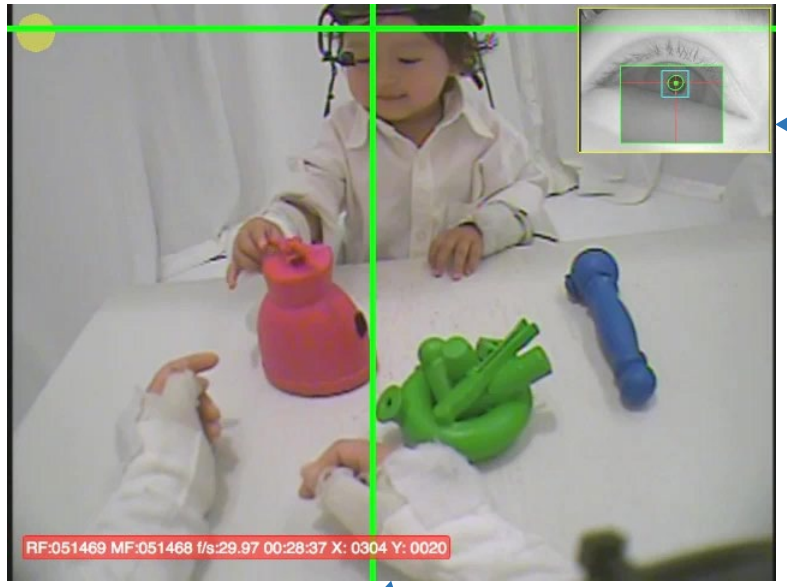
The infant's first person view




From eye camera

Infant's eye tracker

The parent's first person view

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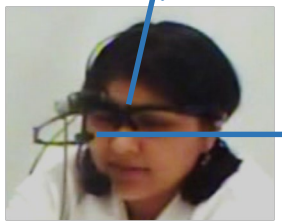


From eye camera

Parent's eye tracker

Infant hand

Infant eye

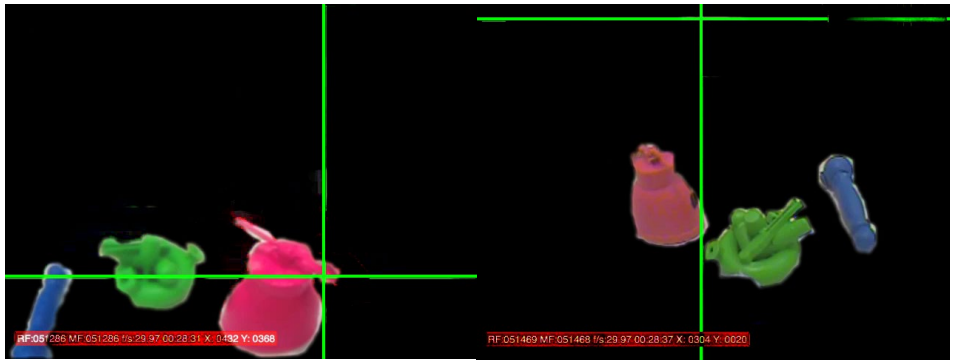
Parent eye

Parent hand

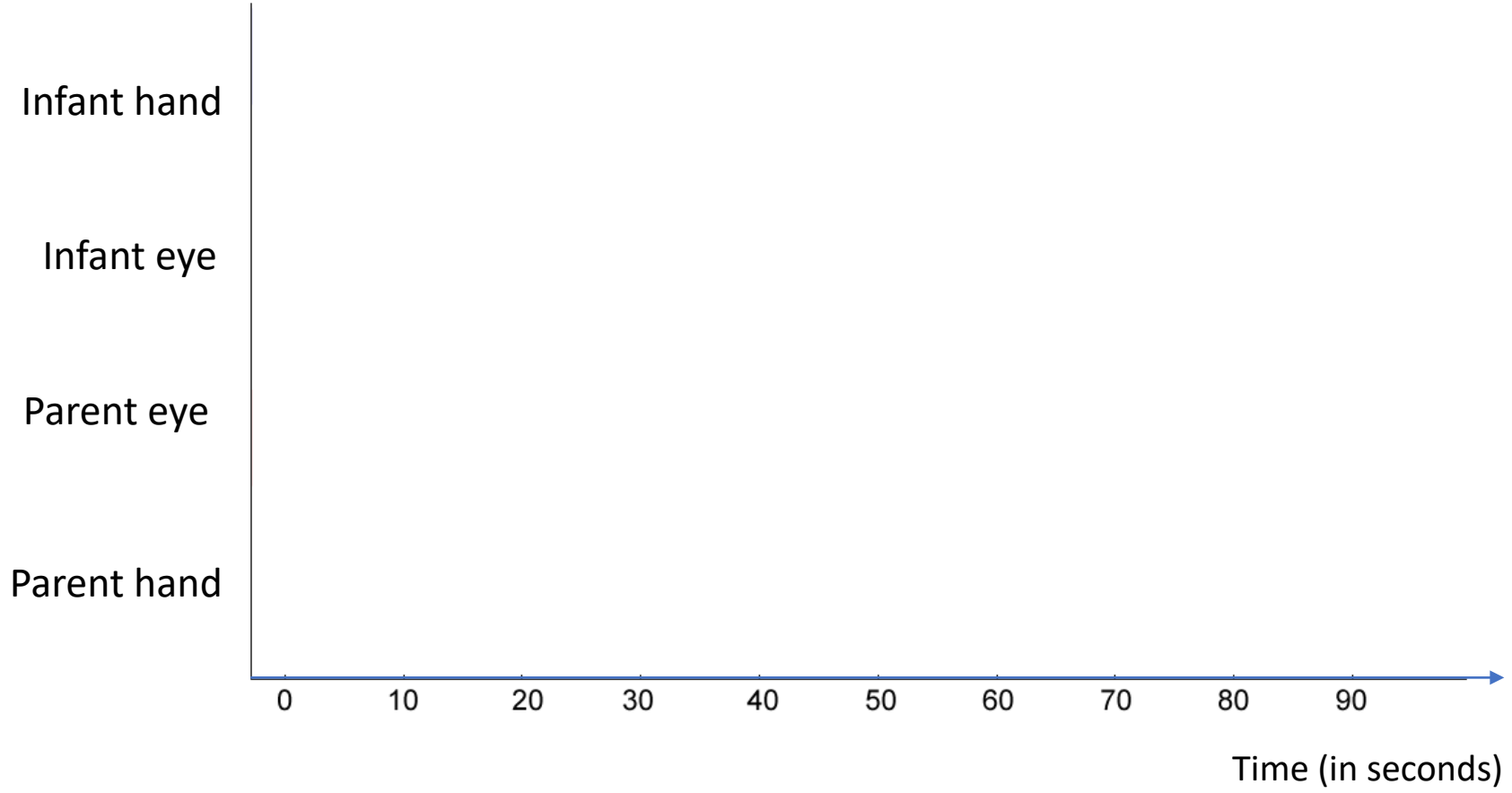
Data collection sample rate:
30 data points / second

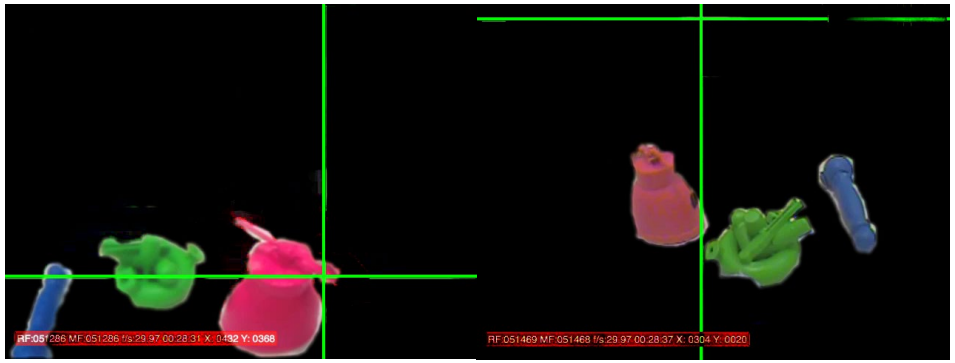
0 10 20 30 40 50 60 70 80 90

Time (in seconds)



blue object green object red object





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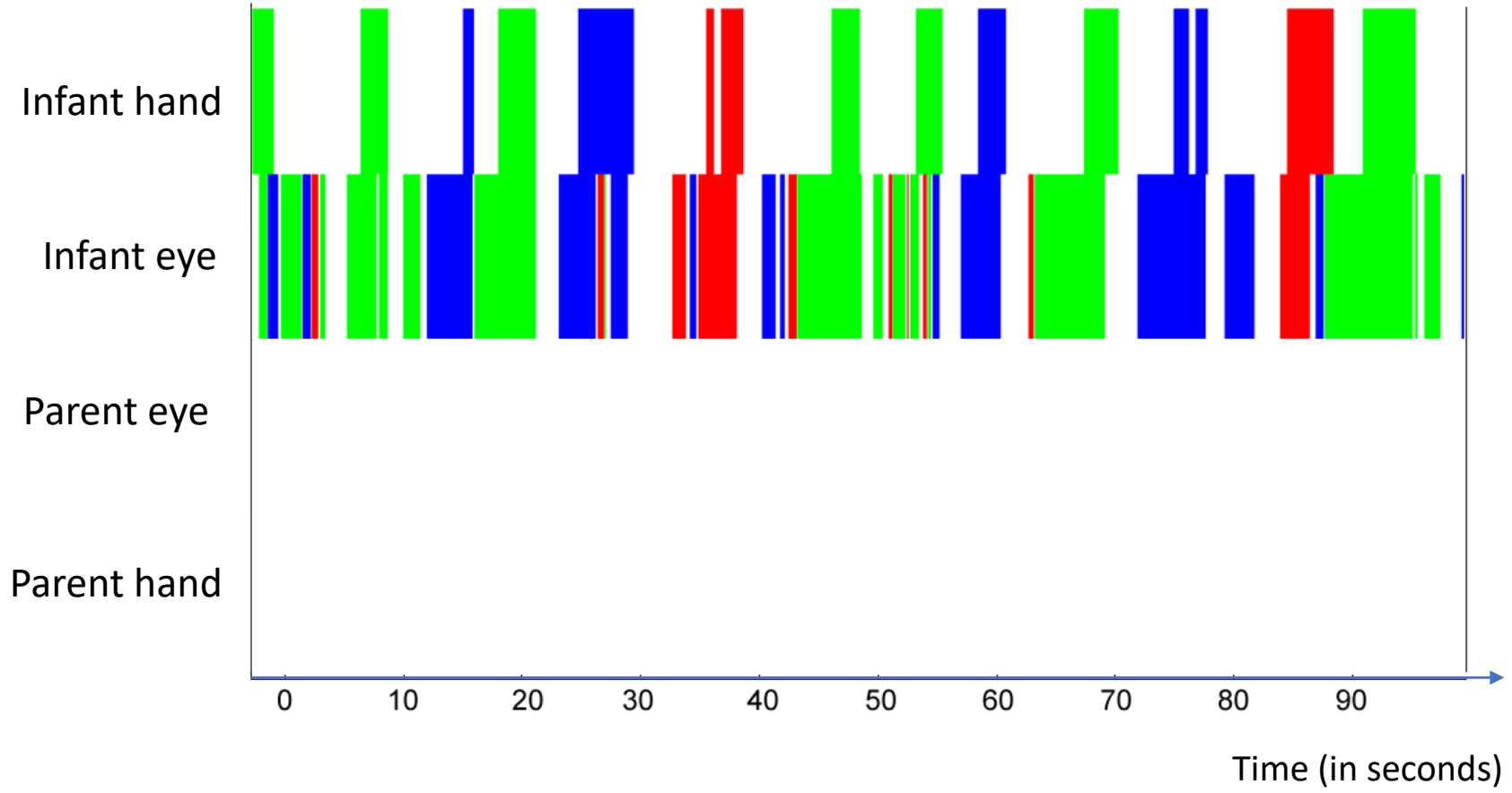

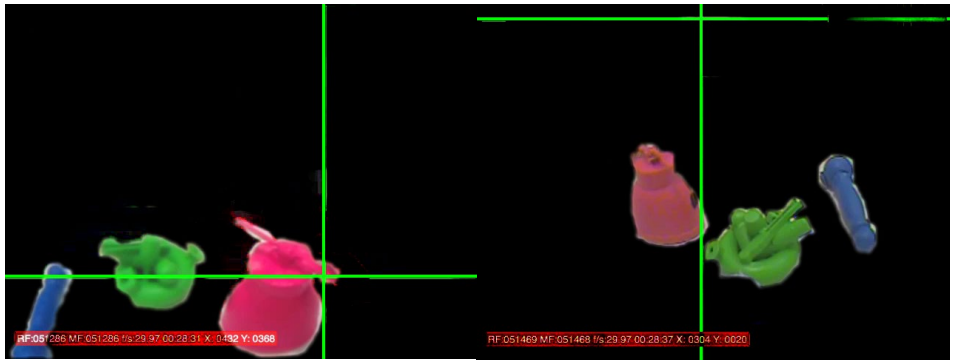

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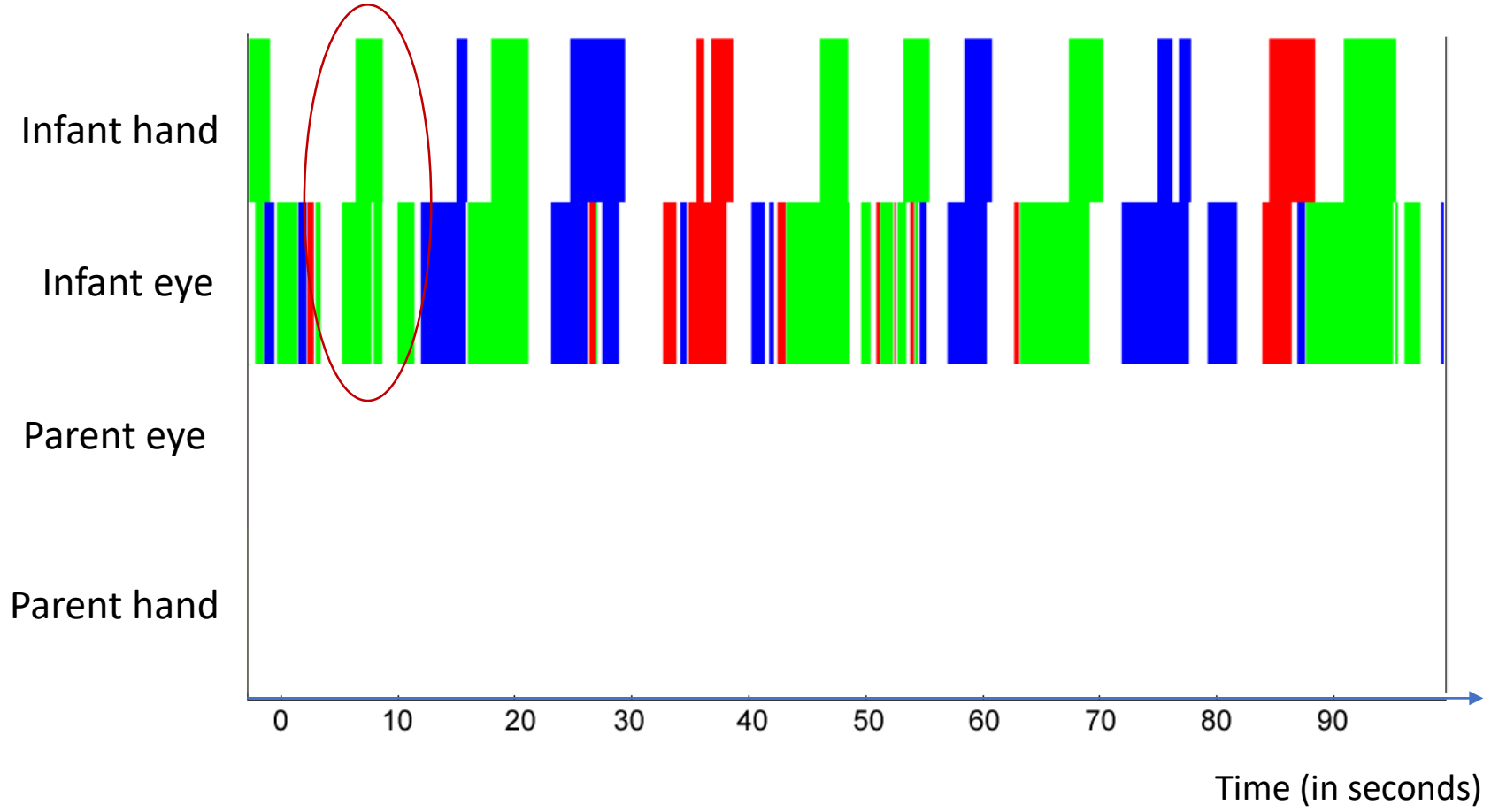

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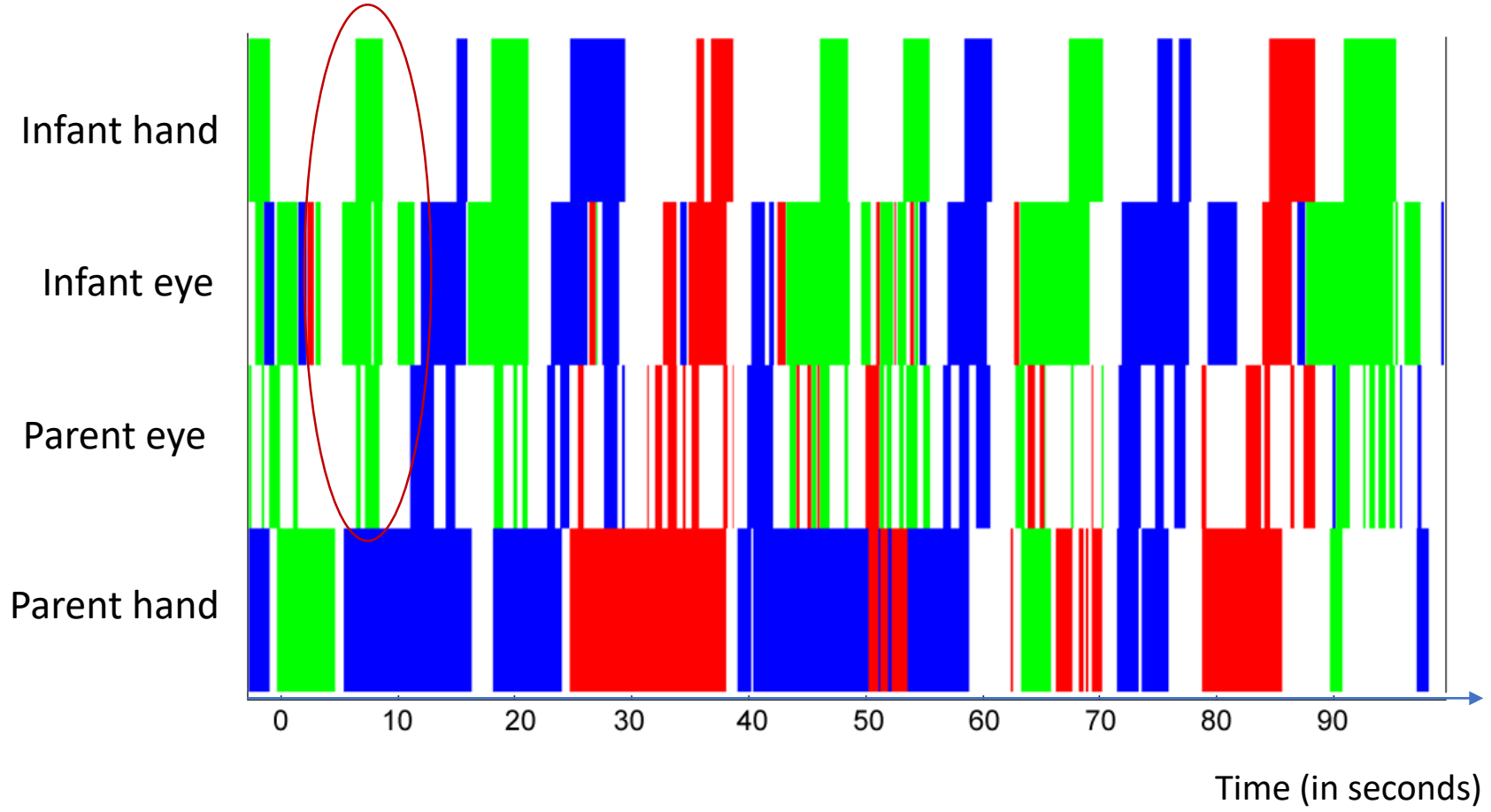

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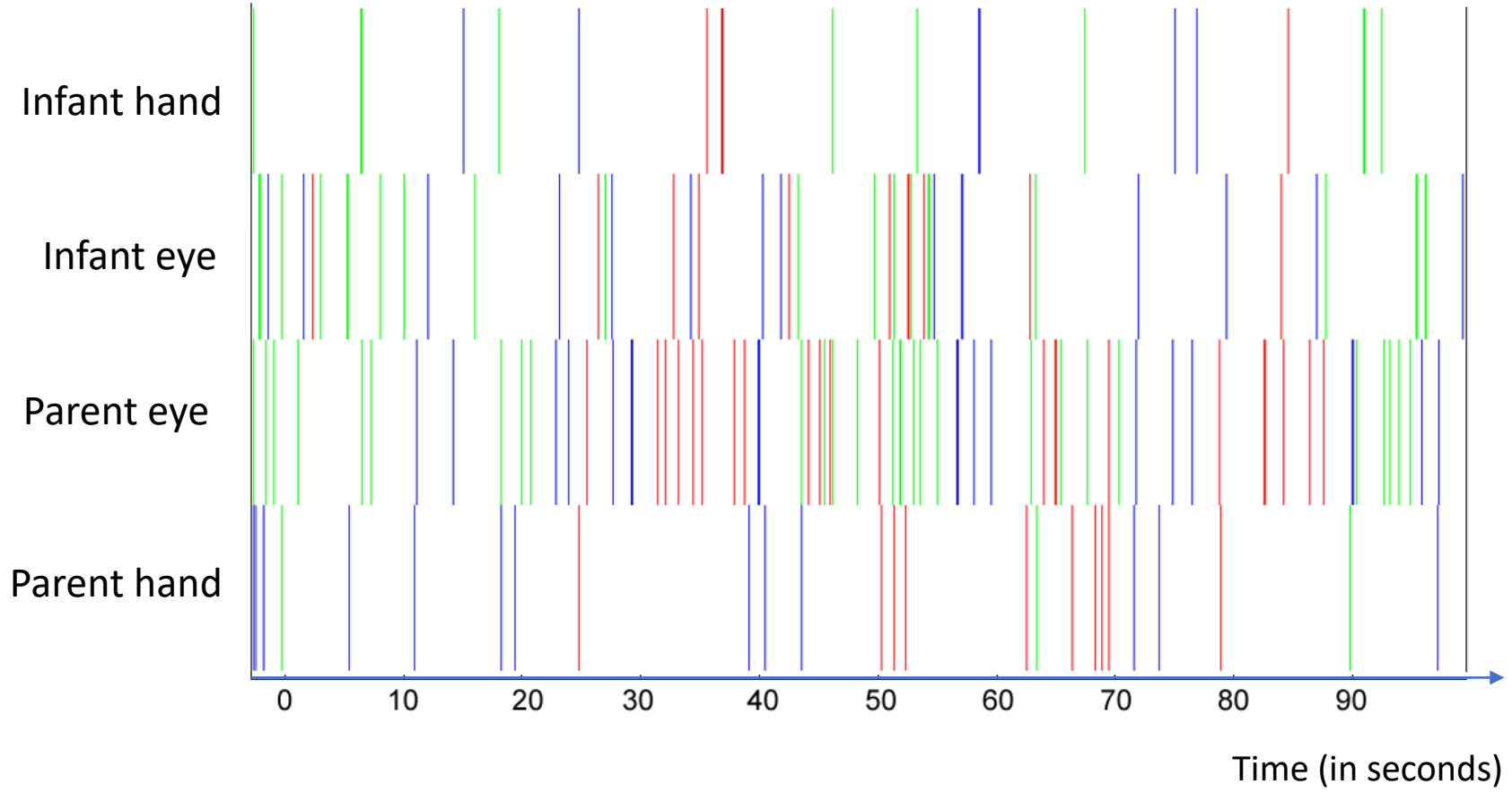

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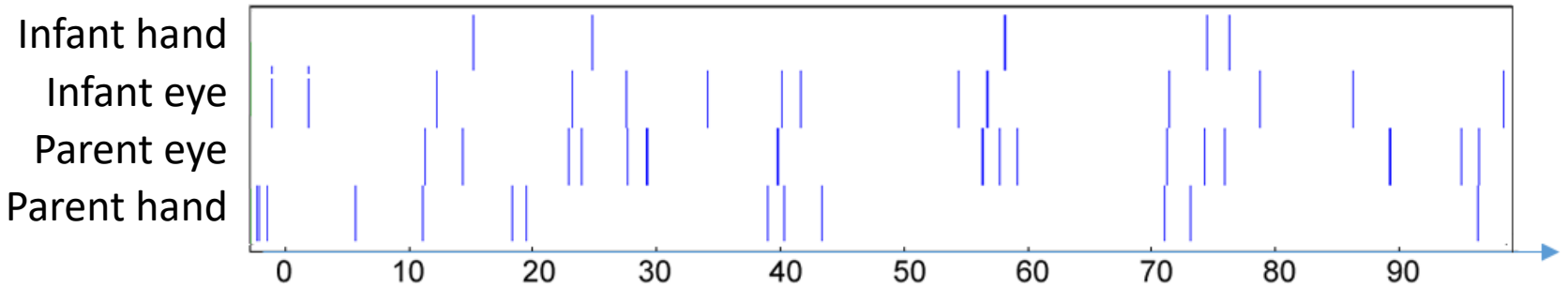
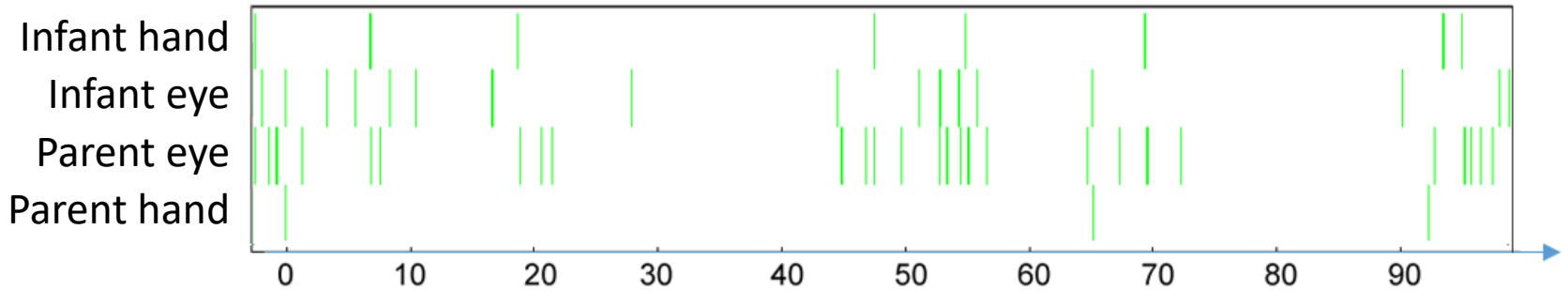
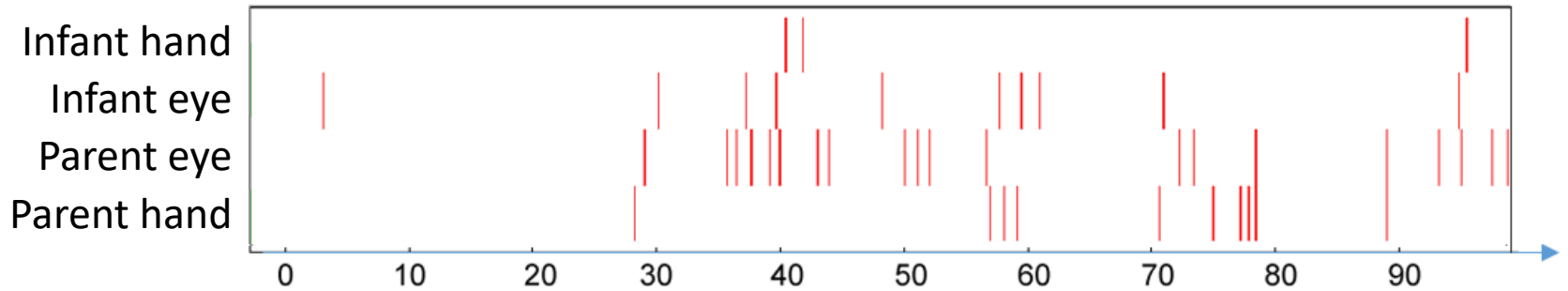
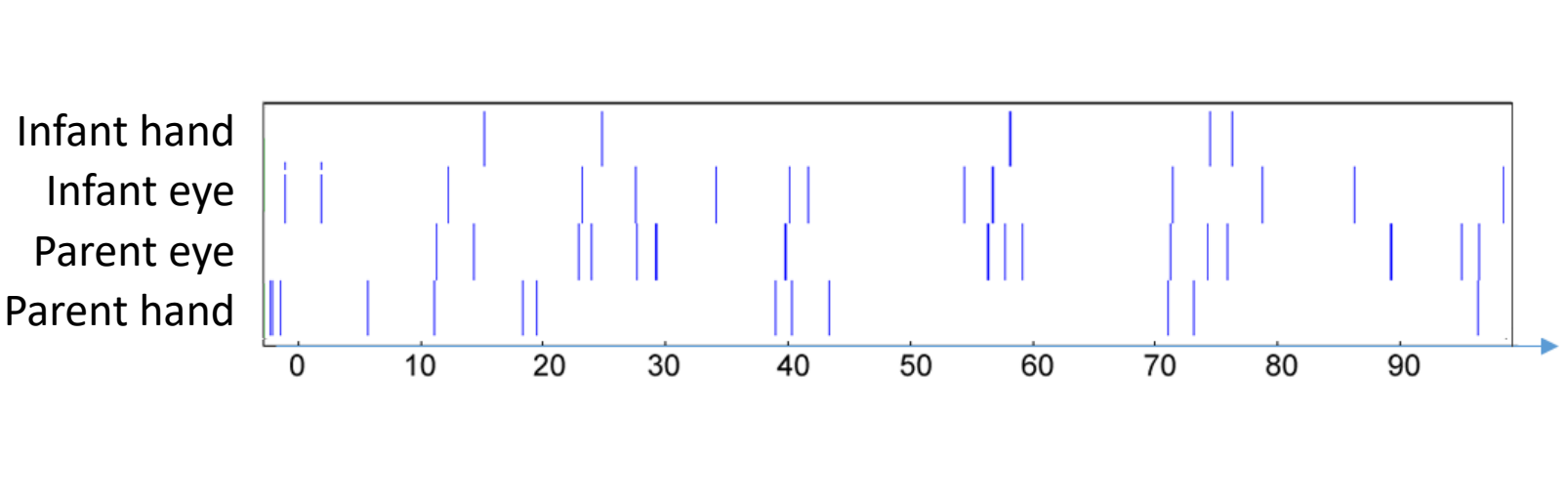
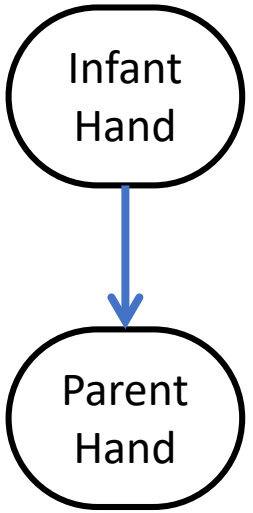
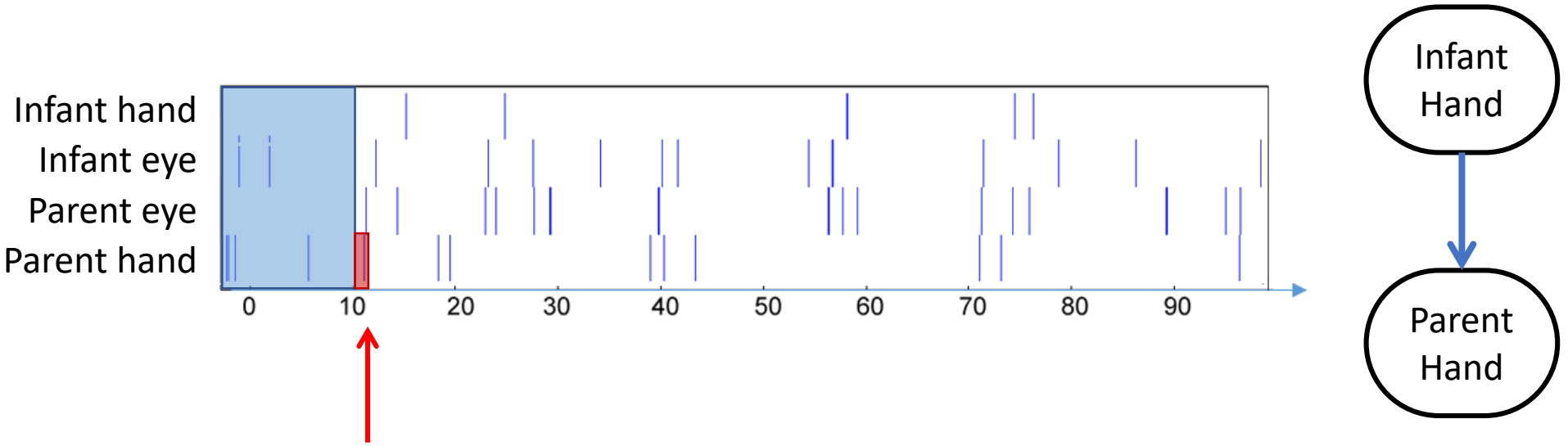


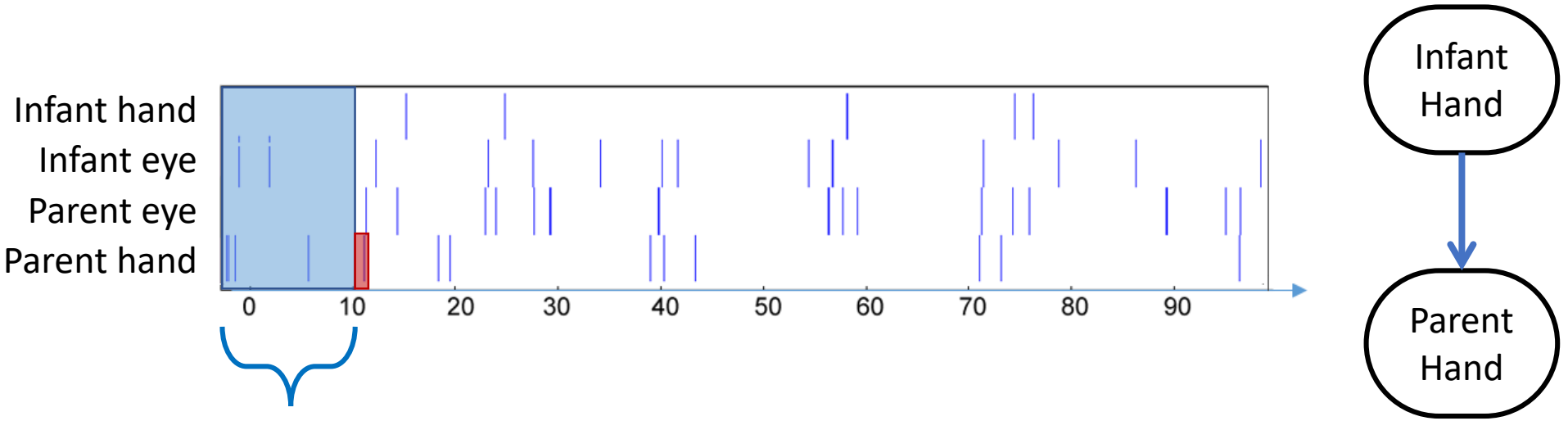




Infant hand
Infant eye
Parent eye
Parent hand
0
10
20
30
40
50
60
70
80
90


Infant Hand
Parent Hand

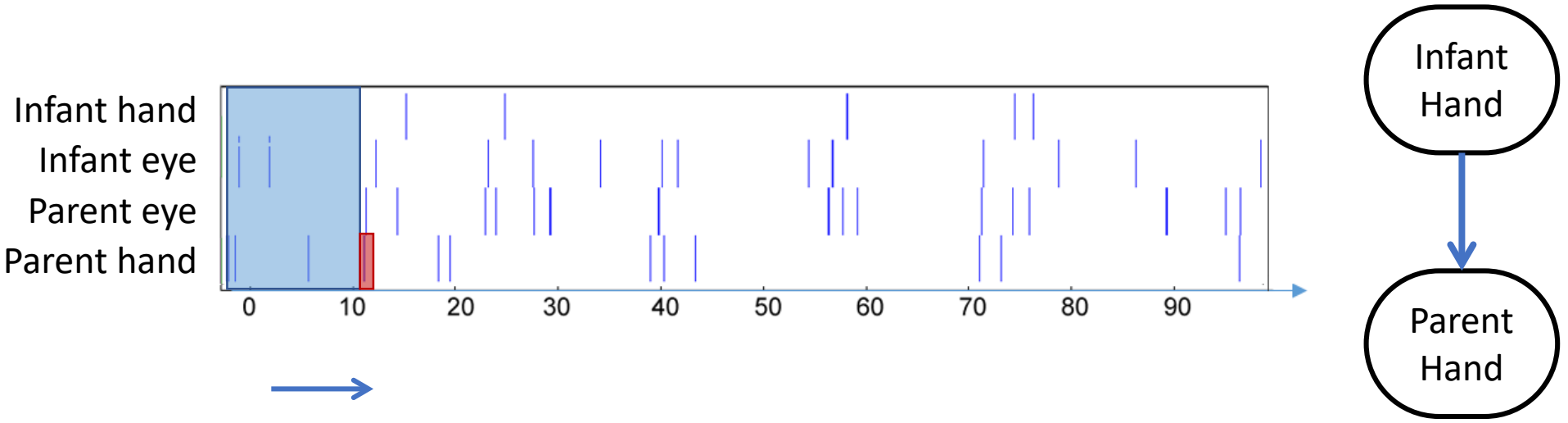



Likelihood of generating the occurrence of parent hand action at ***T***+1




Likelihood of generating the occurrence of parent hand action at ***T***+1

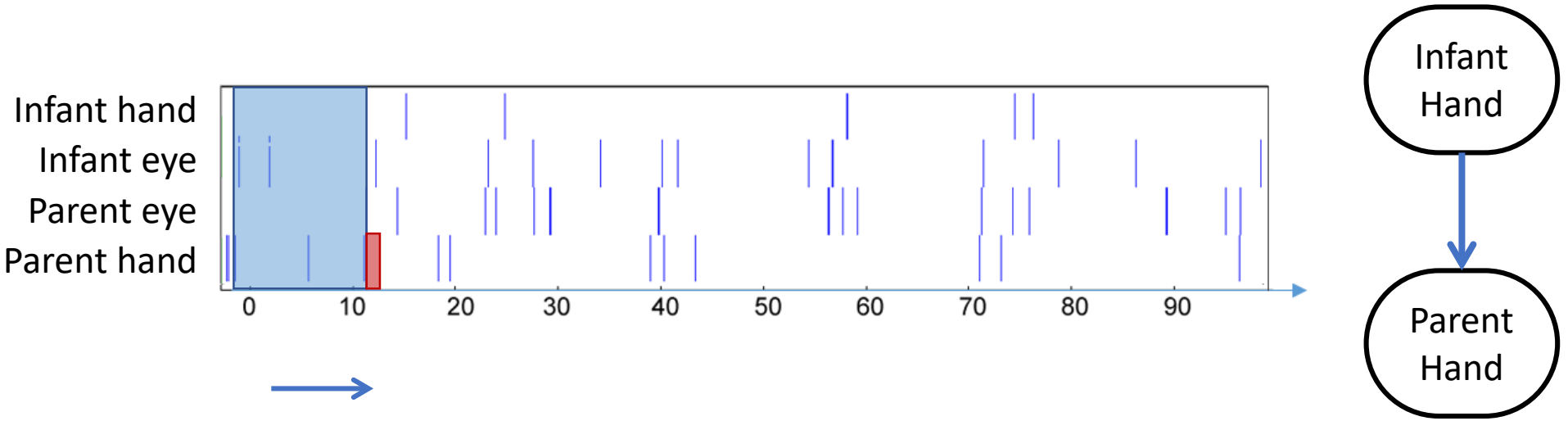
based on the history of all 4 variables between [***T-p***, ***T***]




Likelihood of generating the occurrence of parent hand action at ***T***+1

based on the history of all 4 variables between [***T-p***, ***T***]

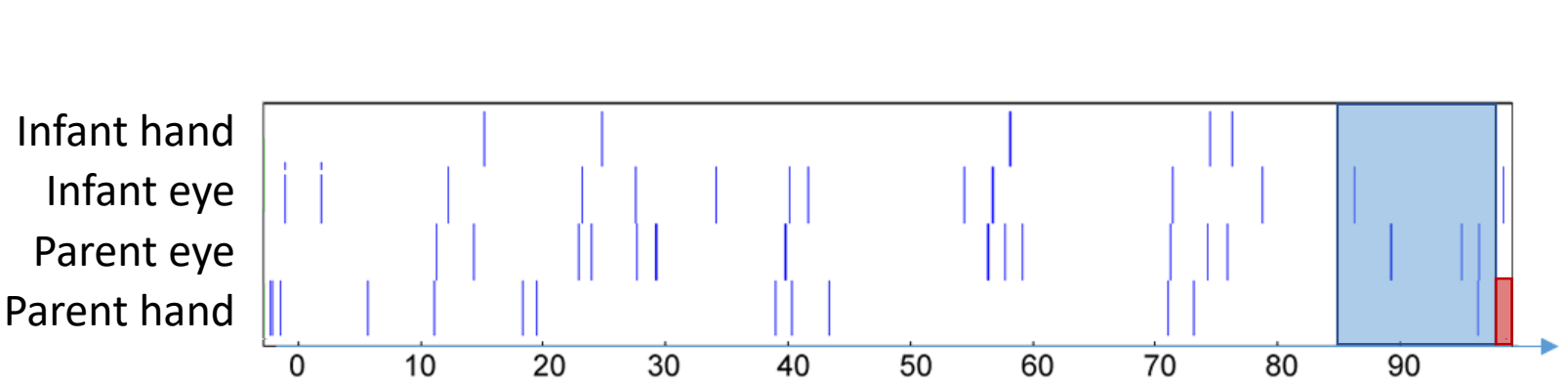
By moving the window forward, we obtain a new set of data to fit into the model




Likelihood of generating the occurrence of parent hand action at ***T***+1

based on the history of all 4 variables between [***T-p***, ***T***]

Optimize the estimation by moving the window forward, and use all data for best prediction

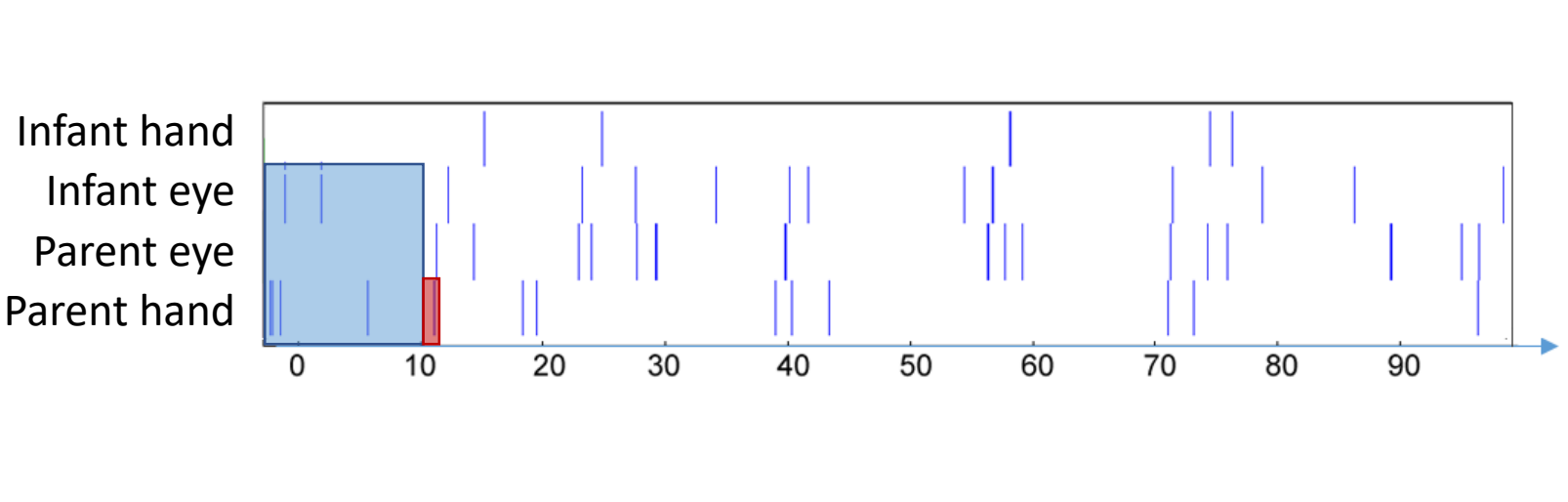



Likelihood of generating the occurrence of parent hand action at ***T***+1

based on the history of all 4 variables between [***T-p***, ***T***]

$$Likelihood_{all}$$

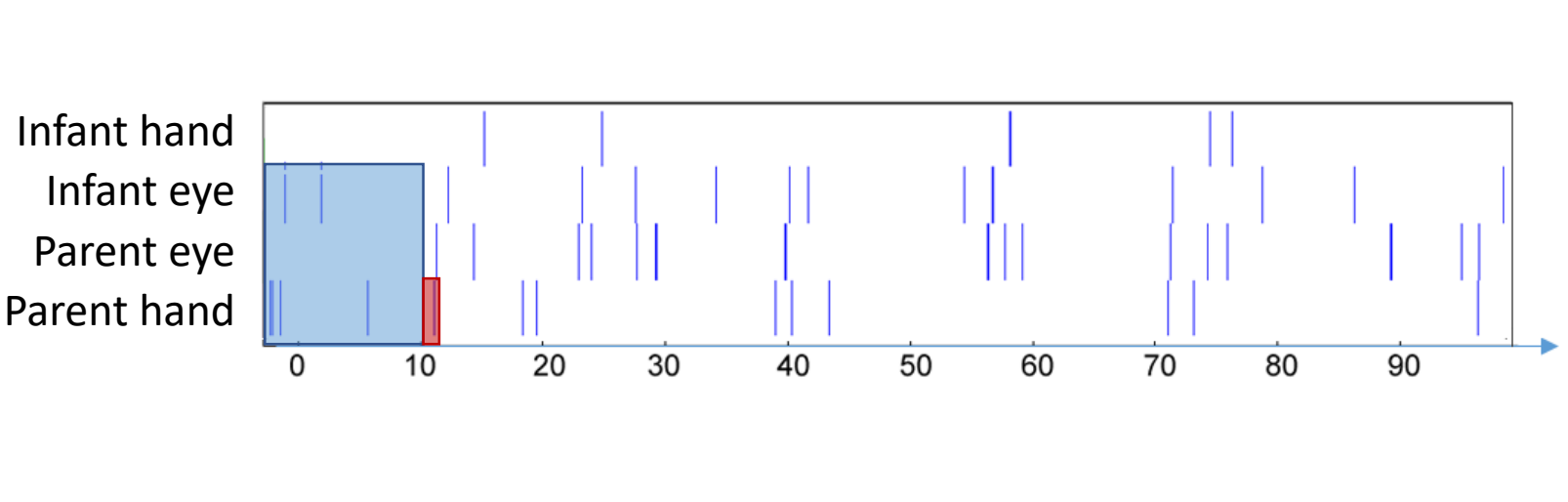
Full model




Then repeat the same process, only taking ‘infant hand’ time series out

$Likelihood_{all}$

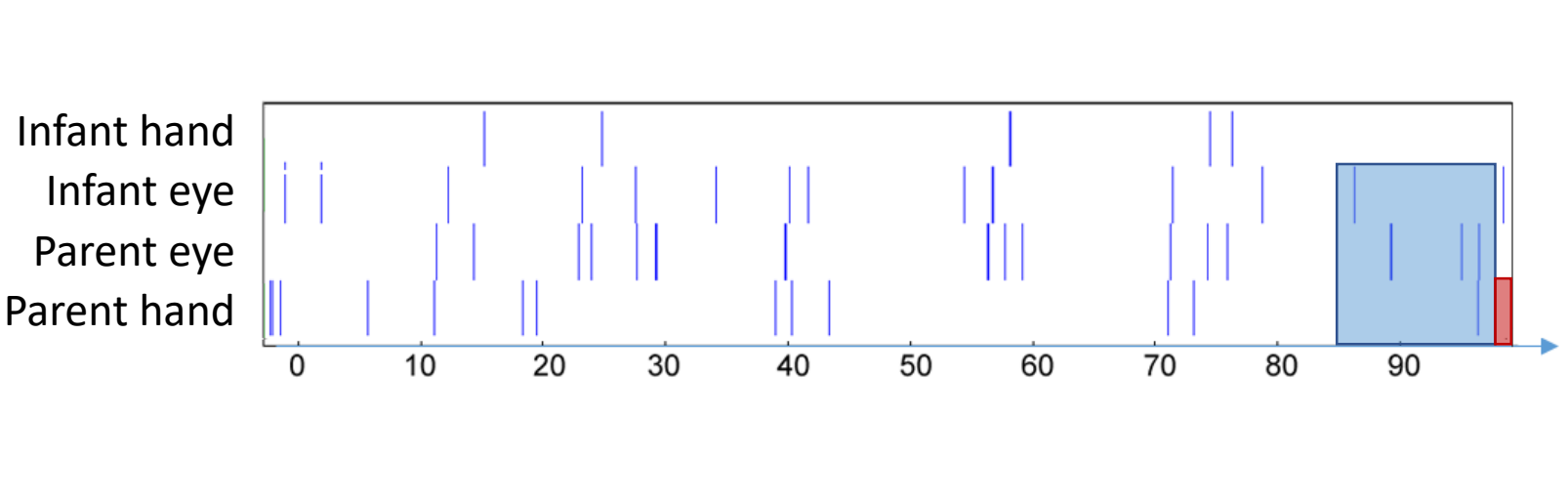
Full model




Then repeat the same process, only taking ‘infant hand’ time series out

$Likelihood_{all}$

Full model



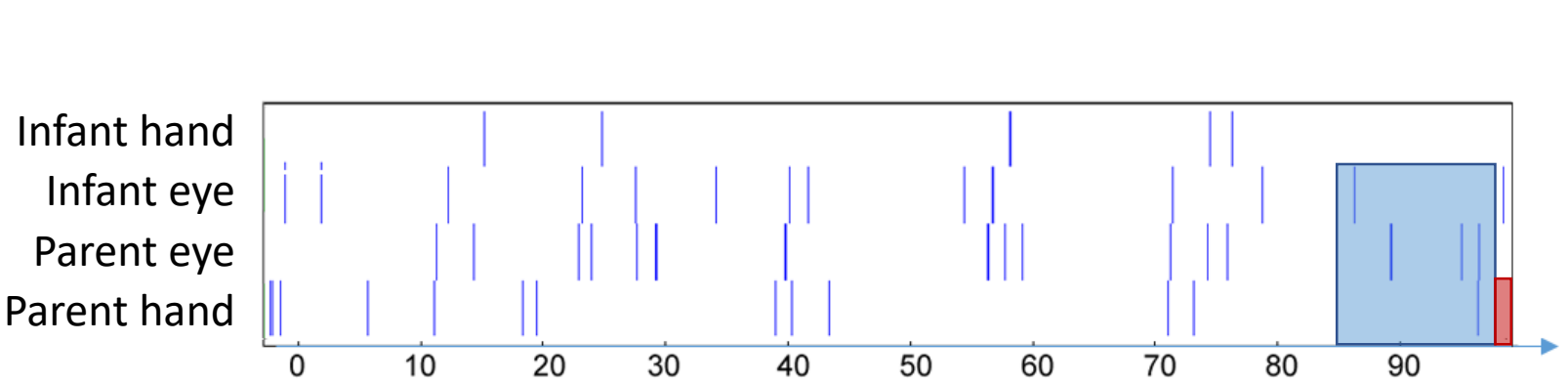

Then repeat the same process, only taking ‘infant hand’ time series out

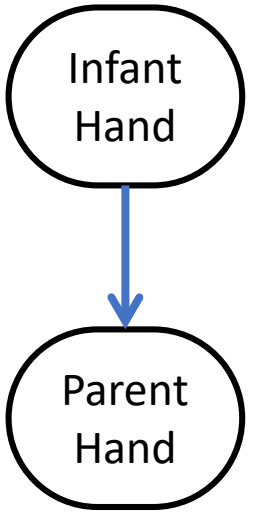
$Likelihood_{all}$

Full model

$Likelihood_{all-infant\ hand}$

Partial model



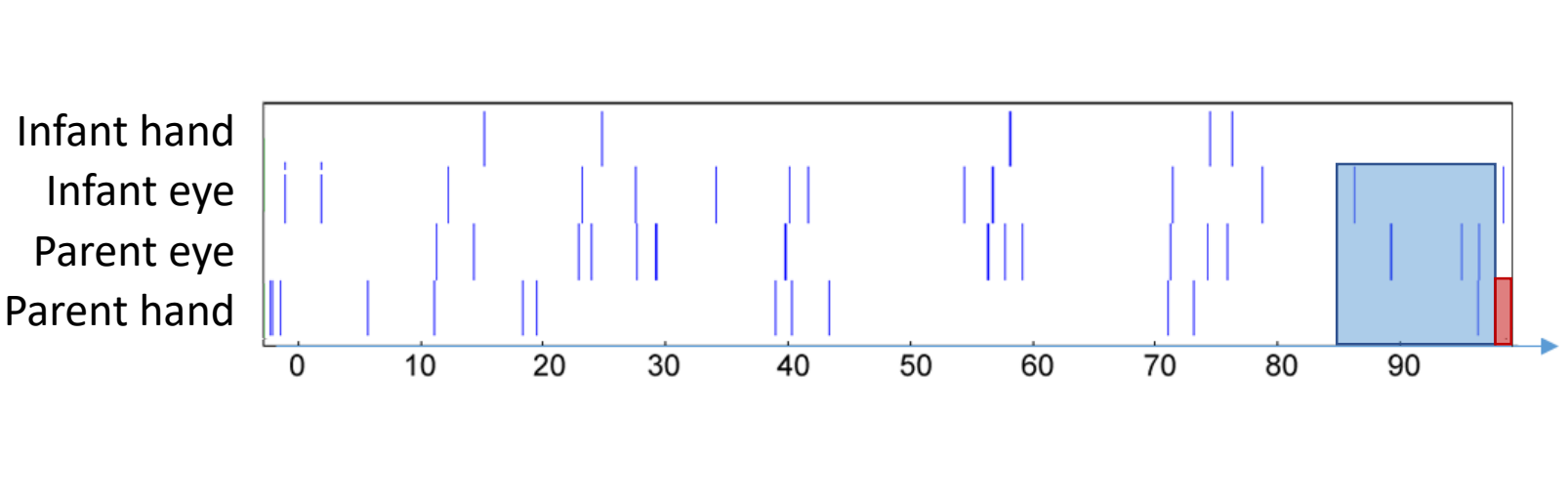




If parent's hand activity could be **better** predicted by the full model
- with incorporating infant hand action history

$$Likelihood_{all} > Likelihood_{all-infant\ hand}$$

Full model

Partial model




Then, infant's hand activity Granger-cause parent's hand action

$$Likelihood_{all} > Likelihood_{all-infant\ hand}$$

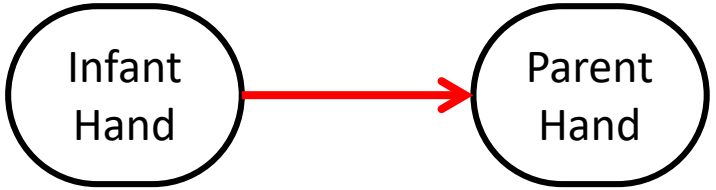
Full model

Partial model

# Granger causality

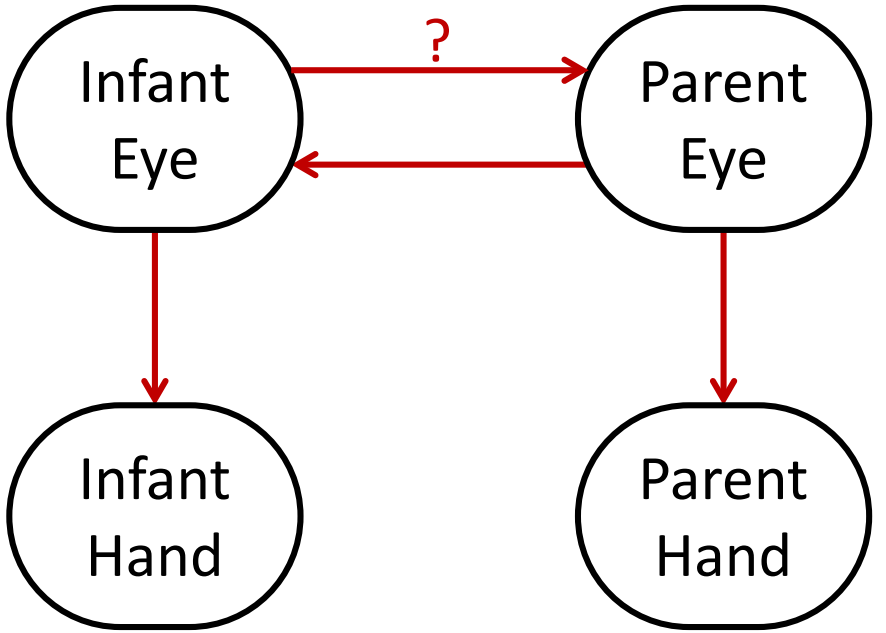
1. The cause occurs before the effect;
2. The cause contains information about the effect that that is unique, and is in no other variable.

A consequence of these statements is that the causal variable can help forecast the effect variable, beyond or incorporating all other variables' predictabilities.



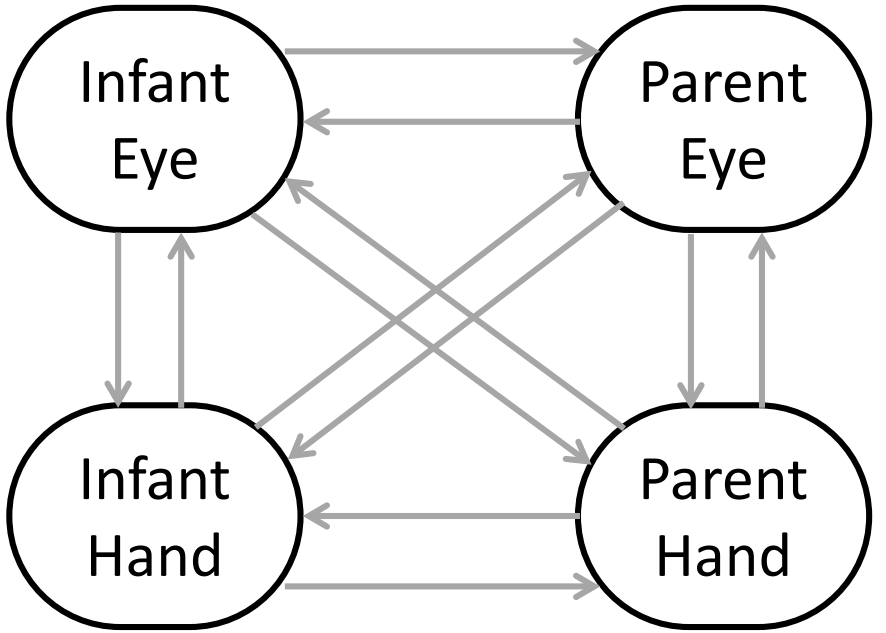
# Quantifying the Change in Coordination

- Use Granger causality to quantify **directional influence from one behavioral variable to another** in the course of development.



# Quantifying the Change in Coordination

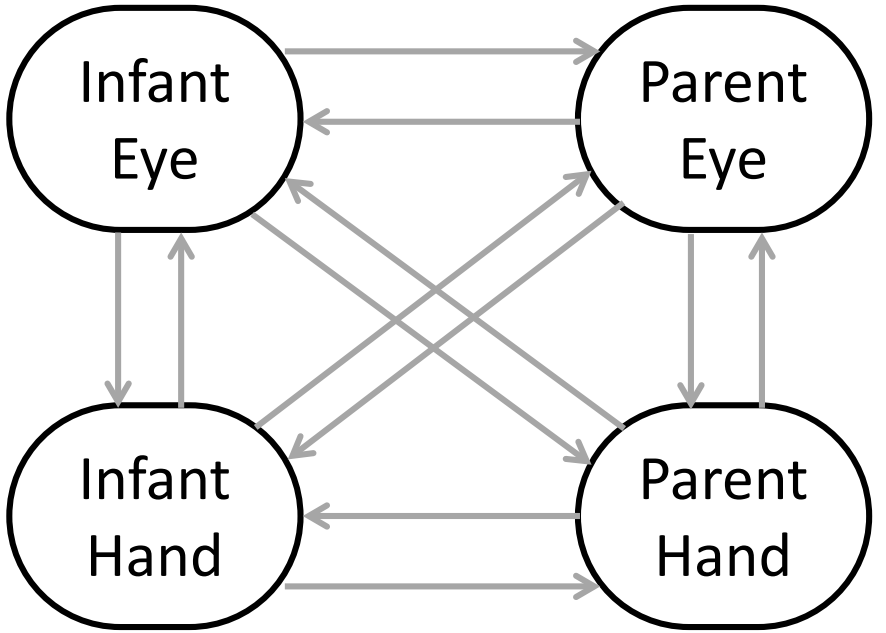
- Each arrow is one type of G-cause links.
- 12 types of directional influences in total.



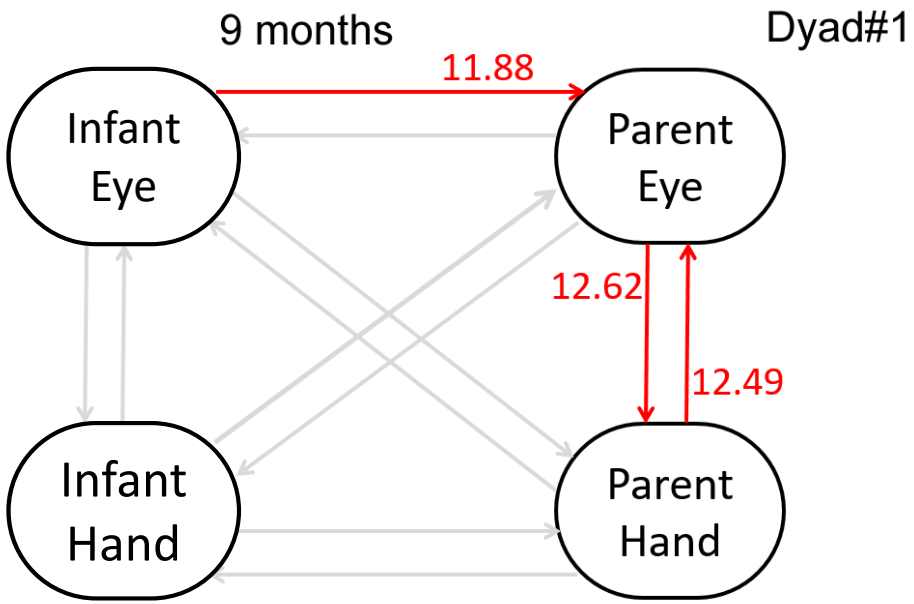
# Quantifying the Change in Coordination

- Each arrow is one type of G-cause links.
- 12 types of directional influences in total.

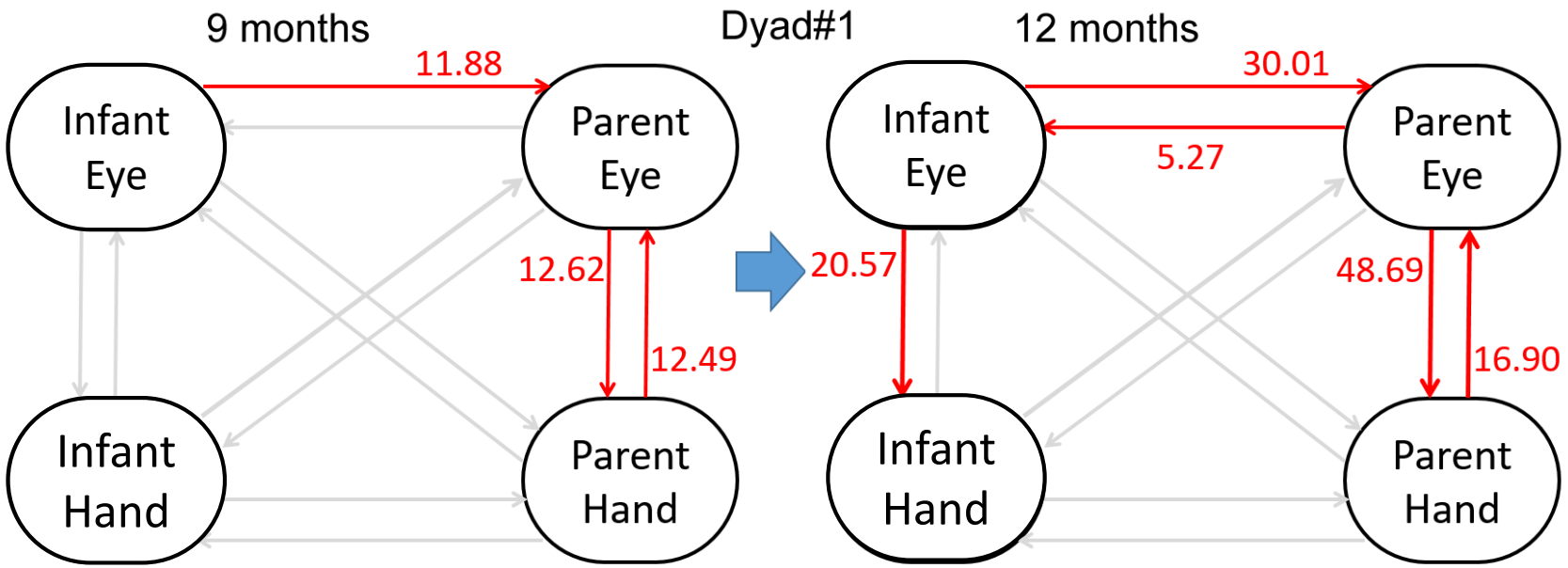
- Dataset:
  21 infant-parent dyads participated in toy play experiment when the infant was 9 and 12 month old



# Directional influences in Infant-Parent Interaction

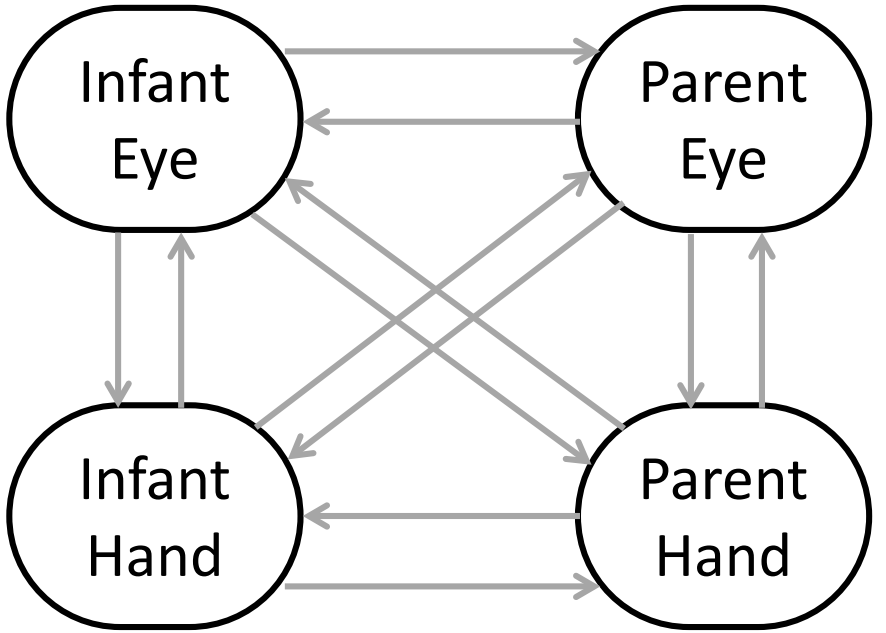


# Directional influences in Infant-Parent Interaction



# Main measures

- The number of significantly positive directional influences
- The strength of directional influences



# Quantitative Evidence for Theoretical Hypothesis

- "At the sensory-motor level, skilled interpersonal coordination, like many other skilled behaviors at the sensory-motor level, should be the product of a complex system, with multiple degrees of freedom." (Yu & Smith, 2016)

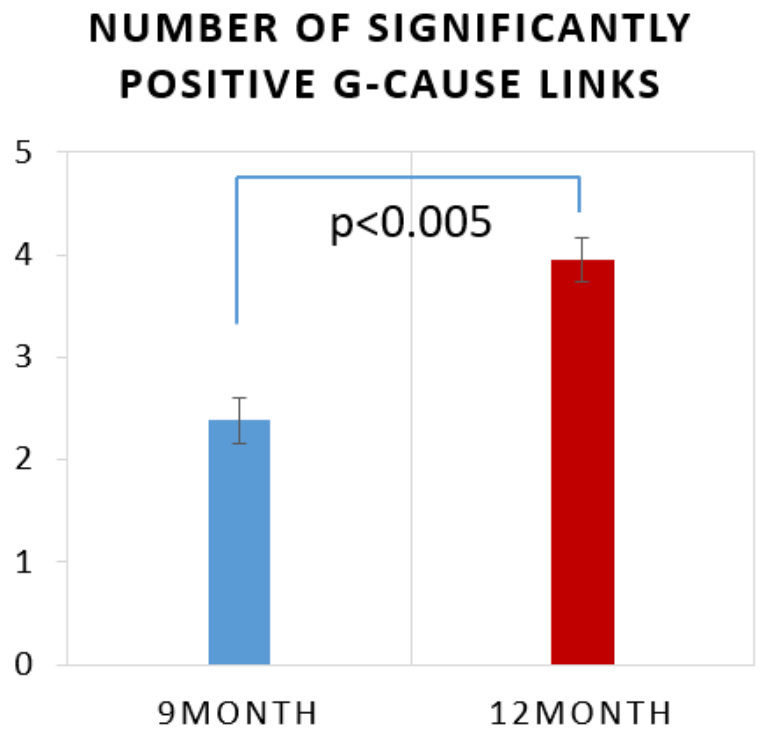
- Coordination in real-time: one task can be accomplished by many routes (Edelman, 1987), to afford adaptability in the face of intrinsic and extrinsic perturbations (Kello & Van Orden, 2009; Kugler & Turvey, 1987; Thelen & Smith, 1998)

# The Development of Infant-Parent Coordination

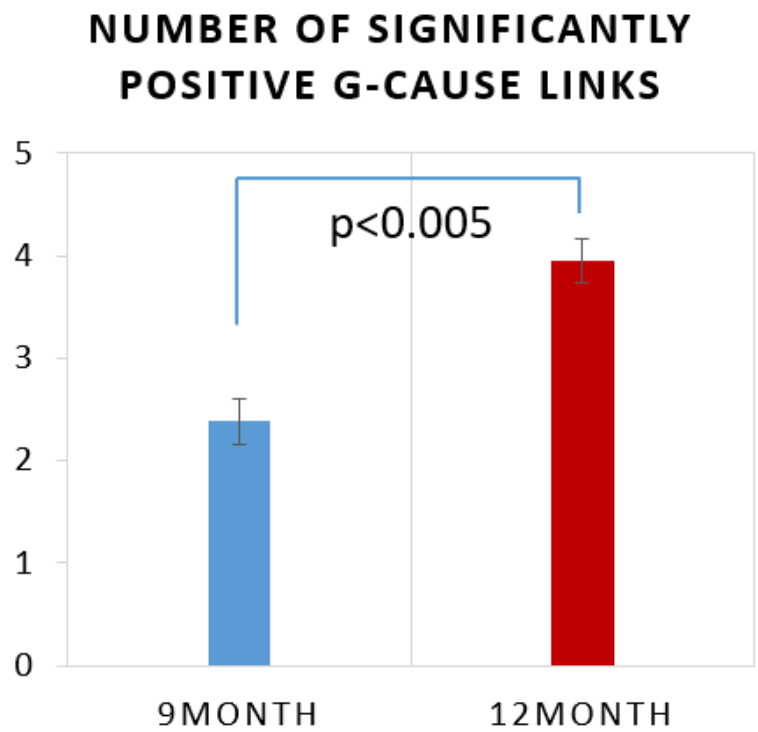
- The *development* hypothesis:

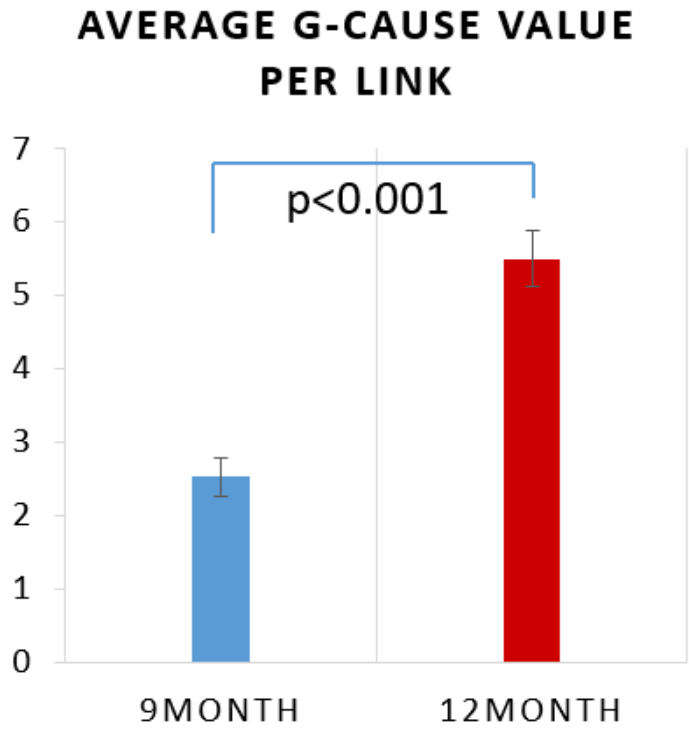
  - The number of significantly positive G-cause links.
  - The average G-cause value of significantly positive links.

  in the infant-parent coordination would **increase** from 9- to 12-months.




(Xu, Abney & Yu, 2017; Xu, Abney, Foster, Smith & Yu, in prep)




(Xu, Abney & Yu, 2017; Xu, Abney, Foster, Smith & Yu, in prep)

# The Development of Infant-Parent Coordination

- The development of infant-parent coordination includes adding redundancy to the social interaction by creating new pathways for coordination to occur.
  - more pathways - **more redundant** coordination
  - stronger influences - **more robust** coordination

(Xu, Abney & Yu, 2017; Yu & Smith, 2016; Edelman, 1987)

# Using Granger Causality to Quantify the Directional Influences among Multiple Time Series

- The causal variable occurs before the effect, and can help forecast the effect variable, beyond or incorporating all other variables' predictabilities.

- "Causality in the Wiener–Granger sense is based on the statistical predictability of one time series that derives from knowledge of one or more others." (Bressler & Seth, 2011)

# Using Granger Causality to Quantify the Directional Influences among Multiple Time Series

- Granger causality makes general assumption about the collected data, naturally accommodates **stochastic processes**, and thus are well suited to the ubiquitous variability that is found in behavioral time series data.

- It is an **exploratory method** that does not require a priori specification of a model.

# Outline

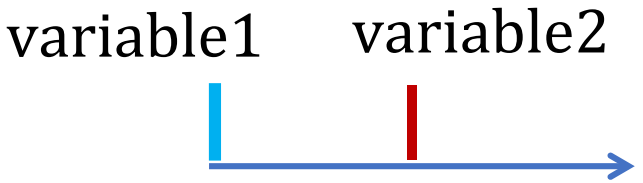
- What is Granger Causality?
- How to calculate it?
  - Using Granger Causality to quantify the directional influences in infant-parent coordinated behaviors (Xu, Abney & Yu, 2017)
- **Run Granger Causality on simulated data sets to understand Granger Causality measures**
  - What factors does this measurement reflect on?
  - What factors in temporal relations will influence the magnitude of G-causality?

https://github.com/lingerxu/granger_point_process

https://github.com/findstructureintime/ICIS2018

# Three factors in temporal relations

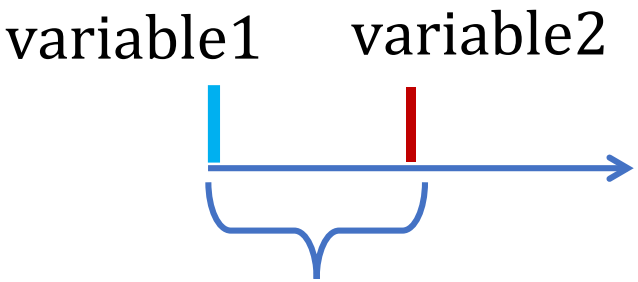
- The frequency of the temporal relationship
  - The higher the frequency, the higher Gcause value



# Three factors in temporal relations

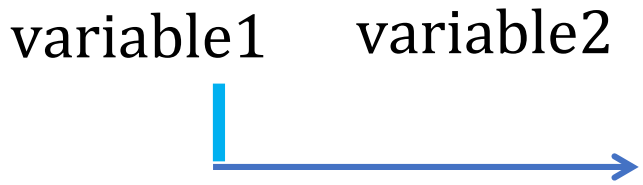
- The frequency of the temporal relationship
  - The higher the frequency, the higher Gcause value

- The response window between a leading event onset and a following event onset
  - The shorter the window, the higher Gcause value



# Three factors in temporal relations

- The frequency of the temporal relationship
  - The higher the frequency, the higher Gcause value
- The response window between a leading event onset and a following event onset
  - The shorter the window, the higher Gcause value
- The rate of successful temporal relationships – how likely an event's occurrence leads to another event's occurrence
  - The higher probability, the higher Gcause value



# Granger causality is not true causality

Granger's definition of causation is based on three assumptions: (Granger 1980)

(1) The past and the present may cause the future, but the future cannot cause the past.

(2) $\Omega_n$(all the knowledge available in the Universe on t)contains no redundant information, so that if some variable $Z_n$ is functionally related to one or more other variables, in a deterministic fashion, then $Z_n$ should be excluded from $\Omega_n$.

(3) All causal relationships remain constant in direction throughout time.

Maziarz, Mariusz. "A review of the Granger-causality fallacy." *The journal of philosophical economics: Reflections on economic and social issues* 8, no. 2 (2015): 86-105.

# Granger causality is not true causality

- Different behaviors operate on different time scales. Frequency does effect Granger Causality.
  - not frequent enough or too frequent sampling

- The system can be non-linear. The causal relations can be non-linear as well.
  - Convergent Cross-Mapping (CCM)

Sugihara, G., May, R., Ye, H., Hsieh, C. H., Deyle, E., Fogarty, M., & Munch, S. (2012). Detecting causality in complex ecosystems. science, 1227079.

# Thank you! Questions?

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