

Multivariate pattern analysis (MVPA) for fNIRS: Advancing from “Where in the brain?” to “What’s in the brain?”

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Do you want
to try the
hands-on
demo?

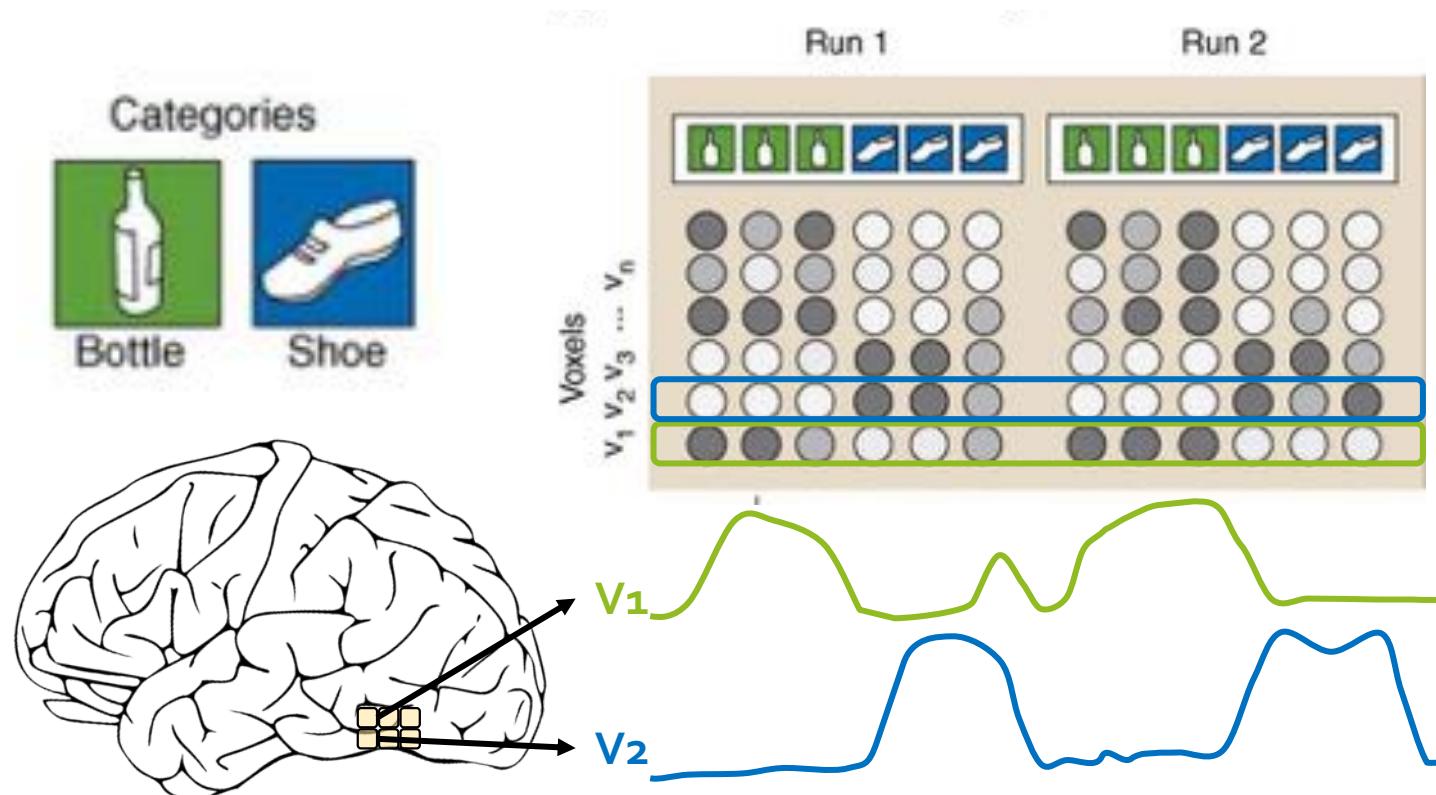
In about an hour, we'll walk through example code & data.

Download here:
<http://teammcpa.github.io/>

Each data set is 300-400 MB, so it'll take some time.
Now is a great time to start!

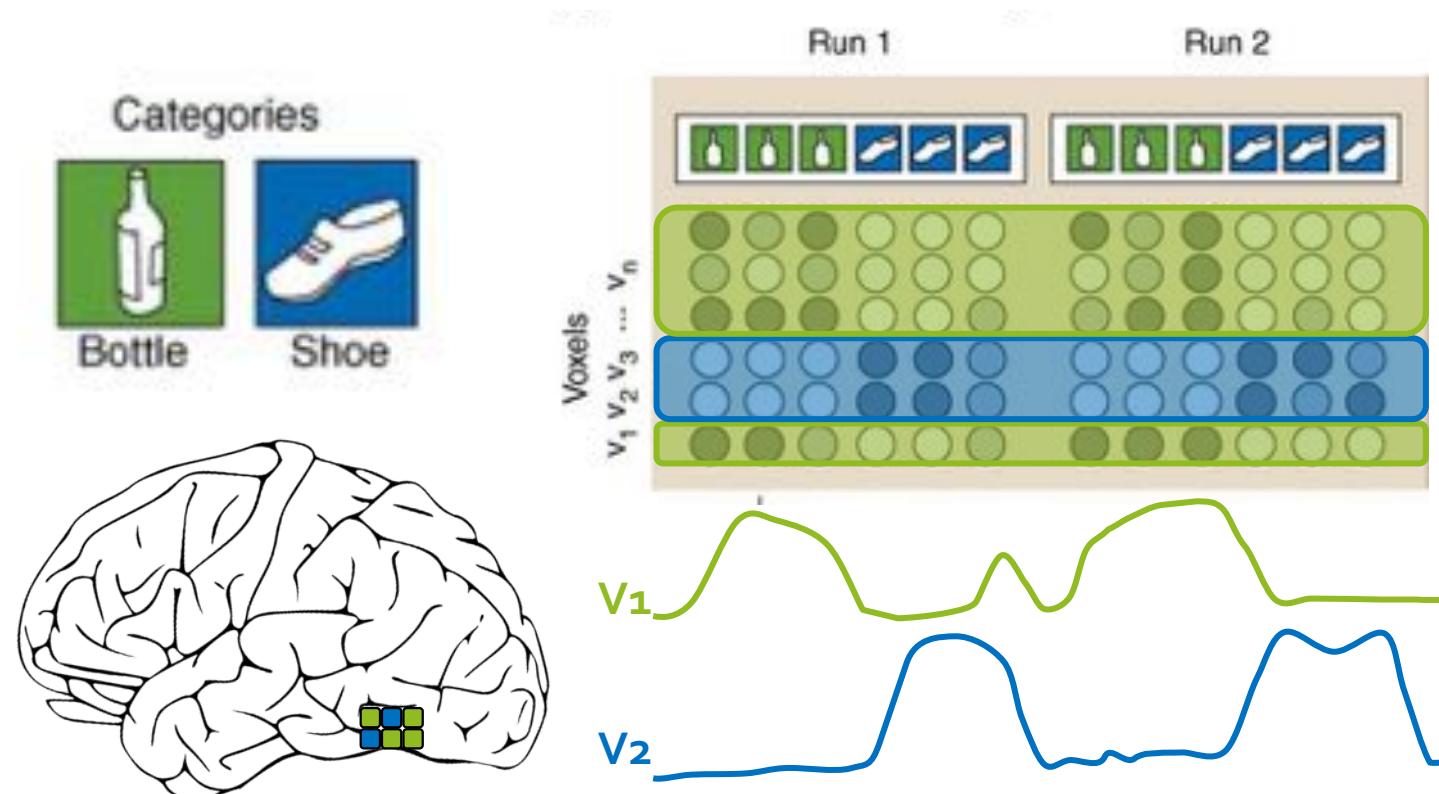
Univariate approach to neuroimaging

We are often interested in using functional neuroimaging to correlate a psychological process with neural responses



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Univariate approach to neuroimaging

Univariate analyses generally prioritize localization over content

“Is this voxel especially responsive to stimulus A?”

vs.

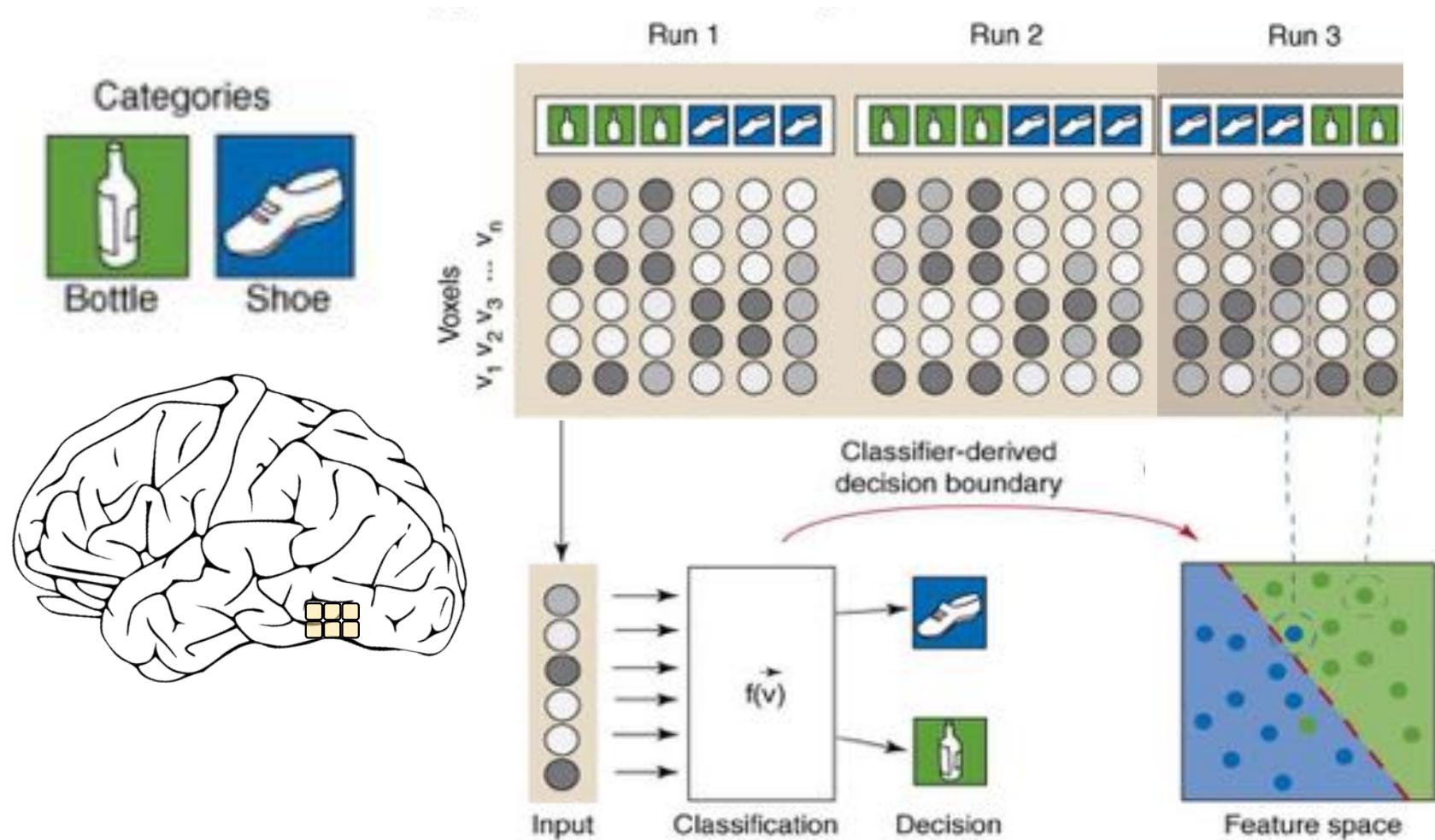
“What kind of information about A is encoded?”

The questions we can answer this way may be limited:

- **There are probably not many grandma voxels**
Mental representations exist in a high-dimensional space
- **Localizing some processes is like asking “Where is the economy?”**
Many cognitive processes are defined by activity across regions

Multivariate approach to neuroimaging

Multivariate pattern analyses **extract regularities** in distributed responses to make a **classification** decision



Univariate vs Multivariate approaches

Univariate approaches

- Average activity for each feature across events
- Look at responses in localized areas
- Natively low-dimensional
- Lower computational load

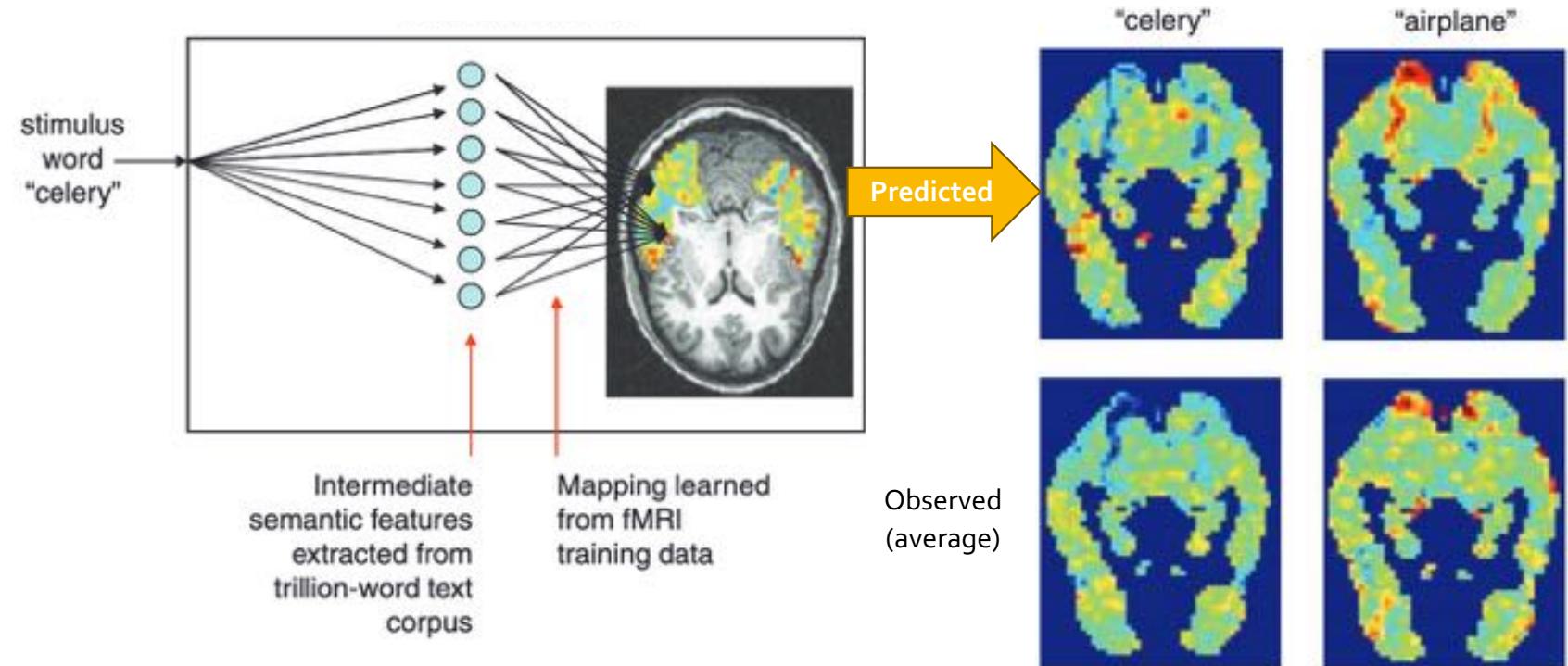
Multivariate approaches

- Pattern of activity over features within each event
- Look at distributed patterns of responses
- Natively high-dimensional
- Higher computational load

Multivariate decoding with fMRI

MVPA enables predictions about new, unseen stimuli

1. Observe BOLD activity elicited by concrete nouns
2. Estimate a regression model for each voxel based on the noun's features
3. Predict BOLD activity for a new noun based on its features



MVPA with fNIRS

fNIRS measures the same physiological response as fMRI

But MVPA with fNIRS involves several new challenges

- The absence of an anatomical image
- Lower spatial resolution
- Smaller number of features (channels)
- Less coverage of the head
- Only samples from the surface of the cortex

Example 1: Audiovisual classification with adults

Example 1

Neurophotonics

Neurophotonics.SPIEDigitalLibrary.org

Decoding semantic representations from functional near-infrared spectroscopy signals

Benjamin D. Zinszer
Laurie Bayet
Lauren L. Emberson
Rajeev D. S. Raizada
Richard N. Aslin

Benjamin D. Zinszer, Laurie Bayet, Lauren L. Emberson, Rajeev D. S. Raizada, Richard N. Aslin,
"Decoding semantic representations from functional near-infrared spectroscopy signals,"
Neurophotonics, 5(1), 011003 (2017), doi: 10.1117/1.NPH.5.1.011003.

Classification of objects in adults with fNIRS



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SPIE

Classification of objects in adults with fNIRS



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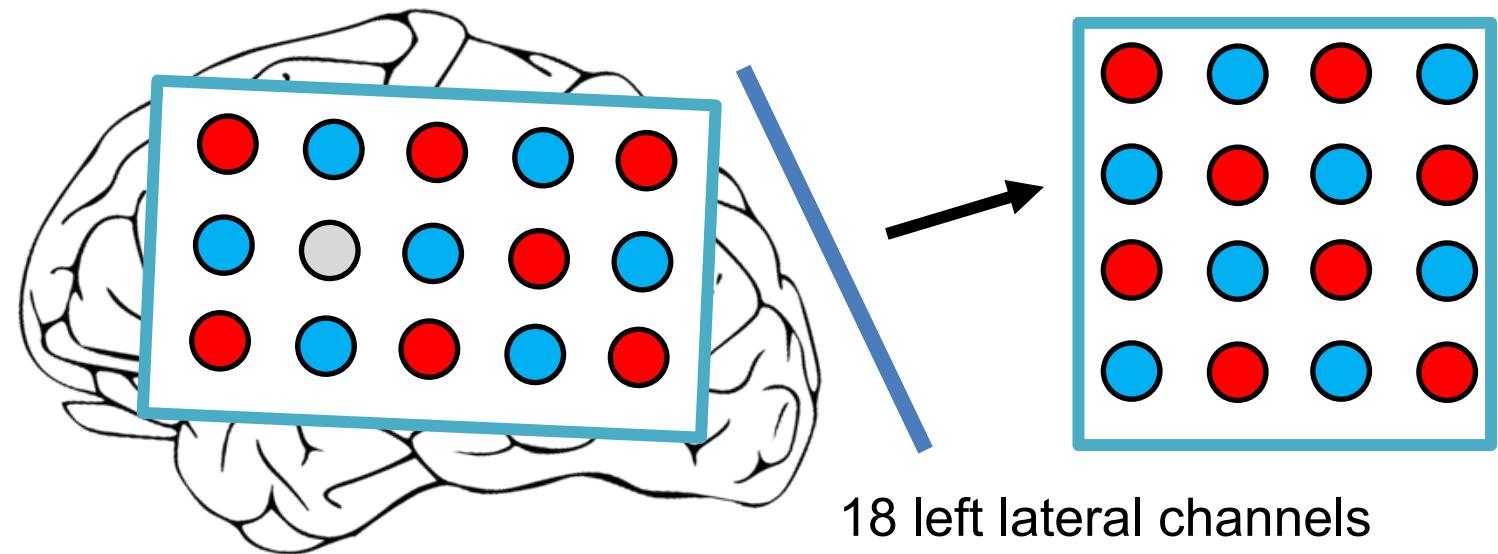
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Classification of objects in adults with fNIRS



18 left lateral channels
24 posterior channels

Zinszer, Bayet, Emberson, Raizada & Aslin (2018)

Github: teammcpa.github.io

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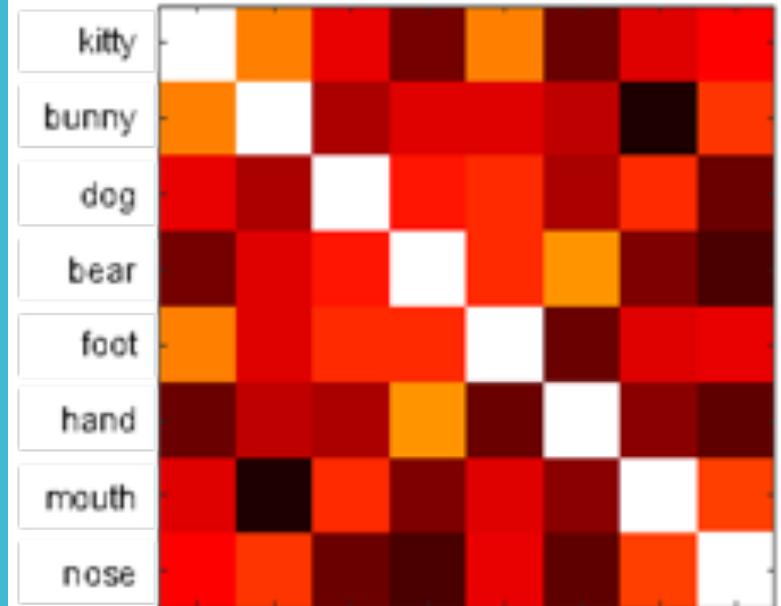
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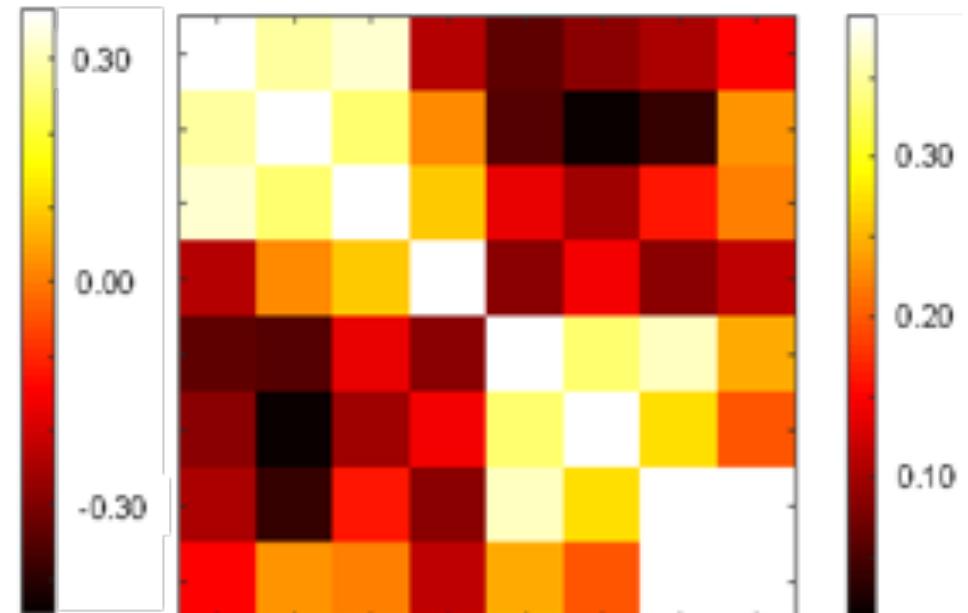
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Classification of objects in adults with fNIRS

Correlational structure of **fNIRS** data



COMPOSES model of word meanings



GloVe model works great for this too!

Zinszer, Bayet, Emberson, Raizada & Aslin (2018)

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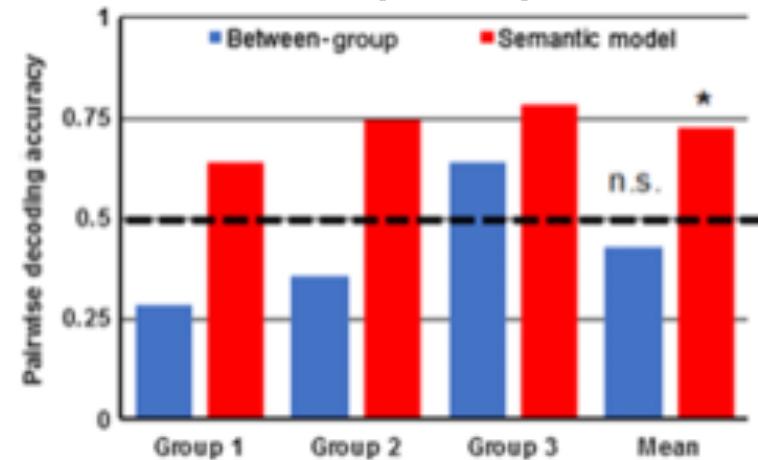
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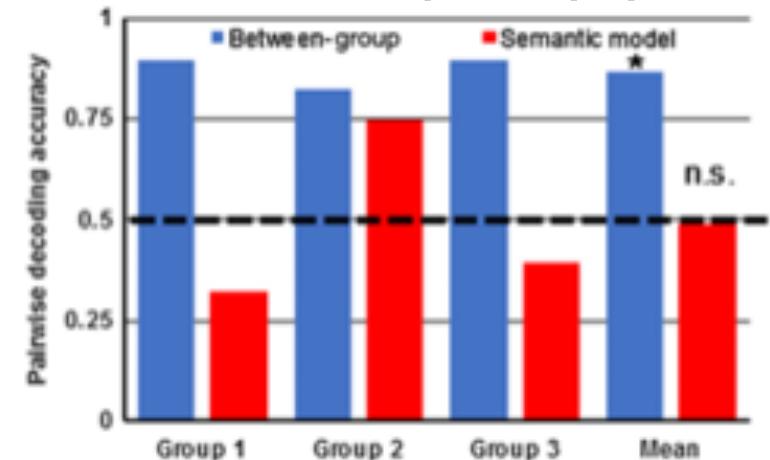
Classification of objects in adults with fNIRS

We answer both "what" and "where" for these objects.

Posterior array (occipital lobe)



Left lateral array (temp+par lobes)



Zinszer, Bayet, Emberson, Raizada & Aslin (2018)

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Design Summary Example 1

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| Design/Analysis Parameter | Value |
|---------------------------|--|
| Task | |
| block vs. event design | Event-related design (3 s dur, 6-9s ISI) |
| # of runs or repetitions | 12 runs through the stimulus set |
| # of days or sessions | 1 session |
| Participants | |
| # trials / participant | 96 trials per participant |
| # participants | N=8 per group, 3 groups |
| Array Coverage | |
| # of channels | 42 |
| regions sampled | occipital, lateral parietal & temporal |
| Analysis choices | |
| hemoglobin (oxy/deoxy) | oxygenated |
| co-register to anatomy | based on 10-20 references |

Part 2: Planning and performing MVPA experiments in fNIRS

Experimental design for an MVPA study

Much like univariate designs, we have a few decisions to make:

Task:

Should stimuli be presented in blocks or as individual events?

How many runs can I complete in a session?

How many sessions should (could) participants attend?

Power:

How many trials per participant?

How many participants?

This is a tough technical problem.

Previous studies typically give an underestimate of the sample that you'll need.

Look at previous work and double it! or more...

Array:

How much scalp coverage do I need (& can have)?

Where should I place the array(s)?

Predictors of success in infant fNIRS

Baek, S., Marques, S., Casey, K., Testerman, M., McGill, F., & Emberson, L. Attrition rate in infant fNIRS research: a meta-analysis. *Infancy*. (in press) [BioRxiv](#).

| Study parameter | Mean values | Effect | % variance |
|--|----------------------|--|------------|
| Design | | | |
| Blocks vs. events | 45% block, 55% event | event → +att | 4% |
| # of channels | >20 on average | +ch → +att | 6% |
| Participants | | | |
| Age of child vs. Infant-related attrition | 5 months | +age → +att | 5% |
| Age of child vs. Signal-related attrition | 5 months | +age → -att (12% if excl. newborns) | 6% |

Note: “att” stands for attrition, or children removed from the dataset either during data collection (infant-related attrition) or data analysis (signal-related attrition). Effects are described as +/- indicating an increase or decrease in the study parameter or in attrition rate.

Example 2: Audiovisual classification with infants

Example 2



RESEARCH ARTICLE Decoding the infant mind: Multivariate pattern analysis (MVPA) using fNIRS

Lauren L. Emberson^{1,2,✉}, Benjamin D. Zinszer^{2,3*}, Rajev D. S. Raizada^{2,3}, Richard N. Aslin^{2,3}

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* These authors contributed equally to this work.
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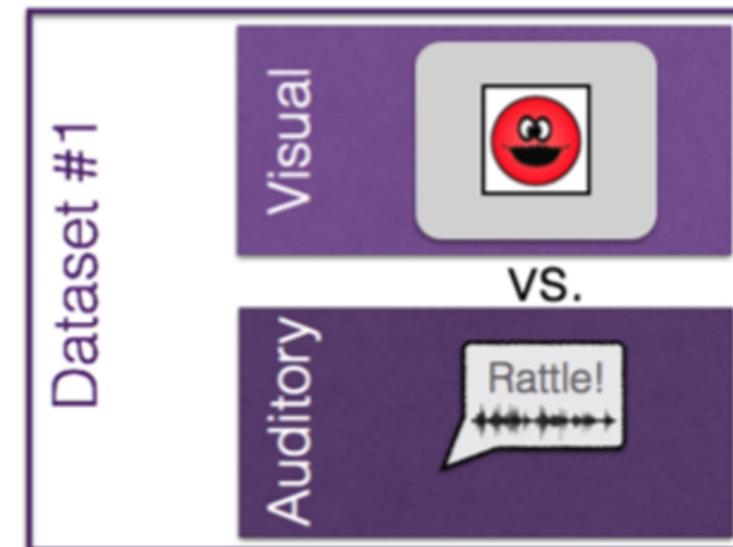
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Does MVPA using fNIRS work with infants?

Archival data from 6 m.o. infants
in two passive viewing studies



Emberson, Zinszer, Raizada, & Aslin (2017)

Github: [teammcpa.github.io](https://github.com/teammcpa)

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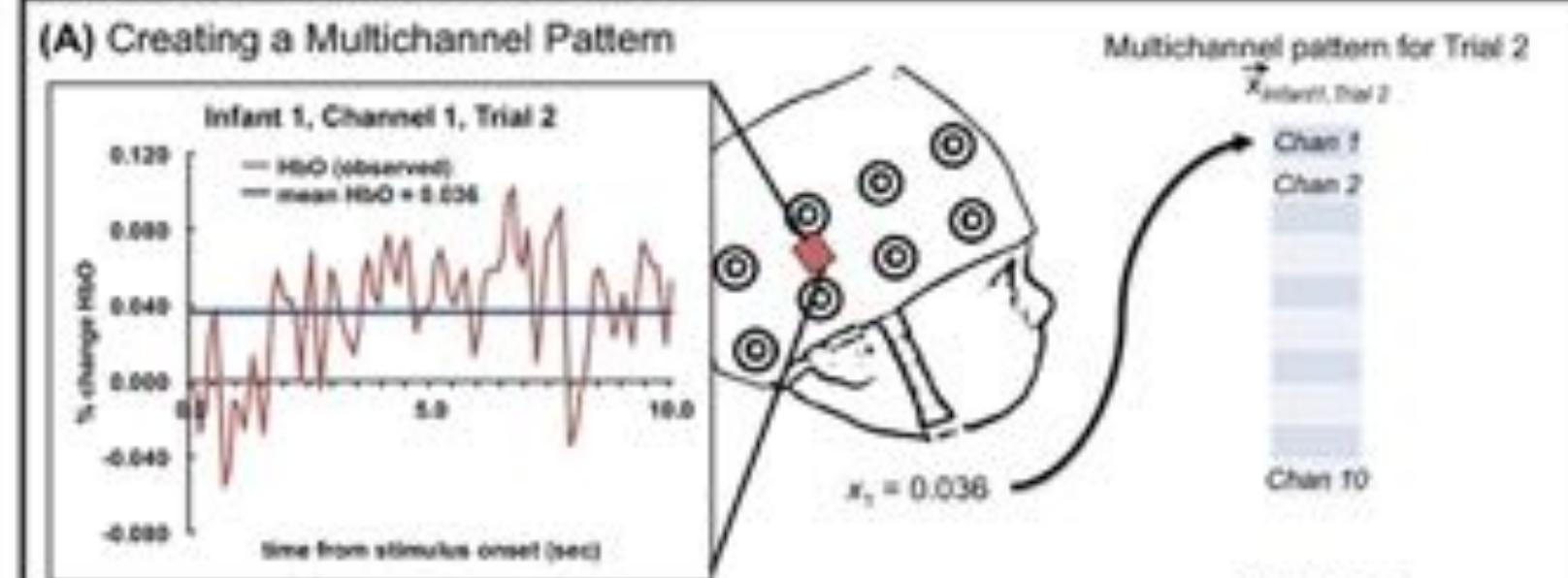
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$$x_{chan} = \frac{1}{t} \sum_{i=1}^t (HbO_{chan,i} - HbO_{chan,1})$$

$$\vec{x} = [x_1, x_2, \dots, x_n]$$

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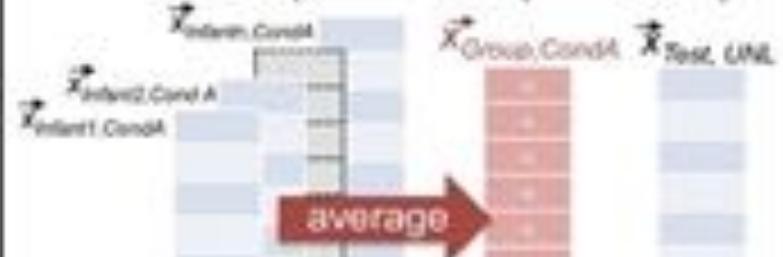
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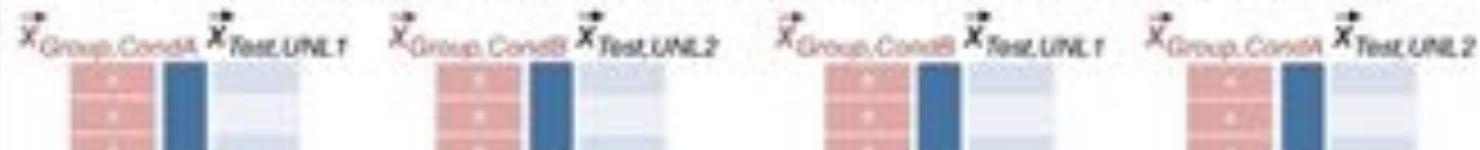
(B) Leave One Infant Out to Create Group Model

Group Model_{CondA} = Average of infant-level patterns
Condition A except the test infant (to be decoded)



(D) Infant-Level Decoding

The test infant's infant-level patterns are correlated with each permutation of the Group Model.



$$\tanh^{-1}(\text{corr}(x_{\text{Group}, \text{CondA}}, x_{\text{Test}, \text{Unl1}})) + \tanh^{-1}(\text{corr}(x_{\text{Group}, \text{CondB}}, x_{\text{Test}, \text{Unl2}}))$$

&

$$\tanh^{-1}(\text{corr}(x_{\text{Group}, \text{CondB}}, x_{\text{Test}, \text{Unl1}})) + \tanh^{-1}(\text{corr}(x_{\text{Group}, \text{CondA}}, x_{\text{Test}, \text{Unl2}}))$$

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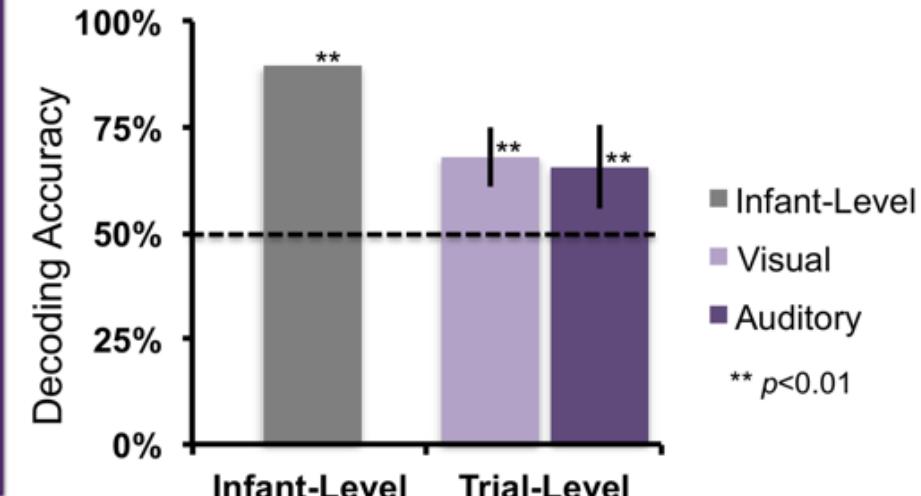
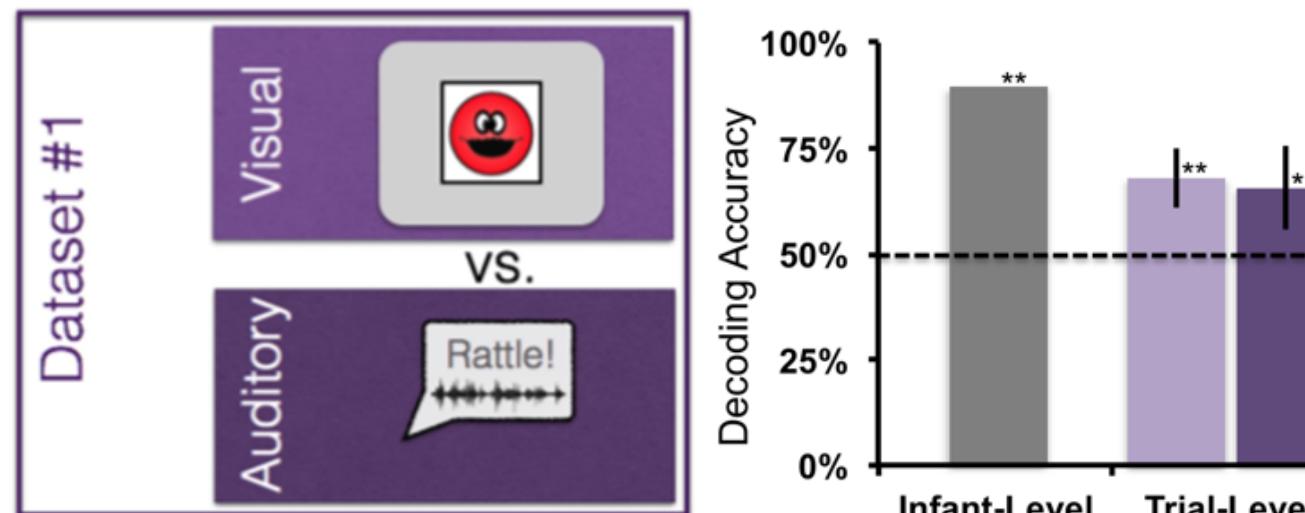
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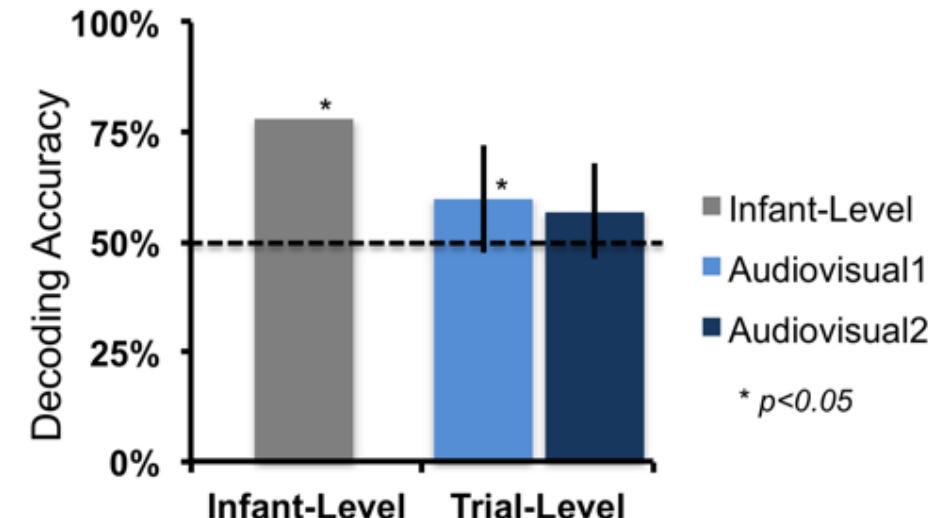
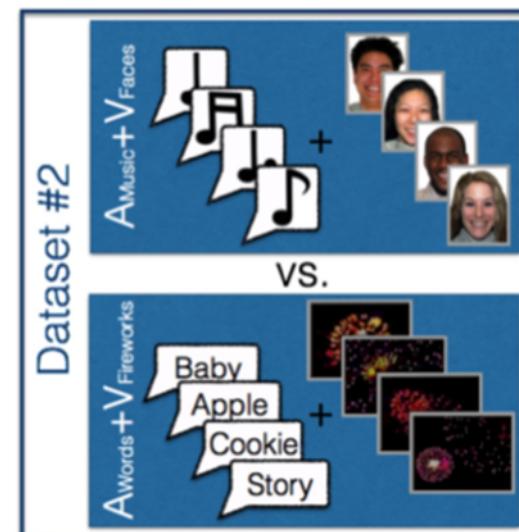
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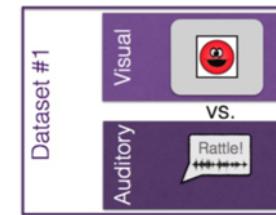
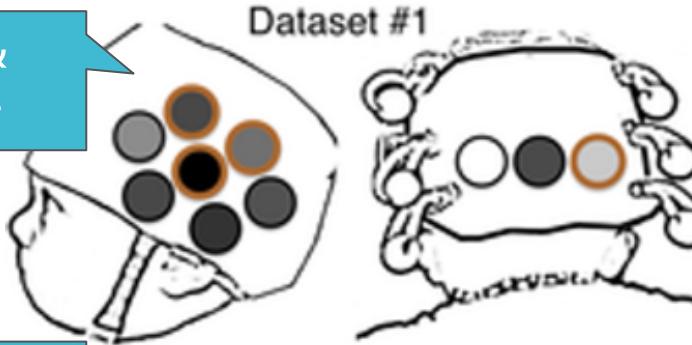
Introduction

The goal of cognitive neuroscience is to use the relationship between activity in the brain and cognitive operations to understand how the mind works. In the last two decades, the use of fMRI has vastly expanded our window on the neural correlates of human cognition. Initially, fMRI analyses predominantly facilitated brain mapping. Experiments could tell us where in the brain clusters of voxels show differential BOLD signals in two or more stimulus conditions. With the addition of multivariate analysis techniques (e.g., multivoxel pattern analysis, MVPA), more sophisticated questions can be asked, such as whether the pattern of BOLD-discriminate between two or more stimulus conditions. Multivariate analyses are an important advance

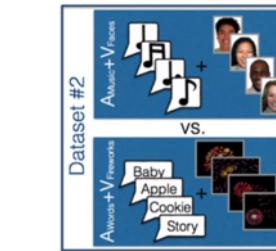
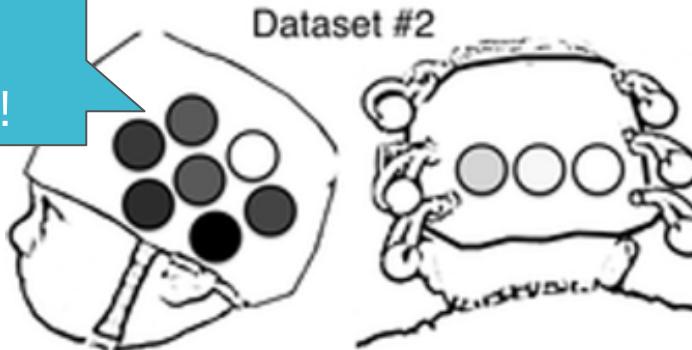
Does MVPA using fNIRS work with infants?

Which channels contribute the most to accurate predictions about stimuli?

Univariate &
MVPA differ



No significant
univariate
results at all!



Emberson, Zinszer, Raizada, & Aslin (2017)

Github: [teammcpa.github.io](https://github.com/teammcpa)

Multivariate vs. Univariate fNIRS

In Example 2 (Emberson et al., 2017, PLoS):

- MVPA and univariate analyses identify **different sets of channels** for an auditory-vs-visual contrast
- Between two classes of audiovisual stimuli, **only MVPA identified channels** contributing to significant classification (there were no univariate results)

The differences between multivariate and univariate analyses of infant fNIRS data are also supported by **systematic comparison** in a *Neuroimage Registered Report* ([Filippetti et al., 2022](#))

↑ It's a great paper that describes many analytic decisions and their rationale! ↑

Registered Report

Are advanced methods necessary to improve infant fNIRS data analysis? An assessment of baseline-corrected averaging, general linear model (GLM) and multivariate pattern analysis (MVPA) based approaches

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^c Simbad2, Dept. of Computer Science, University of Jaén, Jaén, Spain

Design Summary Example 2



RESEARCH ARTICLE

Decoding the infant mind: Multivariate pattern analysis (MVPA) using fNIRS

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Abstract

The MRI environment restricts the types of populations and tasks that can be studied by cognitive neuroscientists (e.g., young infants, face-to-face communication). fNIRS is a neuroimaging modality that records the same physiological signal as fMRI but without the constraints of MRI, and with better spatial localization than EEG. However, research in the fNIRS community largely lacks the analytic sophistication of analogous fMRI work, restricting the application of this imaging technology. The current paper presents a method of multivariate pattern analysis for fNIRS that allows the authors to decode the infant mind (a key fNIRS population). Specifically, multivariate pattern analysis (MVPA) employs a correlation-based decoding method where a group model is constructed for all infants except one; both average patterns (i.e., infant-level) and single trial patterns (i.e., trial-level) of activation are decoded. Between subjects decoding is a particularly difficult task, because each infant has their own somewhat idiosyncratic patterns of neural activation. The fact that our method succeeds at across-subject decoding demonstrates the presence of group-level multi-channel regularities across infants. The code for implementing these analyses has been made readily available online to facilitate the quick adoption of this method to advance the methodological tools available to the fNIRS researcher.



OPEN ACCESS

Citation: Emerson LL, Zinszer BD, Raizada RD, Aslin RN (2017) Decoding the infant mind: Multivariate pattern analysis (MVPA) using fNIRS. PLoS ONE 12(4): e0172500. <https://doi.org/10.1371/journal.pone.0172500>

Editor: Sullivan Ben Hamet, Centre de neurosciences cognitives, FRANCE

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Data Availability Statement: The analysis code is available from GitHub (https://github.com/laurenemerson/DecodingfNIRS_MVPA_analyseFNPaper). Datasets #1 and #2 are available from Princeton data repository (<https://arXiv.princeton.edu/abs/1604.08425v1>).

Funding: This work was funded by the National Institutes of Health, Child Health and Development (NICHD), Grant K08 HD061866-01A1, 4R00NS050116-02, the Canadian Institute of Health Research (CIHR) postdoctoral fellowship 201210MRS-290131-221192 to L.L.E.; and the

| Design/Analysis Parameter | Value |
|---------------------------|---|
| Task | |
| block vs. event design | Exp 1: Event-related (A vs. V) Exp 2: Block (AV1 vs AV2) |
| # of runs or repetitions | Exp 1: 7 trials / category Exp 2: 5 blocks / category |
| # of days or sessions | 1 session |
| Participants | |
| # trials / participant | Exp 1: 14 trials Exp 2: 10 blocks |
| # participants | Exp 1: 19 infants, ~6 m.o. Exp 2: 18 infants, ~6 m.o. |
| Array Coverage | |
| # of channels | 10 |
| regions sampled | occipital, lateral parietal & temporal |
| Analysis choices | |
| hemoglobin (oxy/deoxy) | oxygenated |
| co-register to anatomy | no |

Experimental design for an MVPA study

Much like univariate designs, we have a few decisions to make:

Task:

Should stimuli be presented in blocks or as individual events?

How many runs can I complete in a session?

How many sessions should (could) participants attend?

Power:

How many trials per participant?

How many participants?

Array:

How much scalp coverage do I need (& can have)?

Where should I place the array(s)?

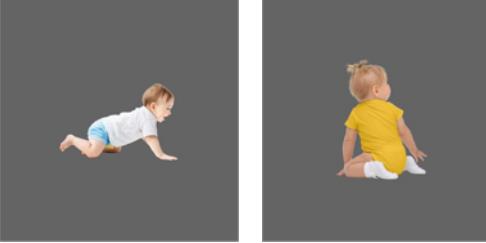
Example 3: A systematic study of infant and adult classification accuracy

Princeton-Yale Consortium for developing MVPA in fNIRS, in progress

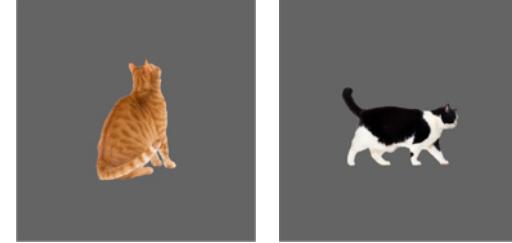
Experimental design for an MVPA study

(Example 3)

Baby



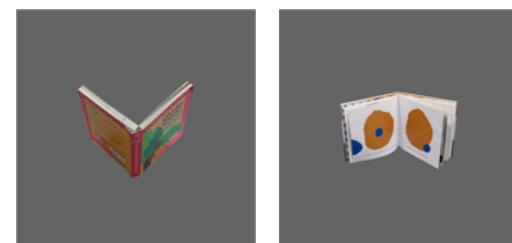
Cat



Bottle



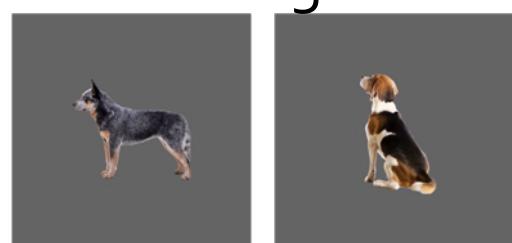
Book



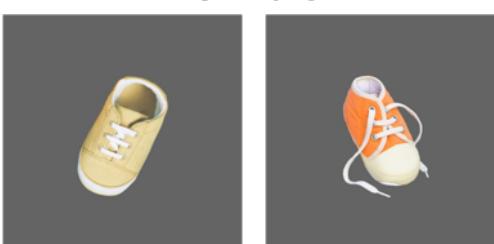
Hand



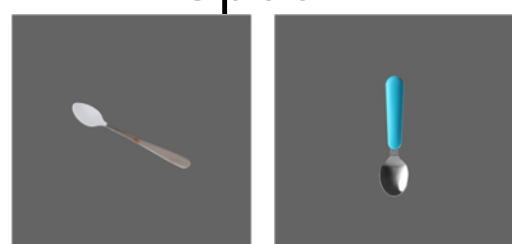
Dog



Shoe



Spoon

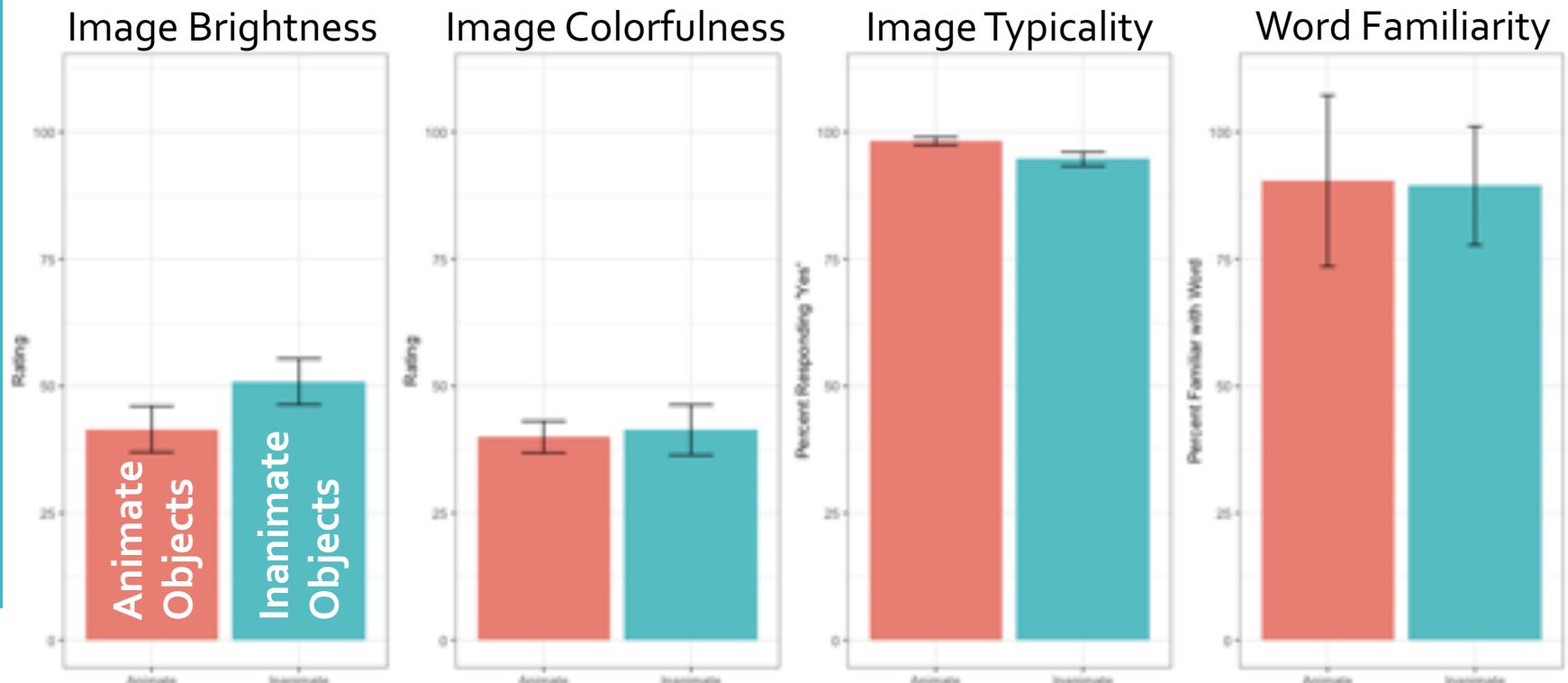


Experimental design for an MVPA study

(Example 1)

Problem: Classifiers are smart, but not wise!
Incidental differences between stimuli can be latched onto and used to improve performance, even if they're irrelevant to your goals.

Solution: Balance low- & high-level features across stimuli



Experimental design for an MVPA study

(Example 1)

Event-related design: Test of generalization (ex: Shoe 1 → Shoe 2)

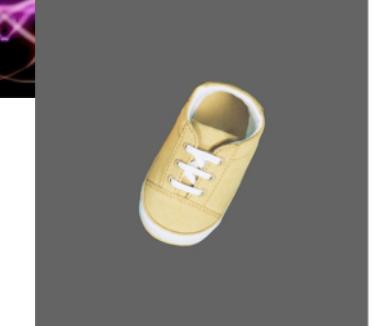
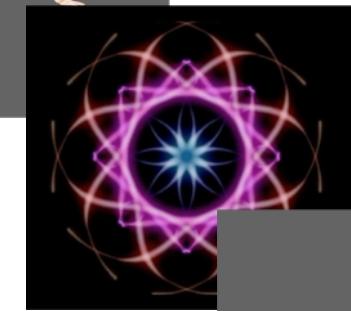
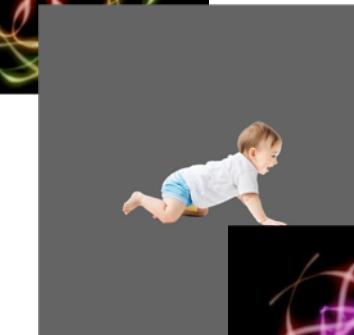
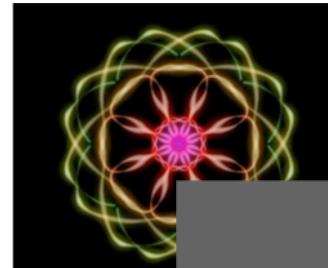
- requires being able to separate stimuli into specific exemplars
- blocking different stimuli together would aggregate their responses instead of testing generalizability between example images

Passive viewing

Stimuli presented on a monitor while child is seated on a parent's lap (or adult on chair)

4.5 sec exposure to looming stimulus image

5-9 sec exposure to interstimulus video



Experimental design for an MVPA study

Array Design

Some things are a bit different from univariate designs:

Remember looking for a wider field of view:

- channels that reliably *do* respond **and**
- channels that reliably *don't* respond

Does the variability within this region reflect my stimulus classes?

You may be using long sessions or many sessions:

- Is this array still tolerable after 30 or 40 minutes? (for adults)
- Which channels are dropping out due to movement or sweat?
- Will it be easy to place this array in the same location twice?

Experimental design for an MVPA study

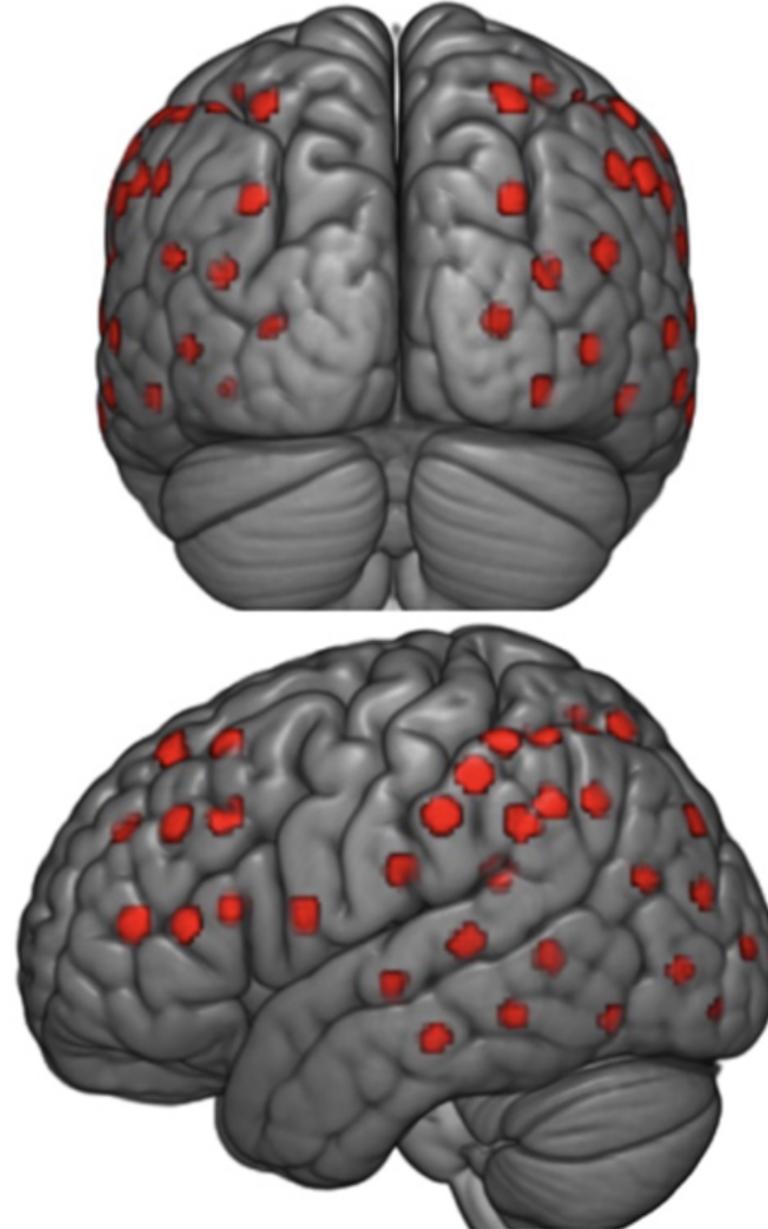
(Example 3)

What we knew we had

- 70 channels in infant cap
- sampling at 13.3 Hz
- anatomical co-registration

What we wanted

- Bilateral distribution
- Some visual cortex coverage (but density not as important!)
- Coverage of regions closely tied to word representation and production: lateral frontal, posterior temporal, inferior parietal



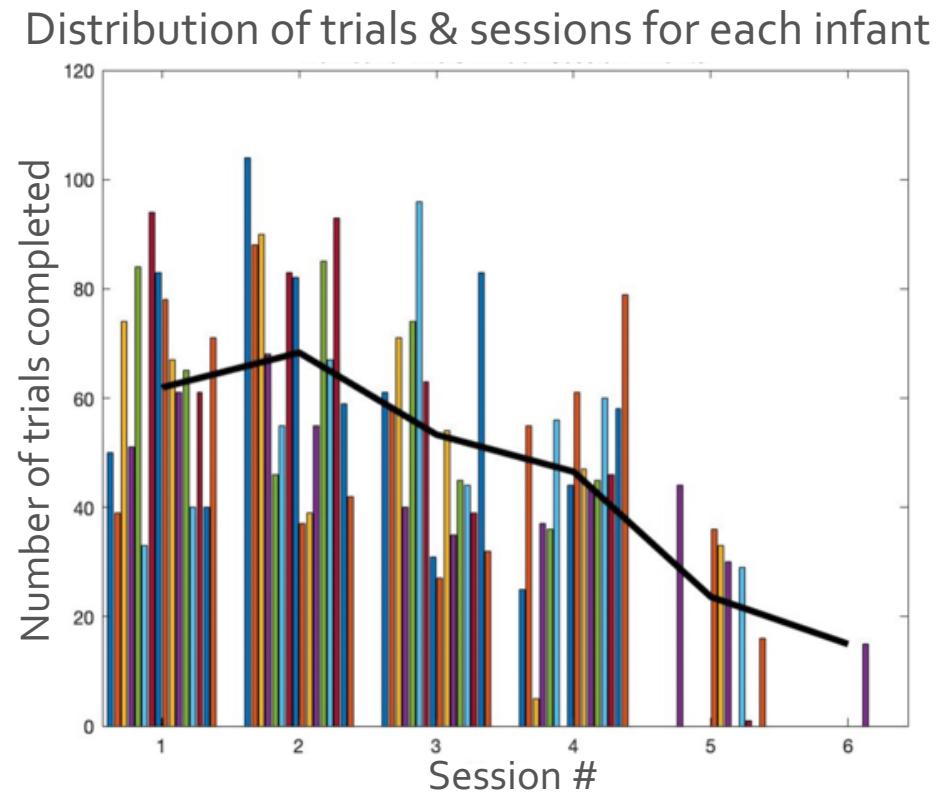
Experimental design for an MVPA study

Trials & Sessions

Problem: You often need *a lot more* repetitions of a condition than you're likely to have time for in a single session.

How can we maximize participant-level data?

- Estimated 15 repetitions needed per image (240 trials)
 - How many trials will infants complete in one visit?
average ~60 trials / visit
 - How many visits needed?
most children finished in 4



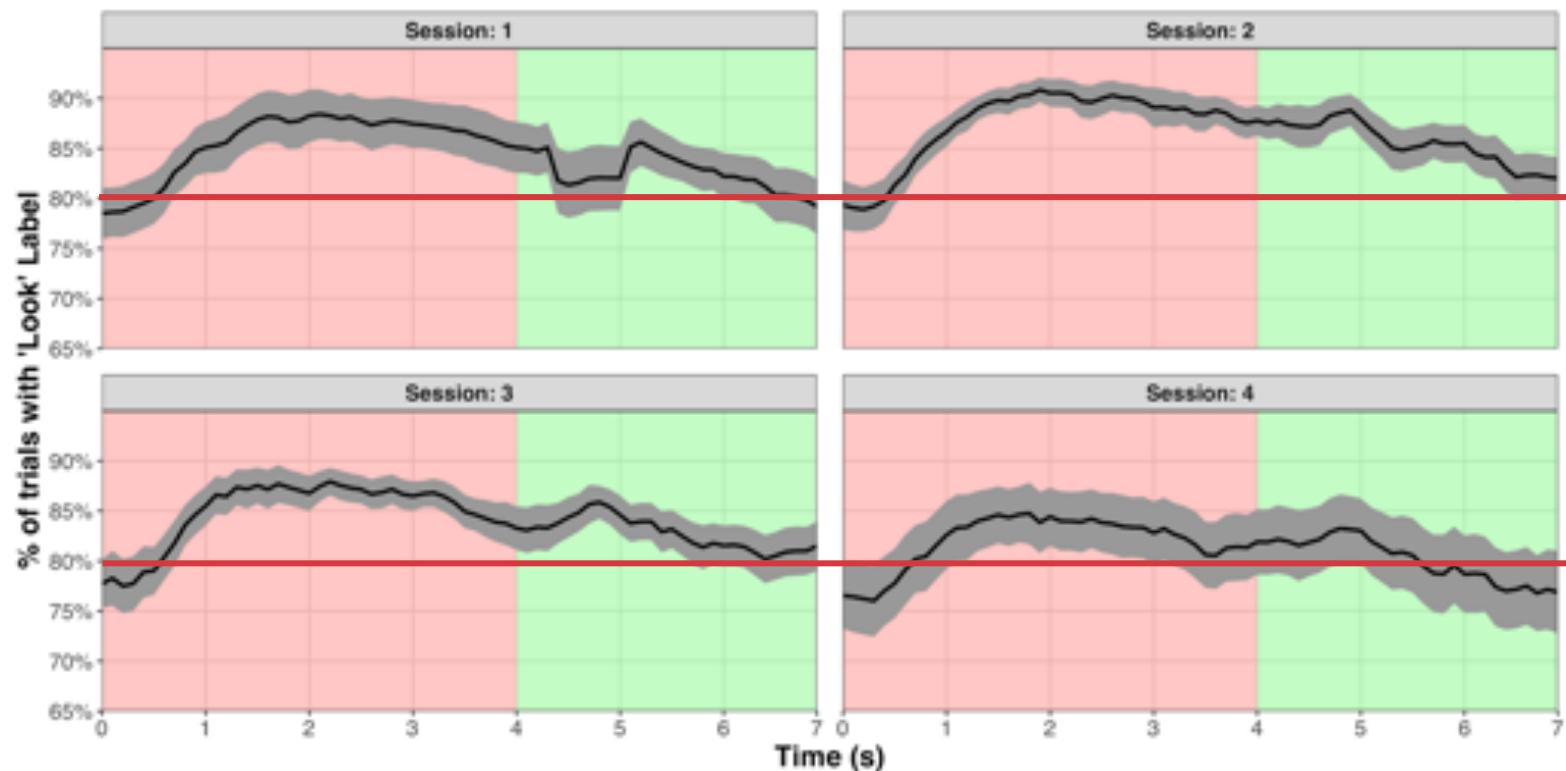
Experimental design for an MVPA study

Trials & Sessions

Problem: You often need *a lot more* repetitions of a condition than you're likely to have time for in a single session.

How can we maximize participant-level data?

In each session, attention to stimuli sustained in over $>80\%$ trials



Creating multivariate patterns

Time window

What is the relevant time window for looking at data?

Take advantage of optimization in previous studies:

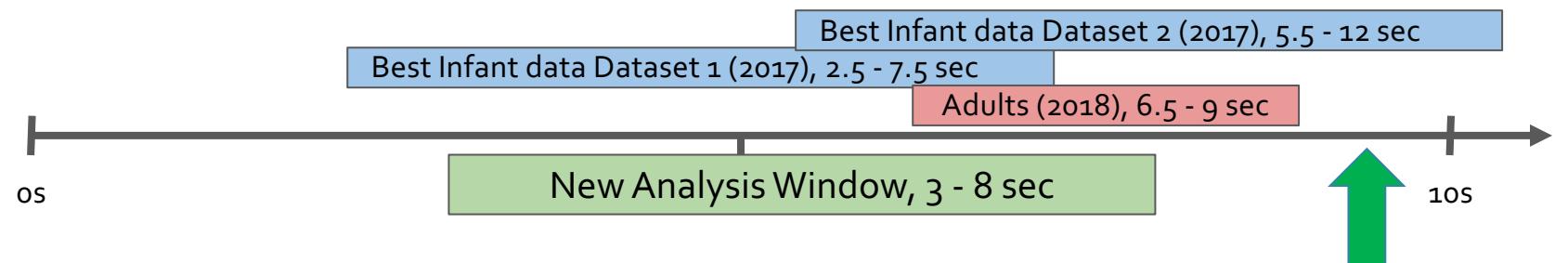
Previous infant MVPA (Emberson et al., 2017):

windows beginning 3-6 sec after stim onset (Dataset #1)

windows 5-6.5 sec in length (Dataset #2)

Previous adult MVPA (Zinszer et al., 2018):

window 6.5-9 sec after stim onset



In a study comparing both adults and infants, we wanted to:

- maximize coverage of both age groups' time windows
- minimize overlap with the next stimulus (SOA 9.5-13.5 sec)

Onset of next stimulus image

Creating multivariate patterns

How you describe your data as a multivariate pattern is one of the most difficult decisions because there are so many options

A good place to start is by balancing:

- **Purpose:** Do I want to test a hypothesis or optimize performance?
- **Transparency:** Can I still say something meaningful about the patterns?
- **Detail:** Have I coaxed every last bit of information out of my data?

Creating multivariate patterns

How you describe your data as a multivariate pattern is one of the most difficult decisions because there are so many options

A good place to start is by balancing: **Just for today**

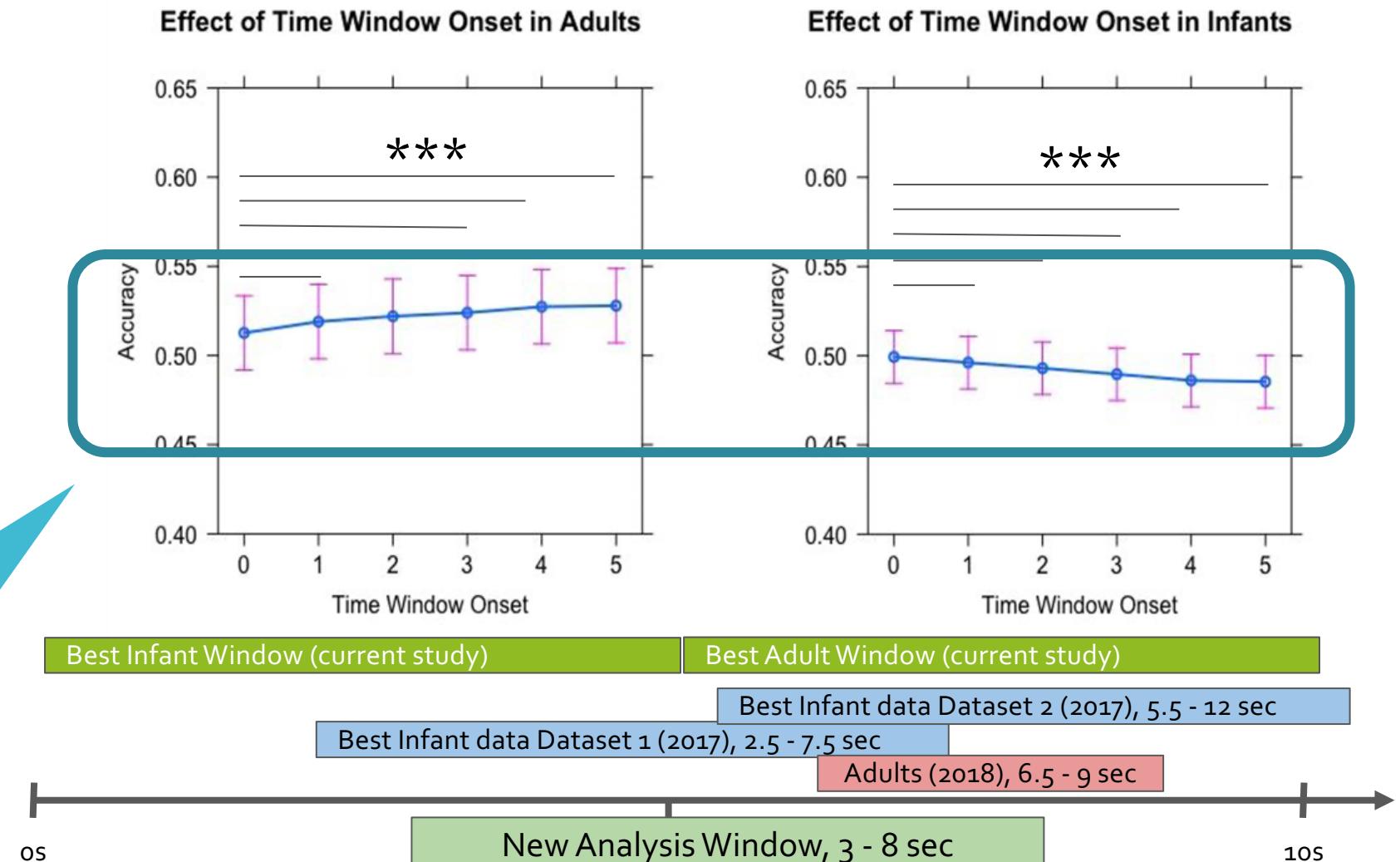
- **Purpose:** Do I want to test a hypothesis or **optimize performance?**
- **Transparency:** Can I still ~~say something meaningful about the patterns?~~
- **Detail:** Have I coaxed **every last bit of information** out of my data?

What is the relevant time window for looking at data?

Analyzing multivariate patterns

These are *tiny* average differences in accuracy.

Estimated across hundreds of parameter combinations, so even tiny nudges help!

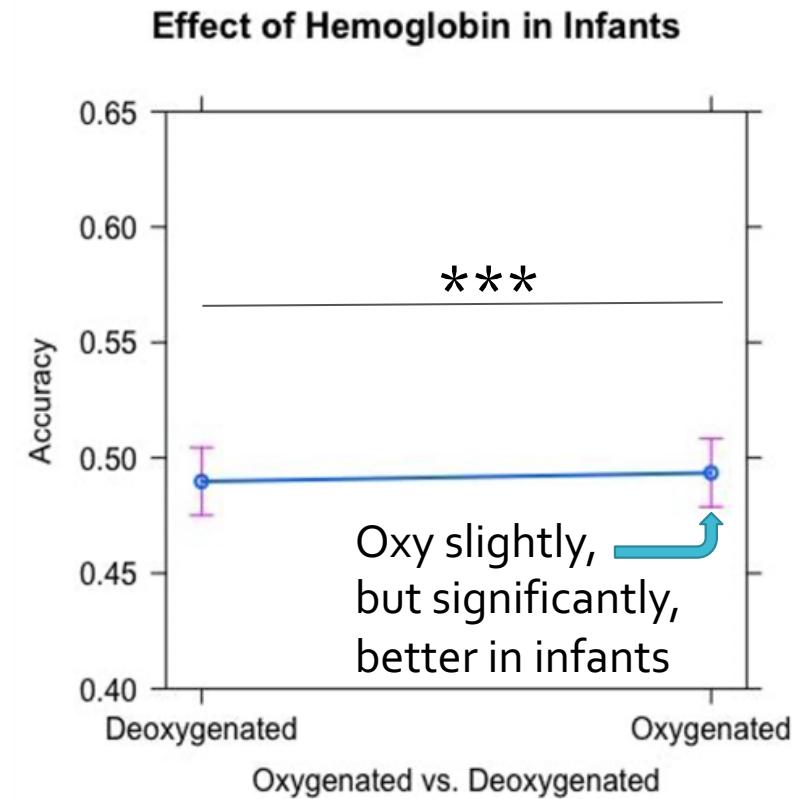
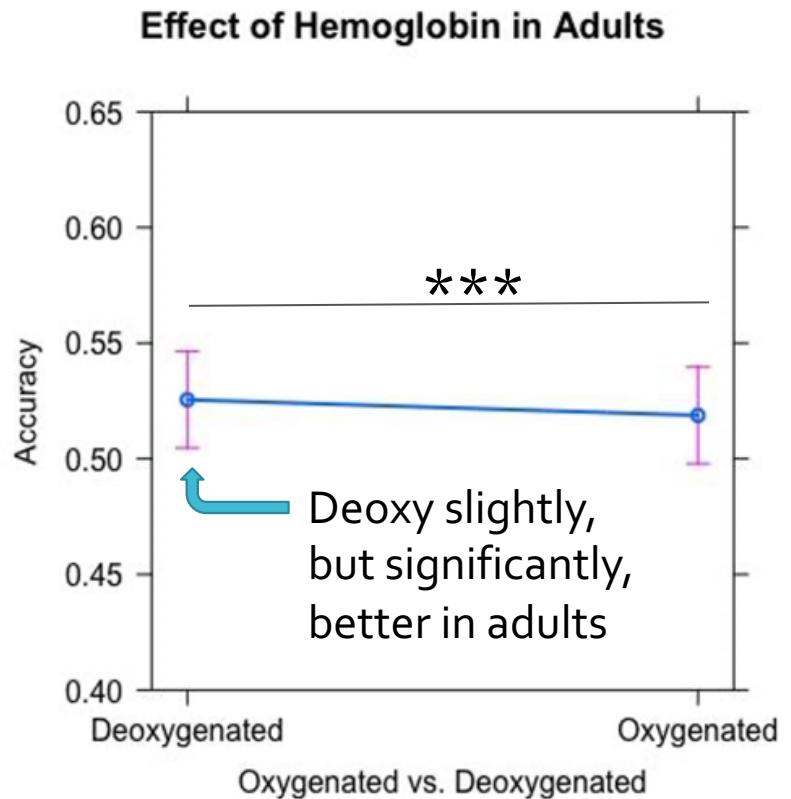


*** = $p < .001$

Analyzing multivariate patterns

How did we do?

Oxygenated or deoxygenated hemoglobin data?



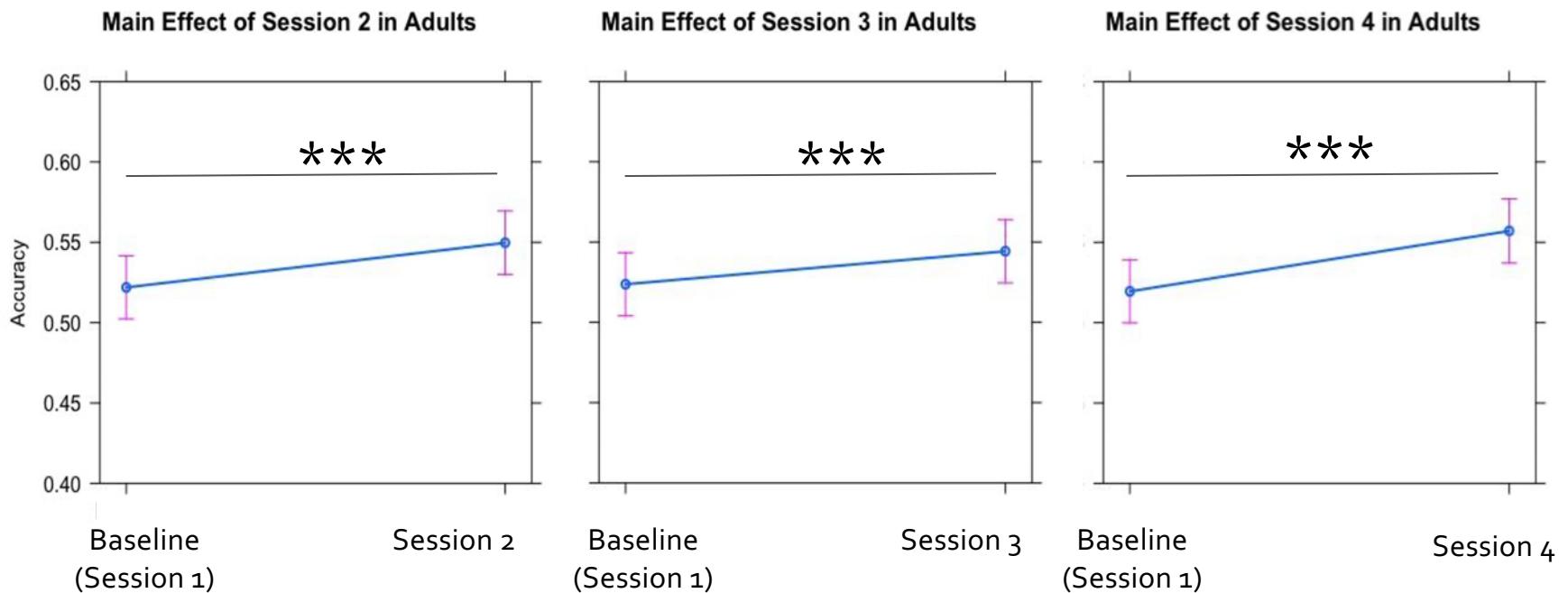
*** = $p < .001$

Analyzing multivariate patterns

How did we do?

Which sessions are the most informative?

Is there added value beyond the first session?



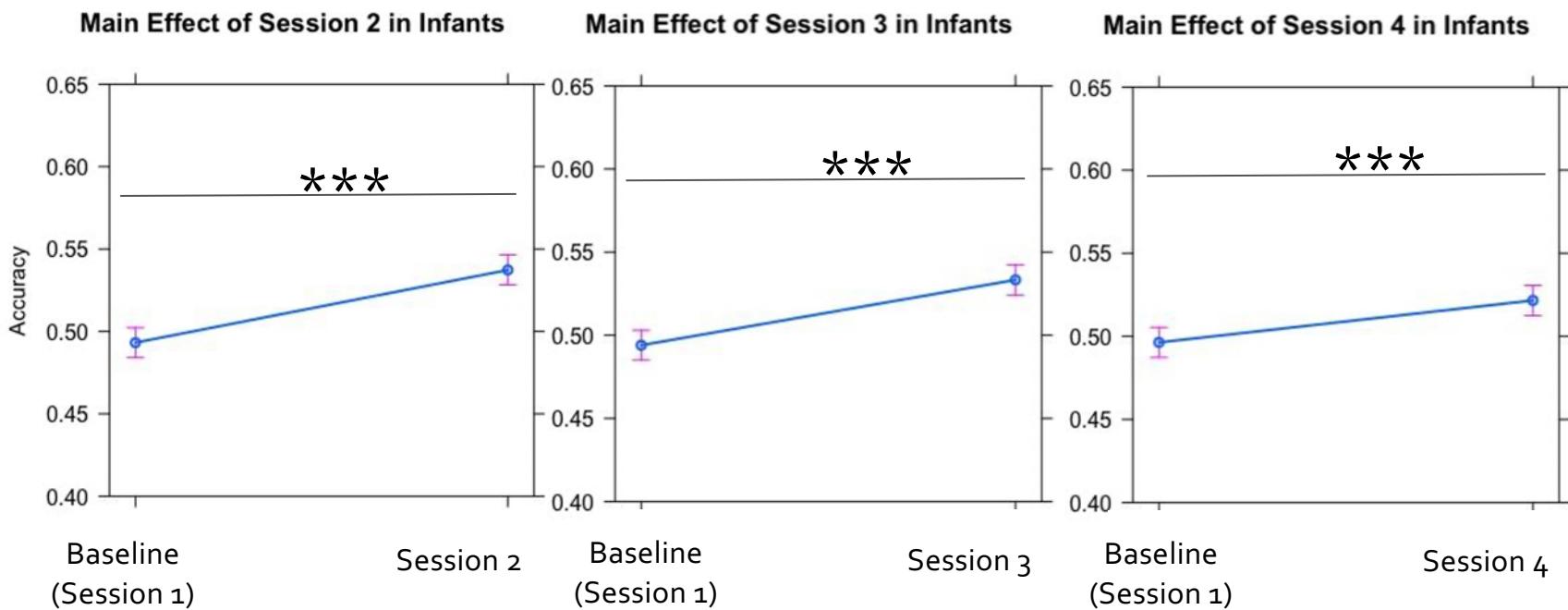
*** = $p < .001$

Analyzing multivariate patterns

How did we do?

Which sessions are the most informative?

Is there added value beyond the first session?



*** = $p < .001$

Design Summary Example 3

| Design/Analysis Parameter | Value |
|---------------------------|--|
| Task | |
| block vs. event design | Event-related (4.5 s dur, 5-9 s ISI) |
| # of runs or repetitions | 30 sets of 8 randomized images |
| # of days or sessions | 3-5 sessions, one week apart |
| Participants | |
| # trials / participant | total 240 |
| # participants | Infants: 16, ~8 m.o. Adults: 16, college students |
| Array Coverage | |
| # of channels | Infants: 70 channels Adults: ~140 channels |
| regions sampled | broad bilateral coverage of 4 lobes |
| Analysis choices | |
| hemoglobin (oxy/deoxy) | oxygenated & deoxygenated |
| co-register to anatomy | no (actually yes, but not reporting today) |

Example 4: Classifying responses to social and non-social stimuli

For the Bill & Melinda Gates Foundation Neuroimaging Consortium

Experimental design for the univariate study (Example 4)

Task: Common social cognition paradigm for infants and children. Allows contrast in visual & auditory domains.

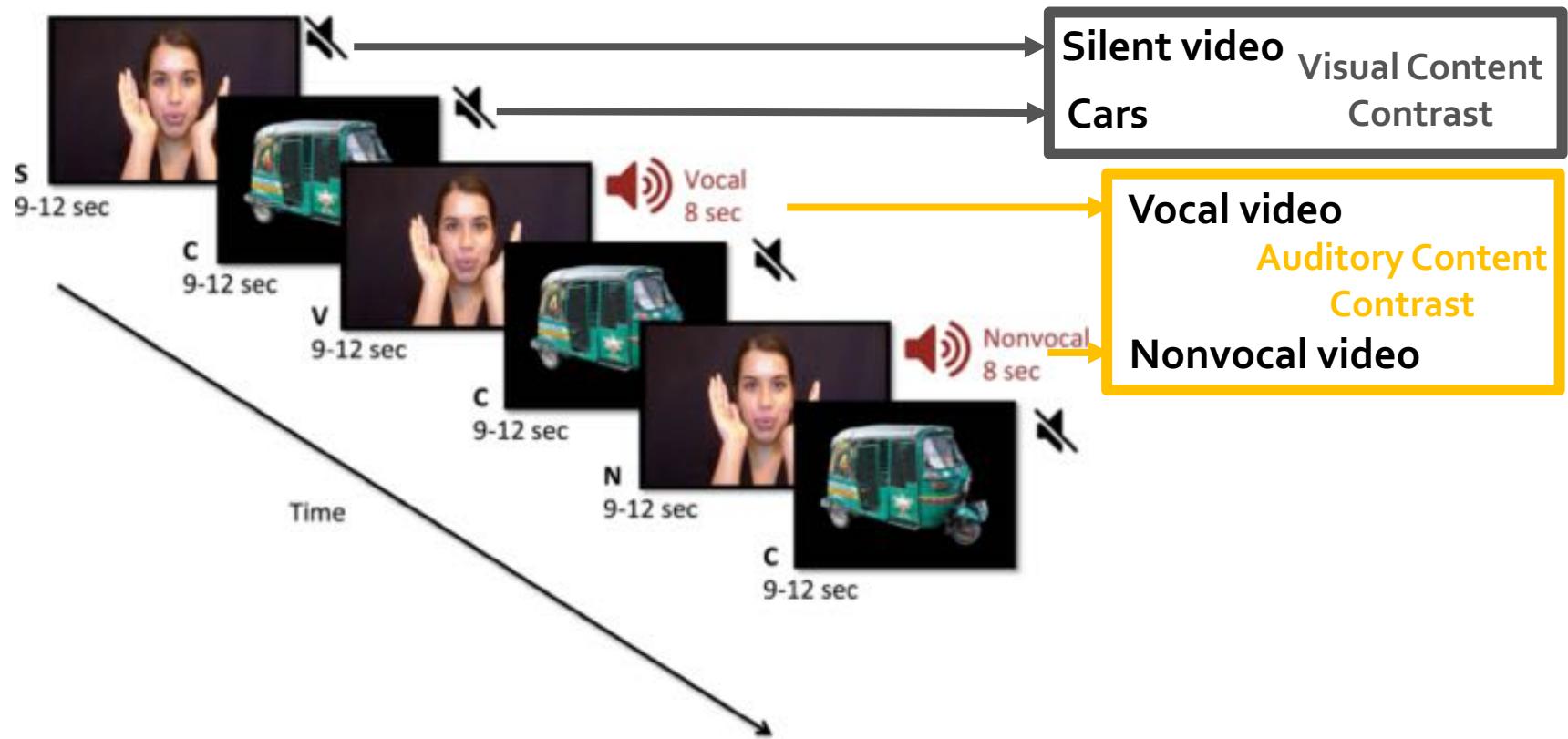


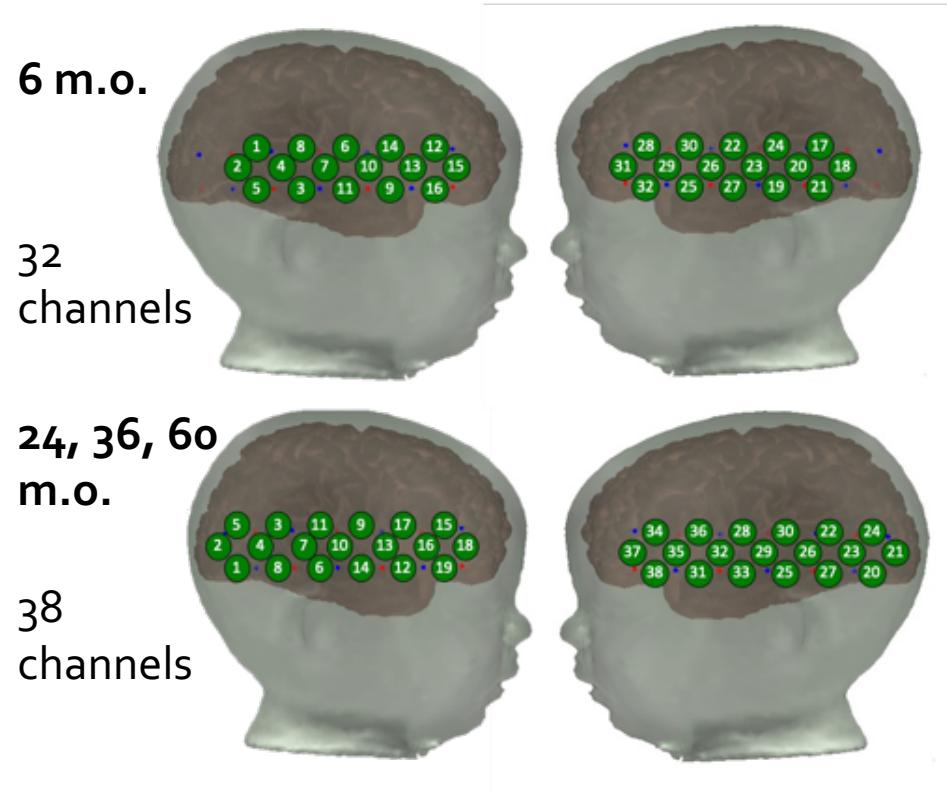
Figure 1 in [Perdue et al., 2019, Developmental Science](#)

Experimental design for the univariate study

(Example 4)

fNIRS data

- Two configurations of array
- 6 m.o. children have fewer channels than others
- Channels don't map 1-to-1 between age groups
- Short data collection, but a lot of children!



Experimental design for the univariate study

(Example 4)

Participants

- Ages 6, 24, 36, and 60 months in Dhaka, Bangladesh
- Recruiting from low SES neighborhoods
- We divided the data into:
 - *Training* group (60%, optimizing the model)
 - *Validation* group (40%, generalizability of the result)

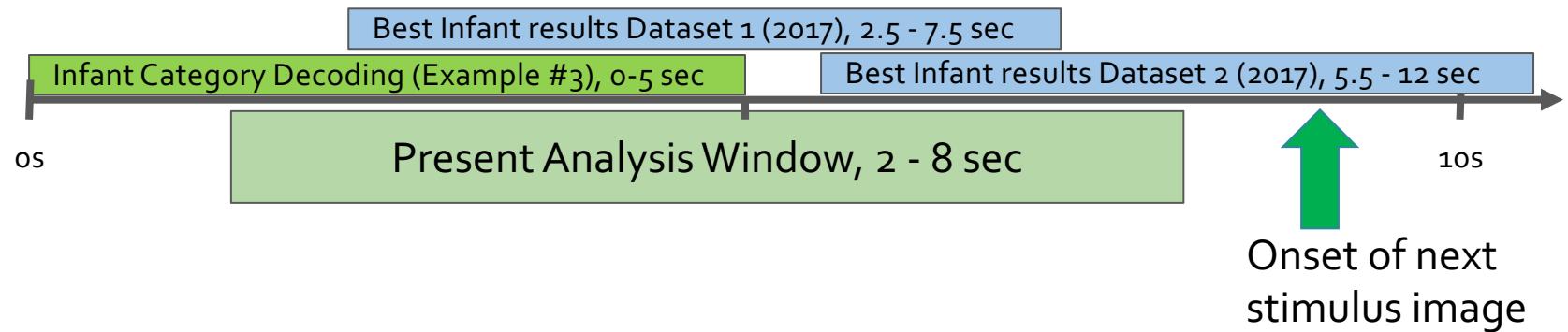
| Sample | N (M / F) | Recruit Age | For Training | For Validation |
|----------|---------------|-----------------|--------------|----------------|
| Infants | 130 (54 / 76) | 6.1 m.o. (1.0) | 71 | 51 |
| Children | 130 (72 / 58) | 36.4 m.o. (0.2) | 73 | 51 |

Analyzing multivariate patterns

Time Window

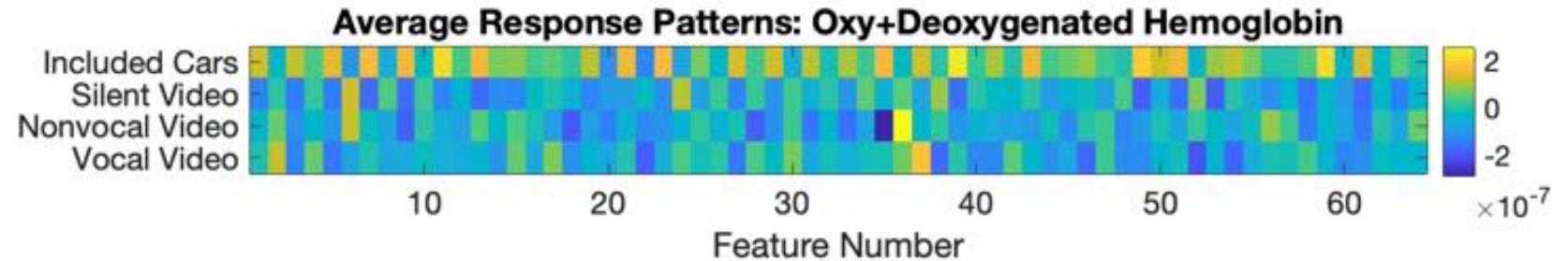
What is the relevant time window for looking at data?

- **Example #3**, we found *earlier windows were better*
 - But the tasks are quite different (visual vs. audiovisual)
- **Emerson et al.'s (2017)** best time windows
 - Early (2.5-7.5 s) for auditory vs. visual contrast
 - Later (5.5-12s) for multimodal AV-1 vs. AV-2 contrast
- **Present study:** Weak *a priori* knowledge of best window
 - widen Emerson et al.'s best window slightly

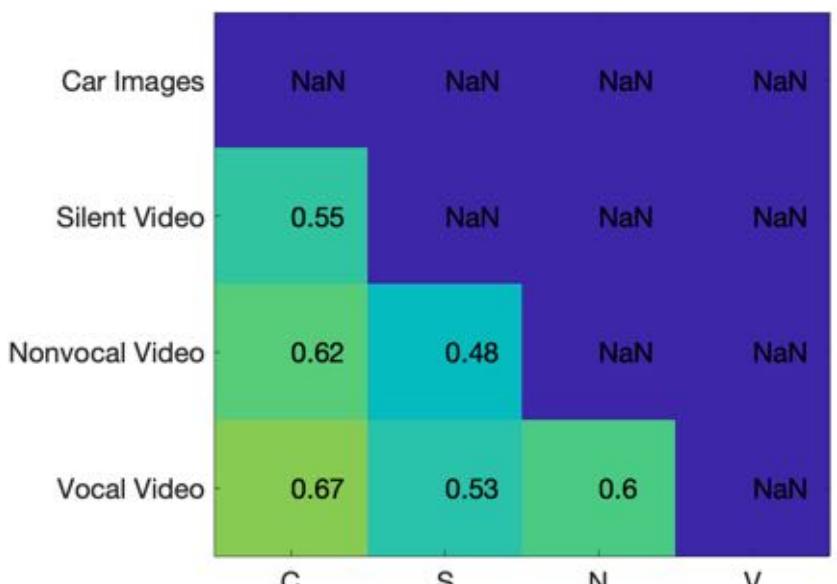


Analyzing multivariate patterns

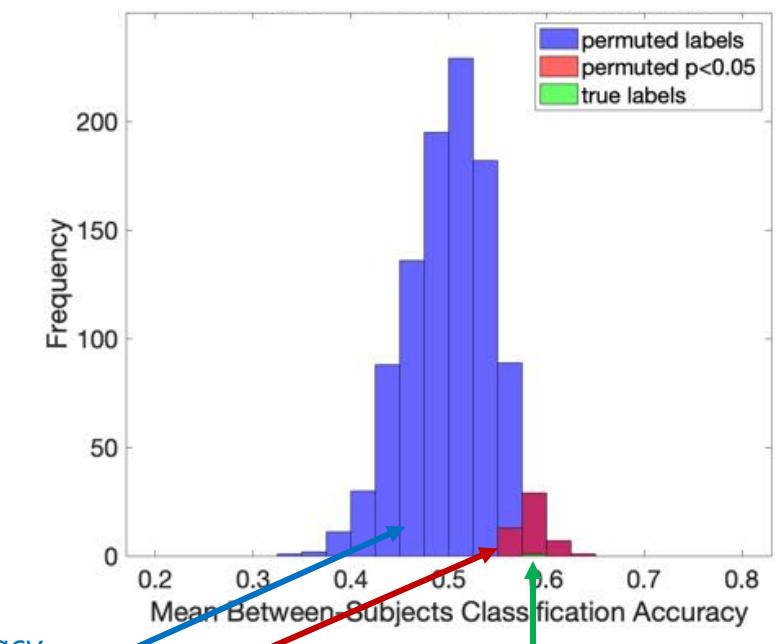
Testing a few parameters



6 m.o. Peekaboo Classification Accuracy



6 m.o. Peekaboo Classification Significance



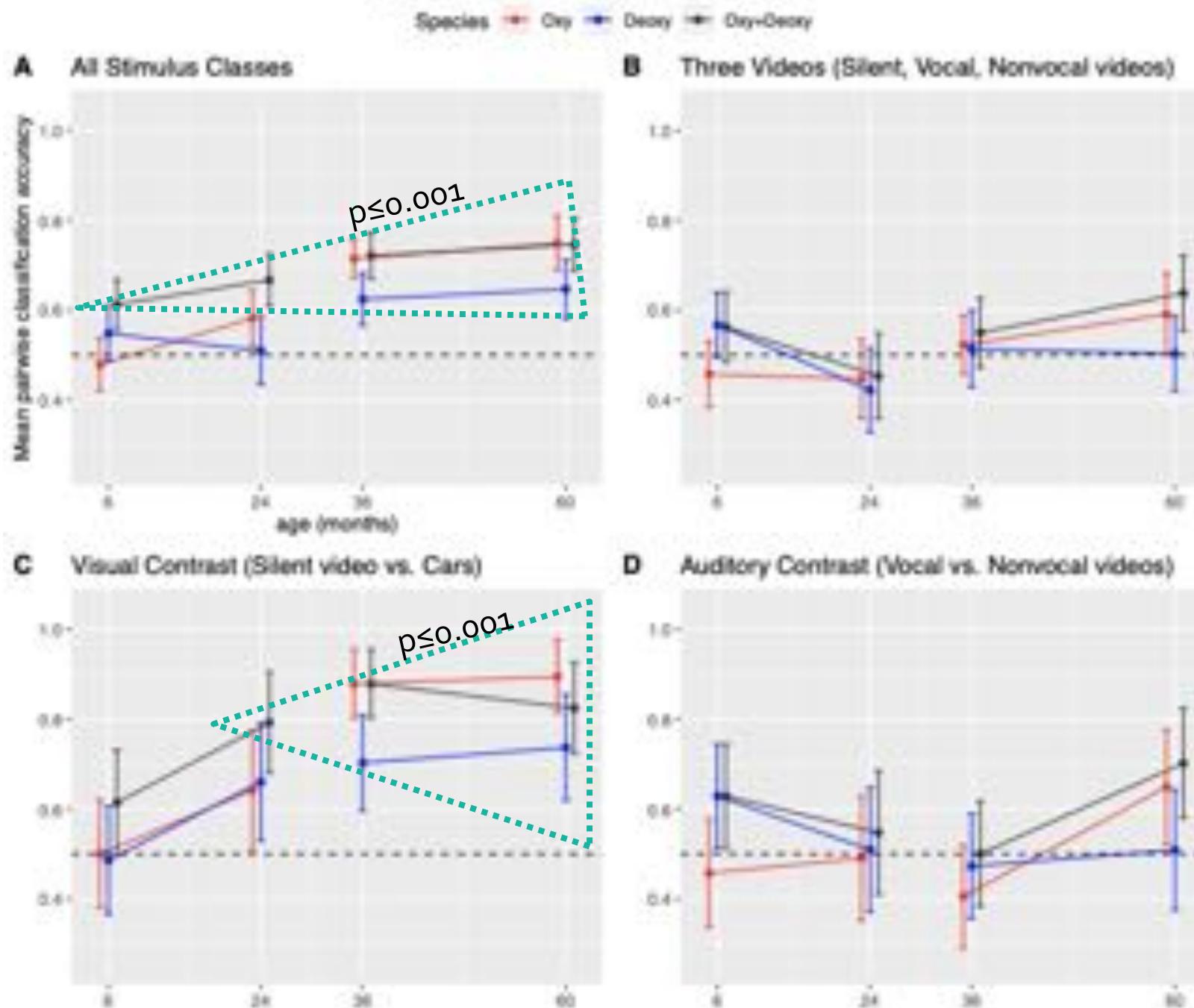
Distribution of classification accuracy for randomly permuted labels

p<0.05 significance

Mean Pairwise Classification Accuracy: 58%, $p=0.03$

Analyzing multivariate patterns

Exploration

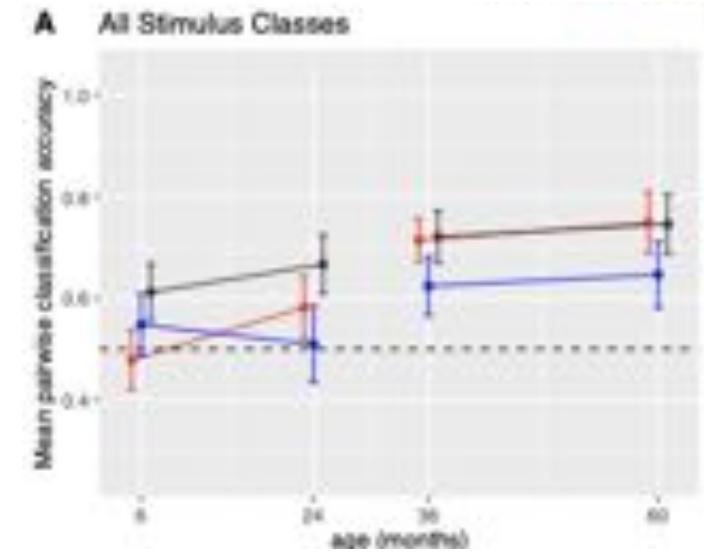


Analyzing multivariate patterns

Interim Findings

Mixed effects linear regression over Subject-x-Hemoglobin data:

- Overall classification improves with age
- Simultaneous consideration of Oxy and Deoxy hemoglobin yields significantly better accuracy (esp. in infant sample)
- Classification accuracy of Oxy hemoglobin increases more with age than Deoxy or the combined feature sets



Let's not get *too excited* until we perform the same trick twice.
Repeat the same analysis with the Validation dataset:

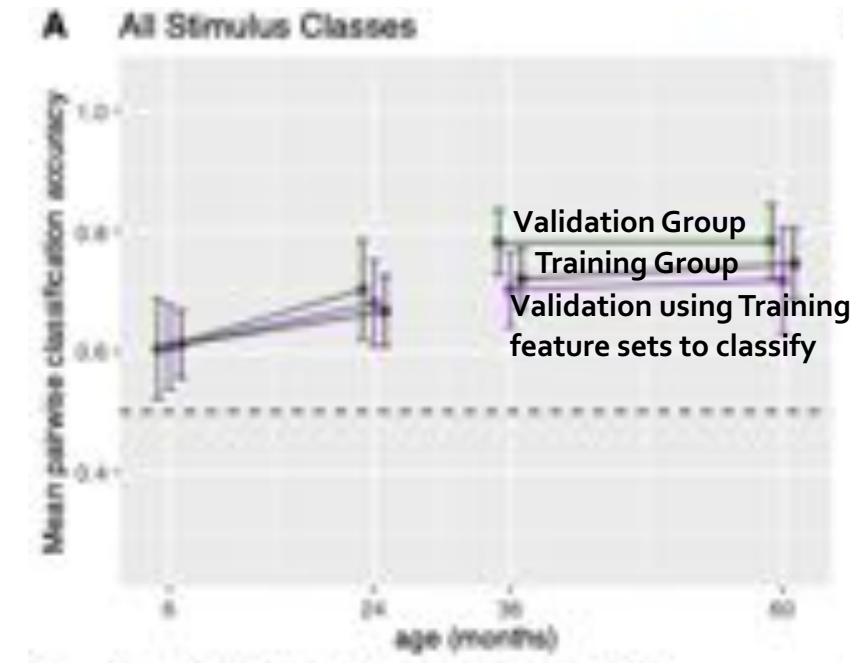
Using the n-fold procedure with **fewer participants (Validation group)**
Classifying each Validation participant **using average Training data**
(do the measured features themselves generalize to new children?)

Analyzing multivariate patterns

Example 4 Findings

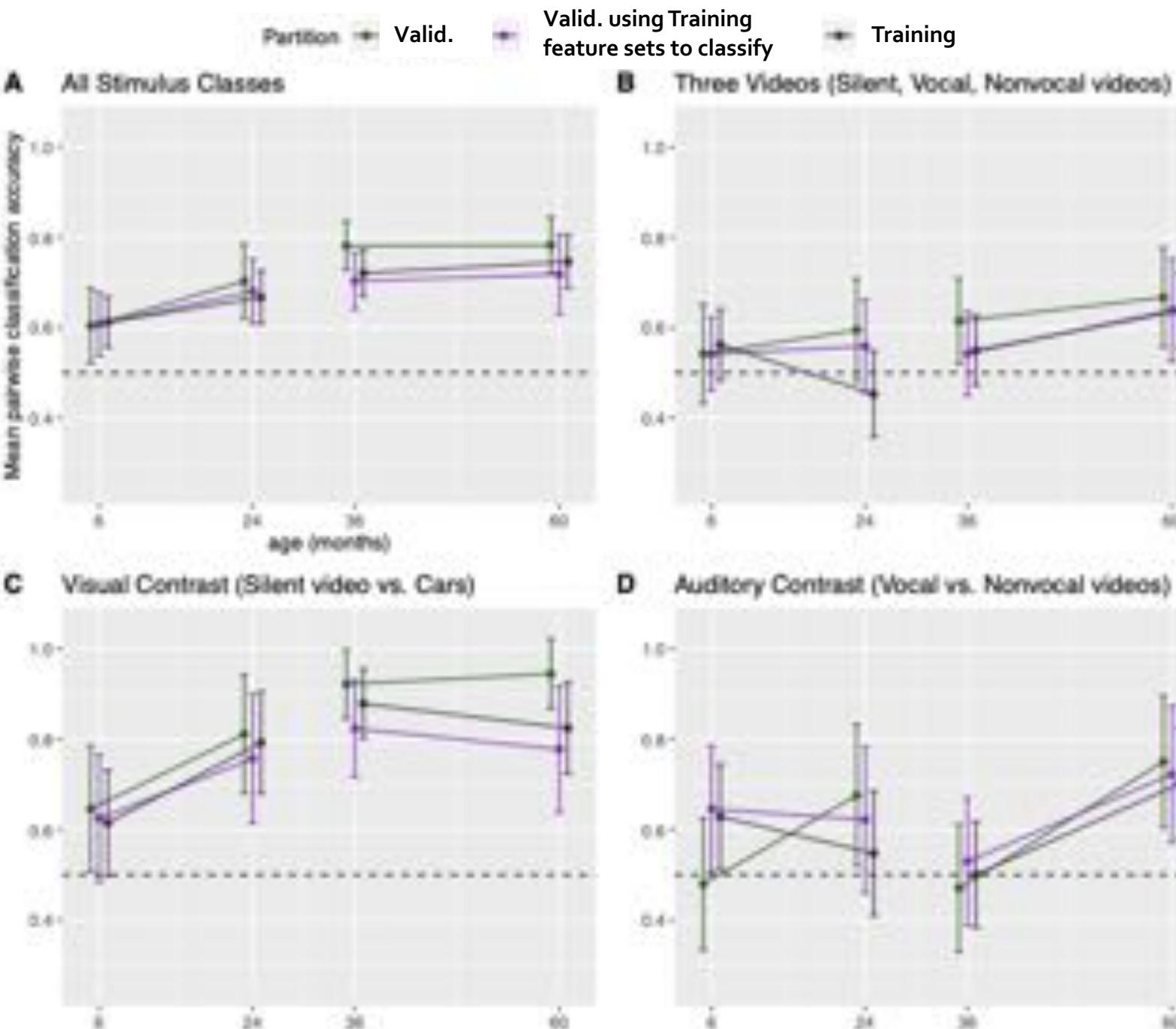
Mixed effects linear regression over Subject-x-Hemoglobin data:

- Overall (4-classes) classification accuracy improves with age
- No main effect of grouping
- No interaction – Age effects seem to be similar in both groups
- Same findings in Visual & Auditory modalities and Three Videos



Analyzing multivariate patterns

Validation



Analyzing multivariate patterns

Example #4 Findings

Some take-away notes:

- Oxy+Deoxy features worked well across two sets of participants
- No major loss of accuracy with slightly smaller sample:
 - Each child in Validation classified by 47 peers in **Validation group**
 - Each child in Validation classified by 70 peers in **Training group**
- Classification of stimuli in the social cognition task improves with age from infancy to early childhood!
- Best classification accuracy is coming from the visual contrast
 - Less interesting than the social / auditory contrast?
 - Age effects are still seen in the other comparisons

Design Summary Example 4

| Design/Analysis Parameter | Value |
|---------------------------|---|
| Task | |
| block vs. event design | Event-related (9-12s duration) |
| # of runs or repetitions | varying ~7 runs of 3 videos + 3 cars |
| # of days or sessions | 1 session |
| Participants | |
| # trials / participant | highly variable |
| # participants | varying 37-74 per group |
| Array Coverage | |
| # of channels | 6 m.o.: 32 channels 24, 36, & 60 m.o.: 38 channels |
| regions sampled | bilateral mainly temporal, inf. frontal |
| Analysis choices | |
| hemoglobin (oxy/deoxy) | oxygenated + deoxygenated combo |
| co-register to anatomy | no (actually yes, but not reporting today) |

Predictors of success in infant fNIRS

Results of infant fNIRS classification studies discussed today

| Analysis parameter | Best values for classification |
|---------------------------------------|--|
| Time window | |
| Emberson et al. (2017) | 4-6s after block onset, ~2s after event onset |
| P-Y Consortium (in prep) | as close to event onset as possible |
| Hemoglobin | |
| P-Y Consortium (in prep) | oxy > deoxy |
| BMGF Consortium (in prep) | combined oxy+deoxy > oxy > deoxy |
| # of lab visits (P-Y, in prep) | additional days after 1 st improve classification |
| Age (BMGF Consortium, in prep) | older is better (6-60 m.o.; except auditory-only) |

Predictors of success in adult fNIRS

Results of adult fNIRS classification studies discussed today

| Analysis parameter | Best values for classification |
|---------------------------------------|--|
| Time window | |
| Zinszer et al. (2018) | only tested 6.5s after event onset |
| P-Y Consortium (in prep) | as late to event onset as possible (tested to 5s) |
| Hemoglobin (P-Y, in prep) | deoxy > oxy |
| # of lab visits (P-Y, in prep) | additional days after 1 st improve classification |

Questions?

“Question! Why didn’t you just try...”

Because that’s the topic of Part 3, after the break!

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