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## INTRODUCTION

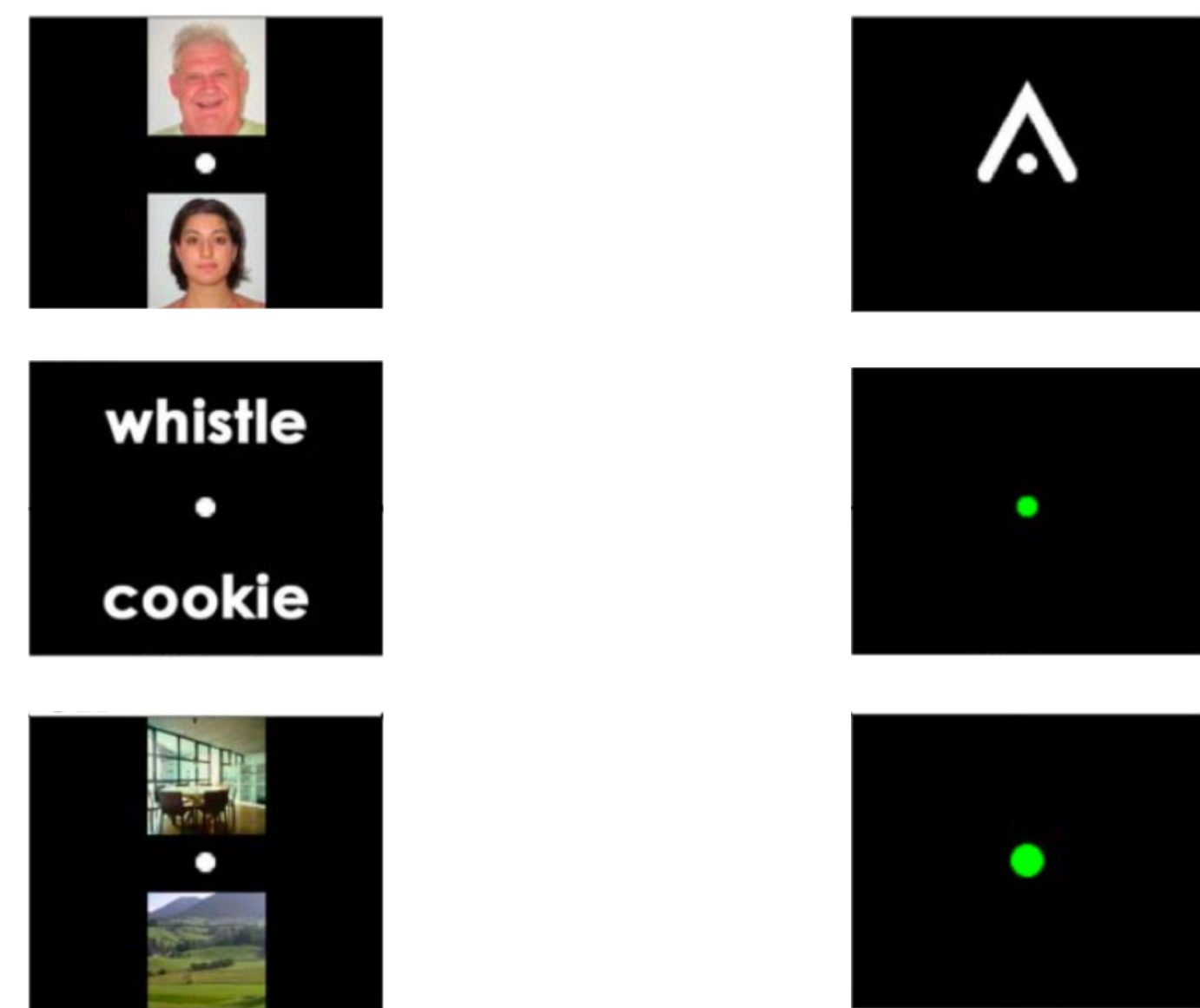
- Many techniques exist for removing overt problems in EEG data (e.g., blinks and other ocular/muscular artifacts)
- However, traditional techniques may miss more subtle effects or poor data due to e.g. participant inattention
- We developed the CABER method to reject (“toss”) such trials
- CABER uses deep multivariate pattern analysis (dMVPA), implemented via DeLINEATE, a deep learning toolbox<sup>1</sup>
- Requires factorial design with at least two orthogonal factors

## DATASETS

### Dataset 1: Perceive/Refresh

- Previous dataset examining neural correlates of refreshing<sup>2</sup>
- N = 37 young, healthy subjects
- Recorded with 32-channel low-impedance EEG cap
- 11,962 epochs total (3,951 Refresh; 8,011 Perceive)
- Artifact rejection: epochs rejected if peak-to-peak amplitude >150μV, or any EEG channel had flat period of >75ms
- Perceive*: Presented with two items (faces, words, or scenes)
- Refresh\**: Think back to and visualize one of the two items

**Perceive (1500ms)** Faces OR words OR scenes  
**Cue\* (1500ms)** Refresh OR NoAct OR Act



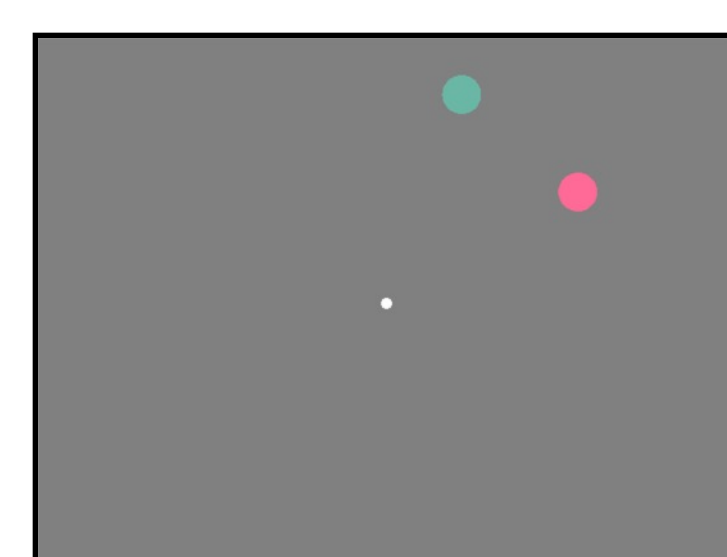
\* NoAct = do nothing. Act = button press. We analyzed only Refresh cues (up/down arrows).

### Dataset 2: Visual Short-Term Memory (VSTM)

- N = 27 young, healthy subjects
- Recorded with 256-channel high-impedance EEG cap
- 4,864 epochs total
- Artifact rejection: channels manually rejected, epochs rejected if peak-to-peak amplitude >100μV
- Subset of channels converted to approximate 10/20 system
- Only encoding period of the VSTM task analyzed
- Presented with either *one* or *two* colored discs, both in either *left* or *right* hemifield, for 1000ms

**Example epoch**

Two items; Right hemifield



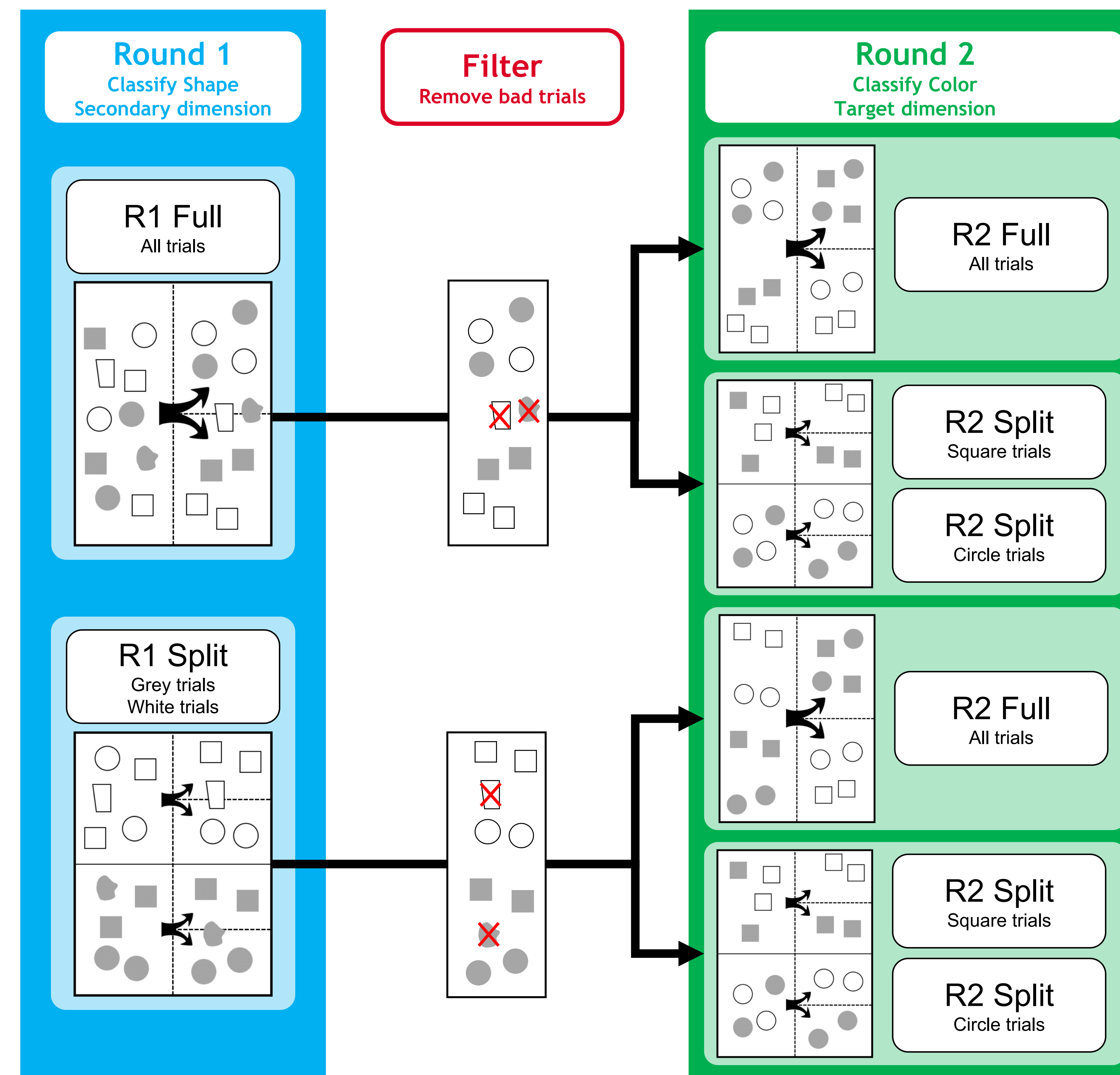
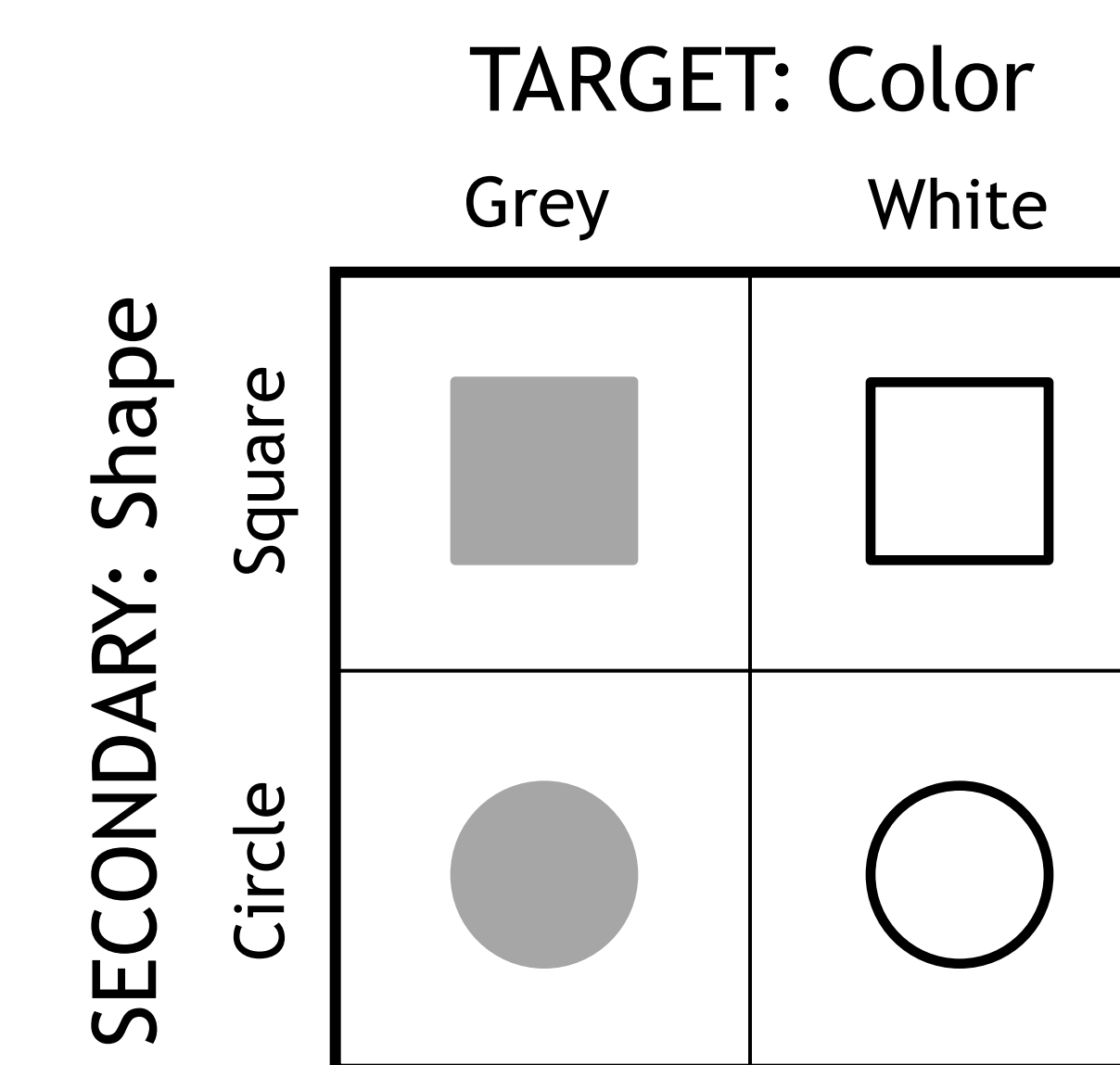
## APPROACH

### Premise of CABER tossing

*If the primary classification of interest is over Dimension A, use classification accuracy over an orthogonal Dimension B to identify high/low quality trials before performing classification over Dimension A.*

### Conceptual example

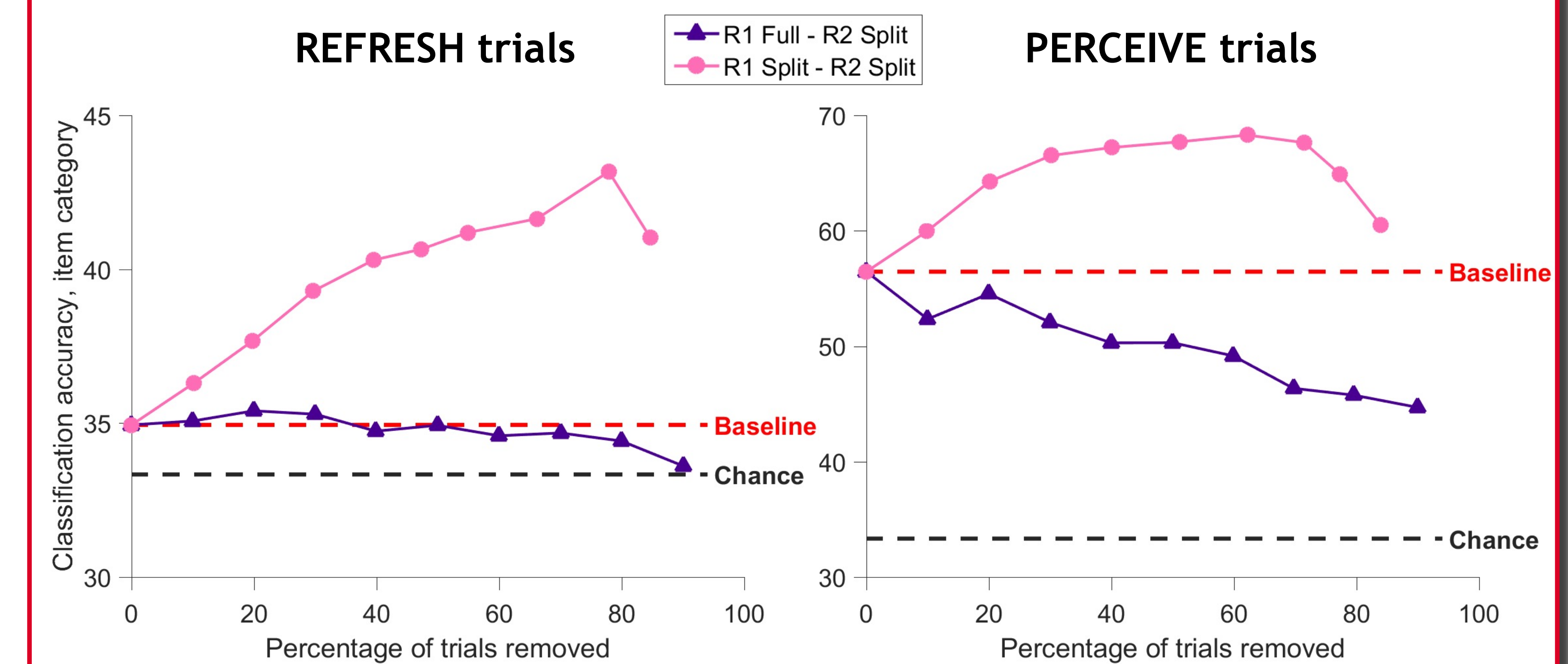
- Dataset with two dimensions (color: grey/white; shape: circle/square)
- Color: dimension of interest, i.e. **target** dimension
- Shape: of secondary interest, i.e. **secondary** dimension
- Three steps:
  - Round 1**: Classify trials over *secondary dimension*, e.g. shape
  - Filter**: Remove trials with low decodability in Round 1
  - Round 2**: Classify trials over *target dimension*, e.g. color
  - Round 3**: Profit
- We explored two manipulations:
  - Effects of removing 10% least decodable trials, vs 20%, 30%, ... 90%
  - When classifying over one dimension, effects of *splitting* (Split) or *not splitting* (Full) the dataset according to the orthogonal dimension



## RESULTS

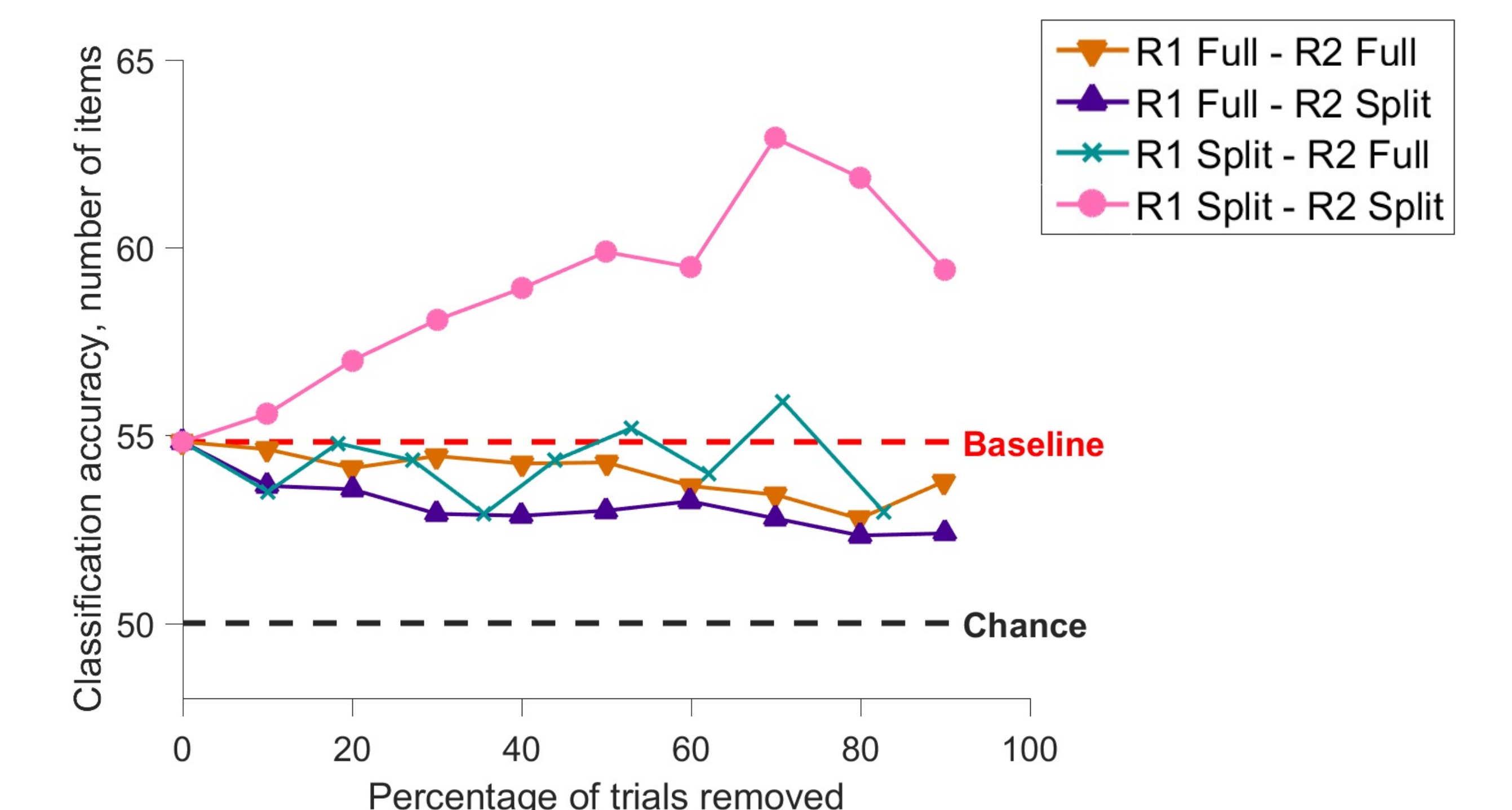
### Dataset 1: Perceive/Refresh

- Target dimension: item category (face/scene/word)
- Secondary dimension: task performed (Perceive/Refresh)
- Baseline accuracy (pre-CABER, no trials removed): 56.5% Perceive, 34.9% Refresh



### Dataset 2: VSTM

- Target dimension: number of items (one/two)
- Secondary dimension: hemifield (left/right)
- Baseline accuracy (pre-CABER, no trials removed): 54.2%



## CONCLUSIONS

- Classification accuracy improved from baseline *only* when Rounds 1 and 2 were split
- Splitting both Round 1 and 2 improved accuracy regardless of how much/little data was removed
- Suggests some kind of overall data quality exists that can be indexed by decoding
- Separable from traditional artifact rejection (AR): CABERing both datasets before and after traditional AR produced same results

## REFERENCES & ACKNOWLEDGEMENTS

- <sup>1</sup>DeLINEATE: A deep learning toolbox for neuroimaging data analysis. <http://delineate.it>  
<http://bitbucket.org/delineate/delineate>
- <sup>2</sup>Johnson MR, McCarthy G, Muller KA, Brudner SN, Johnson MK. 2015. *Journal of Cognitive Neuroscience*, 27: 1823-1839

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