Decoding spontaneous brain activity from fMRI using Gaussian Processes: Tracking brain reactivation

J. Schrouff[1,2], C. Kussé[1], L. Wehenkel[2,3], P. Maquet[1,4], C. Phillips[1,2]

[1] Cyclotron Research Centre, University of Liège, Belgium
[2] Department of Electrical Engineering and Computer Science, University of Liège, Belgium
[3] Giga-R, Systems Biology and Chemical Biology, University of Liège, Belgium
[4] Department of Neurology, Liège University Hospital, Belgium

jschrouff@ulg.ac.be

http://www.cyclotron.ulg.ac.be

PRNI workshop, July 2012

Agenda

- Introduction
- Data and design
- Methods
- Results
- Discussion
- Conclusions and references

Agenda

- Introduction
- Data and design
- Methods
- Results
- Discussion
- Conclusions and references

Introduction

- Univariate + Multivariate
- Controlled environment (timing and content)
- More realistic datasets?

- Memory traces:
  - Theory: reactivation of patterns during post-task rest
  - Shown in animals (Hoffman and McNaughton, 2002)
  - Tambini et al., (2010) showed reinforced correlations
  - But multivariate patterns

Introduction

- Univariate + Multivariate
- Controlled environment (timing and content)
- More realistic datasets?

- Memory traces:
  - Theory: reactivation of patterns during post-task rest
  - Shown in animals (Hoffman and McNaughton, 2002)
  - Tambini et al., (2010) showed reinforced correlations
  - But multivariate patterns

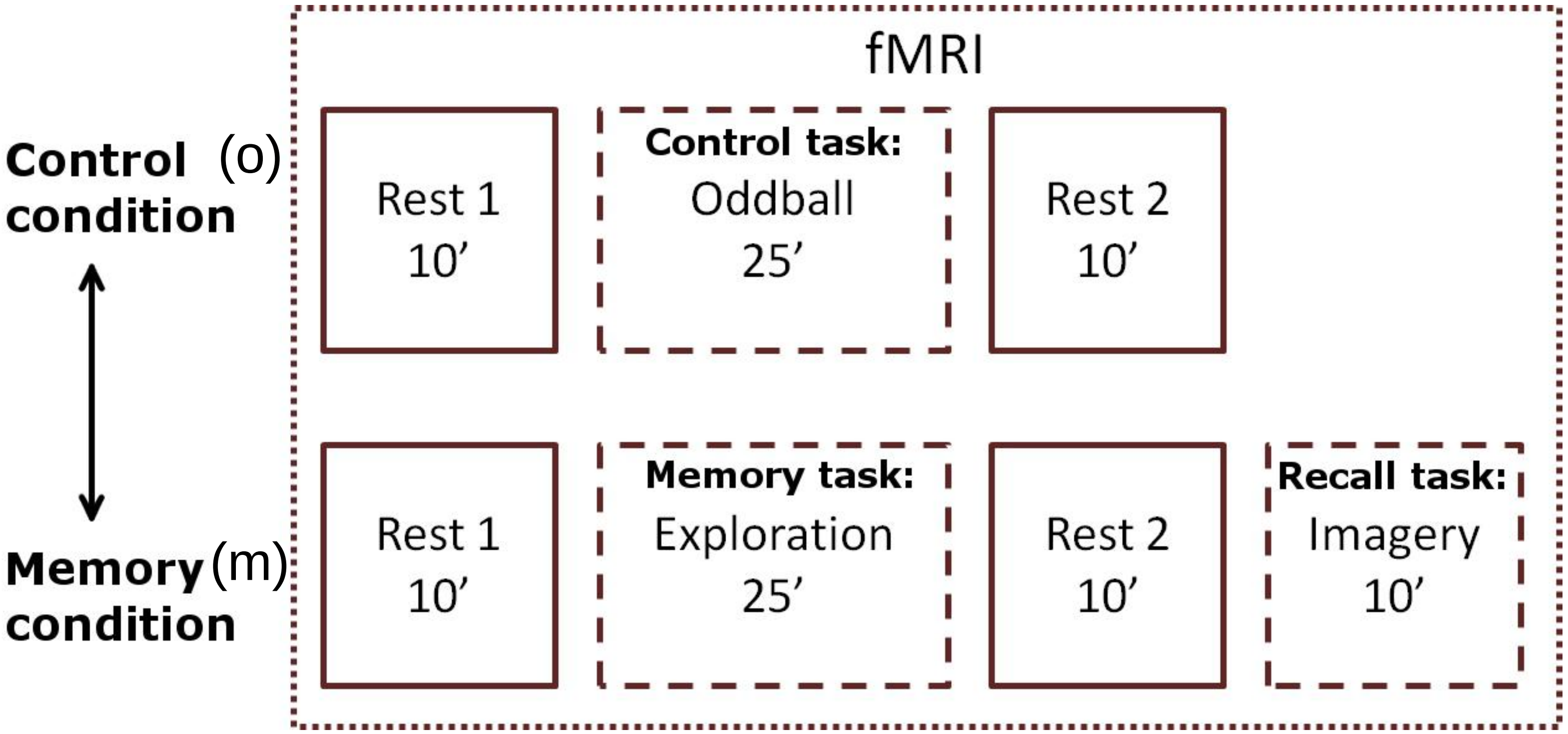
Aim: Apply multivariate techniques on rest sessions following a learning task

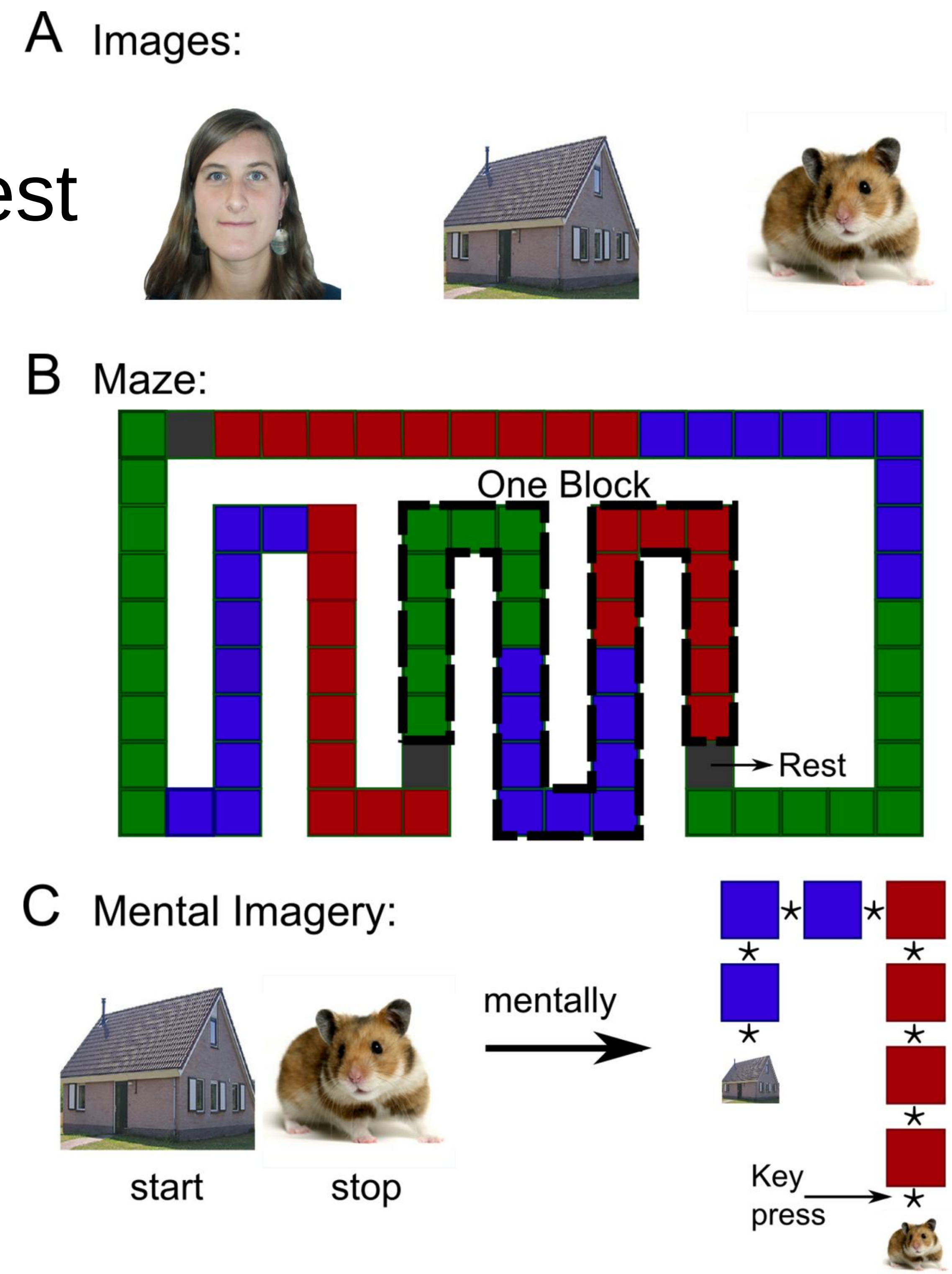
Agenda

- Introduction
- Data and design
- Methods
- Results
- Discussion
- Conclusions and references

Data and design

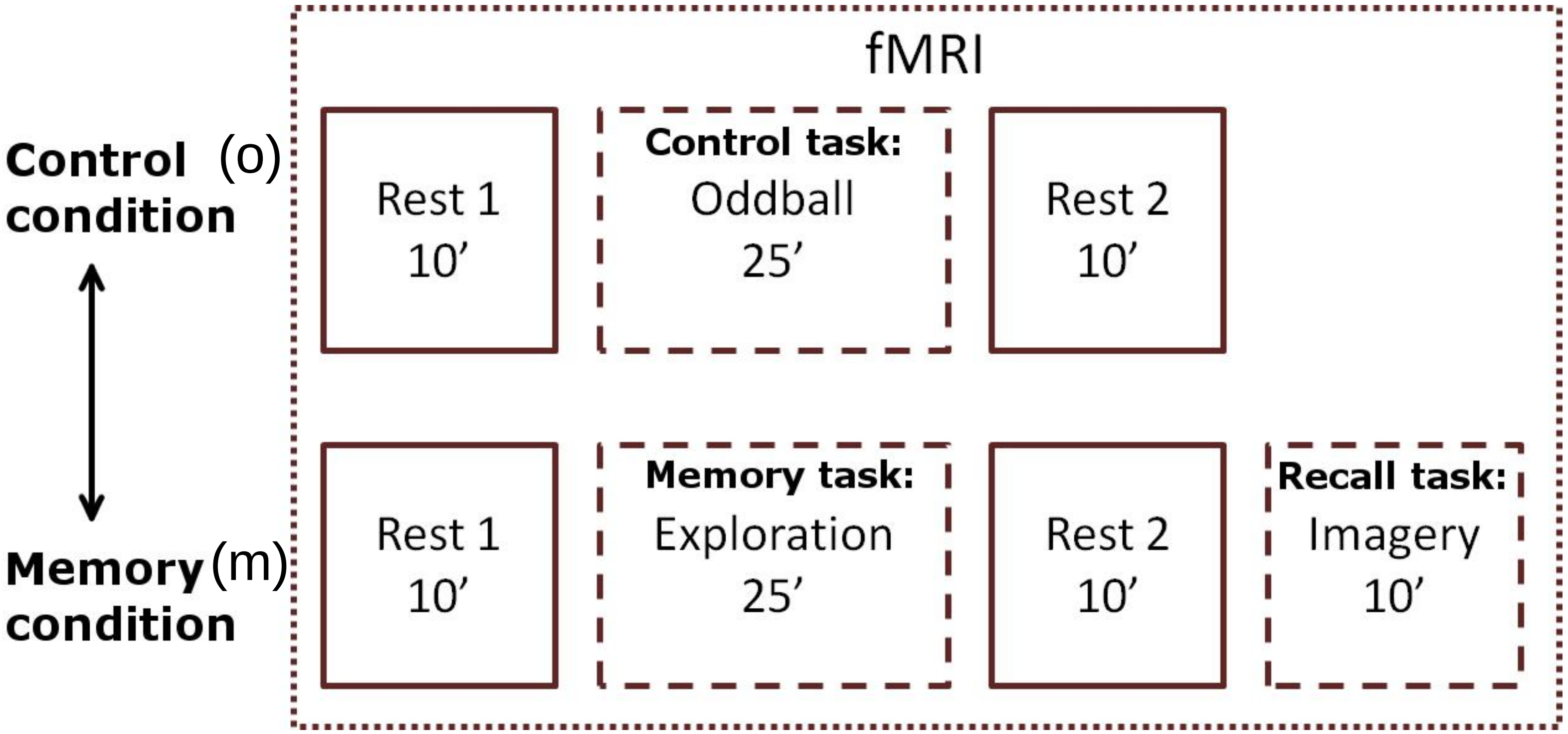
- 14 subjects (7 F, 19-29)
- 2 conditions (fMRI) + memory test

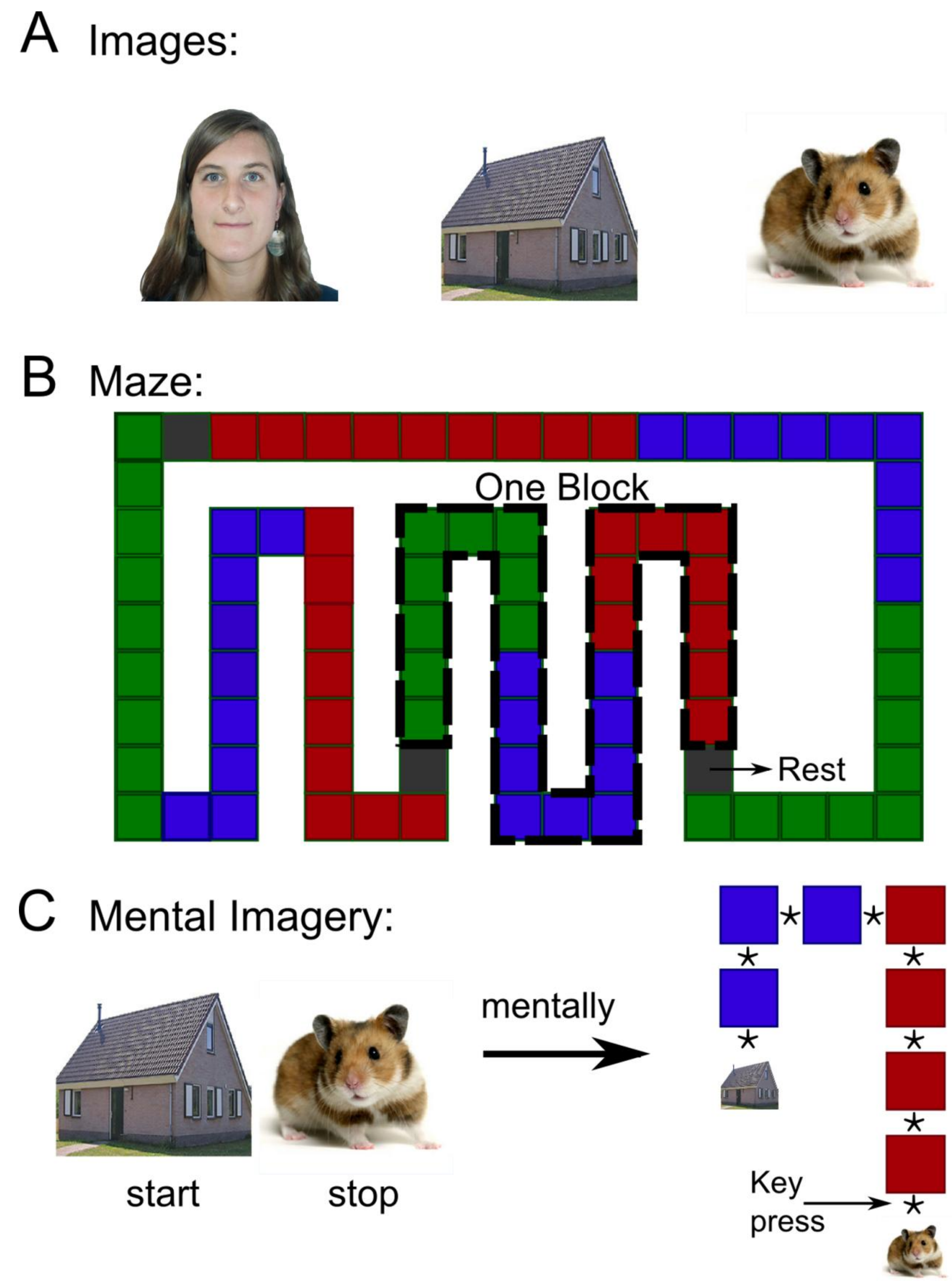




Data and design

- 14 subjects (7 F, 19-29)
- 2 conditions





Goal:

1. Build model on Recall
2. Apply on rest sessions
3. Compare the two conditions

Agenda

- Introduction
- Data and design
- Methods
- Results
- Discussion
- Conclusions and references

Methods: Recall

- Schrouff et al., 2012. PLoS One
- Best procedure:
  - Univariate filter: 1000 most significant voxels in GLM
  - Multivariate wrapper: Recursive Feature Addition, SVM (forward selection, cost function on global accuracy)
  - Gaussian Processes to classify (binary)
  - Error-Correcting Output Code scheme (multiclass):

Class	F vs B	F vs A	B vs A	D_i
Faces	1	1	0.5	*1.4*
Buildings	0	0.5	1	*0.8*
Animals	0.5	0	0	*1.2*
Test point	*0.5*	*0.4*	*0.8*	*Buildings*

- Balanced and class accuracies with p-values

Methods: Rest

Intuitions:

- Each scan = test point ⟶ each scan = prediction
- But no ‘true’ label to compare…

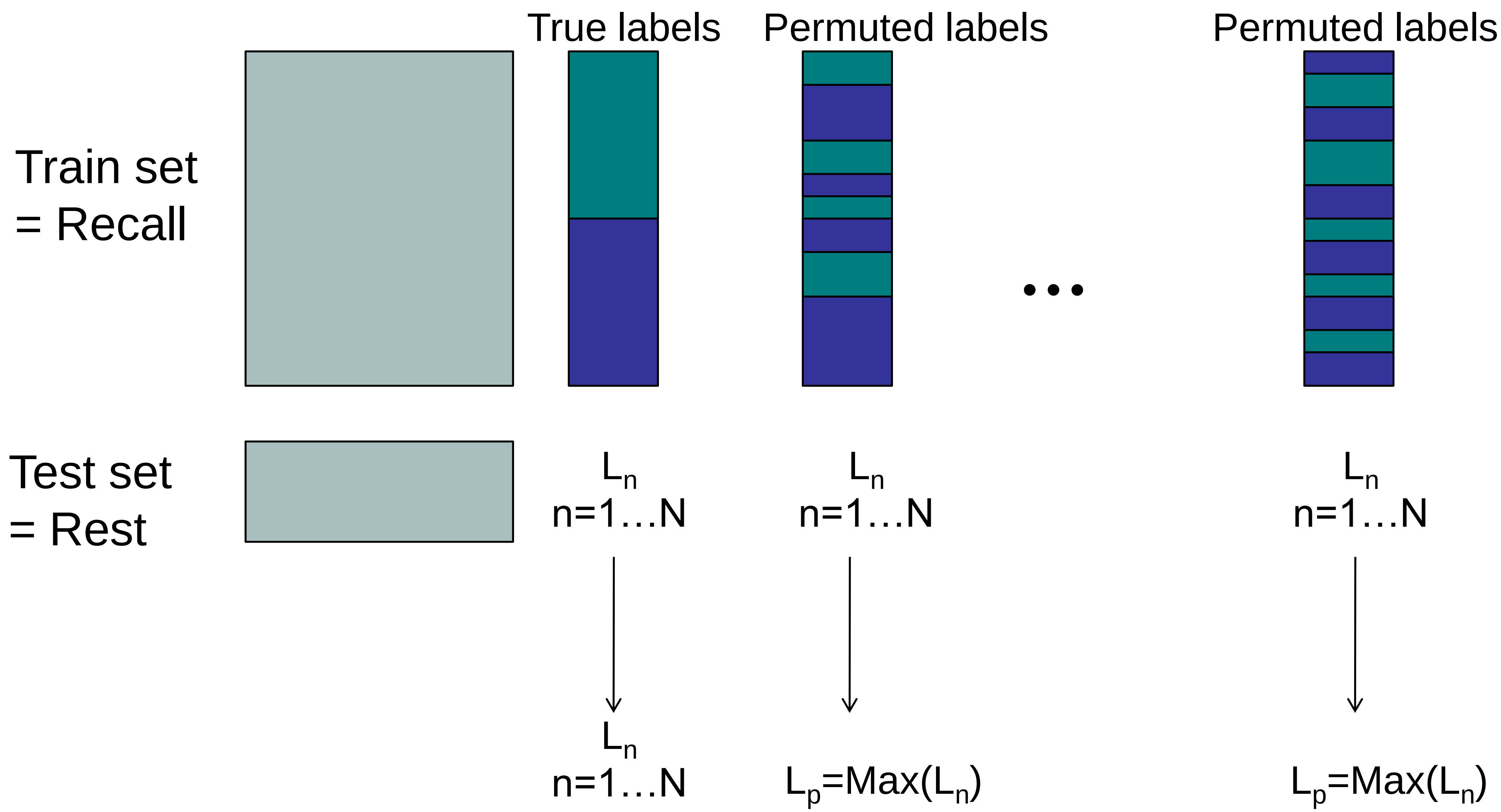
- Confidence of the classifier
- Baseline level?

- Compare conditions ⟶ each rest = number

Methods: Rest

Class	F vs B	F vs A	B vs A	D_i
Faces	1	1	0.5	*1.4*
Buildings	0	0.5	1	*0.8*
Animals	0.5	0	0	*1.2*
Test point	*0.5*	*0.4*	*0.8*	*Buildings*

- $$sD = sort(D_i), \quad i = 1 \ldots K \tag{1}$$
  $$L = |sD(1) - sD(2)| \tag{2}$$



Methods: Rest

$$
\begin{aligned}
L_{perm} &= L_p, & p = 1 \dots P && (1)\\
p(n) &= L_{perm} > L_n && && (2)\\
Pr(Rest) &= \frac{1}{N} \times \sum_{n=1}^{N} p(n) < 0.05 && && (3)
\end{aligned}
$$

- Increase in pattern detection:
  - $Pr(R2_m) - Pr(R1_m)$: memory condition
  - $Pr(R2_o) - Pr(R1_o)$: control condition

- Correlation with D’, behavioral performance:
  - C_m
  - C_o
  - $C_m - C_o$
  - p-values via permutations of D’

Agenda

- Introduction
- Data and design
- Methods
- Results
- Discussion
- Conclusions and references

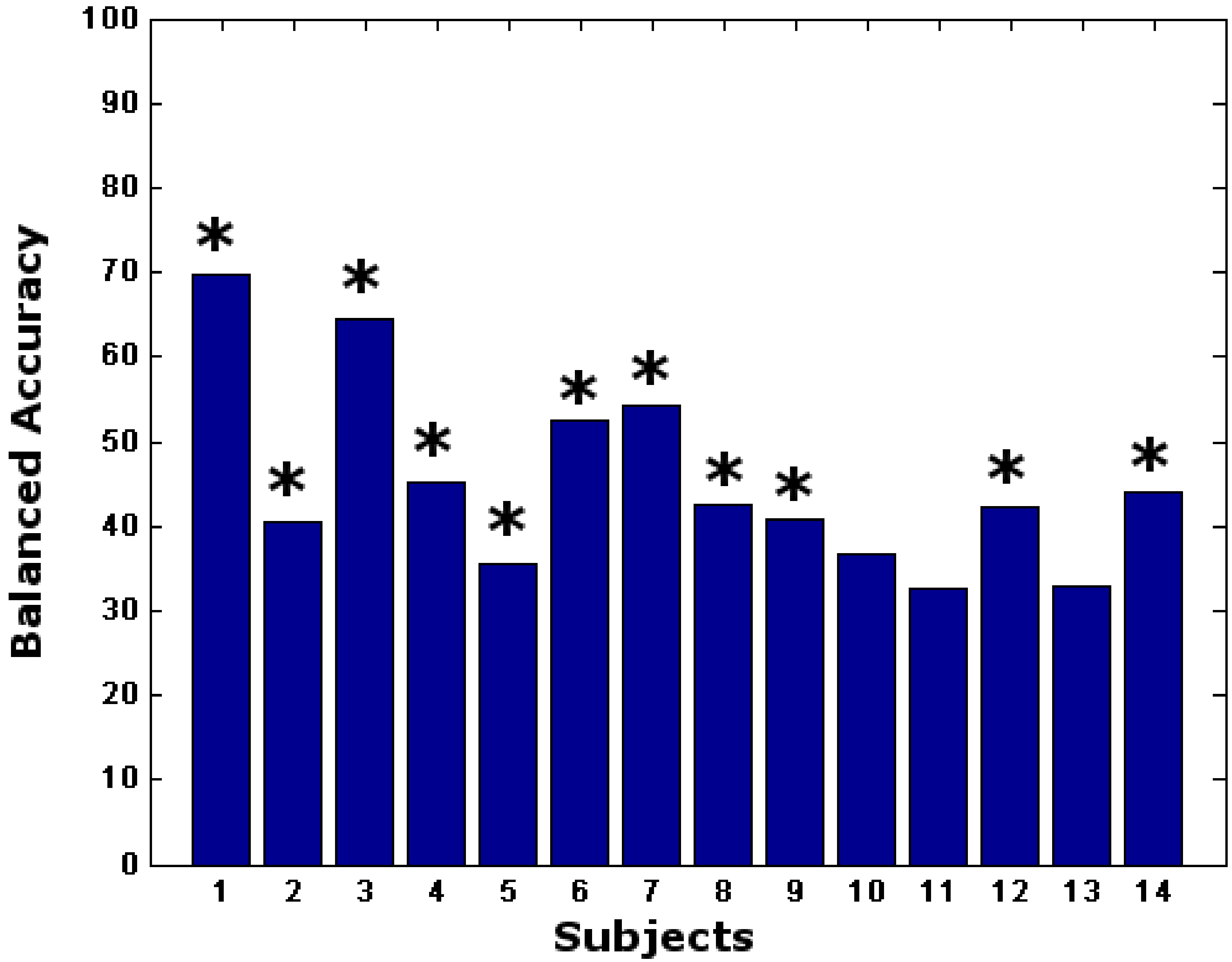
Results: Behavior

- Anxiety, depression: 2 outliers (blue)
- Number of events: less buildings
- Performance: less buildings, 1 outlier (green)

Subjects	D' (Faces)	D' (Buildings)	D' (Animals)	D' (total)
S1	2.7299	2.3960	3.5556	3.6054
S2	4.7430	1.9853	3.8699	3.1680
S3	4.7430	3.8699	3.5556	4.6816
S4	4.7430	2.0822	3.8699	3.2307
S5	3.8699	2.9325	4.7430	4.2904
S6	4.7430	2.4407	4.7430	3.5662
S7	4.7430	1.6514	3.8699	2.9588
S8	3.5556	3.1854	3.8699	4.2904
S9	4.7430	0.7218	3.1854	2.1661
S10	2.3550	3.0503	2.6025	2.5447
S11	3.1854	1.6831	2.4738	3.1824
S12	2.4407	0.9392	3.1253	1.9400
S13	2.3550	1.9848	3.8699	2.5579
S14	2.6025	2.6397	4.7430	3.0062

Results: Recall

- Feature selection: visual path + hippocampus
- Classification: 11/14, 32.98 to 69.78% ($H_0 \neq 33\%$)



Results: Rest

- Increase in Pr

Selection	Pr(m)	Pr(o)	p(dif)
No outliers	1.1136	-0.2636	**0.0578**

- Correlations with D'

Selection	C_m	$p(C_m)$	C_o	$p(C_o)$	p(dif)
No outliers	0.4968	**0.0580**	-0.0137	0.5040	**0.0400**

- Trend for C_m
- Significant difference between C_m and C_o

Agenda

- Introduction
- Data and design
- Methods
- Results
- Discussion
- Conclusions and references

Discussion

- Recall = unbalanced categories with overlapping BOLD
- Rest = no labels

→ Is what we observe the truth?

  - Significant difference between the correlations
  - Supporting the theory of pattern reactivation

- Further investigate:
  - Outliers do not learn?
  - Why Pr(m)<0?
- If new subject: look at Pr(m) to predict performance?

Agenda

- Introduction
- Data and design
- Methods
- Results
- Discussion
- Conclusions and references

Conclusion

- Method for classifying rest sessions
- Promising results but more investigation needed
- Pattern reactivation during post-task rest linked to memory performance?

References:

- K. Hoffman and B. McNaughton, “Coordinated reactivation of distributed memory traces in primate neocortex.” Science, vol. 297, pp. 2070–2073, 2002.
- A. Tambini, N. Ketz, and L. Davachi, “Enhanced brain correlations during rest are related to memory for recent experiences,” Neuron, vol. 65, pp. 280–290, 2010.
- J. Schrouff, C. Kussé, L. Wehenkel, P. Maquet, and C. Phillips, “Decoding semi-constrained brain activity from fMRI using Support Vector Machines and Gaussian Processes,” PLoS one, vol. 7, p. e35860, 2012.
- C. E. Rasmussen and C. K. I. Williams, Gaussian Processes for Machine Learning, ser. Adaptive Computation and Machine Learning, T. Dietterich, Ed. the MIT Press, 2006.
- T. G. Dietterich and G. Bakiri, “Solving multiclass learning problem via error-correcting output codes,” Journal of Artificial Intelligence Research, vol. 2, pp. 263–286, 1995.

Thank you for your attention