# The advantage of brief functional magnetic resonance imaging acquisition runs for multi-voxel pattern detection

CENTER FOR COGNITIVE NEUROSCIENCE

Marc N. Coutanche[1] and Sharon L. Thompson-Schill[1]

[1]*Department of Psychology, University of Pennsylvania*

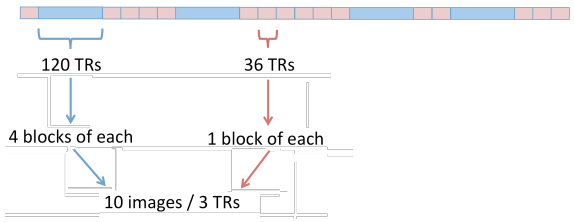
Penn
University of Pennsylvania

## INTRODUCTION

- Functional magnetic resonance imaging (fMRI) scans are split-up into runs (or 'sessions'). Experimenters typically use 4-8 runs, each 5-10 minutes long.
- Runs play a central role in many multi-voxel pattern analysis (MVPA) studies, where cross-validation is often conducted across runs: training on some runs and testing on others (e.g., 'leave-one-run-out').
- When choosing stimuli for an MVPA investigation, it is common to select a range of exemplars (e.g., different chairs; Haxby et al., 2001) and properties (e.g., viewpoint) so that a classifier will lock-on to the pattern of interest ("chairs") and successfully generalize to new unseen examples.
- We could follow the same approach with another source of signal variation: between-run differences. Exposing a classifier to many examples of scanner runs might improve across-run generalization.
- Improving across-run generalization could have great benefits for classification performance: "run-related changes reflecting scanner state and head motion are substantially larger than activity-pattern effects" (Misaki et al., 2010, p. 117).
- We hypothesized that conducting MVPA with data from a large number of short runs would give greater classification accuracy than with data from several long runs.

## METHOD

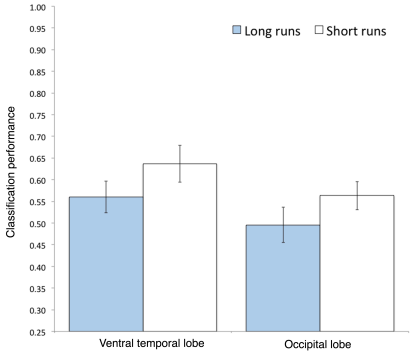
- Eight participants were presented with 4 'long' and 16 'short' runs, with equal numbers of TRs separating the runs of each length.
- Each long run contained 4 blocks of each condition.
- Each short run contained 1 block of each condition.
- Blocks contained 10 presentations of faces, places, fruit or man-made objects in a rapid 1-back design.



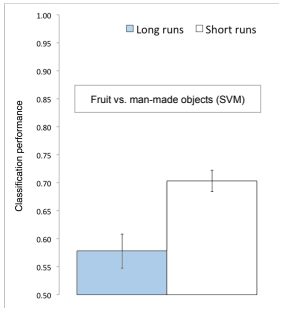

- After pre-processing (without smoothing), activity patterns were extracted for each timepoint and labeled by condition.
- The long and short run data were compared in 4-fold cross-validation, ensuring equivalent amounts of training data.
- For each run-type, the four conditions were classified using Gaussian Naïve Bayes (GNB), correlation-based and linear discriminant analysis (LDA) classifiers.
- Searchlight analyses (Kriegeskorte et al., 2006) were also conducted in ventral temporal (VT) cortex for long and short runs.
- Classification performance was assessed in:
  - VT gray matter (defined through FreeSurfer; Fischl et al., 2002)
  - Occipital gray matter
  - Visually responsive VT voxels
  - Visually responsive occipital voxels

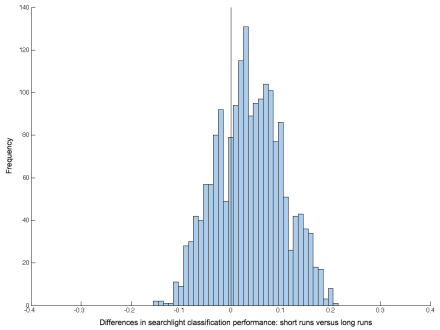
## RESULTS

- MVPA using short runs gave greater classification performance than using long runs, with identical amounts of training data.
- In VT gray matter voxels, GNB (paired $t_7 = 4.40$, $p = 0.003$), correlation-based (paired $t_7 = 3.57$, $p = 0.009$) and LDA (paired $t_7 = 3.57$, $p = 0.009$) classifiers all showed superior performance after training and testing on many short runs, compared to several long runs.
- The same pattern of results was found in occipital cortex and with visually responsive voxels.
- The short and long runs did not differ in behavioral performance ($p = 0.56$) or motion ($p = 0.24$, higher mean in short runs).




- A short-run performance boost was also found in pairwise SVM comparisons.
- The most difficult 2-way comparison, man-made objects vs. fruits, showed the greatest short-run benefit (mean: 12% increase, paired $t_7 = 3.38$, $p = 0.01$).
- Searchlight performance was greater for short runs at the group-level (paired $t_7 = 4.02$, $p = 0.005$) and within-subjects for 7 of 8 participants ($p < 0.001$).




## CONCLUSIONS

- Employing many short runs can lead to improved classification performance for MVPA investigations that seek to generalize across runs (e.g., through leave-one-run-out cross-validation).
- MVPA performance benefits were robust across different classifiers, voxel sets and in searchlight analyses.
- Investigators seeking to detect multi-voxel patterns in unseen runs might consider using many short runs to aid across-run generalization and pattern detection.

## ACKNOWLEDGEMENTS

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## CONTACT

Marc Coutanche: coumarc@psych.upenn.edu

Lab website: http://www.psych.upenn.edu/stslab/

See "Coutanche, M.N., & Thompson-Schill, S.L. (in press). The advantage of brief fMRI acquisition runs for multi-voxel pattern detection across runs. *NeuroImage*." for the manuscript related to this work – available from the lab website.

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