AUTOMATED DETECTION OF MOTION ARTIFACTS IN FMRI DATA

Danielle Cosme, John C. Flournoy, Nathalie Verhoeven, Nandita Vijayakumar, & Jennifer H. Pfeifer
University of Oregon / Department of Psychology

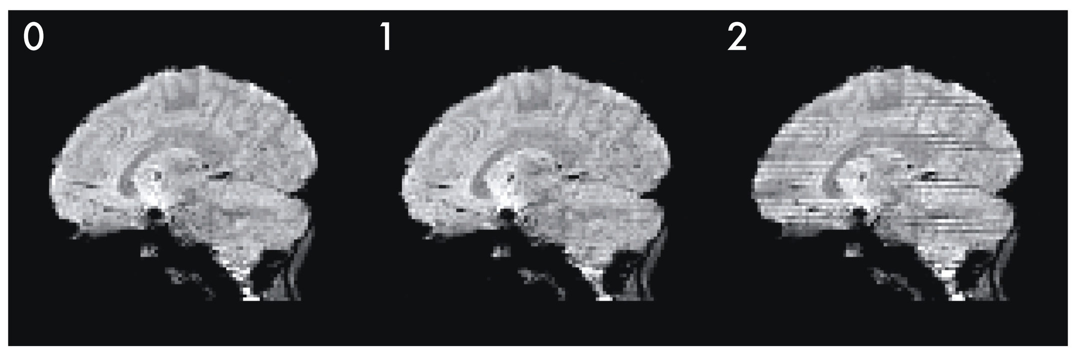
DEVELOPMENTAL SOCIAL NEUROSCIENCE

INTRODUCTION & METHODS

– Motion artifacts are a pernicious problem in pediatric task-based neuroimaging and inadequate censoring of artifacts may decrease the signal to noise ratio
– A common method for modeling motion is to include motion indicators and a “trash regressor” specifying which volumes contain motion artifacts
– Hand coding “trash” volumes is laborious, but other metrics for determining whether a volume contains motion artifacts (e.g. using realignment parameters, DVARS, or framewise displacement) have not yet been rigorously validated with developmental samples
– The goal of this project is to develop a classifier that predicts motion artifacts and assess it’s accuracy and effect on group-level models compared to other common methods

DATASET

– Data from 2 adolescent samples (N_{subs} = 70, N_{vols} = 36,629)



ARTIFACT CODING

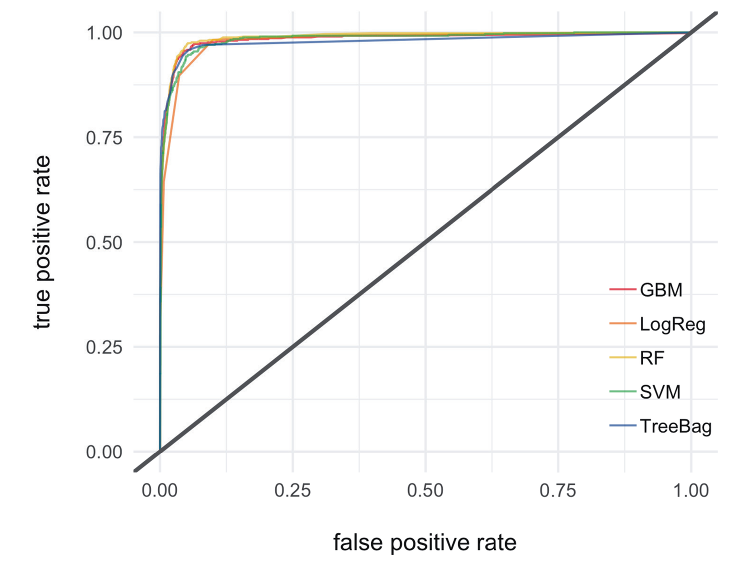
– 0 = no motion artifact, 1 = weak / ambiguous artifact, 2 = definite artifact

MACHINE LEARNING

– Trained a classifier to distinguish between artifacts (2) and non artifacts (0) using Caret[1] in R
– Artifact class frequency: no = 93% yes = 7%
– Features = 26 fmriprep[2] confounds (e.g. rps, DVARS, framewise displacement, a/tCompCor)

DEVELOPMENT (80%)

Training (75%) / Testing (25%)
– Repeated cross-validation
– Used various classifiers
– Optimized hyperparameters
– Tried sampling schemes
– ROC = test metric
– Compared on testing set



HOLD-OUT (20%)

– Re-trained final model on all development data
– Assessed performance in the hold-out set
– Compared accuracy to no information rate (NIR = .932, p < .001)

FINAL MODEL

– Best model = random forest classifier, mtry = 2
– Hold-out: AUC = .999 / Accuracy = .995 [.994, .997] / Balanced Accuracy = .987
Positive prediction value = .998 / Negative prediction value = .959

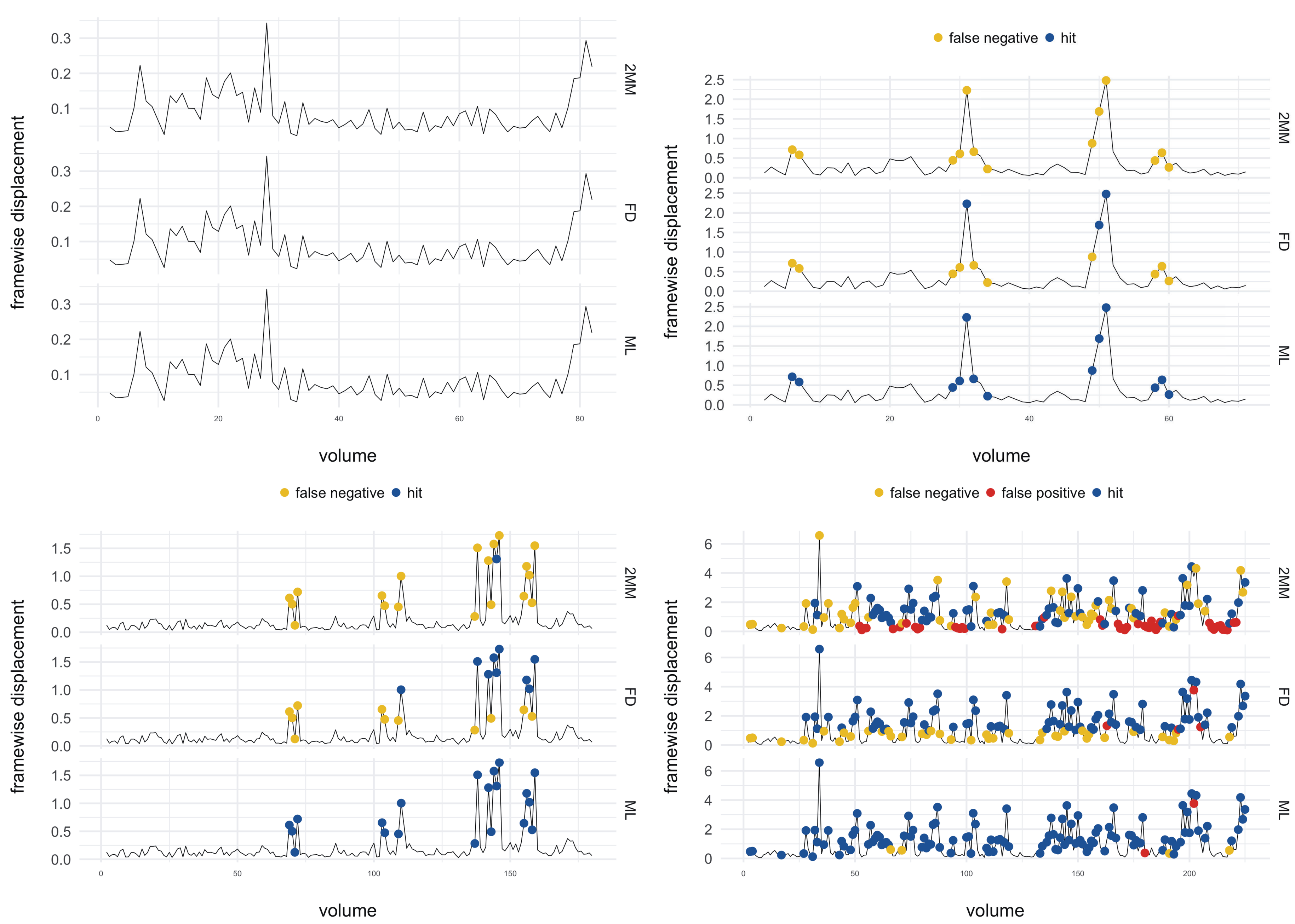
RESULTS

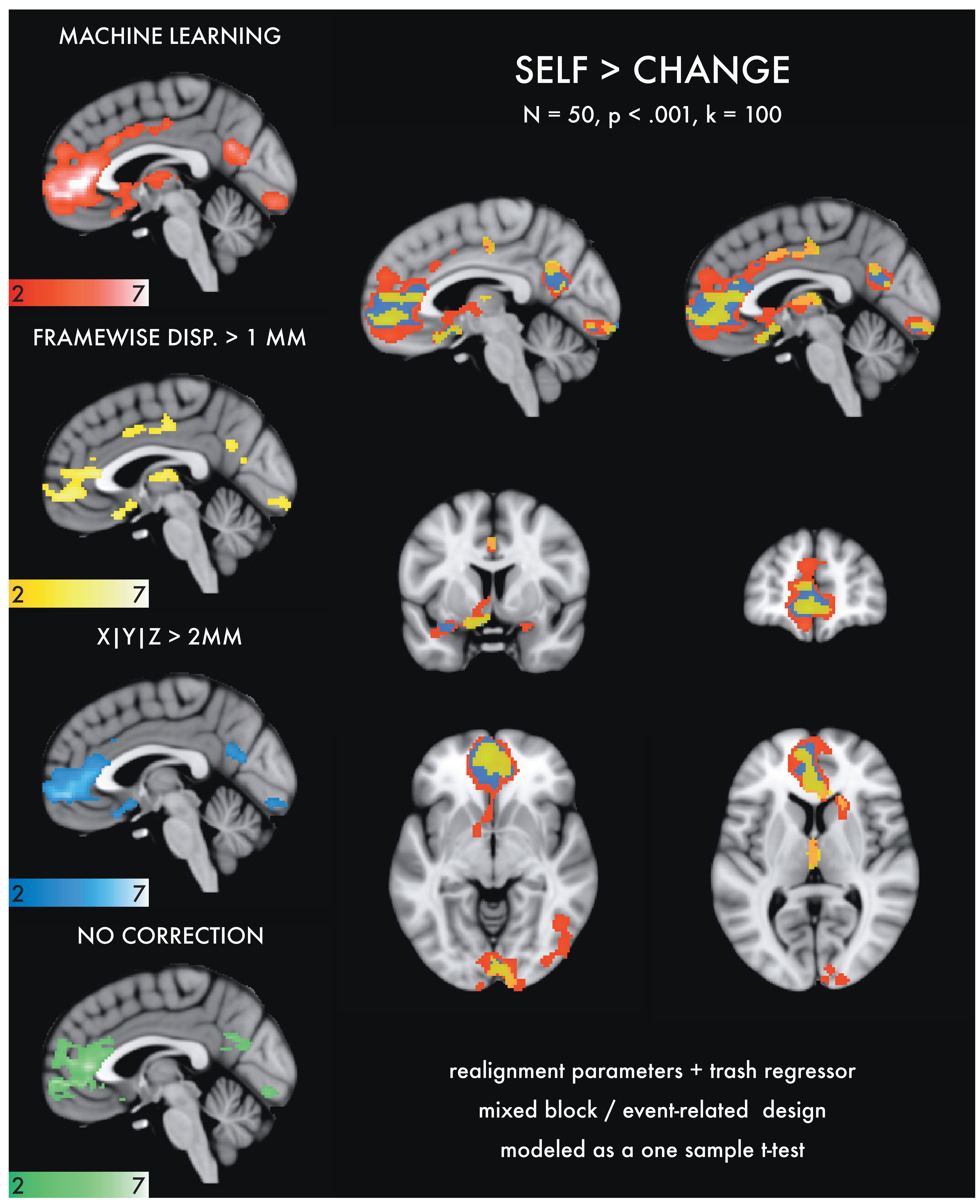
MODEL PERFORMANCE COMPARISON

2MM = X | Y | Z > 2mm, **FD** = framewise displacement > 1mm, **ML** = machine learning prediction

	2MM	FD	ML
ACCURACY	.931	.960	.995
BALANCED ACCURACY	.715	.932	.986
POSITIVE PREDICTION VALUE	.992	.996	.998
NEGATIVE PREDICTION VALUE	.104	.475	.948

VISUAL COMPARISON OF ARTIFACT CODING SCHEMES





CONCLUSIONS & FUTURE DIRECTIONS

– The machine learning classifier predicted out-of-sample motion artifacts with high accuracy
– This classifier out-performed two common automated techniques for coding motion artifacts
– The way motion is modeled affects group-level results, at least in this experimental design
– Future work should include a larger corpus of data from different scanners and populations, and systematically investigate the effect of motion modeling on various experimental designs

NOTES & REFERENCES

Huge thank you to Gracie Arnone, Oscar Bernat, Cameron Hansen, Leticia Hayes, & Nathalie Verhoeven for helping hand code motion artifacts.

IF YOU HAVE DATA AND/OR WANT TO CONTRIBUTE TO THIS PROJECT, PLEASE EMAIL ME!

[1] Kuhn, M. (2008). Caret package. Journal of statistical software, 28(5), 1-26.
[2] Esteban, O., Markiewicz, C., Blair, R. W., Moodie, C., Isik, A. I., Aliaga, A. E., ... & Oya, H. (2018) FMRIPrep: a robust preprocessing pipeline for functional MRI. bioRxiv, 306951.

UNIVERSITY OF OREGON

DANIELLE COSME / UNIVERSITY OF OREGON / DEPARTMENT OF PSYCHOLOGY
DCOSME@UOREGON.EDU

POSTER: dcosme.github.io/cosme_flux_2018.pdf
PROJECT REPO: github.com/dcosme/auto-motion-fmriprep