Effect of Nuisance Signals on Multivariate Analysis of fMRI Time Series

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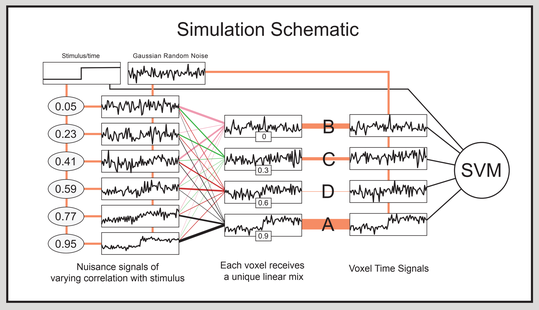
Introduction

Multivariate classifiers have become an increasingly popular analysis tool for fMRI experiments.
We describe how nuisance signals (head motion, respiration) can greatly inflate classification performance in such analyses.
We present two ways of controlling for these confounds, and evaluate their usefulness.

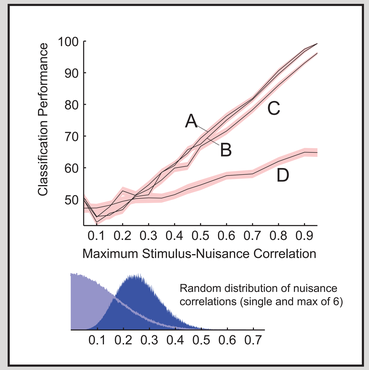
Artifact from Nuisance



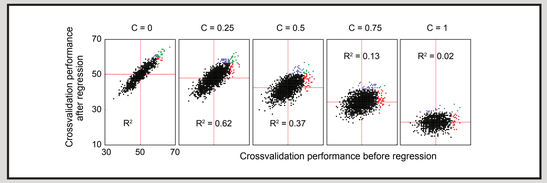
Nuisance signals create an artifact even when they are random.

This will lead to false positives.

When stimulus affects head position or breathing systematically, the problem becomes worse.



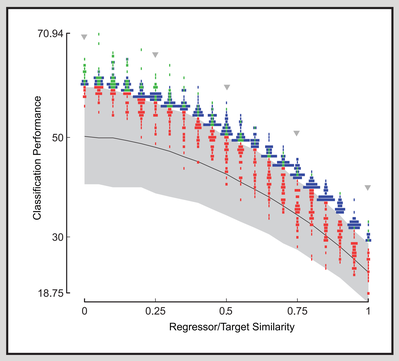
Linear Regression



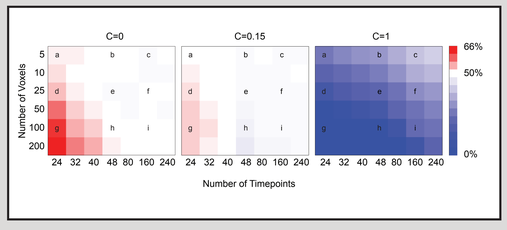
Linear regression creates a bias in the null distribution which gets bigger with increasing regressor/stimulus correlation. Regressing out the class labels equates the signal mean between classes. With m-in-n crossvalidation:

$$(n\text{-}m) * TR_A + m * TE_A = (n\text{-}m) * TR_A + m * TE_B$$

$$TE_A\text{-}TE_B = (n\text{-}m)/m * (TR_B\text{-}TR_A)$$



Even after correcting for this change in performance mean, false positives and false negatives occur.



This distribution bias occurs across different numbers of voxels and time points. Low correlations show an upward shift.

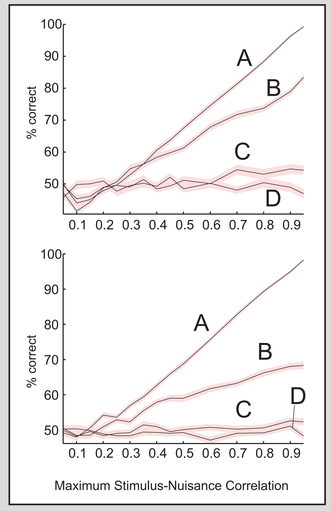
Voxel Selection

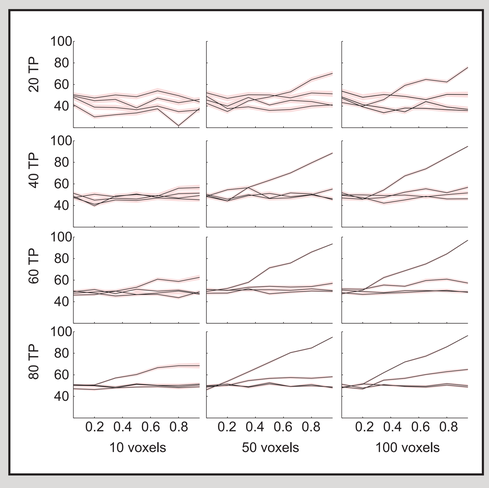
Different voxels receive different amounts of artifact. Excluding voxels with large and/or strongly correlated nuisance signals might avoid performance biases.

Selecting only voxels where the nuisance/stimulus correlation is below 0.2 eliminates the artifact for magnitude groups C and D.

Reducing the threshold to 0.1 adds no clear further benefit.

This holds true across a range of numbers of time points and voxels.





Summary

Mutilvariate classifiers, exemplified here by support vector machines, are biased by random nuisance signals, such as head movement, respiration or heartbeat.

Many kinds of stimulus (eye movements, retinal motion, emotional, attentional) introduce systematic correlations between head motion and the stimulus class, compounding the problem.

Uncorrected, these problems inflate performance and create false positives.

The standard approach of linear regression used in GLM is problematic in SVM. While biases introduced to the null distribution can be compensated for in binary problems, the strong decorrelation of performances indicates high rates of false positives and negatives. For multi-class problems there is no obvious way to account for the distribution bias and regression can not be used at all.

Voxel selection based on the amount of artifact received appears to be a promising technique for control of nuisance artifact.

Acknowledgments

NIH R01EY17605 & The Pew Charitable Trusts

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