A Regularization Method for Linking Brain and Behavior

Inhan Kang[1]; Woojong Yi[1]; Brandon M. Turner, PhD[1]
[1]Department of Psychology, The Ohio State University, Columbus, OH, USA 43210

Introduction

- Model-based cognitive neuroscience combines cognitive models with neurophysiology to map experimentally-derived variables to the changes in the brain activity and to investigate latent brain structure (Turner, Forstmann, Love, Palmeri, & van Maanen, 2017; Forstmann & Wagenmakers, 2015).
- Turner, Wang, and Merkle (2017) suggested factor analysis linking functions for modeling of neural and behavioral data in the joint modeling framework: Factor Analysis Neural Drift Diffusion Model (FA NDDM).
- To overcome the exploratory nature of FA NDDM and obtain a sparse brain network, dimensionality reduction techniques are applied to linking functions.

Method

1. Regularization in a Linear Regression Model

- To estimate the parameters (β) with regularization, we minimize:

$$S(\beta) = (y - X\beta)^T(y - X\beta) + \kappa\|\beta\|_r^r,$$

κ: a tuning parameter for the penalty term, $\|\beta\|_r^r$: r-norm of coefficients ($r = 1$ for Lasso)

$y = X\beta + \epsilon,\ \epsilon \sim N(0, \sigma^2)$
y: DV $[N\times 1]$
X: Covariates$[N\times(p+1)]$
β: Coefficient $[(p+1)\times 1]$

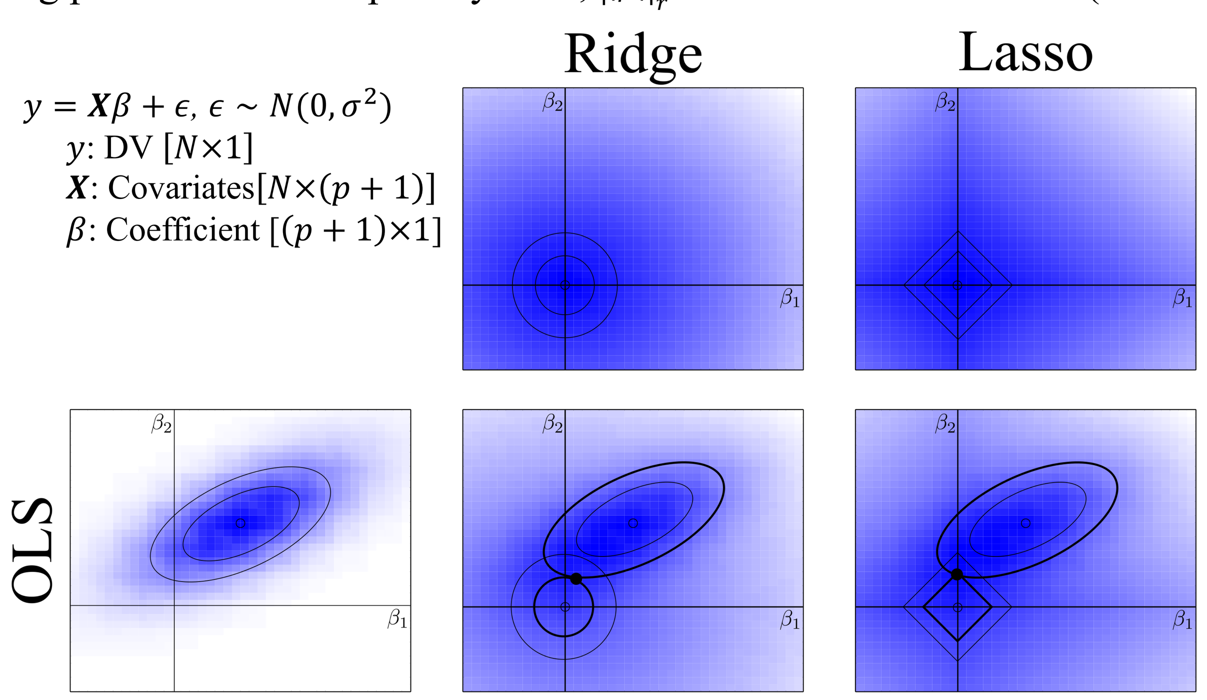
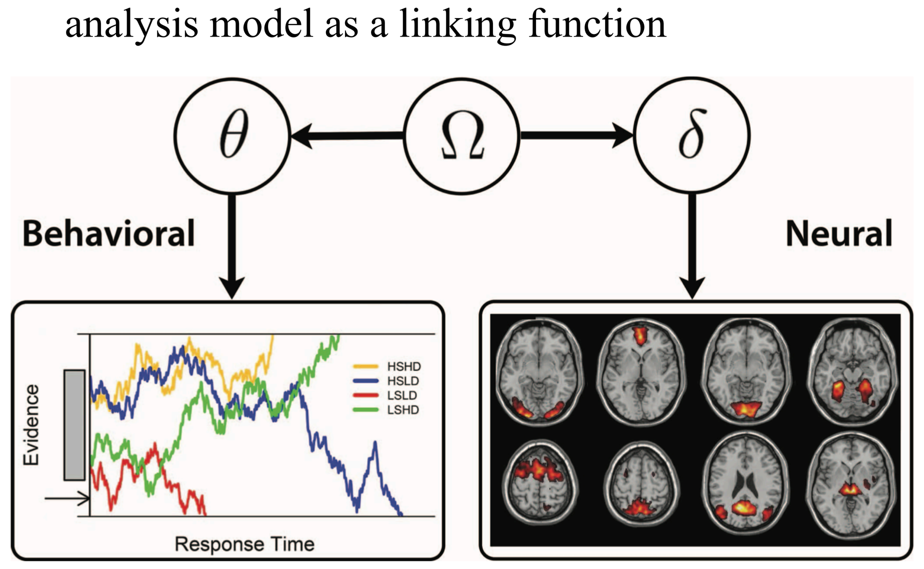


Figure 1. This is a parameter estimation for two parameter coefficients (axes), and the shape of the ordinary least squares solution (OLS) is represented in the most left panel. The next columns illustrate the influence of regularization methods on the OLS, where the marginal (top row) and joint (bottom row) components.

- Regularization methods allow us to simultaneously estimate coefficients and select the variables. Besides, their estimates have smaller mean squared errors (MSE) and prediction errors (PE) (Tibshirani, 1996; Friedman, Hastie & Tibshirani, 2001).
- Regularization can be extended to multivariate methods such as factor analysis (FA).

2. FA NDDM

- Behavioral (B) and neural (N) data are analyzed and connected simultaneously by using factor analysis model as a linking function



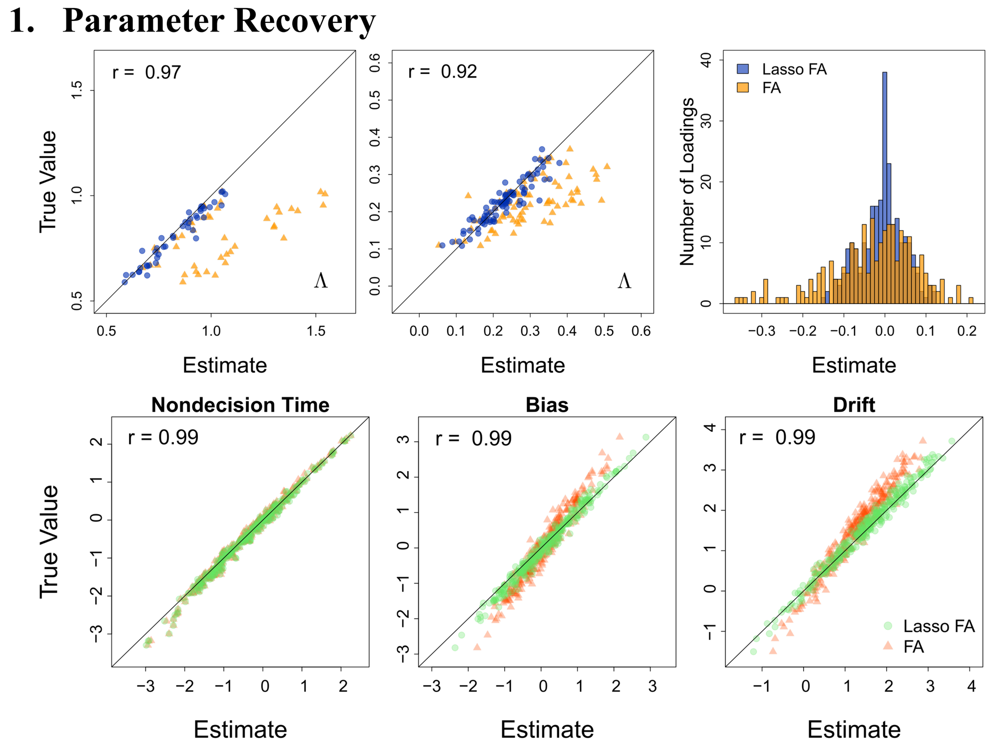
θ: Cognitive components of the diffusion model
- drift rate
- initial bias
- non-decision time

δ: Neural components
($\delta = N$ for the current study)

Ω: Linking function (FA model)
- Cognitive components are connected to the neural data via factor loading matrix
- i.e., the factor loading matrix represents the brain connectivity with the latent process of decision making

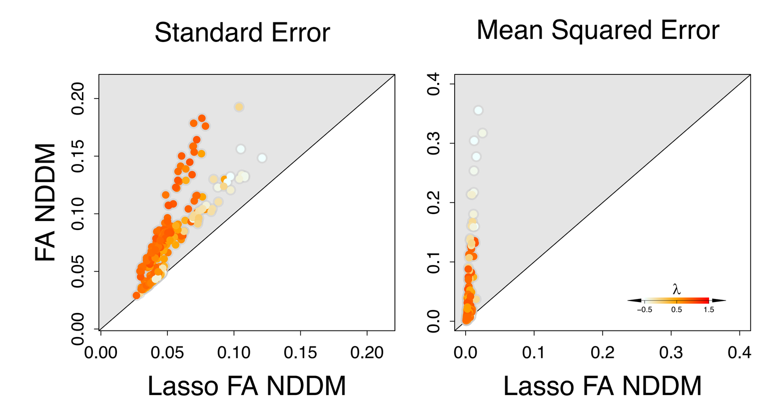
Results

1. Parameter Recovery



1) Factor Loadings
- FA NDDM tends to overestimate the factor loadings due to its hierarchical structure. Applying the Lasso can correct this bias.
- Also, the variable selection property of the Lasso can correctly identify zero factor loadings.

2) Cognitive Components (DDM parameters)
- Cognitive components underlying the decision-making data were underestimated in the FA NDDM as the bias in the factor loading propagated to the DDM parameters.
- Those components can be better estimated by the Lasso FA NDDM.



3) MSE (Risk) Reduction due to the Shrinkage
- As other shrinkage estimators do, the Lasso applied to the FA NDDM can reduce the standard errors of the estimates.
- As it corrected the bias of the loadings in the FA NDDM, the resulting estimates had spectacular reductions in the mean squared errors (MSE).

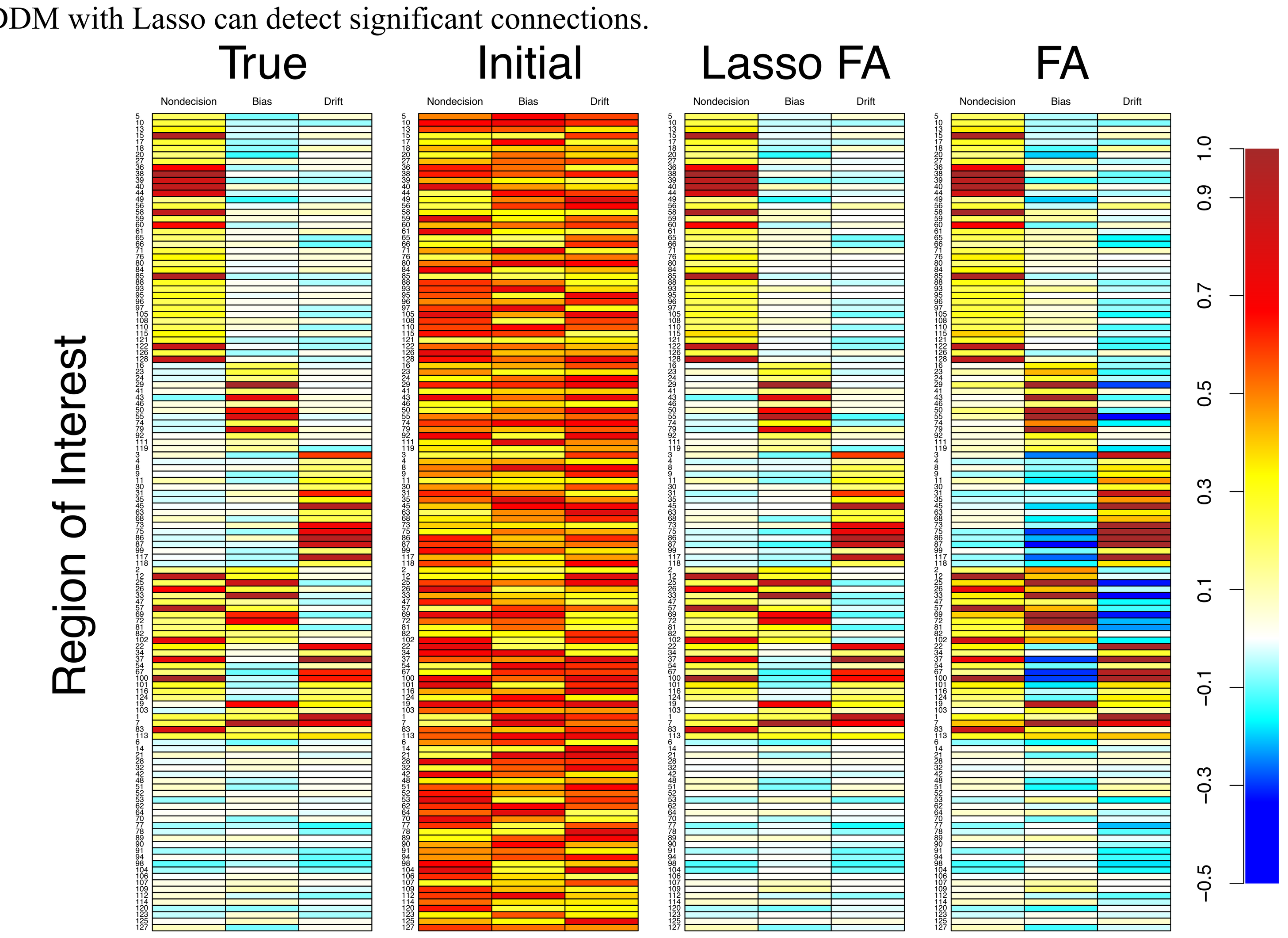
Conditions	Methods	Hit	False Alarm
Simple	FA NDDM	0.992	0.156
	Lasso FA NDDM	0.984	0.000
Overlap	FA NDDM	0.836	0.164
	Lasso FA NDDM	0.988	0.012
Complex	FA NDDM	0.715	0.285
	Lasso FA NDDM	0.941	0.059

Hit: Proportion of correctly detected nonzero loadings
False Alarm: Proportion of zero loadings falsely detected as significant

4) Hit and False Alarm
- FA NDDM can discriminate significant factor loadings from zero loadings, but the performance decreased as a function of complexity in the true structure and noise.
- Lasso FA NDDM outperformed the FA NDDM and its performance was robust across conditions.

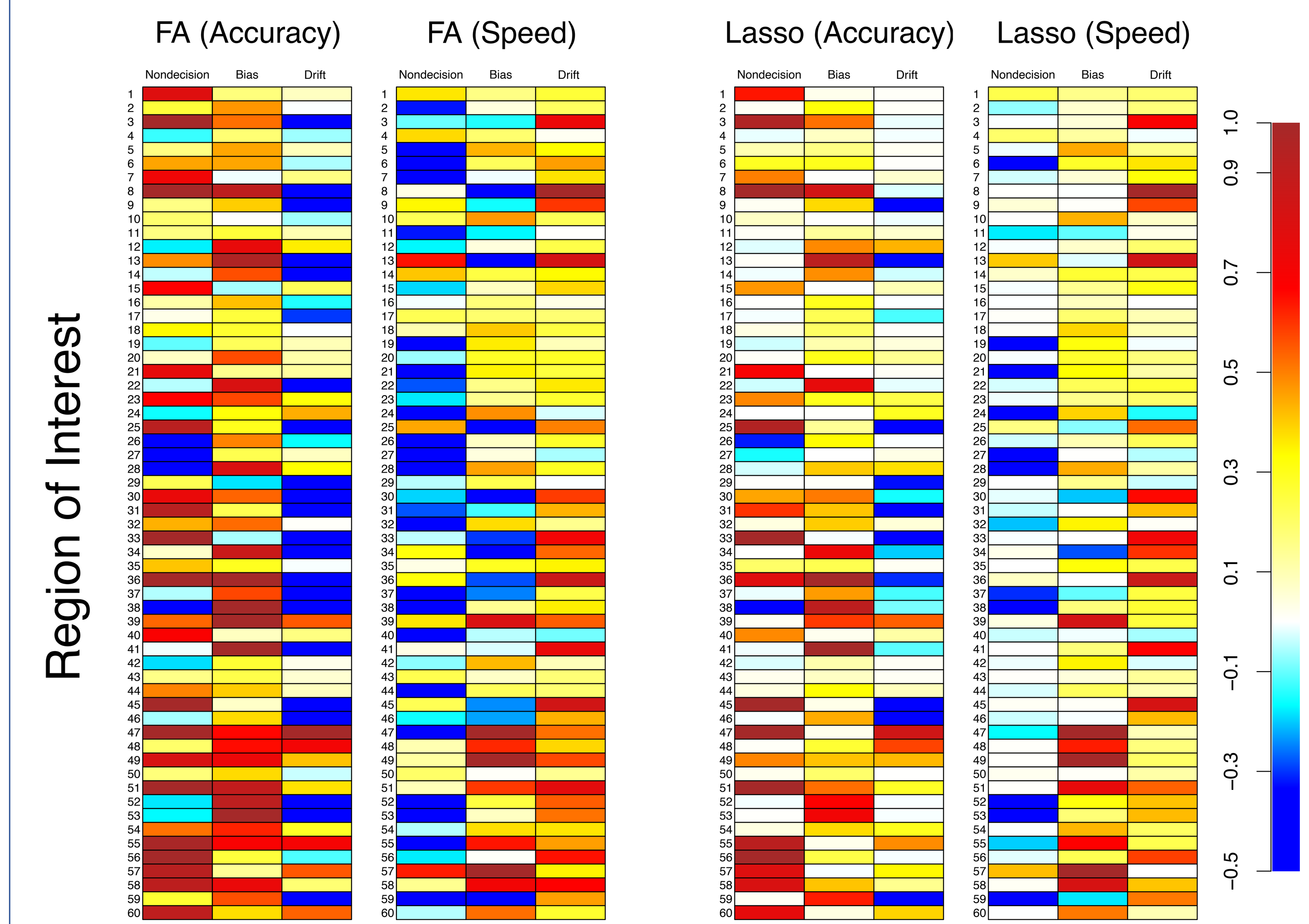
2. Structure Recovery

- Assuming a true brain mapping between cognitive components and neural measures (factor loading Λ), examined if the FA NDDM with Lasso can detect significant connections.



Linking Behavior and Brain

- We applied the Bayesian Lasso FA NDDM to the experiment data. The data are first reported in van Maanen et al. (2011), and they consist of choice and response time from a simple, two-choice random-dot motion task (for more details, see Turner, Wang, and Merkle, 2017, and van Maanen et al., 2011)



- The above figure shows the factor loading matrices estimated for the FA NDDM (left two) and the Lasso FA NDDM (right two). The rows represent different brain regions of interest, whereas the columns correspond to components of cognitive processing assumed in the diffusion decision model.
- The Lasso FA NDDM achieved a more parsimonious brain network by means of its shrinkage effect
- The results show that some brain regions are highly related to more than one or all cognitive components, whereas others might not be noticeably related to them.

Discussion

Major Results
- Shrinkage effects from the Lasso corrected the overestimation bias of the factor loadings in the FA NDDM.
- The resulting estimates of factor loadings are more reliable (lower SE and lower MSE).
- The variable selection property of the Lasso helps to identify a parsimonious latent structure of the brain data.

Discussion
- Alternative regularization techniques (e.g., the Elastic Net, the Slab and Spike Prior) can be implemented in the same way.
- Paradoxical advantage of shrinkage effect.
- Generalization of the method: The proposed method is not limited to the behavioral and neural data examine in this study.

Contact

Inhan Kang*First author
Model-based Cognitive Neuroscience Lab
Email: kang.985@osu.edu

Woojong Yi*Presenting author
Model-based Cognitive Neuroscience Lab (https://turner-mbcn.com/)
Email: woojong.yi.525@gmail.com
Phone: +1) 614-440-8956

The Ohio State University

References

Forstmann, B. U., & Wagenmakers, E.-J. U. (Eds.). (2015). *An Introduction to Model-Based Cognitive Neuroscience*. New York, NY: Springer New York.
Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning* (Vol. 1, No. 10). New York: Springer series in statistics.
Park, T., & Casella, G. (2008). The bayesian lasso. *Journal of the American Statistical Association*, *103*(482), 681-686.
Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267-288.
Turner, B. M., Wang, T., & Merkle, E. C. (2017). Factor analysis linking functions for simultaneously modeling neural and behavioral data. *NeuroImage*, *153*, 28-48.
Turner, B. M., Forstmann, B. U., Love, B. C., Palmeri, T. J., & Van Maanen, L. (2017). Approaches to analysis in model-based cognitive neuroscience. *Journal of Mathematical Psychology*, *76*, 65-79.
van Maanen, L., Brown, S. D., Eichele, T., Wagenmakers, E. J., Ho, T., Serences, J., & Forstmann, B. U. (2011). Neural correlates of trial-to-trial fluctuations in response caution. *Journal of Neuroscience*, *31*(48), 17488-17495.

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