## Matrix-normal models for fMRI analysis

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The matrix-variate normal distribution


One generative model includes many existing analyses
$\mathbf{Y}_{i} \mid \mathbf{F}_{i}, \mathbf{B}_{i}, \mathbf{W}_{i}, \Sigma_{i}, \Omega \sim$
$\mathcal{M N}\left(\mathbf{F}_{i} \mathbf{Z}+\mathbf{B}_{i} \mathbf{X}+\mathbf{J W}, \rho_{i}^{2} \Sigma, \Omega\right)$
$\mathbf{F}_{i} \mid \mathbf{C}, \mathbf{U} \sim \mathcal{M N}(0, \mathbf{C}, \mathbf{U})$
$\mathbf{Z} \mid \mathbf{D}, \mathbf{V} \sim \mathcal{M} \mathcal{N}(0, \mathbf{D}, \mathbf{V})$
$\mathbf{B}_{i} \mid \mathbf{G}, \mathbf{K} \sim \mathcal{M} \mathcal{N}\left(\boldsymbol{\beta}_{0}, \mathbf{G}, \mathbf{K}\right)$
$\mathbf{W}_{i} \mid \mathbf{H}, \mathbf{R} \sim \mathcal{M} \mathcal{N}\left(\mathbf{W}_{0}, \mathbf{H}, \mathbf{R}\right)$.


- $\mathbf{Y}_{i}$ : data for subject $i . \mathbf{X} / \mathbf{J}$ are temporal/spatial design matrices.
- This poster: temporal cov. $\Omega$ is $\operatorname{AR}(1)$, spatial $\Sigma$ is diagonal.


Matrix-Normal RSA: faster and more accurate at large data and/or low SNR

- Mitigates bias like BRSA ([1]; poster 260.05).
- Fewer parameters (different noise model).

- Try both!

- Resting state data, unrelated design matrix
- FZ should absorb all $\stackrel{\text { en }}{\underline{\omega}}$ variance, $\mathbf{B} \rightarrow 0, \mathbf{K} \rightarrow 0$.
- MN-RSA more conservative under null for most subjects.


Matrix-normal ISFC: maximumlikelihood estimation, valid correlations

## Est. Corr, synth. data

( 500 TRs, 30 src., 10 subjs.)


brainiak.matnormal: a prototyping tool for matrix-normal models MN-RSA can be implemented in $\approx 50$ lines of code! rsa-cov = CovFullRankCholesky (size=k)
space_noise_cov = CovDiagonal (size=v)
space-noise-cov $=$ CovDiagonal(size
timenoisecov $=$ CovAR1(size $=t)$


spacenoisecov.logp ${ }^{+}+$
matnorm_logp_marginal_row (Y, row_cov=time_noise_cov col-cov=space_noise_cov,
marg=X, marg_cov=rsa_cov)
optimizer.minimize(loss)
$\mathrm{U}=$ rsa-cov. Sigma
Automatic marginalization and covariance structure selection.

## References

Cai, M. B., Schuck, N. W., Pillow, J. W., \& Niv, Y. NIPS 2016; [2] Chen, P.-H., Chen, J., Yeshurun, Y., Hasson, U., Haxby, J., \& Ramadge, P. J. NIPS 2015; [3] Simony, E., Honey, C. J., Chen, J., Lositsky, O., Yeshurun, Y., Wiesel, A., \& Hasson, U. Nat. Comms. 7:12141 (2016).

