

# Statistical Analysis Programs in R for fMRI Data

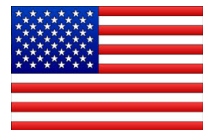


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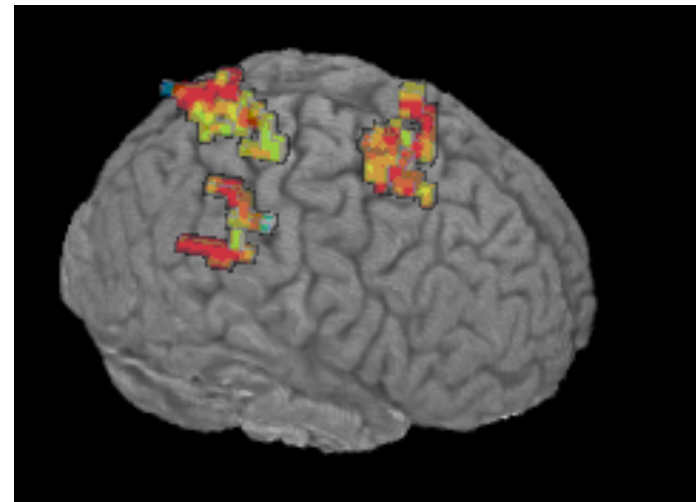
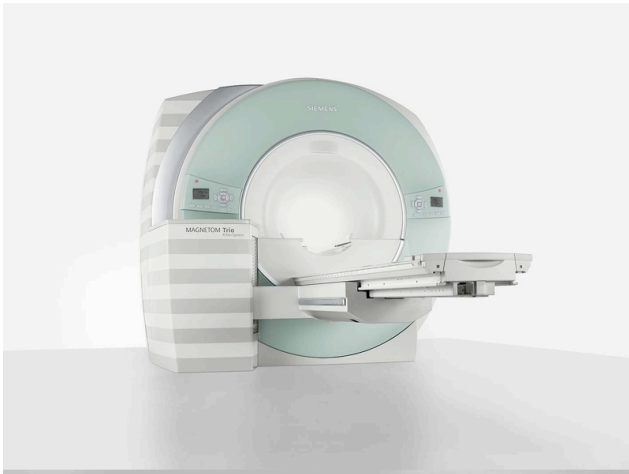
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# Overview

- ❑ What is FMRI?
  - ❑ What kinds of analysis involved in FMRI data analyses
  - ❑ Programs in R for FMRI data analyses (of **NIfTI/AFNI** data)
    - Group analysis
      - Mixed-effects meta analysis (MEMA): **3dMEMA**
      - Linear mixed-effects analysis (LME): **3dLME**
    - Connectivity analysis
      - Granger causality (vector autoregressive or VAR): **3dGC, 1dGC**
      - Intra-class correlation analysis (ICC): **3dICC** and **3dICC\_REML**
      - Structural equation modeling (SEM): **1dSEMr**
    - Data-drive analysis: Independent component analysis (ICA): **3dICA**
    - Kolmogorov-Smirnov test: **3dKS**
  - ❑ Summary
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# FMRI in Neuroimaging

- ❑ Typical scanner: 3 Tesla = 60000 × earth's magnetic field
- ❑ Measure changes in blood flow (hemodynamic response): BOLD signal
  - Indirect measure associated with neural activity during a task/condition
- ❑ Started in early 1990s; Little invasion, no radiation, *etc.*
- ❑ Interdisciplinary: physics, statistics, psychology, neuroanatomy, cognitive science, ...
- ❑ Mind reading? Not there yet, but analyses produce colored blobs denoting activation regions in the brain



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# Data type in FMRI

- ❑ Brain volume
    - Anatomical: 3D
      - Typical spatial resolution:  $1 \times 1 \times 1 \text{ mm}^3$ ; Dimensions:  $256 \times 256 \times 128 \sim 8$  million voxels
    - Functional: 4D
      - Typical spatial resolution:  $2.75 \times 2.75 \times 3.0 \text{ mm}^3$ ; Dimensions:  $80 \times 80 \times 33 \sim 20,000$  voxels
      - Typical temporal resolution:  $\sim 2\text{s}$ ; Dimension: a few hundred time points
    - Number of subjects: 10-20
  - ❑ Surface
  - ❑ ROI
  - ❑ Behavioral
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# Analysis types in FMRI

- ❑ Individual subjects: time series regression
    - Voxel-wise or massively univariate model  $y = X\beta + \varepsilon$ ,  $\varepsilon \sim N(0, \sigma^2 V)$
    - $\sigma^2$  and  $V$  vary spatially (across voxels)
    - REML + GLSQ
    - Runtime: 1 minute or more
  - ❑ Group analysis: summarizing across subjects
    - $t$ -test, ANOVA, regression
    - Runtime: seconds
  - ❑ Connectivity analysis: search for or test network in the brain
    - Correlation analysis, structural equation modeling, Granger causality, dynamic causal modeling, *etc.*
  - ❑ Multivariate approach: data-driven
    - PCA/ICA, SVM, kernel methods, *etc.*
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# AFNI = Analysis of Functional NeuroImages

- Developed to provide an environment for fMRI data analyses
  - Started in 1994 by Bob Cox at MCW, Milwaukee, Wisconsin
  - **Open source** mainly in C, plus some R and Matlab
- Important principles in the development of AFNI:
  - Allow user to stay close to the data and view it in many different ways
  - Power to assemble pieces in different ways to make customized analyses
    - “With great power comes great responsibility”  
— **to understand the analyses and the tools**
  - Provide mechanism/tools, not policy/assembling line



# Conventional group analysis in FMRI

- ❑ Take regression coefficient  $\beta$ 's from each subject, and run  $t$ -test, AN(C)OVA, LME
  - One-sample  $t$ -test:  $y_i = \alpha_0 + \delta_i$ , for  $i$ th subject;  $\delta_i \sim N(0, \tau^2)$
- ❑ Three assumptions
  - Within/intra-subject variability (standard error, sampling error) is relatively small compared to cross/between/inter-subjects variability
  - Within/intra-subject variability roughly the same across subjects
  - Normal distribution for cross-subject variability (no outliers)
- ❑ Violations prevalent, leading to suboptimal/invalid analysis
  - Common to see 40 - 100% variability due to within-subject variability
  - Non-uniform within/intra-subject variability across subjects
  - Not rare to see outliers

# Mixed-Effects Meta Analysis

- For each effect estimate ( $\beta$  or linear combination of  $\beta$ 's)
  - How good is the  $\beta$  estimate?
    - Reliability/precision/efficiency/certainty/confidence: standard error (SE)
    - Smaller SE  $\rightarrow$  more accurate estimate
  - $t$ -statistic of the effect
    - Signal-to-noise or effect vs. uncertainty:  $t = \beta/SE$
    - SE contained in  $t$ -statistic:  $SE = \beta/t$
  - Trust those  $\beta$ 's with high reliability/precision (small SE) through weighting/compromise
    - $\beta$  estimate with high precision (lower SE) has more say in the final result
    - $\beta$  estimate with high uncertainty gets downgraded
  - One-sample model:  $y_i = \alpha_0 + \delta_i + \varepsilon_i$ , for  $i$ th subject
    - $\delta_i \sim N(0, \tau^2)$ ,  $\varepsilon_i \sim N(0, \sigma_i^2)$ ,  $\sigma_i^2$  known



# New group analysis program: 3dMEMA

- ❑ Algorithms (MoM/REML + WLS) similar to R package **metafor** (Wolfgang Viechtbauer) with parallel computing using R package **snow**
- ❑ Runtime: a few minutes or more with 4 CPUs
- ❑ Analysis types
  - 1-, 2-, paired-sample test
  - Covariates: age, IQ, behavioral data, between-subjects factors, *etc.*
- ❑ Input: effect estimate +  $t$  from individual subjects
- ❑ Output
  - Group level: group effect +  $Z/t$
  - Cross-subject heterogeneity +  $\chi^2$ -test
  - Individual level: ICC +  $Z$
- ❑ Assessing outliers with 4 estimated quantities
  - Cross-subject variance (heterogeneity)  $\tau^2$  at group level
  - $\chi^2$ -test for  $H_0: \tau^2=0$  at group level
  - Intra-class correlation for each subject
  - $Z$ -statistic for the residuals for each subject
- ❑ Outliers modeled through a Laplace distribution of cross-subject variability

# Comparison: 3dMEMA vs. FLAME1+2

- Frequentist (REML) vs. Bayesian (MCMC)
- Runtime: a Mac OS X 10.6.2 with 2×2.66 GHz dual-core Intel Xeon. Group analysis: 10 subjects, 218379 voxels. FSL ver. 4.1.4

	3dMEMA with 4 parallel jobs	3dMEMA with 2 parallel jobs	3dMEMA with a single processor	Flame 1+2 (FSL)
Without modeling outliers	3	4.5	8	385
Modeling outliers	22.5	34.5	65	847

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# Linear Mixed-Effects Analysis

- $Y_i = X_i\beta + Z_i b_i + \varepsilon_i$ ,  $b_i \sim N_q(0, \Psi)$ ,  $\varepsilon_i \sim N_{n_i}(0, \sigma^2 \Lambda_i)$ ,  $q=1$
  - Parameters:  $\beta$ ,  $\Psi$ , and  $\sigma^2 \Lambda_i$
  - Fixed/mean/systematic effects in population  $X_i\beta$
  - Random effects  $Z_i b_i$ 
    - Across-subjects variability: deviation of each subject from mean effects  $X_i\beta$
  - Random effect  $\varepsilon_i$ 
    - Within-subject variability (across multiple effects)
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# Linear Mixed-Effects Analysis: **3dLME**

- ❑ Use function **lme()** in R package **nlme** (Pinheiro *et al.*)
  - ❑ Parallel computing using R package **snow** (Tierney *et al.*)
  - ❑ Contrasts through R package **contrast** (Kuhn *et al.*)
  - ❑ Runtime: a few minutes or more with 4 CPUs
  - ❑ **3dLME** is more flexible than conventional approach
    - Popular ANOVA, paired-, one- and two-sample  $t$ -test: special cases of LME
      - ANOVA: compound symmetry in  $\Psi$
    - Capable to model various structures in  $\Psi$  and  $\sigma^2\Lambda_i$
    - Much easier to deal with missing data and covariates
    - Modeling subtle HRF shape through multiple basis functions
      - Zero intercept with  $H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$  ( $k = \#$  time points in HRF)
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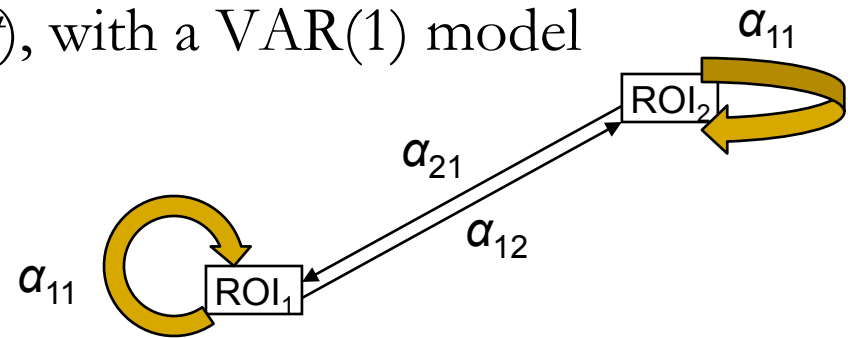
# Granger Causality or VAR

- Granger causality: A Granger causes B if
  - time series at A provides **statistically significant** information about time series at B at some time delays (order)

- 2 ROI time series,  $y_1(t)$  and  $y_2(t)$ , with a VAR(1) model

$$y_1(t) = \alpha_{10} + \alpha_{11}y_1(t-1) + \alpha_{12}y_2(t-1) + \varepsilon_1(t)$$

$$y_2(t) = \alpha_{20} + \alpha_{21}y_1(t-1) + \alpha_{22}y_2(t-1) + \varepsilon_2(t)$$



- Matrix form:  $Y(t) = \alpha + AY(t-1) + \varepsilon(t)$ , where

$$Y(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} \quad \alpha = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} \quad A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \quad \varepsilon(t) = \begin{bmatrix} \varepsilon_1(t) \\ \varepsilon_2(t) \end{bmatrix}$$

- $n$  ROI time series,  $y_1(t), \dots, y_n(t)$ , with VAR( $p$ ) model

$$Y(t) = \alpha + \sum_{i=1}^p A_i Y(t-i) + \varepsilon(t) \quad \alpha = \begin{bmatrix} \alpha_{10} \\ \vdots \\ \alpha_{n0} \end{bmatrix} \quad Y(t) = \begin{bmatrix} y_1(t) \\ \vdots \\ y_n(t) \end{bmatrix} \quad A_i = \begin{bmatrix} \alpha_{11i} & \cdots & \alpha_{1ni} \\ \vdots & \ddots & \vdots \\ \alpha_{n1i} & \cdots & \alpha_{nni} \end{bmatrix} \quad \varepsilon(t) = \begin{bmatrix} \varepsilon_1(t) \\ \vdots \\ \varepsilon_n(t) \end{bmatrix}$$

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# GC in AFNI: 3dGC and 1dGC

- Exploratory approach: ROI search with **3dGC**
  - Not a solid approach; can explore possible ROIs in a network
  - Bivariate model: Seed vs. rest of brain
  - 3 paths: seed to target, target to seed, and self-effect
  - Use R packages **vars** (Bernhard Pfaff) and **snow** (Tierney *et al.*)
- Path strength significance testing in a network: **1dGC**
  - Assume all ROIs are known in the network
  - Multivariate model with pre-selected ROIs
  - Use R package **vars** for VAR modeling (Bernhard Pfaff)
  - Use R package **network** for plotting (Butts *et al.*)
  - Preserve path sign (+ or -), in addition to its direction, from individual subjects all the way to group level analysis

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# Intra-Class Correlation (ICC)

## ❑ Classical definition

- Variability of a random variable relative to total variance
- ICC varieties in *Shrout and Fleiss* (1979), *Psychological Bulletin*, Vol. 86, No.2, 420-428
  - Based on mean squares of variance in ANOVA framework
  - Problem: not rare to have **negative** ICC values, and difficult to interpret
- Applied to fMRI data
  - Reliability of scanning sessions/sites

## ❑ Extended definition

- Linear mixed-effects model
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# 3dICC and 3dICC\_REML

## □ 3dICC

- Use function `lm()` in R
- Parallel computing using R package `snow` (Tierney *et al.*)
- 2-way and 3-way random-effects ANOVA model
- May get negative ICC values

## □ 3dICC\_REML

- Use function `lmer()` in R package `lme4` (Bates and Maechler)
  - No negative ICC values
  - Missing data allowed
  - No limit on # random variables
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# Miscellaneous Tools

- ❑ SEM or path analysis, analysis of covariance: **1dSEMr**
    - Causal model for a network of ROIs
    - Use R package **sem** (John Fox)
  - ❑ Independent component analysis: **1dICA**
    - Use R package **fastICA** (Marchini *et al.*)
    - Spatial ICA
  - ❑ Kolmogorov-Smirnov test: **3dKS**
    - Use R package **snow** (Luke Tierney *et al.*)
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# Summary

- ❑ Statistical analysis programs in R for FMRI data analysis of NIfTI/AFNI datasets
    - Mixed-effects meta analysis (MEMA): **3dMEMA**
    - Linear mixed-effects analysis (LME): **3dLME**
    - Granger causality (vector autoregressive or VAR): **3dGC**, **1dGC**
    - Intra-class correlation analysis (ICC): **3dICC** and **3dICC\_REML**
    - Structural equation modeling (SEM): **1dSEMr**
    - Independent component analysis (ICA): **3dICA**
    - Kolmogorov-Smirnov test: **3dKS**
  - ❑ All programs available for download with AFNI, and at <http://afni.nimh.nih.gov/sscc/gangc>
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