# Got ROIs?

# Efficient Modeling through Information Pooling

afni26_ROI-based-modeling.pdf

Gang Chen

Scientific and Statistical Computing Core

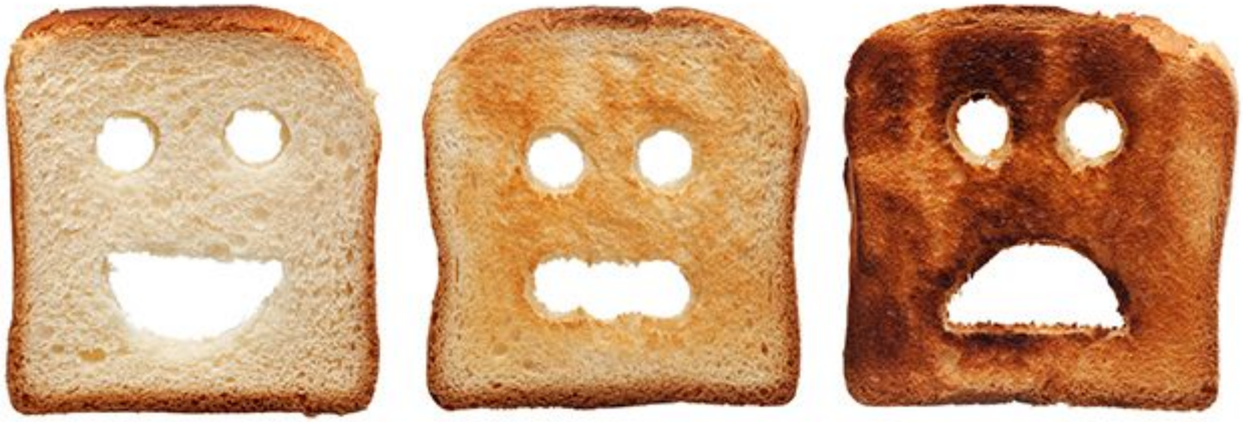
National Institute of Mental Health

National Institutes of Health, USA

# Preview

- **Efficient modeling through information pooling**
  - How to effectively avoid multiplicity penalty?
- **Demo dataset #1**
  - Resting state: seed-based correlation analysis
  - Handling multiple testing through ROI-based group analysis
    - How to avoid penalty of modeling across voxels or ROIs?
  - Program available in AFNI: BayesianGroupAna.py
- **Demo dataset #2**
  - Group analysis with correlation matrices among ROIs
  - Handling multiple testing for inter-region data (IRD) analysis
    - How to avoid penalty of modeling across voxels or ROIs?
  - More applications
    - **DTI data: white matter connectivity network**
    - **Naturalistic data analysis**

Are you eating acrylamide for breakfast?



Both sides good One side BURNT Both sides BURNT

- Conditional probability
- Knowledge updating

# Conventional Statistical Framework: NHST

- **Two types of errors: null hypothesis significance testing (NHST)**
  - What is $\mathbf{H_0}$ in FMRI studies? $\mathbf{H_0}$ = no effect (activation, difference, …) at a voxel
  - **Type I error** = Prob(reject $H_0$ when $H_0$ is true) = false positive = $p$ value

    **Type II error** = Prob(accept $H_0$ when $H_1$ is true) = false negative = $b$

    **power** = 1–$b$ = probability of detecting true activation
  - Goal: control type I error rate while increasing power (decreasing type II errors)
  - Significance level **α** (magic number 0.05) : $p < \alpha$

### Justice System: Trial

Hidden Truth

| | Defendant Innocent | Defendant Guilty |
|---|---|---|
| Reject Presumption of Innocence (Guilty Verdict) | **Type I Error** (defendant very unhappy) | **Correct** |
| Fail to Reject Presumption of Innocence (Not Guilty Verdict) | **Correct** | **Type II Error** (defendant very happy) |

### Statistics: Hypothesis Test

Hidden Truth

| | $H_0$ True<br>Not Activated | $H_0$ False<br>Activated |
|---|---|---|
| Reject $H_0$ (decide voxel is activated) | **Type I Error** (false positive) | **Correct** |
| Don't Reject $H_0$ (decide voxel isn't activated) | **Correct** | **Type II Error** (false negative) |

## Problems with NHST

- World is not always discretely YES or NO
  - Dichotomous: Guilt vs. Innocence (mostly)
  - Not dichotomous ("activate" vs. "inactivate") in a brain region
    - Real data for effect estimates are not 0s in the brain
    - Practical goal: what is strength of evidence for a claim?
- Straw man: null hypothesis – witch hunt
  - $H_0$: scientifically uninteresting; unrealistic characterization of brain regions (especially *en masse*)
  - "False positive": dichotomous misnomer for real data
- Interpretation: conditional probability $P$ (evidence | $H_0$)
  - $p$ (evidence | $H_0$) $\neq$ $p$ (H0 | data) *!* 😀
- Abusive interpretation
  - Statistically insignificant = Non-existing effect?
  - Choose a voxelwise threshold (e.g., 0.001) and be "done"

# Problems with NHST

- Thresholding under NHST: dichotomized decision
  - *p*-value of 0.05 vs 0.051, or cluster size of 54 vs 53 voxels
  - Difference between "significant" & "insignificant" results
  - Selection bias about effect estimates in results reporting
    - Power analysis based on literature: not very useful
    - One source of reproducibility problem
    - Unreliable meta analyses (many effects get lost)
- Cluster thresholding – "iceberg above water" approach
  - Using spatial extent as a leverage to control false positives
  - Cluster threshold of 54 voxels: cannot report 53 voxels*?*
  - Penalizing anatomically small regions: discrimination*!*
    - Unfair: 2 regions with same signal strength: 1 large and 1 small size
    - 2 regions with same signal strength: 1 case (distant) and 1 case (contiguous)
  - Sidedness for whole brain: one- or two-sided?

# Appetizer #1: everybody loves GLM!

- **Dataset #1**
  - Subjects: $n$ = 124 children; resting-state data
  - Individual subjects: seed-based correlation for each subject
    - 3D correlation between seed and whole brain ("functional connectivity")
  - Explanatory variable (behavior data): Theory of Mind Index $x_i$

- **Voxel-based group analysis: GLMs**
  - Focus: association between and seed-based correlation (z-score)
  - Pretense: voxels unrelated
  - GLMs: mass univariate

  $m$ = 100,000 voxels →
  $m$ = 100,000 models

$$
\begin{aligned}
\text{1st voxel:}\quad & \boldsymbol{z}_1 = a_1 + b_1\boldsymbol{x} + \boldsymbol{\epsilon}_1 \\
\text{2nd voxel:}\quad & \boldsymbol{z}_2 = a_2 + b_2\boldsymbol{x} + \boldsymbol{\epsilon}_2 \\
& \ldots \\
m\text{th voxel:}\quad & \boldsymbol{z}_m = a_m + b_m\boldsymbol{x} + \boldsymbol{\epsilon}_m
\end{aligned}
$$

# GLMs: dealing with multiplicity!

- **Voxel-based group analysis: GLMs**
  - Penalty time for pretense: multiple testing ($m$ = 100,000), magic 0.05
  - Show time for various correction methods
    - Voxel-wise $p$, FWE, FDR, spatial smoothness, clusters, …
    - Simulations, random field theory, permutations, …
    - How would dataset turn out under GLM? 4 lucky clusters manage to survive

| voxel $p$ | cluster threshold | surviving ROIs | ROIs |
|---|---|---|---|
| 0.001 | 28 | 2 | R PCC, PCC/PrC |
| 0.005 | 66 | 4 | R PCC, PCC/PrC., L IPL, L TPJ |
| 0.01 | 106 | 4 | R PCC, PCC/PrC., L IPL, L TPJ |
| 0.05 | 467 | 4 | R PCC, PCC/PrC., L IPL, L TPJ |

# Switching from voxels to ROIs: motivations

- **Motivations of ROI-based approach**
  - Avoiding arbitrary thresholding and clustering
  - No discrimination against small regions
  - All regions judged by their strength, not physical size

- **ROI definitions**
  - Anatomical atlases
  - Functional parcellations
  - Previous studies
  - Split current data
    - **Part for localization and ROI definition, part for ROI-based analysis**

# Switching from voxels to ROIs: still GLMs

- **ROI-based group analysis : GLMs**
  - Focus: association between and seed-based correlation (*z*-score)
  - Pretense: ROIs unrelated
  - GLMs: mass univariate
    $m$ = 100 ROIs →
    $m$ = 100 models
  - Penalty time for pretense:
    multiple testing – what to do?
    - Bonferroni? Unbearable
    - What else?

$$
\begin{aligned}
\text{1st ROI:} \quad & \boldsymbol{z}_1 = a_1 + b_1 \boldsymbol{x} + \boldsymbol{\epsilon}_1 \\
\text{2nd ROI:} \quad & \boldsymbol{z}_2 = a_2 + b_2 \boldsymbol{x} + \boldsymbol{\epsilon}_2 \\
& \dots \\
m\text{th ROI:} \quad & \boldsymbol{z}_m = a_m + b_m \boldsymbol{x} + \boldsymbol{\epsilon}_m
\end{aligned}
$$

# Switching from GLMs to LME

- **ROI-based group analysis : Linear Mixed-Effects modeling**
  - One model integrates all ROIs
  - ROIs loosely constrained instead of being unrelated
    - Gaussian distribution: Is it far-fetched?
    - Similar to cross-subject variability
  - Goal: effect of interest $b + \beta_j$
  - Fixed vs. random effects?
  - What can we get out of LME?
    - Estimates for fixed effects
    - Variances for random effects
  - ***Cul-de-sac!***

Overall effect: shared by all ROIs and subjects

Effect by *i*th subject

Unique effect by *j*th ROI

$$z_{ij} = a + bx_i + \pi_i + \alpha_j + \beta_j x_i + \epsilon_{ij}$$

$$\pi_i \overset{iid}{\sim} \mathcal{N}(0, \tau^2), (\alpha_j, \beta_j)^T \overset{iid}{\sim} \mathcal{N}(\mathbf{0}, \boldsymbol{\lambda})$$

$$\epsilon_{ij} \sim \mathcal{N}(0, \sigma^2), i = 1, 2, ..., n, \ \ j = 1, 2, ..., m$$

# One more jump from LME to BML

- **ROI-based group analysis : Bayesian Multi-Level modeling**
  - One model integrates all ROIs: same as LME, but under Bayesian
  - ROIs loosely constrained instead of being unrelated
    - Gaussian distribution: is it far-fetched?
    - Similar to cross-subject variability
  - Goal: effect of interest $b + \beta_j$
  - Same model as LME plus priors
    - Markov chain Monte Carlo (MCMC)
    - Inferences via posterior distribution
  - ***Ka-ching!***

Effect by *i*th subject

Overall effect: shared by all ROIs

Unique effect by *j*th ROI

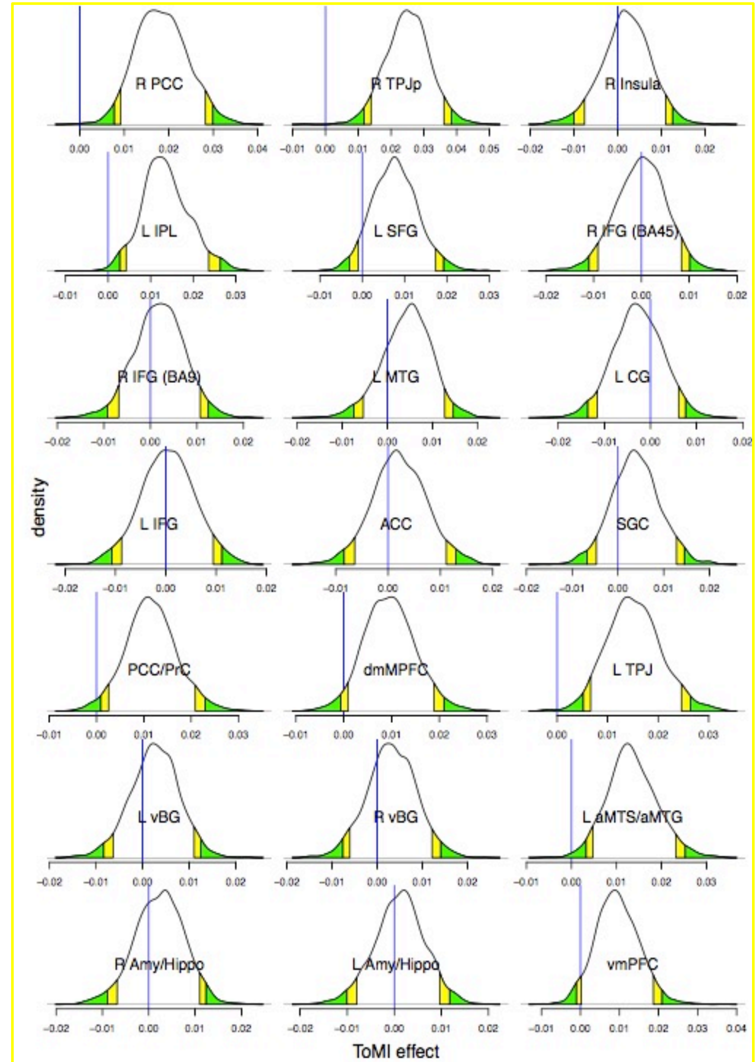
$$y_{ij}|x_i, a, b, \pi_i, \alpha_j, \beta_j \sim \mathcal{N}(a + bx_i + \pi_i + \alpha_j + \beta_j x_i, \sigma^2)$$

$$\pi_i \sim \mathcal{N}(0, \tau^2), \ (\alpha_j, \beta_j)^T \sim \mathcal{N}((0,0)^T, \boldsymbol{\lambda})$$

$$i = 1, 2, ..., n, \ j = 1, 2, ..., m$$

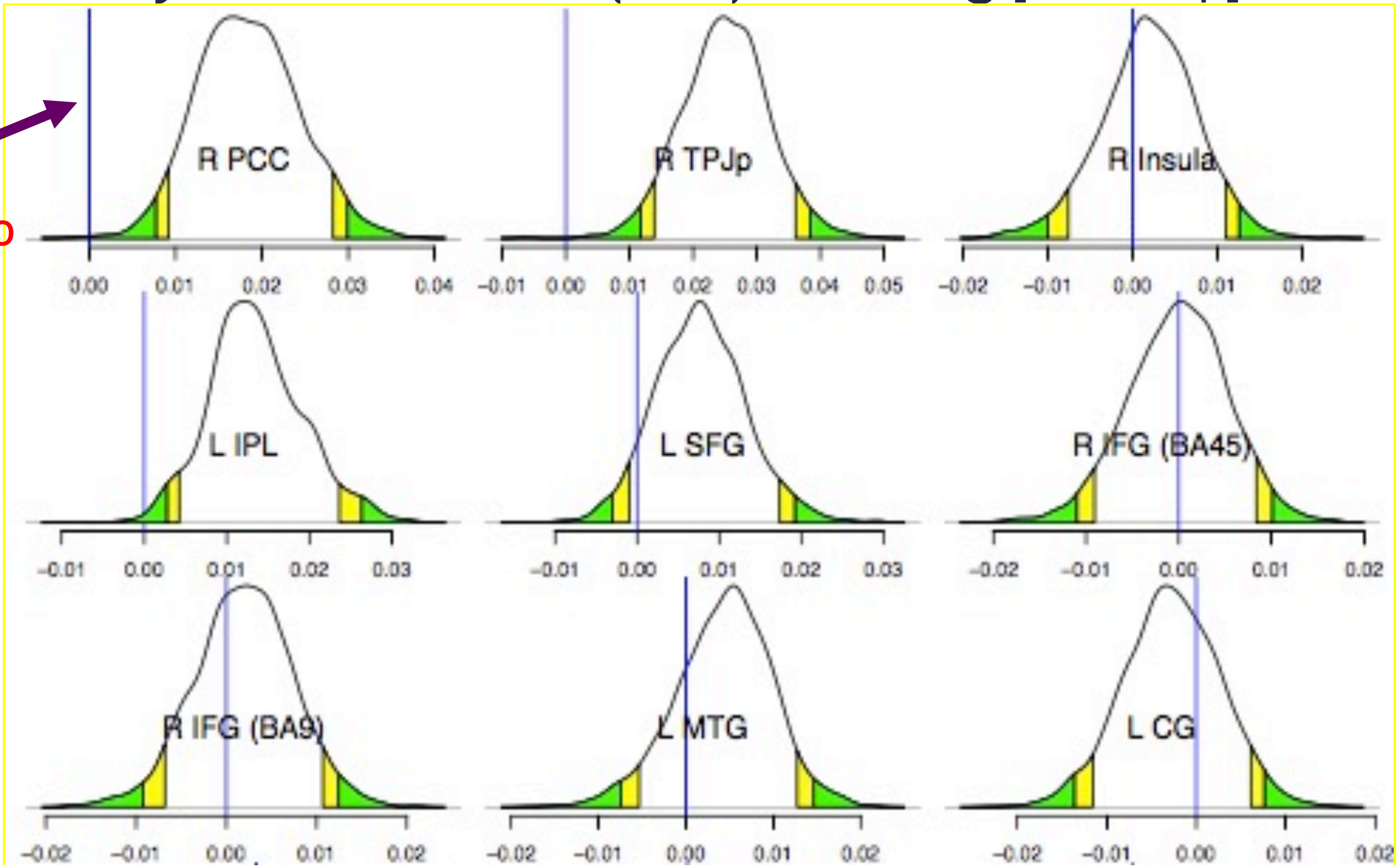
# Inferences from BML: full distributions

- **ROI-based BML: 21 ROIs**
- **Full report with richer information: posterior distributions for each ROI**
  - No dichotomization
  - No results hiding
  - No discrimination against small regions
- **8 ROIs with strong evidence of effect compared to**
  - ROI-wise GLM with Bonferroni
  - Voxel-wise GLM at cluster level



# Bayesian Multilevel (BML) Modeling [blown up]

Blue Line: effect of ZERO



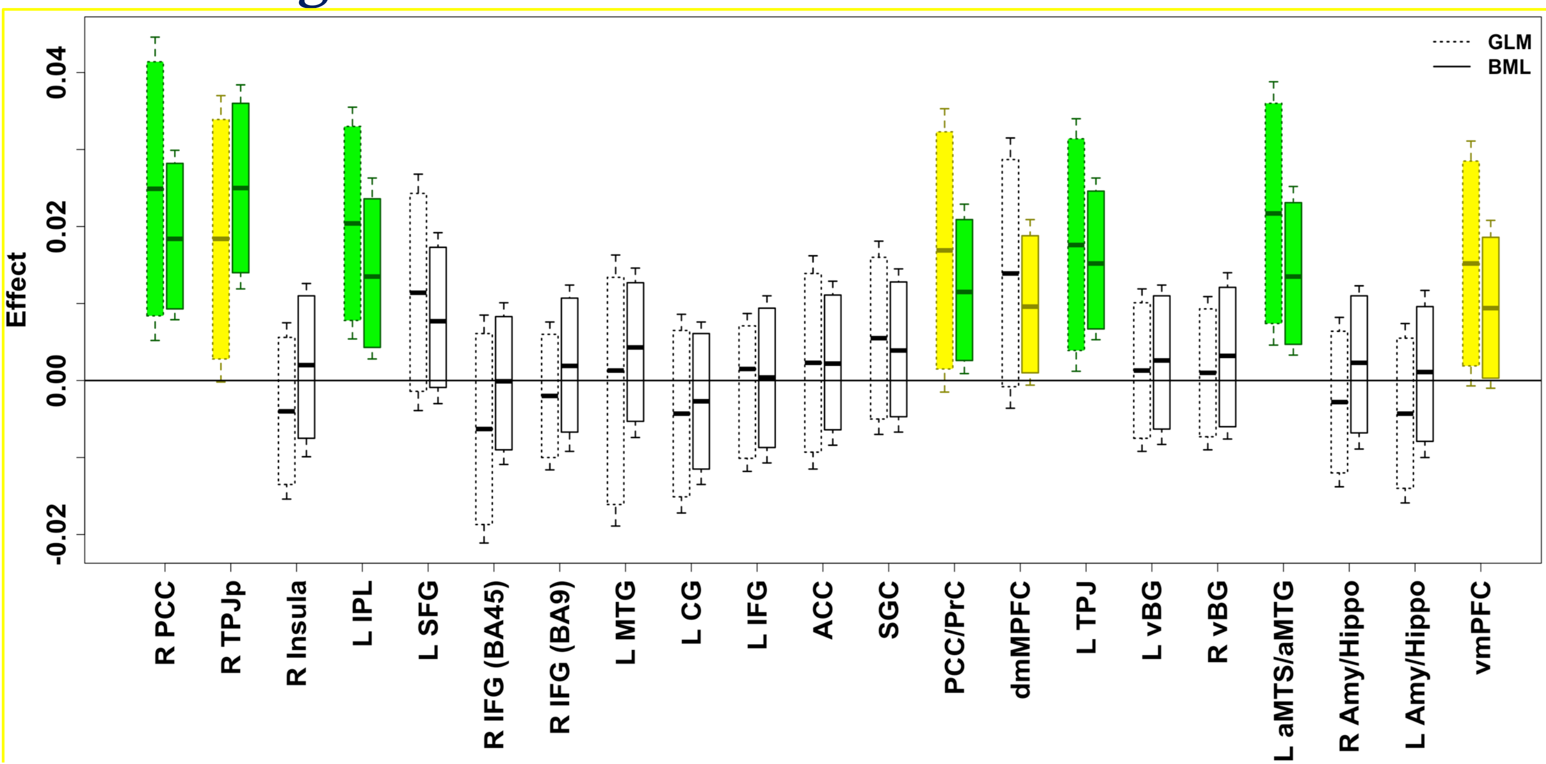
# Inferences from BML: quantile interval

- ROI-based BML: 21 ROIs
- full report with a table of quantile intervals
- 8 ROIs with strong evidence for effect of interest

| result / ROI | ToMI effect | | standard error | | 2.5% | | 5% | | 95% | | 97.5% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GLM | BML | GLM | BML | GLM | BML | GLM | BML | GLM | BML | GLM | BML |
| R PCC | 0.025 | 0.018 | 0.010 | 0.006 | 0.005 | 0.008 | 0.008 | 0.009 | 0.041 | 0.028 | 0.045 | 0.030 |
| R TPJp | 0.018 | 0.025 | 0.009 | 0.007 | -0.000 | 0.012 | 0.003 | 0.014 | 0.034 | 0.036 | 0.037 | 0.038 |
| R Insula | -0.004 | 0.002 | 0.006 | 0.006 | -0.015 | -0.010 | -0.014 | -0.008 | 0.006 | 0.011 | 0.007 | 0.013 |
| L IPL | 0.020 | 0.014 | 0.008 | 0.006 | 0.005 | 0.003 | 0.008 | 0.004 | 0.033 | 0.024 | 0.035 | 0.026 |
| L SFG | 0.011 | 0.008 | 0.008 | 0.006 | -0.004 | -0.003 | -0.001 | -0.001 | 0.024 | 0.017 | 0.027 | 0.019 |
| R IFG (BA45) | -0.006 | 0.000 | 0.007 | 0.005 | -0.021 | -0.011 | -0.019 | -0.009 | 0.006 | 0.008 | 0.008 | 0.010 |
| R IFG (BA9) | -0.002 | 0.002 | 0.005 | 0.005 | -0.012 | -0.009 | -0.010 | -0.007 | 0.006 | 0.011 | 0.008 | 0.012 |
| L MTG | -0.001 | 0.004 | 0.009 | 0.005 | -0.019 | -0.007 | -0.016 | -0.005 | 0.013 | 0.013 | 0.016 | 0.015 |
| L CG | -0.004 | -0.003 | 0.007 | 0.005 | -0.017 | -0.014 | -0.015 | -0.011 | 0.007 | 0.006 | 0.009 | 0.008 |
| L IFG | -0.002 | 0.000 | 0.005 | 0.005 | -0.012 | -0.011 | -0.010 | -0.009 | 0.007 | 0.009 | 0.009 | 0.011 |
| ACC | 0.002 | 0.002 | 0.007 | 0.005 | -0.012 | -0.008 | -0.009 | -0.006 | 0.014 | 0.011 | 0.016 | 0.013 |
| SGC | 0.006 | 0.004 | 0.006 | 0.005 | -0.007 | -0.007 | -0.005 | -0.005 | 0.016 | 0.013 | 0.018 | 0.014 |
| PCC/PrC | 0.017 | 0.012 | 0.009 | 0.005 | -0.001 | 0.001 | 0.002 | 0.003 | 0.032 | 0.021 | 0.035 | 0.023 |
| dmMPFC | 0.014 | 0.010 | 0.009 | 0.005 | -0.004 | -0.001 | -0.001 | 0.001 | 0.029 | 0.019 | 0.032 | 0.021 |
| L TPJ | 0.018 | 0.015 | 0.008 | 0.005 | 0.001 | 0.005 | 0.004 | 0.007 | 0.031 | 0.025 | 0.034 | 0.026 |
| L vBG | 0.001 | 0.003 | 0.005 | 0.005 | -0.009 | -0.008 | -0.007 | -0.006 | 0.010 | 0.011 | 0.012 | 0.012 |
| R vBG | 0.001 | 0.003 | 0.005 | 0.005 | -0.009 | -0.008 | -0.007 | -0.006 | 0.009 | 0.012 | 0.011 | 0.014 |
| L aMTS/aMTG | 0.022 | 0.013 | 0.009 | 0.006 | 0.005 | 0.003 | 0.007 | 0.005 | 0.036 | 0.023 | 0.039 | 0.025 |
| R Amy/Hippo | -0.003 | 0.002 | 0.006 | 0.005 | -0.014 | -0.009 | -0.012 | -0.007 | 0.006 | 0.011 | 0.008 | 0.012 |
| L Amy/Hippo | -0.004 | 0.001 | 0.006 | 0.005 | -0.016 | -0.010 | -0.014 | -0.008 | 0.005 | 0.010 | 0.007 | 0.012 |
| vmPFC | 0.015 | 0.009 | 0.008 | 0.006 | -0.001 | -0.001 | 0.002 | 0.000 | 0.029 | 0.019 | 0.031 | 0.021 |

# Inferences from BML: standard error

- ROI-based BML: 21 ROIs
- full report with bar graph quantile intervals (better visualization)
    - Nothing hidden under sea level
- 8 ROIs with strong evidence for effect of interest



# BML: model validations

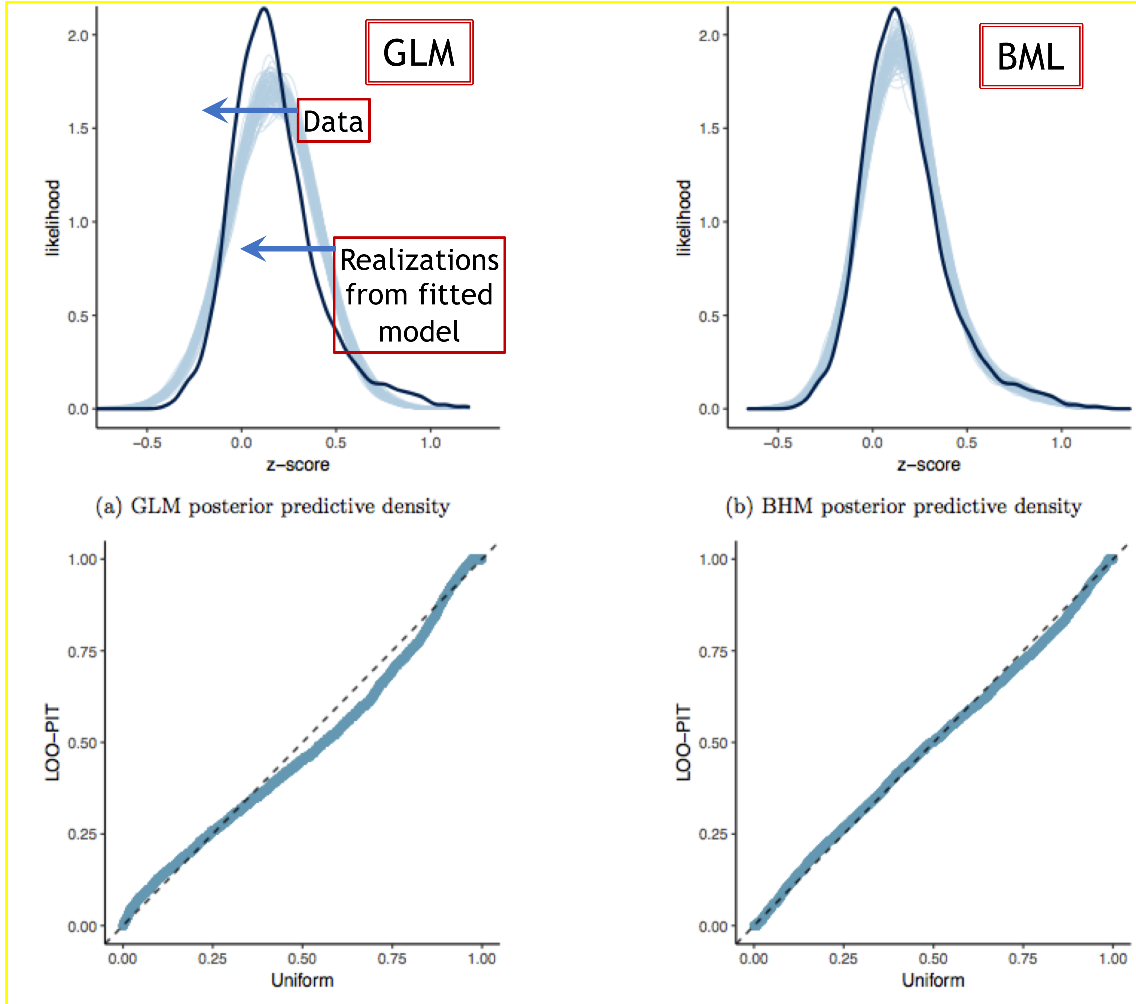
- **ROI-based BML with 21 ROIs: cross-validation**
  - Leave-one-out information criterion (LOOIC)

**Cross-validation**

| | LOOIC | SE |
|---|---|---|
| GLM | -300.39 | 98.25 |
| BML | -2247.06 | 86.42 |
| GLM - BML | 1946.67 | 96.35 |

  - Posterior predictive checking

- **Effects of BML**
  - Regularizing ROIs: don't fully trust individual ROI data
  - Sacrificing fit at each ROI; achieving better overall fit



(a) GLM posterior predictive density
(b) BHM posterior predictive density
(c) GLM cross-validation: Q-Q plot (uniform)
(d) BHM cross-validation: Q-Q plot (uniform)

# Appetizer #2: more love for GLM!

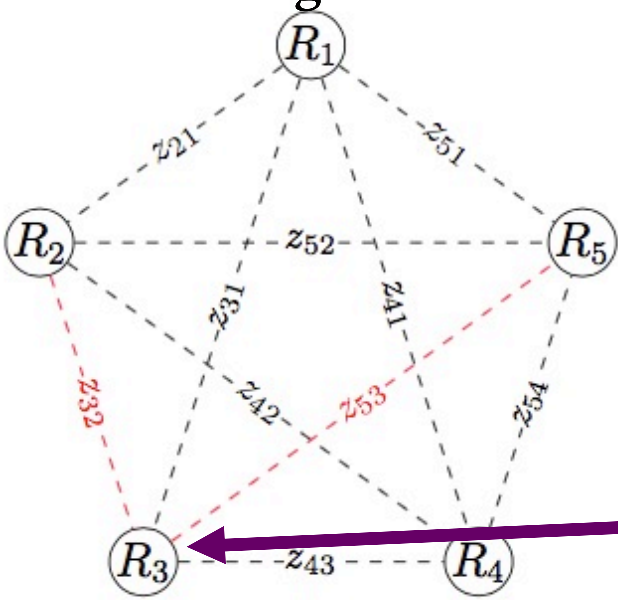
- **Dataset #2: correlation matrix**
  - Subjects: $n$ = 41 children; response-conflict task
  - Individual subjects: correlation matrix among $m$ = 16 ROIs
  - How to go about group analysis?
    - **GLM for each element in correlation matrix**
    - **Binarization approach: graph theory**
  - More broadly: matrix-based analysis (MBA) ("network modeling")
    - **Inter-region correlation (IRC)**
    - **Structural attribute matrix (SAM)**

- **Focus on GLM**
  - Student $t$-test or GLM on each element
    - $M$ = 120 mass univariate models
  - Pretense again: all elements are unrelated
  - Penalty time again: permutations?

$$\boldsymbol{Z}_k^{(m)} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ \vdots \\ R_m \end{array} \begin{array}{c} \begin{array}{ccccc} R_1 & R_2 & R_3 & \cdots & R_m \end{array} \\ \begin{pmatrix} - & z_{12k} & z_{13k} & \cdots & z_{1mk} \\ z_{21k} & - & z_{23k} & \cdots & z_{2mk} \\ z_{31k} & z_{32k} & - & \cdots & z_{3mk} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ z_{m1k} & z_{m2k} & z_{m3k} & \cdots & - \end{pmatrix} \end{array}$$

# Dealing with inter-region data (IRD)

- **Complexities of IRD**
  - Some of them are unrelated, but others are correlated
  - Correlation structure is intricate
  - $0 \leq \rho \leq 0.5$
  - Can we do a better job than GLMs or dichotomization?
    - **Challenge: How to characterize the complex structure?**




$$
\boldsymbol{P}^{(5)} = \begin{array}{c} \\ z_{21} \\ z_{31} \\ z_{41} \\ z_{51} \\ z_{32} \\ z_{42} \\ z_{52} \\ z_{43} \\ z_{53} \\ z_{54} \end{array}
\begin{array}{c}
\begin{array}{cccccccccc} z_{21} & z_{31} & z_{41} & z_{51} & z_{32} & z_{42} & z_{52} & z_{43} & z_{53} & z_{54} \end{array} \\
\begin{pmatrix}
1 & \rho & \rho & \rho & \rho & \rho & \rho & 0 & 0 & 0 \\
\rho & 1 & \rho & \rho & \rho & 0 & 0 & \rho & \rho & 0 \\
\rho & \rho & 1 & \rho & 0 & \rho & 0 & \rho & 0 & \rho \\
\rho & \rho & \rho & 1 & 0 & 0 & \rho & 0 & \rho & \rho \\
\rho & \rho & 0 & 0 & 1 & \rho & \rho & \rho & \rho & 0 \\
\rho & 0 & \rho & 0 & \rho & 1 & \rho & \rho & 0 & \rho \\
\rho & 0 & 0 & \rho & \rho & \rho & 1 & 0 & \rho & \rho \\
0 & \rho & \rho & 0 & \rho & \rho & 0 & 1 & \rho & \rho \\
0 & \rho & 0 & \rho & \rho & 0 & \rho & \rho & 1 & \rho \\
0 & 0 & \rho & \rho & 0 & \rho & \rho & \rho & \rho & 1
\end{pmatrix}
\end{array}
$$

# IRD: switching from GLM to LME

- **IRD analysis through linear mixed-effects modeling**
  - One model integrates all ROIs: LME
  - ROIs loosely constrained instead of being unrelated
    - Gaussian distribution: Is it far-fetched?
    - Similar to cross-subject variability
  - Goal: effects of interest
    - Each region pair (RP): $b_o + \xi_i + \xi_j$
    - Each region: $b_o + \xi_i$
  - **LME wouldn't work!**
  - ***Cul-de-sac!***

Overall effect: shared by all ROIs and subjects

Effect by *i*th ROI

Effect by *j*th ROI

Effect by *k*th subject

$$z_{ijk} = b_0 + \xi_i + \xi_j + \pi_k + \epsilon_{ijk},$$

$$\xi_i, \xi_j \overset{iid}{\sim} \mathcal{N}(0, \lambda^2), \pi_k \overset{iid}{\sim} \mathcal{N}(0, \tau^2), \epsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$$

$$i, j = 1, 2, ..., m \ (i > j), k = 1, 2, ..., n,$$

# IRD: one more jump – from LME to BML

- **IRD analysis through Bayesian multilevel (BML) modeling**
  - One model integrates all ROIs: BML (essentially same as LME)
  - ROIs loosely constrained
    - Gaussian distribution: Is it far-fetched?
    - Similar to cross-subject variability
  - Goal: effects of interest
    - Each region pair (RP): $b_o + \xi_i + \xi_j$
    - Each region: $b_o + \xi_i$
  - LME plus priors
    - MCMC
    - Posterior distribution
  - ***Ka-ching!***

Overall effect: shared by all ROIs and subjects

Effect by *i*th ROI

Effect by *j*th ROI

Effect by *k*th subject

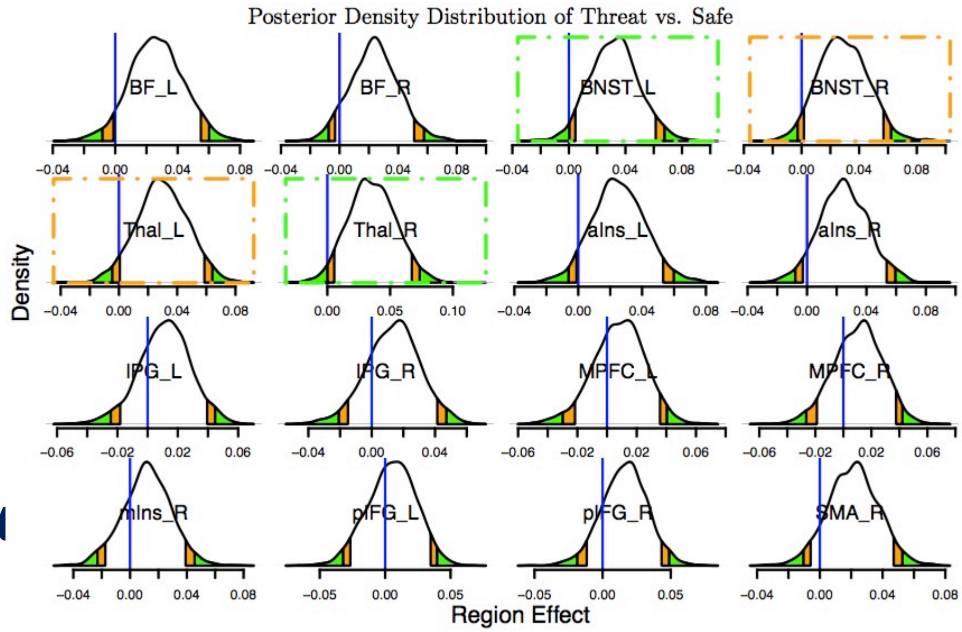
$$z_{ijk}|b_0, \xi_i, \xi_j, \pi_k \sim \mathcal{N}(b_0 + \xi_i + \xi_j + \pi_k, \sigma^2),$$

$$\xi_i \overset{iid}{\sim} \mathcal{N}(0, \lambda^2), \xi_j \overset{iid}{\sim} \mathcal{N}(0, \lambda^2), \pi_k \overset{iid}{\sim} \mathcal{N}(0, \tau^2)$$

$$i, j = 1, 2, ..., m \ (i > j), k = 1, 2, ..., n.$$

# IRD – ROI effect from BML: full distributions

- **ROI-based BML: 16 ROIs**
- **Full report with richer information: posterior distributions for each ROI**
  - No dichotomization
  - Nothing hidden under sea level
- **4 ROIs with strong evidence of effect compared to**
  - Region effect inferences: unavailable from GLM and graph theory
  - Hubness?

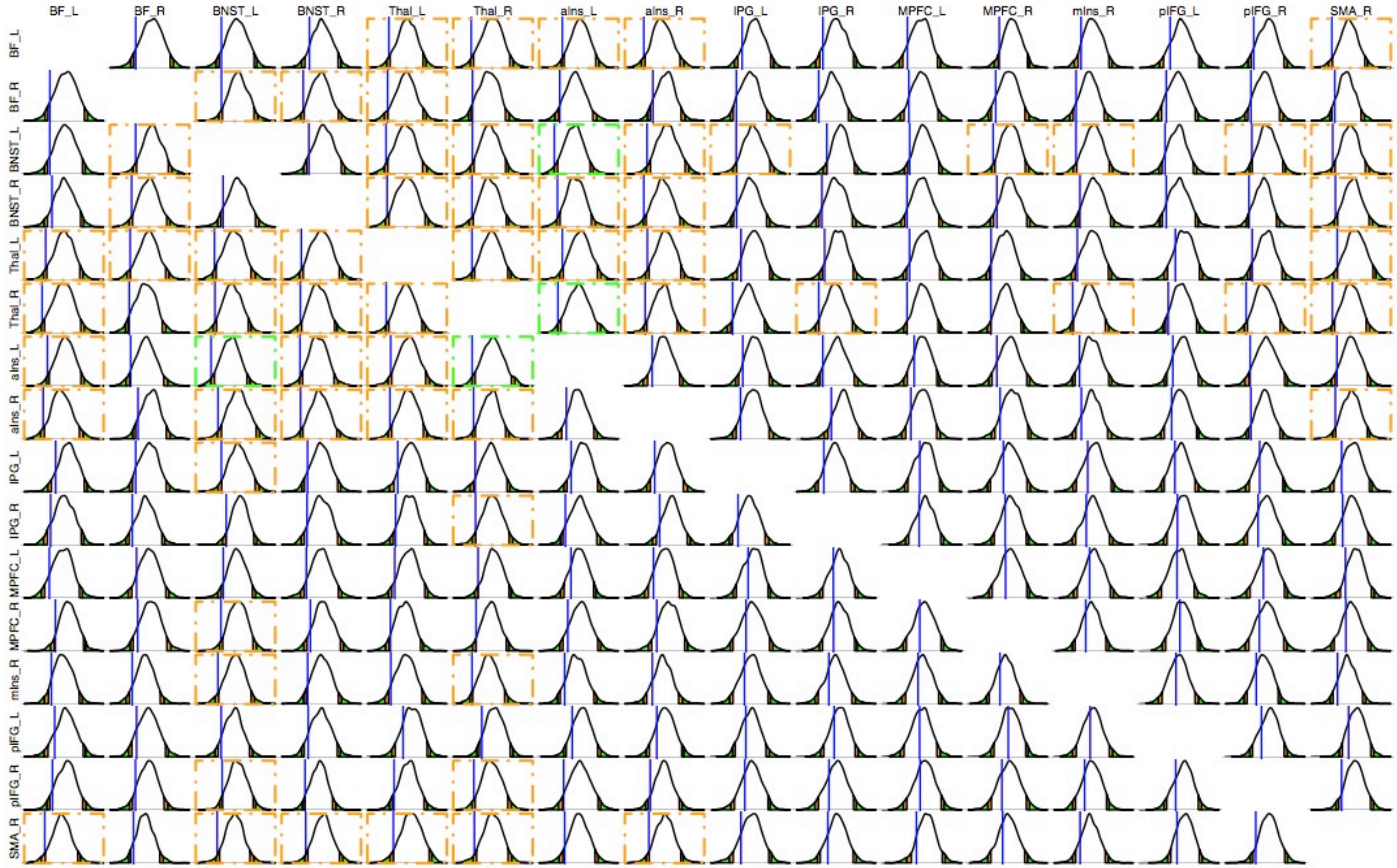


# IRD– ROI effect from BML: quantile interval

- ROI-based BML: 16 ROIs
- full report with quantile intervals
- 4 ROIs with strong evidence for region effect

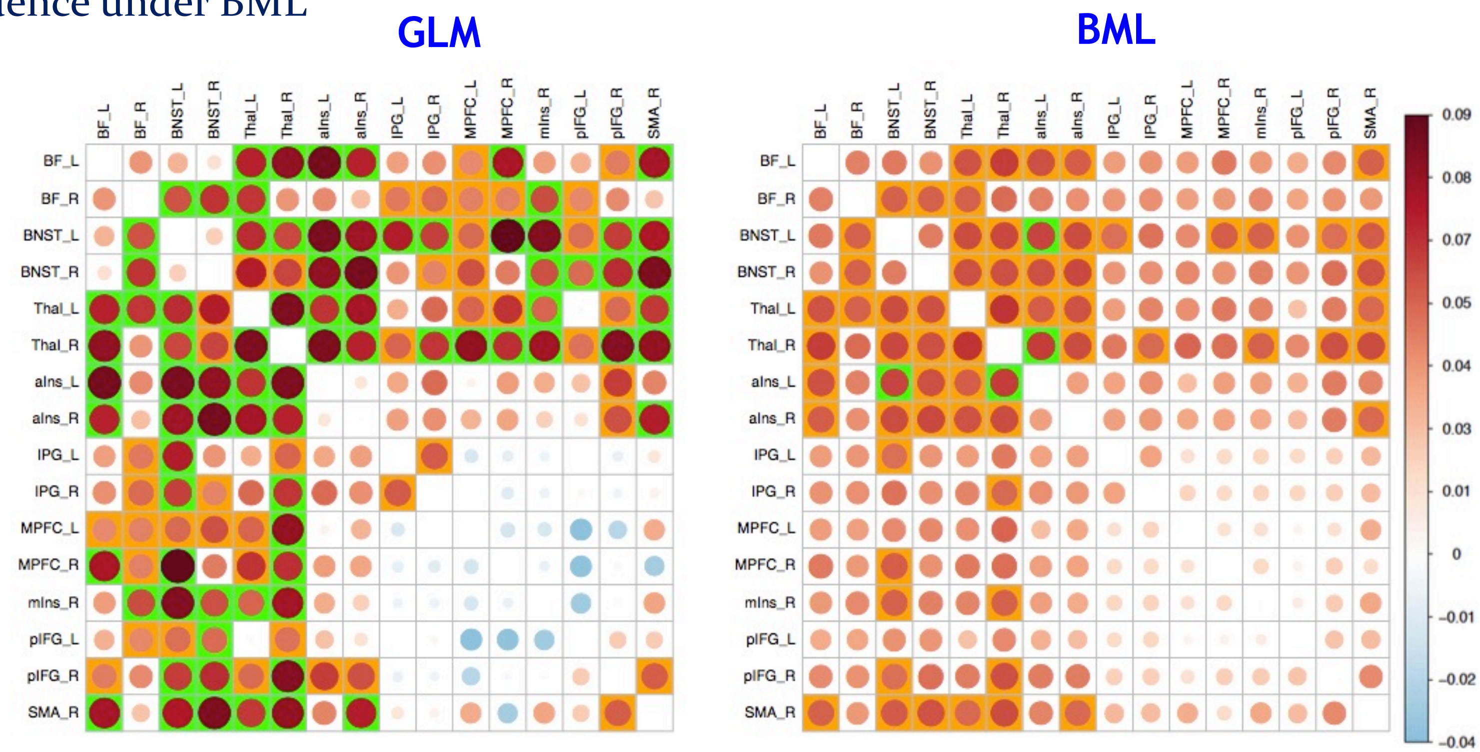
| ROI | mean | std err | 2.5% | 5% | 50% | 95% | 97.5% |
|---|---|---|---|---|---|---|---|
| BF_L | 0.026 | 0.017 | -0.008 | -0.001 | 0.026 | 0.055 | 0.060 |
| BF_R | 0.024 | 0.016 | -0.007 | -0.003 | 0.024 | 0.051 | 0.057 |
| BNST_L | 0.032 | 0.017 | 0.001 | 0.005 | 0.032 | 0.061 | 0.067 |
| BNST_R | 0.029 | 0.017 | -0.002 | 0.002 | 0.028 | 0.057 | 0.062 |
| Thal_L | 0.030 | 0.017 | -0.004 | 0.001 | 0.029 | 0.059 | 0.064 |
| Thal_R | 0.036 | 0.019 | 0.000 | 0.006 | 0.035 | 0.067 | 0.073 |
| aIns_L | 0.025 | 0.017 | -0.006 | -0.001 | 0.025 | 0.053 | 0.060 |
| aIns_R | 0.025 | 0.017 | -0.008 | -0.003 | 0.025 | 0.054 | 0.059 |
| IPG_L | 0.011 | 0.017 | -0.024 | -0.018 | 0.012 | 0.039 | 0.045 |
| IPG_R | 0.014 | 0.017 | -0.021 | -0.015 | 0.014 | 0.041 | 0.047 |
| MPFC_L | 0.008 | 0.017 | -0.030 | -0.021 | 0.009 | 0.036 | 0.040 |
| MPFC_R | 0.010 | 0.017 | -0.026 | -0.019 | 0.011 | 0.038 | 0.042 |
| mIns_R | 0.012 | 0.017 | -0.023 | -0.017 | 0.012 | 0.039 | 0.045 |
| pIFG_L | 0.005 | 0.019 | -0.032 | -0.026 | 0.006 | 0.035 | 0.039 |
| pIFG_R | 0.016 | 0.017 | -0.018 | -0.011 | 0.017 | 0.043 | 0.049 |
| SMA_R | 0.021 | 0.016 | -0.010 | -0.006 | 0.021 | 0.047 | 0.052 |

# IRD – RP effect from BML: full distributions



# IRD– RP effect from BML

- **ROI-based BML: 16 ROIs**
- **full report for all region pairs (RPs)**
- **Comparisons with GLMs: nothing hidden under sea level**
    - 63 RPs identified by GLMs with *p* of 0.05: none survived after correction with NBS via permutations
    - 33 RPs with strong evidence under BML



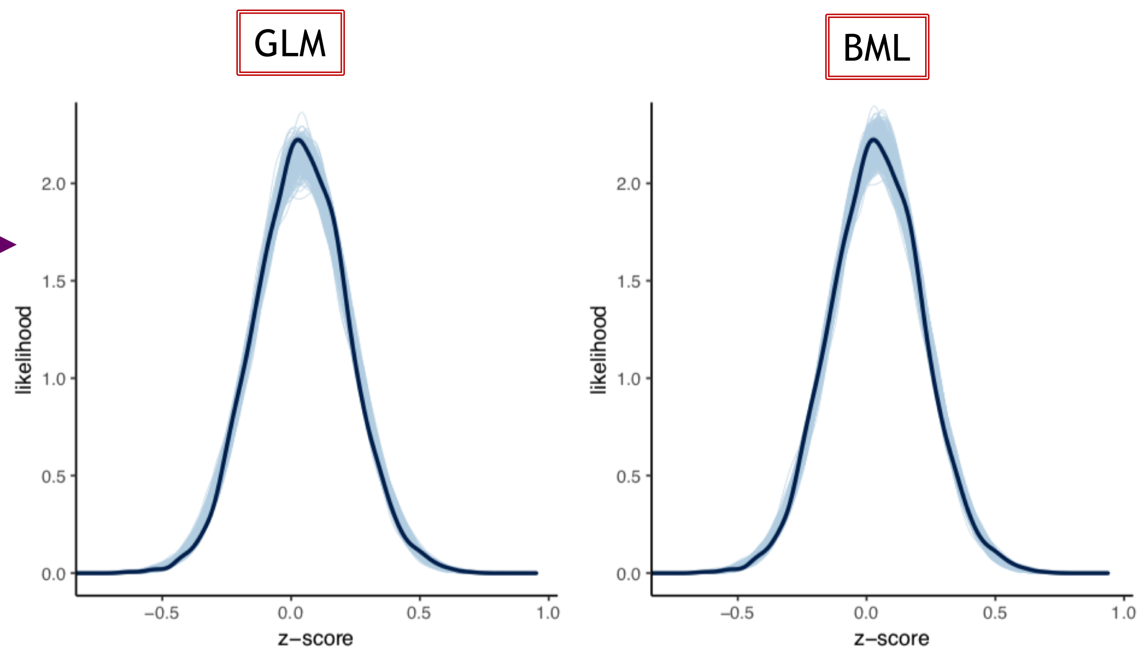
# BML: model validations

- **ROI-based BML with IRD of 16 ROIs: cross-validation**
  - Leave-one-out information criterion (LOOIC)

**Cross-validation**

| Model | LOOIC | SE |
|---|---|---|
| GLM | -2808.31 | 101.65 |
| BML0 | -4543.77 | 102.97 |

  - Posterior predictive checking




- **Effects of BML**
  - Regularizing ROIs: don't fully trust individual ROI data
  - Sacrificing fit at each ROI; achieving better overall fit

# Summary

- **Efficient modeling through information pooling**
  - How to effectively avoid multiplicity penalty?
- **Demo dataset #1**
  - Resting state: seed-based correlation analysis
  - Handling multiple testing through ROI-based group analysis
    - How to avoid penalty of modeling across voxels or ROIs?
  - Program available in AFNI: BayesianGroupAna.py
- **Demo dataset #2**
  - Group analysis with correlation matrices among ROIs
  - Handling multiple testing for inter-region data (IRD) analysis
    - How to avoid penalty of modeling across voxels or ROIs?
  - More applications
    - **DTI data: white matter connectivity network**
    - **Naturalistic data analysis (*1:20PM, Sept. 25*)**

Acknowledgements

- **Paul-Christian Bürkner** (Department of Psychology, University of Münster)
- **Yaqiong Xiao**, **Elizabeth Redcay**, **Luiz Pessoa**, **Joshua Kinnison** (Depart of Psychology, University of Maryland)
- **Zhihao Li** (School of Psychology and Sociology, Shenzhen University, China)
- **Lijun Yin** (Department of Psychology, Sun Yat-sen University, China)
- **Paul A. Taylor, Daniel R. Glen, Justin K. Rajendra, Richard C. Reynolds, Robert W. Cox** (SSCC/NIMH, National Institutes of Health)