

Overview

Tuesday, Aug 28 2001

- Spatial Inference
 - ... in SPM
- Combining Results
 - ... fixed and random effects

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Spatial Inference: Recap

- We fit a model at every point in the brain
 - Each model is ignorant of neighboring models
- Each model summarized with a t or F statistics
- Images of these statistics are thresholded
 - Set-, Cluster- & Voxel-level p-values assigned
- “Implicit Spatial Modeling”

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Spatial Inference: SPM

- Important to understand each component of SPM p-value results page
- Top
 - Interactive MIP
 - Drag & Drop to move
 - Right click to get menu
 - Interactive Design Matrix
 - Click to get values
- Middle
 - Interactive table of corrected & uncorrected p-values
 - Click on x,y,z to move cursor
 - Click on number to show it in Matlab window
 - Right click in margin to get menu

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Spatial Inference: SPM

- Bottom
 - Details on results
 - Key key key!
 - Smoothness must be $> \approx 2-3$ voxel size
 - This is needed for _____ to be valid

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Spatial Inference: SPM etc

- SPM.mat
 - Contains essentials of fitted model results
 - Design matrix, number of voxels, etc
- SPMcfg.mat
 - “SPM Configuration file”
 - Input to ‘Estimate’ button
 - Specifies everything necessary to fit a model

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Spatial Inference: SPM etc

- SPM_fmRIDesMtx.mat
 - Specification of fMRI design
 - Does *not* contain any filenames
 - If identical design is used, can copy these into other analysis directories
 - For example
 - I could have created one SPM_fmRIDesMtx.mat that the whole class could use, since all of our subject’s had identical paradigms
- “Explore Design button works with any of these.”

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Combining Results

- Often have results we want to combine
 - Same subject, different contrasts
 - Same subject, different acquisition
 - Same subject, different days
 - Different subjects
- How to integrate these results?
- Two fundamentally different approaches
 - Fixed Effects
 - Mixed/Random Effects
 - “Random Effects” has become standard, though strictly it is a Mixed Effects model

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Combining Results: Fixed Effects

- Fixed effects test an intersection of null hypotheses
 - \mathcal{H}_0 : The effect zero in *all* sessions
 - \mathcal{H}_0 : The effect zero in *all* subjects
- Fixed effects hypotheses are easily tested
 - Chuck all the data into SPM
 - Test the grand hypothesis
 - Example: 4 subjects, each with 2 conditions

The contrast of interest is then

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Combining Results: Fixed Effects

- “Grand” model approach not perfect
 - Can be huge, slow analysis
 - Thousands of scans!
 - Tons of disk space
 - Assumes homogeneous variance across subjects
- But can be very sensitive

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Combining Results: Fixed Effects

- Simpler approach is to combine statistic images
- Metaanalysis approach
 - K analyses, each produces $Z_k, k = 1, \dots, K$
 - Under null hypothesis, each $Z_k \sim \mathcal{N}(0, 1)$
 - $\bar{Z} \sim \mathcal{N}(0, 1/K)$
 - So summarize K statistics with
$$\sqrt{K}\bar{Z} = \frac{1}{\sqrt{K}} \sum Z_k$$
- Weaker assumptions than Grand Model approach
 - Only have to assume that each individual model is valid
 - (Not that all have common variance)
- Unfortunately, not supported within SPM
 - Can calculate with “ImCalc”
 - But can’t get table of p-values

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Combining Results: Fixed Effects Shortcomings

- Doesn’t account for intersubject variability in response
 - Significance can be due to a single subject
- Susceptible to hypothesis testing facility
 - Given enough data, you’ll *always* reject the null!
 - This makes sense.
 - Do you ever really believe
“ \mathcal{H}_0 : Effect is 0.00000000000000”?

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Combining Results: Conjunction of Contrasts

- Tries to address weakness of fixed effects approach
- Standard fixed effects approach can be driven by one “best” subject/contrast/effect
- SPM’s Conjunction
 - Take the *minimum* of multiple statistics
 - Then only can see effect if *all* large
- Example
 - 4 subjects, each with 2 conditions
 - Create 4 contrasts, one for each subject
 - “Conjunction” of the four is just minimum of four statistic images

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Combining Results: Conjunction of Contrasts

- SPM Conjunction
 - Random field theory requires individual contrasts to be orthogonal
 - Two contrasts orthogonal if *inner product* is zero
 - These are orthogonal: [-1 1 0 0] & [0 0 -1 1]
 - These are not: [0 -1 1 0] & [0 0 -1 1]

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Combining Results: Contrast Masking

- Can combine contrast/statistic images with masks
- Example... Two factor study
 - Faces vs Places (A1 vs A2)
 - Familiar vs Unfamiliar (B1 vs B2)
 - In SPM
[A1 A2 B1 B3]

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Combining Results: Contrast Masking

- To view familiarity effect *but only* where there was a Faces effect...
 - Select “Familiar-Unfamiliar” in contrast manager
 - “Yes” to “mask with other contrast”
 - Specify “Faces-Places” contrast
 - Set “uncorrected mask p-value”
 - e.g. 0.001
 - Select “inclusive” mask
 - Want to see voxels where Faces-Places > threshold
 - *et voila*
- No account of thresholding in subsequent inference
 - But only would increase significance

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Combining Results: Random Effects

- What is a “random effect”?
 - Well, have one already
 $Y = X\beta + \epsilon$
- Random effect models treat *response magnitude* as random
 - So far $X\beta$, i.e. $c\beta$ has been *fixed!*
 - Only randomness is residual or measurement error

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Combining Results: Visualizing Random Effects

Fixed Effect

Random Effects

_____	_____
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____

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Combining Results: Understanding Random Effects

- With fixed effects
 - Combing over subjects, only question is
“Is average response large relative to scan-to-scan variability”
- With random effects
 - Combing over subjects, question is
“Is average response large relative to subject-to-subject variability”

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Combining Results: Understanding Random Effects

- Fixed Effects Model & Null Hypothesis
 - $Y(t) = \mu + \alpha f(t) + \epsilon(t)$
 - Fixed, known: $f(t)$
 - Fixed, unknown: μ, α
 - Random: $\epsilon(t)$
 - Distⁿ assumption: $\epsilon(t) \sim \mathcal{N}(0, \sigma^2)$
 - $\mathcal{H}_0: \mu = 0$
Mean of each subject's response is zero

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Combining Results: Understanding Random Effects

- Random Effects Model & Null Hypothesis
 - $Y_i(t) = \mu_i + \alpha_i f(t) + \epsilon_i(t)$
 - Fixed, known: $f(t)$
 - Fixed, unknown: μ_i
 - Random: $\alpha_i, \epsilon_i(t)$
 - Distⁿ assumption: $\epsilon_i(t) \sim \mathcal{N}(0, \sigma^2)$
 $\alpha_i \sim \mathcal{N}(\theta, \tau^2)$
 $\epsilon_i(t), \alpha_i$ independent
 - $\mathcal{H}_0: \theta = 0$
Mean of the *population* of the subject's response is zero

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Combining Results: Random Effects in SPM

- SPM only fits fixed effects models
 - In general, random effects models can't be fit with least squares
 - Generally requires iterative fitting
- One special *very useful* case
 - Assume each subject has same experimental design
 - Same number of scans, same design matrix
 - Assume each subject's residual error (σ^2) is the same
 - Fit each subject, create a contrast for each
 - Compute a one sample t test on contrast images
- This approach impliments random effects inference!

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Combining Results: Random Effects in SPM

- What if not all have same design matrix
 - An issue of a balanced design
 - If not too unbalanced, probably OK
 - If way unbalanced, probably way dodgy

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Combining Results: Random Effects in SPM

- Example
 - Places vs Faces
 - After study, subjects asked to score familiarity of images
 - Result used to define dichotomous Familiar/Nonfamiliar factor
 - Interest is in Places-Faces only for Familiar stimuli
 - Problem!
 - If some subjects find only 10% familiar, and other find 90%
 - there will be horrible imbalance in the design matrix
 - Put another way, some subjects will be able to offer 90% of their data to the contrast, others only 10%

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Inference Quiz

- I-1 What is the most important value in the footer of SPM's results display?
- I-2 What is you favorite color? (Blue, no...) Er, no, What is your favorite hidden trick on the SPM results page?
- I-3 Are these two contrasts orthogonal?
 - [0 1 0 -1]
 - [-1 0 -1 0]
- I-4 Are these two contrasts orthogonal?
 - [1 1 0 1 1 -1]
 - [1 0 -1 1 -1 1]
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