
Statistics of FMRI

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Scientific and Statistical Computing Core

NIMH/NIH



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Overview of fMRI Statistics

- What is statistics? What is statistical testing?
 - Experiment design
 - ✧ How to efficiently squeeze the signal of interest into the data
 - Typical statistical models involved in fMRI
 - ✧ Regression: individual level
 - ✧ General linear model (GLM): group level
 - Student's t-tests: one-, two-sample, or paired
 - Multiple regression
 - AN(C)OVA
 - Linear mixed-effects (LME) model
 - Miscellaneous
-

What is statistics?

- ❑ In God we trust. All others must bring **data**!
 - ✧ Related to *state* and *status*: science of state
 - ✧ German *statistik* by Gottfried Achenwall (1749)
 - ❑ Statistics is about dealing with variation (noise)
 - ✧ Noise is annoying, but contains a lot of useful information
 - ✧ Art of noise handling
 - ❑ Science of data analysis based on variation
 - ✧ Data collection
 - ✧ Model building, comparison, selection and analysis
 - ✧ Inference and interpretation
 - ✧ Presentation and prediction
-

Is our brain statistically wired?

□ Example 1

- Should we buy lottery tickets and insurances?

□ Example 2

- Average deaths due to snakebites in the USA and Canada per year? **15**
- Average deaths in air transport per year in the USA? **200**
- Average number of people killed by cars annually in the USA? **40,000**

□ Example 3

- Suppose I flip a coin 5 times, and get all heads. What is the chance of getting a head in the next toss?

□ Example 4

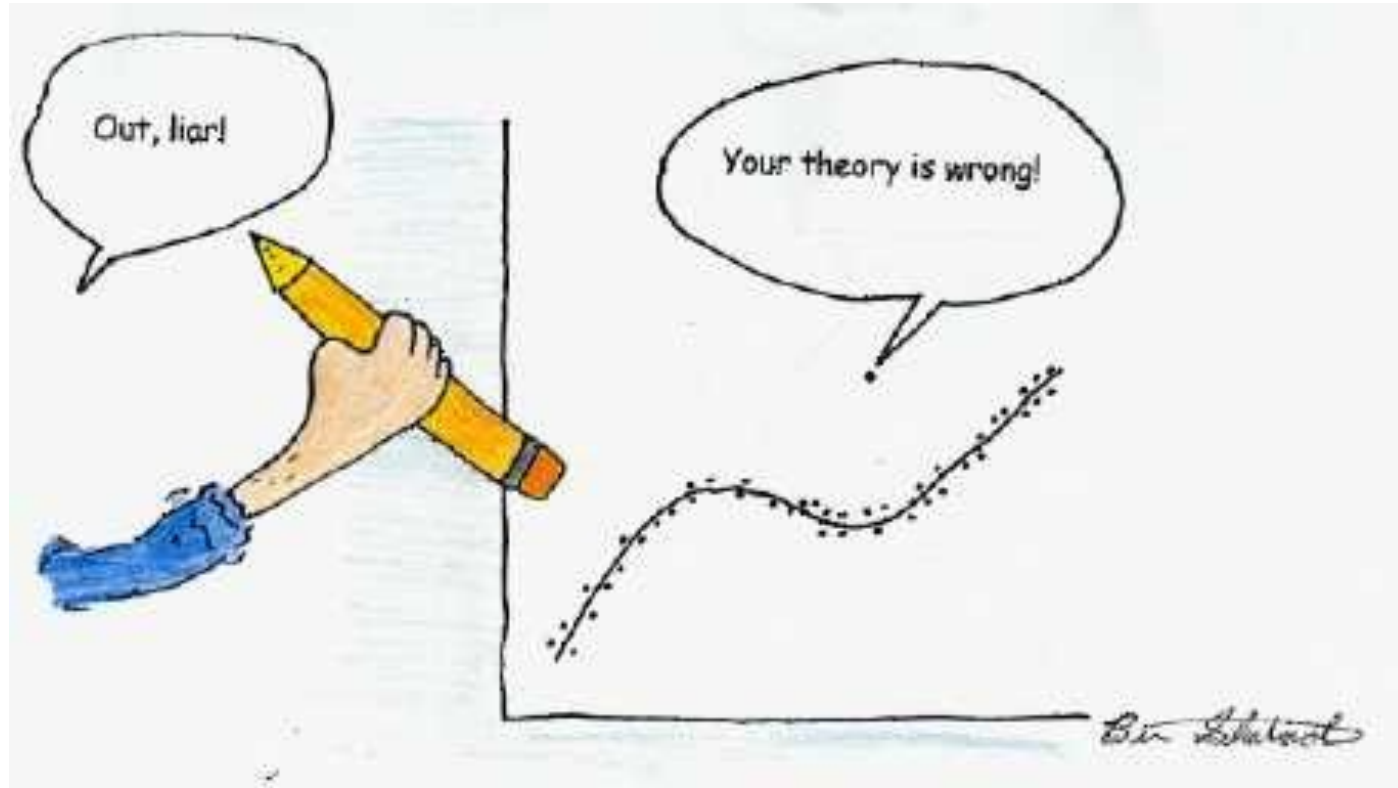
- HIV prevalence = 0.1%, false + of HIV test = 5%, power of HIV test ~ 100%. $P(\text{HIV+} \mid \text{test+}) = ?$

$$P(\text{HIV+} \mid \text{test+}) = \frac{P(\text{test+}, \text{HIV+})}{P(\text{test+})} = \frac{P(\text{test+} \mid \text{HIV+})P(\text{HIV+})}{P(\text{test+} \mid \text{HIV+})P(\text{HIV+}) + P(\text{test+} \mid \text{HIV-})P(\text{HIV-})} = \frac{1.0 \times 10^{-3}}{1.0 \times 10^{-3} + 0.05 \times (1 - 10^{-3})} \approx 0.02$$

Statistics in daily life

- ❑ Census in Bible
 - ❑ Stereotype: economical thinking
 - ❑ Miss a step when walking downstairs
 - ❑ Lottery and gambling
 - ✧ Dream of a huge gain out of an unlikely occurrence by paying > **expected** value
 - ❑ Insurance
 - ✧ Risk management: hedge the risk of contingency losses
 - ✧ Opposite of lottery: Avoid a huge incidental loss by paying > **expected** cost
 - ✧ Airbags, ABS, alarm systems, security monitoring system...
 - ❑ Surveys, clinical trials, ...
-

Statistics: massaging data?



Statistics: or massaging statisticians?



- SOMETIMES I HAVE TO GO THROUGH
MANY DIFFERENT STATISTICIANS TO
GET THE RIGHT RESULTS.



Experiment Designs

- FMRI experiment types
 - ✧ Task-based
 - Block design
 - Event-related
 - Mixed type
 - ✧ Resting state
 - Relaxing with eyes closed
 - ✧ Naturalistic FMRI
 - Movie watching, music/speech listening
-

Experiment Design: task-based

- ❑ **Principle:** *Jam all possible information into the design before data acquisition*
- ❑ Factors for an efficient design at the individual level
 - ✧ Number of time points (TRs)
 - Important for individual analysis, but may affect group level **implicitly**
 - Power: proportional to \sqrt{DF}
 - Limited by subject's tolerance in scanner: 30-90 min per session
 - ✧ TR length: mostly 2 sec
 - Shorter TR yields more time points (and potentially more power), but
 - Power improvement limited by weaker MR signal
 - Shorter TR → shorter ISI → higher event freq → higher correlation → less power
 - Usually limited by hardware considerations

Experiment Design: individual level

- Factors for an efficient design at the individual level
 - ✧ Complexity of the experiment: number of conditions/tasks (regressors)
 - Limited by scanning time and confounded by low frequencies
 - ✧ Sample size: number of trials per condition/task
 - The more the better, but no magic number: block or event-related?
 - ✧ Event arrangement
 - How to design? How to define the “best” design?
 - Efficiency: achieve highest statistical power within fixed scanning time
 - Randomizing trials: sequence and inter-stimulus interval (ISI)
-

Experiment Design: individual level

□ Factors for an efficient design at the individual level

✧ HDR modeling

- Fixed-Shape Method (FSM): assuming an empirical response curve; economical but high risk of inaccuracy
 - Adjusted-Shape Method (ASM): more wiggle room for shape variability; focus on the major shape
 - Estimated-Shape Method (ESM): capable of achieve accurate shape characterization and power; challenging on group analysis
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Experiment Design: group level

- ❑ Factors for an efficient design at the group level
 - ✧ Number of subjects (n)
 - Important for group analysis: inter-subject vs. intra-subject variation
 - Power (success to detect signal if present) roughly proportional to \sqrt{n}
 - Design type: block vs. event-related
 - Recommended: 20+
 - ✧ Design of the study
 - Complexity: factors, levels, covariates, contrasts of interest, ...
 - With multiple groups, counterbalance, if possible, potential confounding effects such as age, gender, IQ, education background, socioeconomic status, etc.
 - ❑ At the end of the day
 - ✧ Group level matters the most!
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Modeling

□ Data visualization

- ✧ Any excessive head motion? Spikes? Abnormalities?

□ Modeling building/selection

- ✧ Individual level: time series regression

- Regressors of interest
- Regressors of no interest
- Noise

- ✧ Group level

- t -tests, Regression, ANOVA, ANCOVA, GLM, LME, ...
 - Nonparametric methods
 - Ranking methods
 - Permutations
 - Bootstrapping
-

Overview: Individual subject analysis

- ❑ Basics of linear regression model
- ❑ FMRI task-based experiment types
 - ✧ Block design; Event-related experiment; Mixed
- ❑ FMRI data decomposition: three components
 - ✧ **Effects of no interest:** baseline, slow drift, others; **Effects of interest;** *Noise*
 - ✧ Effects of interest - understanding BOLD vs. stimulus: IRF
- ❑ 3 modeling strategies
 - ✧ Model-based: presumed or fixed-shape IRF (FSM)
 - ✧ Data-driven: no assumption about IRF shape (ESM)
 - ✧ Intermediate: one major IRF plus shape adjustment (ASM)

Basics of Regression

- Statistical modeling (information extraction)
 - ✧ Two goals
 - Prediction: machine learning – support vector machine (SVM)
 - Inferences: activation detection
- **Regression**: relationship between a response / outcome (dependent) variable and one or more explanatory (independent) variables (regressors)
 - ✧ Simple regression - fit data with a straight line: Sir Francis Galton's original meaning - regression to mean
 - When 2 variables are not perfectly correlated, regression to mean exists
 - Psychology (Daniel Kahneman): Rewards for good performance vs. punishment of mistakes (correlation vs. causation)
 - Lost in most cases including FMRI
 - ✧ Some statisticians call it (general) **linear model**

Basics of Regression

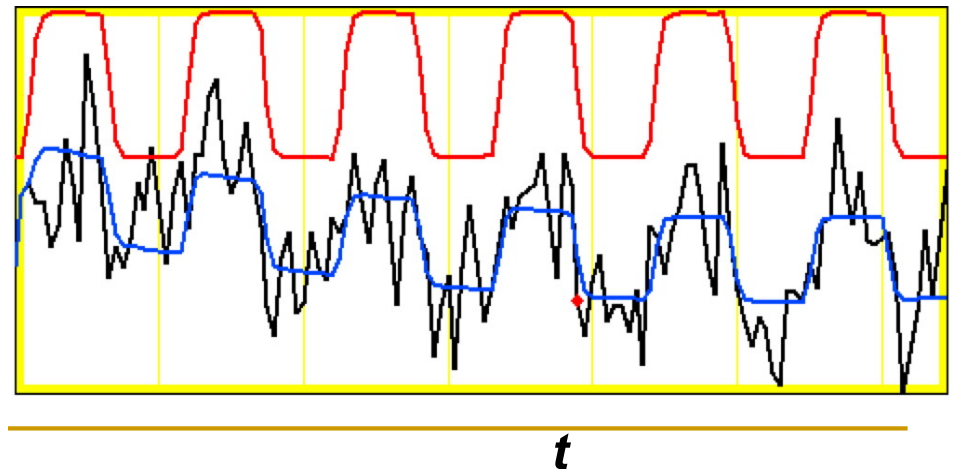
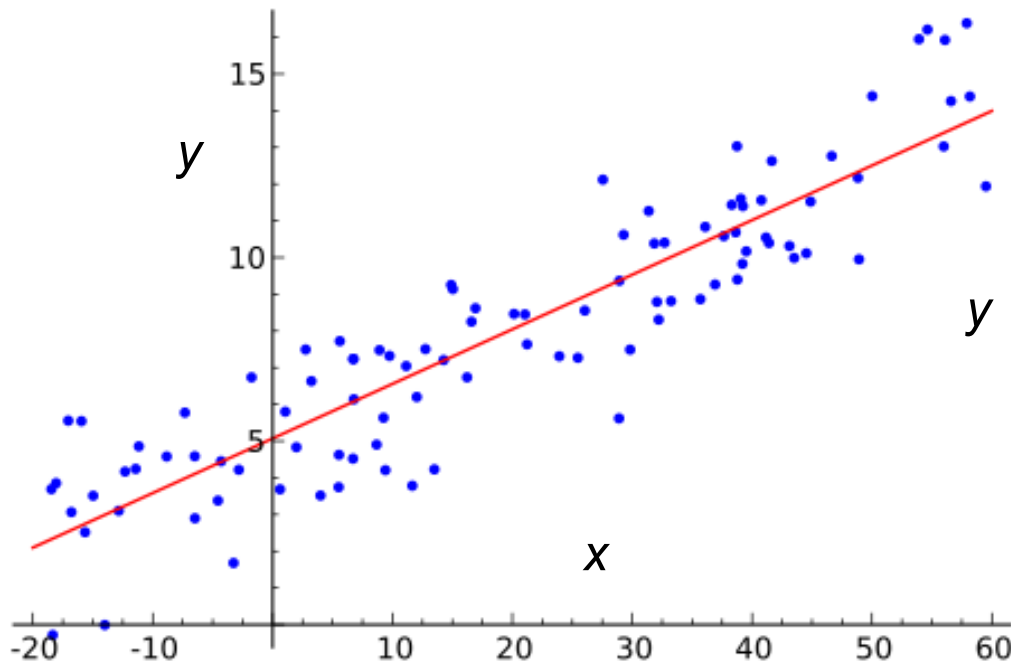
□ Mathematical formulation

✧ $y_i = \alpha + \beta_1 x_{1i} + \dots + \beta_k x_{ki} + \varepsilon_i$, i : time index

✧ $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, $\mathbf{X} = [1, x_1, x_2, \dots, x_k]$

✧ Assumptions

- linearity
- white noise (independence) and Gaussianity $\varepsilon \sim N(0, \sigma^2 \mathbf{I})$



Basics of Regression

- ❑ Solution for regression $y = X\beta + \varepsilon$
 - ✧ Project data y onto the space of explanatory variables (X)
 - ✧ OLS $\hat{\beta} = (X^T X)^{-1} X^T y$
- ❑ Interpreting β values: slope, marginal effect, or effect estimate associated with a regressor (explanatory variable)
- ❑ Various statistical tests
 - ✧ t -test for each β ($H_0: \beta_{\text{sad}} = 0$)
 - ✧ t -test for linear combination of β values - general linear test (GLT), *e.g.*, $H_0: \beta_{\text{hap}} - \beta_{\text{sad}} = 0$, or $H_0: 0.5^*(\beta_{\text{hap}} + \beta_{\text{sad}}) - \beta_{\text{neu}} = 0$
 - ✧ F -test for composite null hypothesis, *e.g.*, $H_0: \beta_{\text{hap}} = \beta_{\text{sad}} = \beta_{\text{neu}}$ or $H_0: \beta_{\text{hap}} = \beta_{\text{sad}} = \beta_{\text{neu}} = 0$
 - ✧ Omnibus or overall F -test for the **whole** model, *e.g.*, $H_0: \text{all } \beta\text{'s} = 0$, or for a **partial** model $H_0: \text{all } \beta\text{'s of interest} = 0$

Regression with fMRI

- Time series regression: data y is time series
 - ✧ Regressors: idealized responses or basis functions
 - ✧ Special handling: noise not white $\varepsilon \sim N(0, \sigma^2 \Sigma)$, but with temporal or serial correlation
 - Banded variance-covariance matrix Σ
 - ✧ AKA general linear model (GLM) in other fMRI packages
 - General vs. generalized
- Same model for all voxels in the brain
 - ✧ Simultaneously solve the models: voxel-wise analysis, massively univariate method
 - ✧ $y = X\beta + \varepsilon$: same design matrix X across the brain

FMRI Data

□ Data partition: **Data = Signal + Noise**

- ✧ **Data** = acquisition from scanner (voxel-wise time series)
- ✧ **Signal** = BOLD response to stimulus; effects of interest + no interest
 - **We don't fully know the real signal!**
 - Look for idealized components, or search for signal via repeated trials
 - Of interest: effect estimate (response amplitude) for each condition
 - Of no interest: baseline, slow drift, head motion effects, ...
- ✧ **Noise** = components in data that interfere with signal
 - Practically the part we have don't know and/or we don't care about, or the part we can't explain in the model
 - Will have to make some assumptions about its distribution

□ **Data = baseline + slow drift + other effects of no interest + response₁ + ... + response_k + noise**

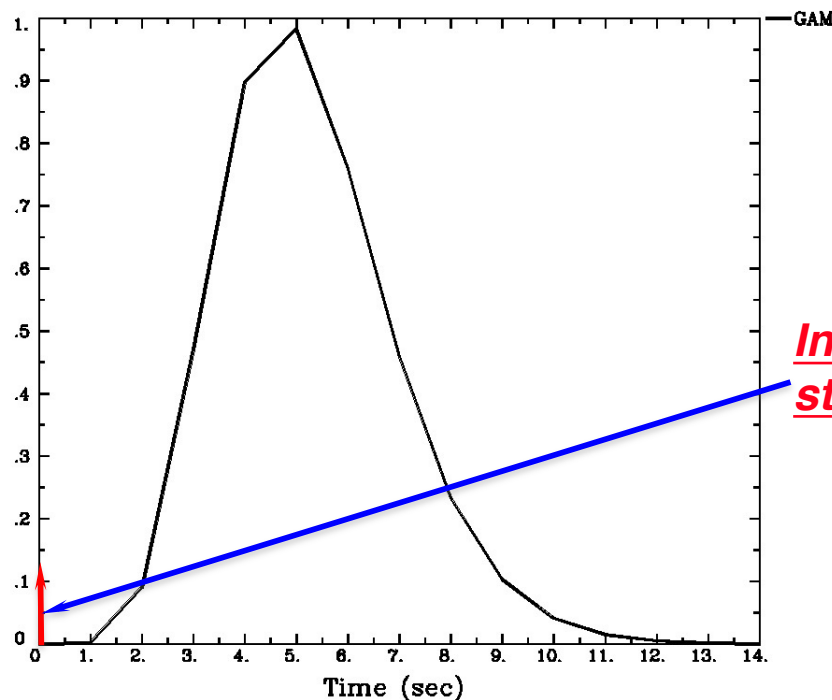
- ✧ How to handle the effects of no interest?
- ✧ How to construct the regressors of interest (responses)?
- ✧ Assumptions about the noise?

Effects of interest

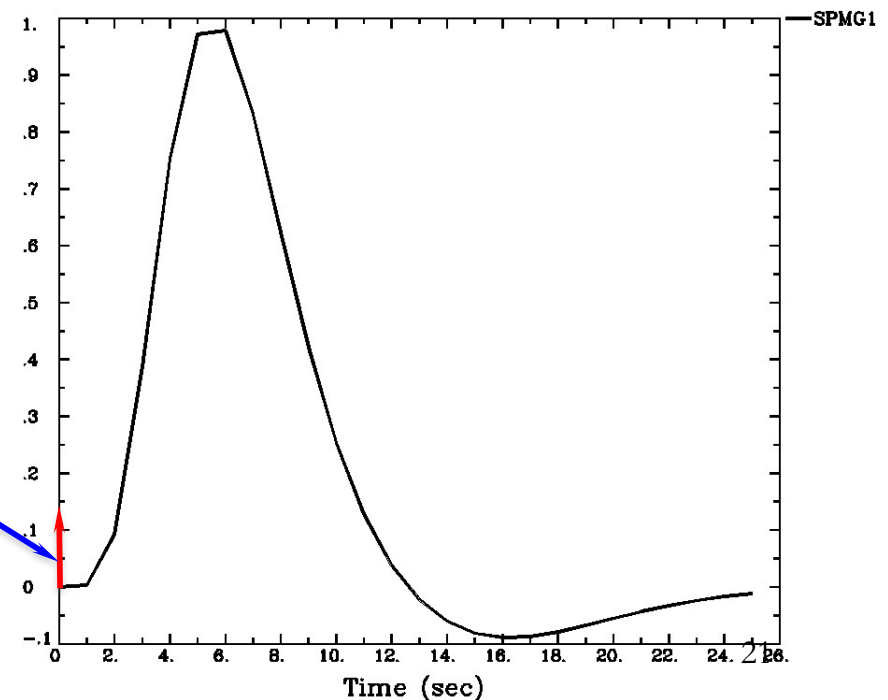
- data = effects of no interest + response₁ + ... + response_k + noise
- 3 components: baseline + drift + other effects of no interest
 - ✧ Baseline (and drift) can be modeled as an additive effect (AFNI), or an effect of interest (cf. SPM and FSL)
 - ✧ Drift: psychological / physiological effect + thermal fluctuation; modeled with polynomials
 - ✧ $y_i = \alpha_0 + \alpha_1 t_i + \alpha_2 t_i^2 + \beta_1 x_{1i} + \dots + \beta_k x_{ki} + \dots + \varepsilon_i$
 - ✧ $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, $\mathbf{X} = [1, t, t^2, x_1, x_2, \dots, x_k, \dots]$
 - ✧ Other effects of no interest: head motion effects, censored time points, ...

Constructing Regressors: FSM

- Assuming a fixed-shape $h(t)$ for HDR to an **instantaneous** stimulus: impulse response function (IRF)
 - $GAM(p,q): h(t) = [t / (p * q)]^p * exp(p - t / q)$
 - DA variation: SPM (undershoot) - **canonical**
 - Default IRF: $h(t) = t^{8.6} exp(-t / 0.547)$ [MS Cohen, 1997]
 - Build HDF based on presumed IRF through **convolution**
 - Roll** IRF $h(t)$ with stimulus timing $S(t): x(t) = h(t) \otimes S(t)$

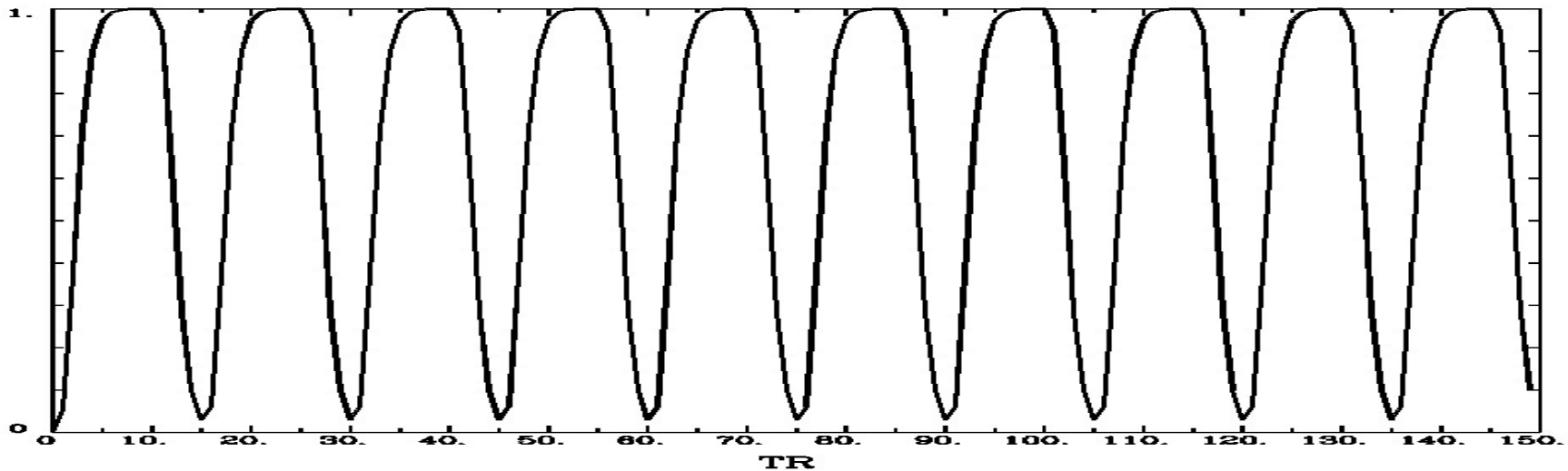


**Instant
stimulus**



FSM for Block Design

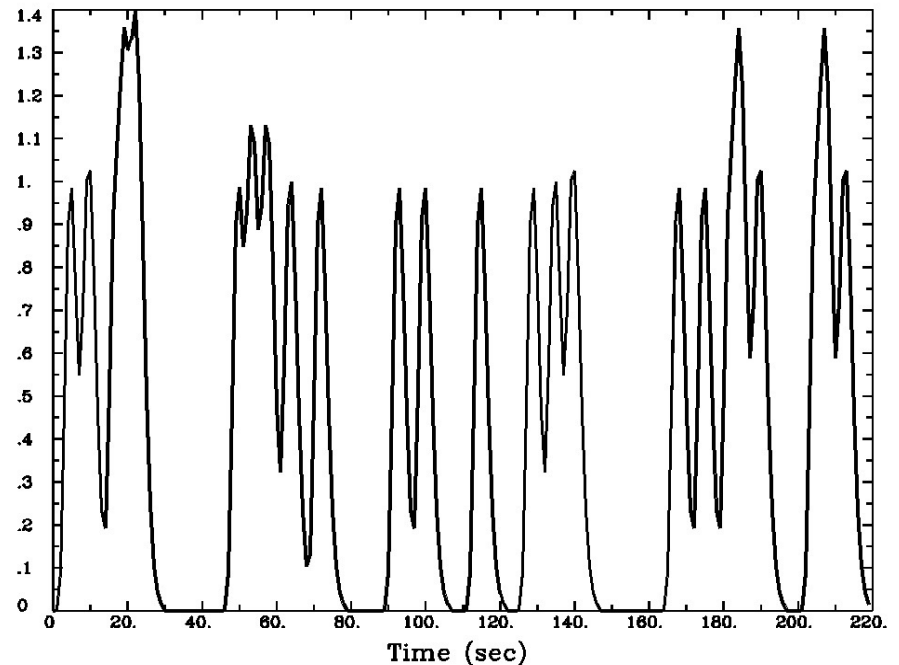
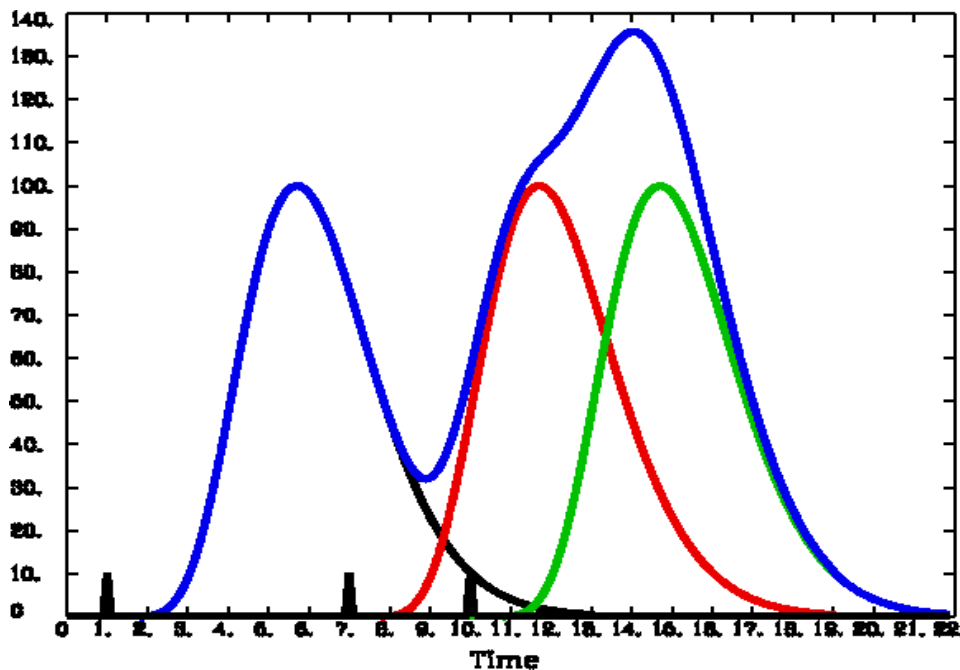
- Presuming a fixed shape IRF $h(t)$ for each **instantaneous** stimulus – **3 parameters**: onset, duration, peak
 - ✧ For each block, $h(t)$ is convolved with **stimulus timing** and **duration** (d) to get idealized response (temporal pattern) as an explanatory variable (regressor): **BLOCK(d, p)**
 - Equivalent to convolving a series of consecutive events
 - Linearity assumed within each block: plateau-like response
 - p : scale HDF to 1 for easy interpretation of β



Block: 10 s on and 10 s off; TR=2 s; 150 time points

FSM for Event-Related Design

- Fixed shape IRF $h(t)$ for an **instantaneous** stimulus – 2 **parameters**: timing and peak
 - ✧ For multiple trials of a condition / task, $h(t)$ is convolved with **stimulus timing** to get idealized response (temporal pattern) as an explanatory variable (regressor): $GAM(p,q)$ or $BLOCK(0)$



Assessing FSM

- Used 99% of time, but not necessarily the optimal
 - ✧ Assumes brain responds with **same shape** across 4 levels: **subjects**, activated **regions**, stimulus **conditions / tasks**, **trials**
 - Difference in **magnitude** β and its significance
 - Strong assumption about **4** levels regarding shape
 - ✧ Easy to handle: one value per effect
 - ✧ Works relatively well
 - Block design: shape usually not important due to accumulating effects (modeled via convolution) of consecutive events
 - Really plateau? Same magnitude across blocks?
 - Event-related experiment
 - Linearity when two responses overlap? Same effect across events?
- Not desirable if you
 - ✧ Care about subtle shape difference across subjects, across regions, across conditions, and across trials
 - ✧ Improve model fitting

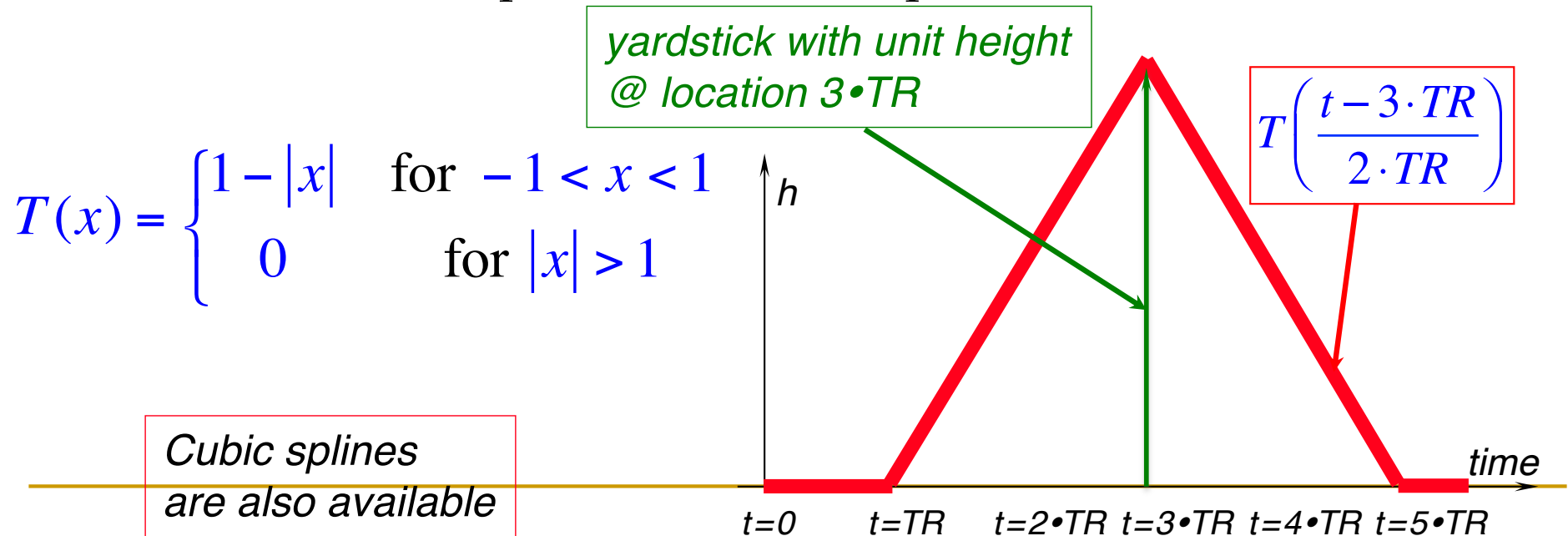
ESM: No Constraint on IRF Shape

□ Yardstick (or TENT) perspective

- ✧ Set multiple yardsticks (or tents) at various equally-spaced locations to cover the potential BOLD response period
 - Each yardstick or TENT is a **basis function**
- ✧ BOLD response measured by yardstick heights at all locations
 - Condition effect is reflected by as many as number of yardsticks

□ Yardsticks (percent signal change sticks): TENT functions

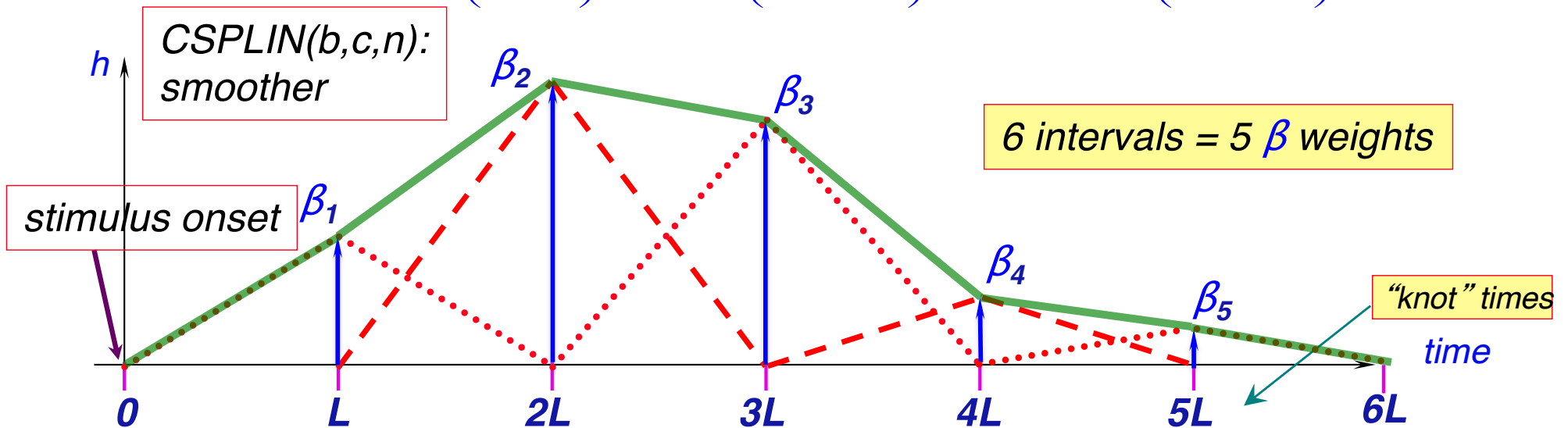
- ✧ Also known as 'piecewise linear splines'



Tent Functions = Linear Interpolation

- 5 equally-spaced tent functions (yardsticks): linear interpolation between “knots” with $\text{TENTzero}(b,c,n) = \text{TENTzero}(0,12,7)$

$$h(t) = \beta_1 \cdot T\left(\frac{t-L}{L}\right) + \beta_2 \cdot T\left(\frac{t-2 \cdot L}{L}\right) + \dots + \beta_5 \cdot T\left(\frac{t-5 \cdot L}{L}\right)$$



- Tent parameters are easily interpreted as function values (e.g., L : tent radius; β_2 = response (tent height) at time $t = 2L$ after stimulus onset)
- Relationship of tent spacing L and TR ($L \geq \text{TR}$), e.g., with TR=2s, $L=2, 4$ s

Assessing ESM

□ Pros

- ✧ Usually for event-related experiments, but can be used for BLOCK
 - Multiple basis functions for blocks: within-block attenuation/habituation
 - Cross-block attenuation/habituation?
- ✧ Likely to have more accurate estimate on HDR shape across subjects, conditions / tasks, brain regions
- ✧ Likely to have better model fit
- ✧ Likely to be statistically more powerful

□ Cons

- ✧ Difficult to summarize at group level: **group analysis capability**
- ✧ A few times more regressors than alternatives: DF's
- ✧ Risk of highly correlated regressors: multicollinearity
 - Try changing the number of basis functions
- ✧ Over-fitting: picking up something (head motion) unrelated to HDR

Why Group Analysis?

- ❑ Reproducibility and generalization
 - ✧ **Science strives for generality**: summarizing subject results
 - ✧ Typically 10 or more subjects per group
 - ✧ Exceptions: pre-surgical planning, lie detection, ...
 - ❑ Why not one analysis with a mega model for all subjects?
 - ✧ Computationally unmanageable
 - ✧ Heterogeneity in data or experiment design across subjects
 - ✧ Model quality check at individual subject level
-

Toy example of group analysis: FSM

- Responses from a group of subjects under one condition
 - ✧ What we have: $(\beta_1, \beta_2, \dots, \beta_{10}) = (1.13, 0.87, \dots, 0.72)$
- Centroid: average $(\beta_1 + \beta_2 + \dots + \beta_{10}) / 10 = 0.92$ is not enough
 - ✧ Variation / reliability measure: diversity, spread, deviation
- Model building
 - ✧ Subject i 's response = group average + deviation of subject i :
simple model GLM (one-sample t -test)

$$\hat{\beta}_i = b + \epsilon_i, \epsilon_i \sim N(0, \sigma^2)$$

- ✧ If individual responses are consistent, ϵ_i should be small
 - t -test: significance measure = $\frac{\hat{b}}{\hat{\sigma}/n}$
 - **2 measures: b (dimensional) and t (dimensionless)**

Models at Group Level: FSM

- Conventional approach: taking β (or linear combination of multiple β 's) only for group analysis
 - Assumption: all subjects have same precision (reliability, standard error, confidence interval) about
 - All subjects are treated equally
 - Student's t -test: paired, one- and two-sample: not random-effects models in strict sense as usually claimed
 - AN(C)OVA, GLM, LME
- Alternative: taking both effect estimates and t -statistics
 - t -statistic contains precision information about effect estimates
 - Each subject is weighted based on precision of effect estimate

Classical ANOVA: 2 × 3 Mixed ANCOVA

- ✧ Factor A (**Group**): 2 levels (patient and control)
- ✧ Factor B (**Condition**): 3 levels (pos, neg, neu)
- ✧ Factor S (**Subject**): 15 ASD children and 15 healthy controls
- ✧ Covariate (**Age**): **cannot** be modeled; **no** correction for sphericity violation

$$F_{(a-1, a(n-1))}(A) = \frac{MSA}{MSS(A)},$$

$$F_{(b-1, a(b-1)(n-1))}(B) = \frac{MSB}{MSE},$$

$$F_{((a-1)(b-1), a(b-1)(n-1))}(AB) = \frac{MSAB}{MSE},$$

where

$$MSA = \frac{SSA}{a-1} = \frac{1}{a-1} \left(\frac{1}{bn} \sum_{j=1}^a Y_{.j}^2 - \frac{1}{abn} Y_{\dots}^2 \right),$$

$$MSB = \frac{SSB}{b-1} = \frac{1}{b-1} \left(\frac{1}{an} \sum_{k=1}^b Y_{..k}^2 - \frac{1}{abn} Y_{\dots}^2 \right),$$

$$MSAB = \frac{SSAB}{(a-1)(b-1)} = \frac{1}{(a-1)(b-1)} \left(\frac{1}{n} \sum_{j=1}^a \sum_{k=1}^b Y_{.jk} - \frac{1}{bn} \sum_{j=1}^a Y_{.j}^2 - \frac{1}{an} \sum_{k=1}^b Y_{..k}^2 + \frac{1}{abn} Y_{\dots}^2 \right),$$

$$MSS(A) = \frac{SSS(A)}{a(n-1)} = \frac{1}{a(n-1)} \left(\frac{1}{b} \sum_{i=1}^n \sum_{j=1}^a Y_{ij}^2 - \frac{1}{bn} \sum_{j=1}^a Y_{.j}^2 \right),$$

$$MSE = \frac{1}{a(b-1)(n-1)} \left(\sum_{i=1}^n \sum_{j=1}^a \sum_{k=1}^b Y_{ijk}^2 - \frac{1}{n} \sum_{j=1}^a \sum_{k=1}^b Y_{.jk} - \frac{1}{b} \sum_{i=1}^n \sum_{j=1}^a Y_{ij}^2 + \frac{1}{bn} \sum_{j=1}^a Y_{.j}^2 + \frac{1}{abn} Y_{\dots}^2 \right)$$

Univariate GLM: 2 x 3 mixed ANOVA

- Group: 2 levels (patient and control)
- Condition: 3 levels (pos, neg, neu)
- Subject: 3 ASD children and 3 healthy controls

Difficult to incorporate covariates

- Broken orthogonality*

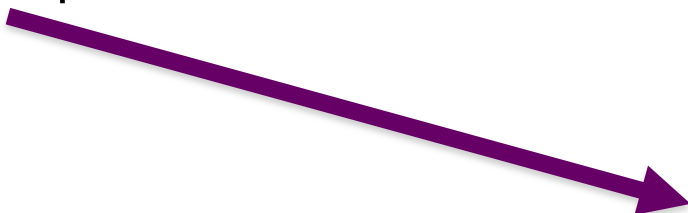
No correction for sphericity violation

$$\begin{array}{c} \text{Subj} \\ 1 \\ 1 \\ 1 \\ 2 \\ 2 \\ 2 \\ 3 \\ 3 \\ 3 \\ 4 \\ 4 \\ 4 \\ 5 \\ 5 \\ 5 \\ 6 \\ 6 \\ 6 \end{array} \begin{pmatrix} \beta_{11} \\ \beta_{12} \\ \beta_{13} \\ \beta_{21} \\ \beta_{22} \\ \beta_{23} \\ \beta_{31} \\ \beta_{32} \\ \beta_{33} \\ \beta_{41} \\ \beta_{42} \\ \beta_{43} \\ \beta_{51} \\ \beta_{52} \\ \beta_{53} \\ \beta_{61} \\ \beta_{62} \\ \beta_{63} \end{pmatrix} = \begin{pmatrix} X_0 & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 & X_7 & X_8 & X_9 \\ 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & -1 & -1 & -1 & -1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & -1 & -1 & -1 & -1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 & -1 & -1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 1 & -1 & -1 & 0 & 0 \\ 1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 0 \\ 1 & -1 & 1 & 0 & -1 & 0 & 0 & 0 & 1 & 0 \\ 1 & -1 & 0 & 1 & 0 & -1 & 0 & 0 & 1 & 0 \\ 1 & -1 & -1 & -1 & 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & -1 & 1 & 0 & -1 & 0 & 0 & 0 & 0 & 1 \\ 1 & -1 & 0 & 1 & 0 & -1 & 0 & 0 & 0 & 1 \\ 1 & -1 & -1 & -1 & 1 & 1 & 0 & 0 & 0 & 1 \\ 1 & -1 & 1 & 0 & -1 & 0 & 0 & 0 & -1 & -1 \\ 1 & -1 & 0 & 1 & 0 & -1 & 0 & 0 & -1 & -1 \\ 1 & -1 & -1 & -1 & 1 & 1 & 0 & 0 & -1 & -1 \end{pmatrix} \begin{pmatrix} \alpha_0 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \\ \alpha_8 \\ \alpha_9 \end{pmatrix} + \begin{pmatrix} \delta_{11} \\ \delta_{12} \\ \delta_{13} \\ \delta_{21} \\ \delta_{22} \\ \delta_{23} \\ \delta_{31} \\ \delta_{32} \\ \delta_{33} \\ \delta_{41} \\ \delta_{42} \\ \delta_{43} \\ \delta_{51} \\ \delta_{52} \\ \delta_{53} \\ \delta_{61} \\ \delta_{62} \\ \delta_{63} \end{pmatrix}$$

Flexible Approach: Multivariate GLM

- **Group:** 2 levels (patient and control)
- **Condition:** 3 levels (pos, neg, neu)
- **Subject:** 3 ASD children and 3 healthy controls
- **Age:** quantitative covariate

$$B_{n \times m} = X_{n \times q} A_{q \times m} + D_{n \times m}$$



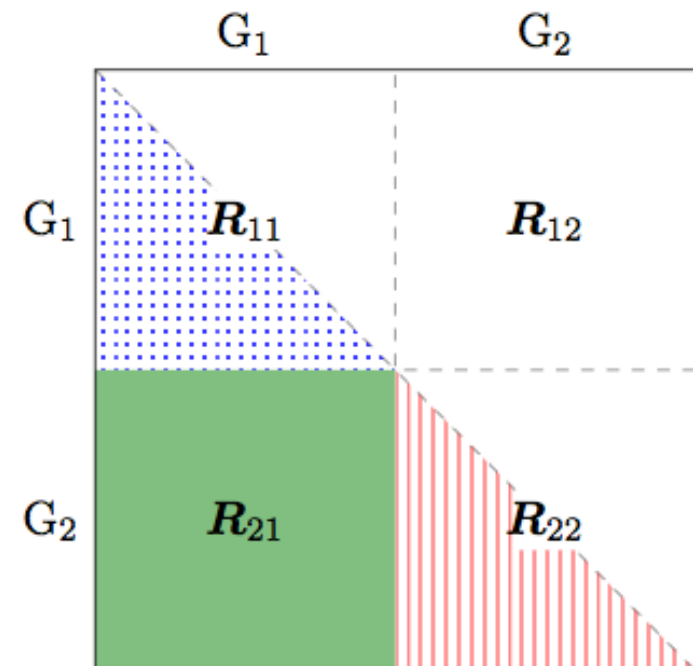
<i>Subj</i>	<i>Pos</i>	<i>Neg</i>	<i>Neu</i>	<i>Int</i>	<i>Grp</i>	<i>Age</i>	<i>Pos</i>	<i>Neg</i>	<i>Neu</i>	<i>Subj</i>
1	β_{11}	β_{12}	β_{13}	1	1	-6	α_{01}	α_{11}	α_{21}	1
2	β_{21}	β_{22}	β_{23}	1	1	10	α_{02}	α_{12}	α_{22}	2
3	β_{31}	β_{32}	β_{33}	1	1	4	α_{03}	α_{13}	α_{23}	3
4	β_{41}	β_{42}	β_{43}	1	-1	-4				4
5	β_{51}	β_{52}	β_{53}	1	-1	-1				5
6	β_{61}	β_{62}	β_{63}	1	-1	-3				6

$B_{n \times m} = X_{n \times q} A_{q \times m} + D_{n \times m}$

Inter-Subject Correlation (ISC)

- Analysis methodology
 - Regression with task-related regressors won't work
 - Voxel-wise correlation between any subject pair
 - $n = 4$ subjects \Rightarrow 6 ISC; $n = 5$ subjects \rightarrow 10 ISC
 - n subjects $\Rightarrow n(n-1)/2$ ISC – which are not all independent!
 - How to go about group analysis?

$$\begin{array}{c} S_1 \\ S_2 \\ S_3 \\ \vdots \\ S_n \end{array} \begin{pmatrix} S_1 & S_2 & S_3 & \cdots & S_n \\ - & z_{12} & z_{13} & \cdots & z_{1n} \\ z_{21} & - & z_{23} & \cdots & z_{2n} \\ z_{31} & z_{32} & - & \cdots & z_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & z_{n3} & \cdots & - \end{pmatrix}$$



Inter-Subject Correlation (ISC)

- Analysis methodology

- How to go about group analysis?

- Difficulty: The ISCs are not independent with each other
- The correlations are correlated themselves!

- Solutions

- Permutations
- Bootstrapping
- LME

	Z_{21}	Z_{31}	Z_{41}	Z_{51}	Z_{32}	Z_{42}	Z_{52}	Z_{43}	Z_{53}	Z_{54}
Z_{21}	1	ρ	ρ	ρ	ρ	ρ	ρ	0	0	0
Z_{31}	ρ	1	ρ	ρ	ρ	0	0	ρ	ρ	0
Z_{41}	ρ	ρ	1	ρ	0	ρ	0	ρ	0	ρ
Z_{51}	ρ	ρ	ρ	1	0	0	ρ	0	ρ	ρ
Z_{32}	ρ	ρ	0	0	1	ρ	ρ	ρ	ρ	0
Z_{42}	ρ	0	ρ	0	ρ	1	ρ	ρ	0	ρ
Z_{52}	ρ	0	0	ρ	ρ	ρ	1	0	ρ	ρ
Z_{43}	0	ρ	ρ	0	ρ	ρ	0	1	ρ	ρ
Z_{53}	0	ρ	0	ρ	ρ	0	ρ	ρ	1	ρ
Z_{54}	0	0	ρ	ρ	0	ρ	ρ	ρ	ρ	1

Multiple Testing Correction

Two types of errors

- What is H_0 in fMRI studies? 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 = β
 - power** = $1 - \beta$ = 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

Statistics: Hypothesis Test

Hidden Truth

Hidden Truth

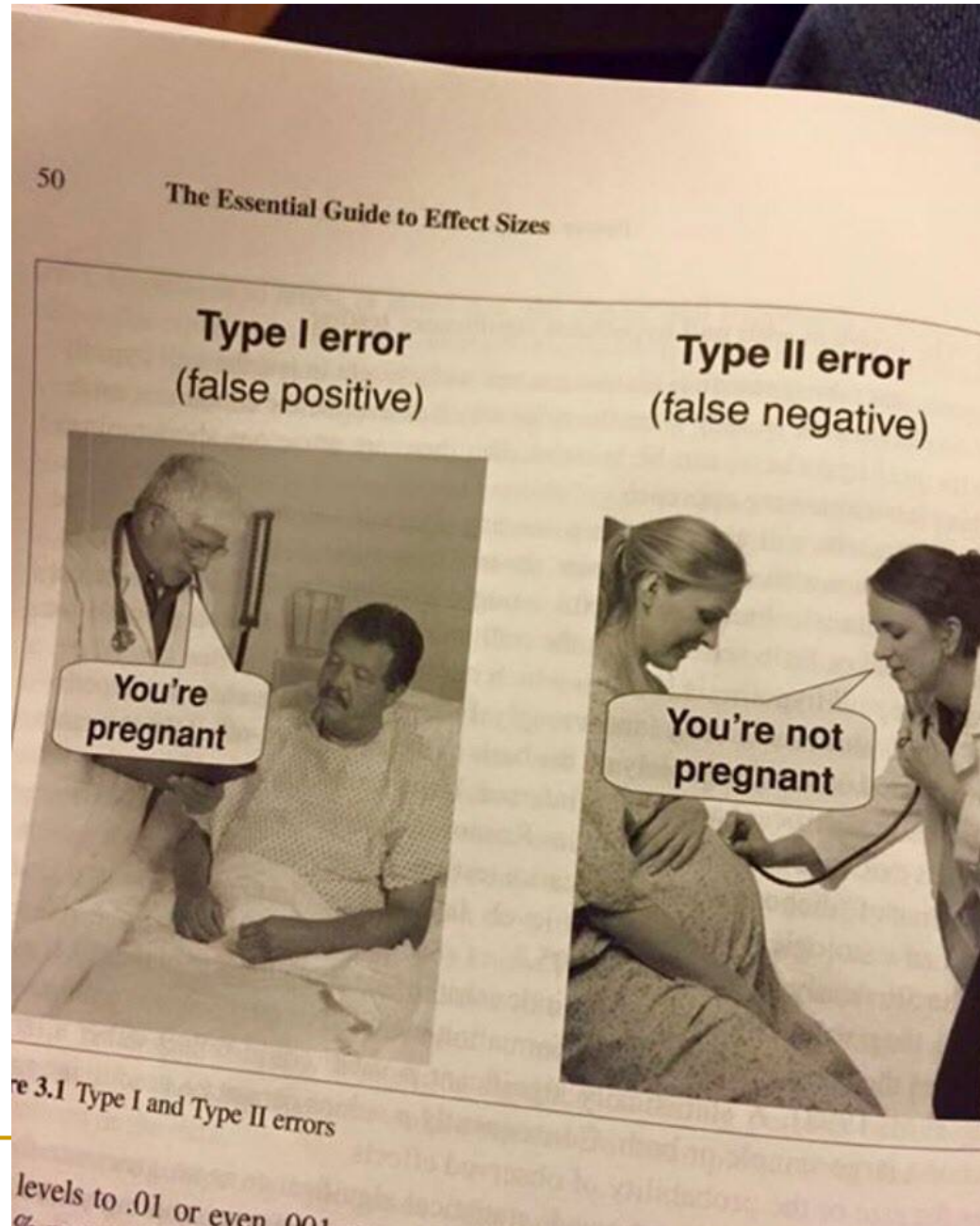
	Defendant Innocent	Defendant Guilty
Reject Presumption of Innocence (Guilty Verdict)	Type I Error (defendant very unhappy)	Correct
Fail to Reject Presumption of Innocence (Not Guilty Verdict)	Correct	Type II Error (defendant very happy)

Reject H_0
(decide voxel is activated)

Don't Reject H_0
(decide voxel isn't activated)

	H_0 True Not Activated	H_0 False 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)

Multiple Testing Correction



Multiple Testing Correction

■ Two types of correction

- Same test repeated many times (number of voxels)
 - Family-wise error (FWE)
 - Counterbalance between cluster size and voxel-wise significance
 - Difficulties: not to over-penalize yourself due to spatial correlation, but spatial structure is neither Gaussian nor homogeneous!
 - Correction via permutations with quantifying the counterbalance
- Multiple tests in a study: six pairwise comparisons among four levels of a factor
 - Little attention in neuroimaging community

Miscellaneous

- Science is about reproducibility
 - ✧ Widespread obsession with p -values in FMRI
 - Colored blobs of t -values
 - Peak voxel selected based on peak t -value
 - ✧ **Unacceptable** in some fields if only p -value is reported
 - Basic and Applied Social Psychology bans p -value
 - Neuroimaging: an exception currently!

 - 2-tier approach
 - ✧ Start with a liberal thresholding of p : 0.05 or even 0.1
 - ✧ Report rigorous results (multiple testing correction)
 - ✧ Also report the clusters under voxel-wise p of 0.05 but still have some spatial extent with some cautionary words
-

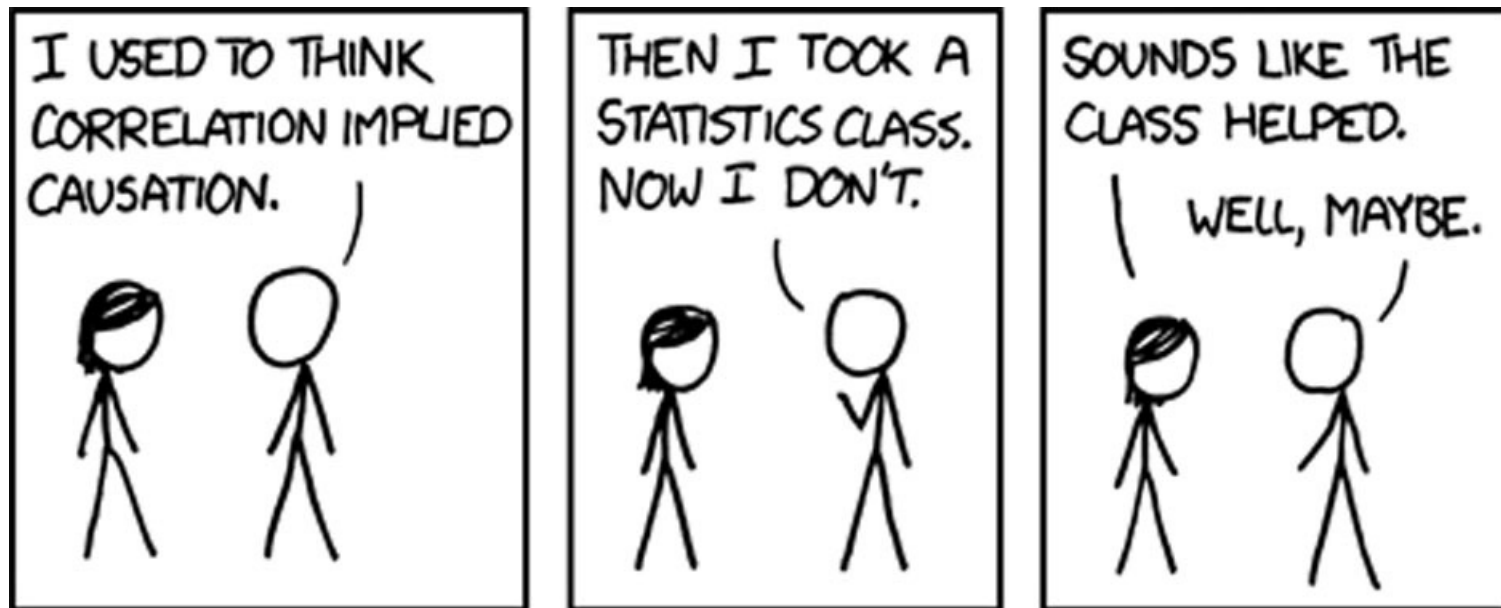
Miscellaneous

- ❑ Statistical significance (p -value) may become obsession
 - ✧ Published papers: Big and tall parents (violent men, engineers) have more sons, beautiful parents (nurses) have more daughters
 - ✧ P-hacking
 - ❑ Two types of significance
 - ✧ Practical significance: lower cholesterol level by 2.7 mmol/L
 - ✧ Statistical significance
 - ❑ Limitations of statistical inference
 - ✧ Binary decision: a statistically non-significant effect does not mean practically non-significant
 - ✧ The difference between a statistically significant effect and a non-significant one is not necessarily statistically significant
-

Miscellaneous

❑ Correlation vs. causation

- ✧ Incidence of childhood leukemia: several times greater in certain Denver suburbs than in other parts of the country
 - High-voltage power lines?
- ✧ Lots of correlation analysis in FMRI



Lastly

- ❑ Essentially all models are wrong, but some are useful.
(George E. P. Box)
 - ❑ Statistics are like a bikini. What they reveal is suggestive, but what they conceal is vital. (Aaron Levenstein)
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