Hands-On Session: Regression Analysis

- What we have learned so far
  - Use data viewer 'afni' interactively
  - Model HRF with a shape-prefixed basis function
    - Assume the brain responds with the same shape
      - in any active regions
      - regardless stimulus types
    - Differ in magnitude: β is what we focus on
- What we will do in this session
  - Play with a case study
  - Spot check for the original data using GUI 'afni'
  - Data pre-processing for regression analysis
  - Basic concepts of regressors, design matrix, and confounding effects
  - Statistical testing in regression analysis
  - Statistics thresholding with data viewer 'afni'
  - Model performance (visual check of curve fitting and test via full F or R^2)

Preparing Data for Analysis

- Six preparatory steps are common:
  - Temporal alignment (sequential/interleaved): **`3dTshift`**
  - Image registration (aka realignment): **`3dvolreg`**
  - Spatial normalization (standard space conversion): **`adwarp, @auto_tlrc, anlign_epi_anat.py`**
  - Blurring: **`3dmerge, 3dBlurToFWHM, 3dBlurInMask`**
  - Masking: **`3dAutomask`** or **`3dClipLevel`**
  - Conversion to percentile: **`3dTstat`** and **`3dcalc`**
  - Censoring out time points that are bad: **`3dToutcount`** (or **`3dTqual`**) and **`3dvolreg`**

- Not all steps are necessary or desirable in any given case

A Case Study

- **The Experiment**
  - ★ Cognitive Task: Subjects see photographs of two people interacting
    - o Mode of communication - 3 *categories*: telephone, email, or face-to-face.
    - o A*ffect*: negative, positive, or neutral in nature.
  - ★ Experimental Design: 3x3 Factorial design, BLOCKED trials
    - o Factor A: **CATEGORY** - (1) Telephone, (2) E-mail, (3) Face-to-Face
    - o Factor B: **AFFECT** - (1) Negative, (2) Positive, (3) Neutral

    - o A random 30-second block of photographs for a task (ON), followed by a 30-second block of the control condition of scrambled photographs (OFF)...
    - o Each run has 3 ON blocks, 3 OFF blocks. 9 runs in a scanning session.

★ Illustration of Stimulus Conditions

AFFECT

		Negative	Positive	Neutral
Telephone		“Your project is lame, just like you!”	“You are the best project leader!”	“You finished the project.”
E-mail		"Ugh, your hair is hideous!"	"Your new haircut looks awesome!"	"You got a haircut."
Face-to-Face		“I curse the day I met you!”	“I feel lucky to have you in my life.”	“I know who you are.”

★ Data Collected

- 1 Anatomical (MPRAGE) dataset for each subject
  - ➥ 124 axial slices
  - ➥ voxel dimensions = 0.938 x 0.938 x 1.2 mm
- 9 runs of Time Series (EPI) datasets for each subject
  - ➥ 34 axial slices x 67 volumes (TRs) = 2278 slices per run
  - ➥ TR = 3 sec; voxel dimensions = 3.75 x 3.75 x 3.5 mm
- Sample size, n=16 (all right handed)

Multiple Stimulus Classes

- Summary of the experiment
  - 9 related communication stimulus types in a 3x3 design of Category by Affect (stimuli are shown to subject as pictures)
    - **Telephone, Email** & **Face-to-face** = categories
    - **Negative, Positive** & **Neutral** = affects
      - ✓ telephone stimuli: tneg, tpos, tneu
      - ✓ email stimuli: eneg, epos, eneu
      - ✓ face-to-face stimuli: fneg, fpos, fneu
  - Each stimulus type has 3 presentation blocks of 30 s duration
  - Scrambled pictures (baseline) are shown between blocks
  - 9 imaging runs, 64 useful time points in each
    - Originally, 67 TRs per run, but skip first 3 for MRI signal to reach steady state (i.e., eliminate initial transient spike in data)
    - So 576 TRs of data, in total (64×9)
  - Registered (`3dvolreg`) dataset: `rall_vr+orig`
    - Slice timing is not important in this case

Regression with Multiple Model Files

- Script file **rall_decon** does the job:
- Run this script by typing **tcsh rall_regress** (takes a few minutes)

```
3dDeconvolve -input rall_vr+orig -polort 2                              \
    -jobs 2                                                             \
    -concat '1D: 0 64 128 192 256 320 384 448 512'                      \
    -num_stimts 15 -local_times                                         \
    -stim_times 1 '1D: 0 | | | 120 | | | | | 60'     'BLOCK(30)'        \
        -stim_label 1 tneg                                              \
    -stim_times 2 '1D: * | | 120 | | 0 | | | | 120' 'BLOCK(30)'         \
        -stim_label 2 tpos                                              \
    -stim_times 3 '1D: * | 120 | | 60 | | | | | 0'   'BLOCK(30)'        \
        -stim_label 3 tneu                                              \
    -stim_times 4 '1D: 60 | | | | | 120 | 0 | |'     'BLOCK(30)'        \
        -stim_label 4 eneg                                              \
    -stim_times 5 '1D: * | 60 | | 0 | | | 120 | |'   'BLOCK(30)'        \
        -stim_label 5 epos                                              \
    -stim_times 6 '1D: * | | 0 | | 60 | | | 60 |'    'BLOCK(30)'        \
        -stim_label 6 eneu                                              \
    -stim_times 7 '1D: * | 0 | | | 120 | | 60 | |'   'BLOCK(30)'        \
        -stim_label 7 fneg                                              \
    -stim_times 8 '1D: 120 | | | | | 60 | | 0 |'     'BLOCK(30)'        \
        -stim_label 8 fpos                                              \
    -stim_times 9 '1D: * | | 60 | | | 0 | | 120 |'   'BLOCK(30)'        \
        -stim_label 9 fneu                                              \
```

linear trend
try to use 2 CPUs
run start indexes
stimulus times
stimulus label
'|' indicates new run
response model

continued …

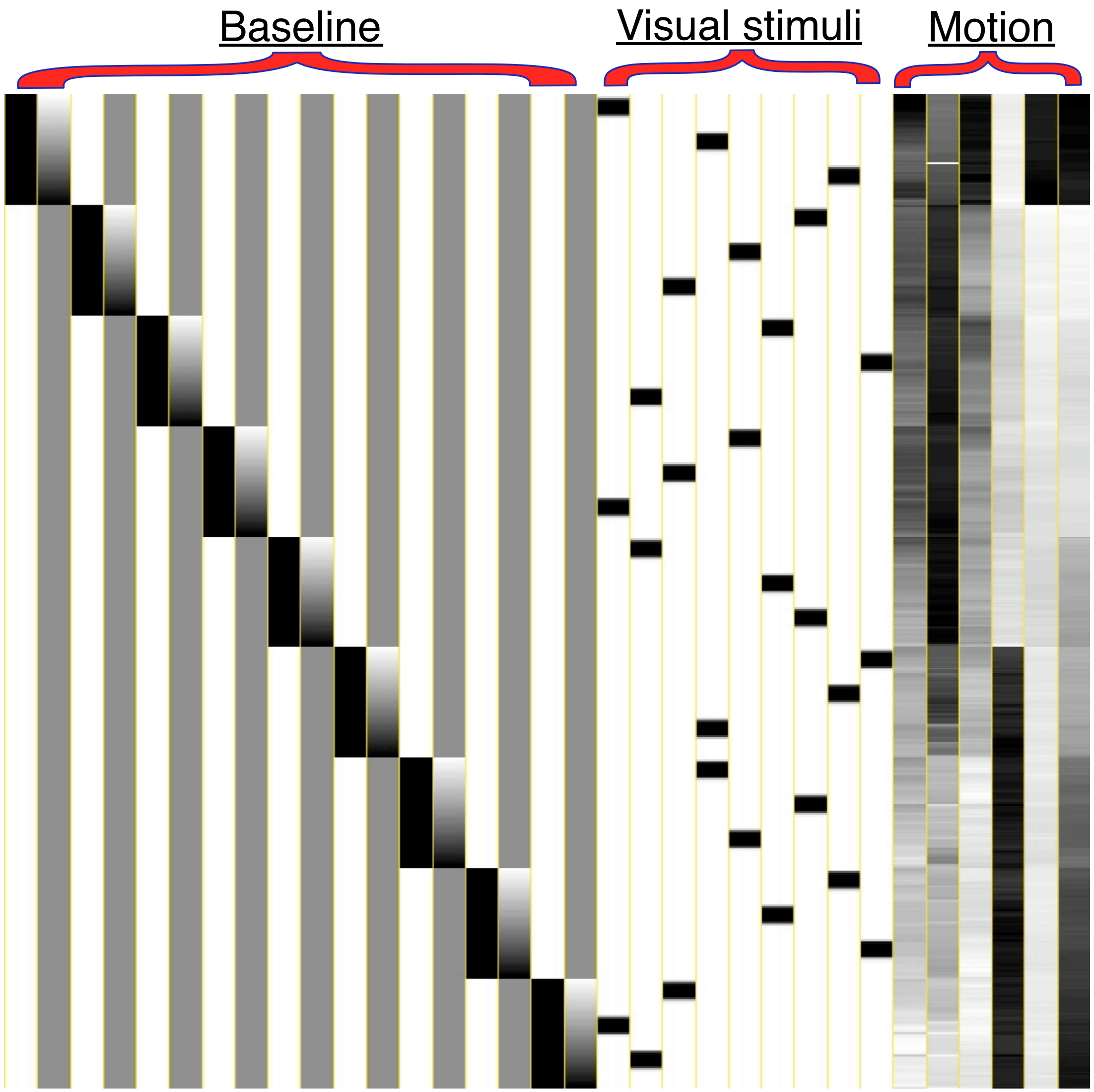
Regression with Multiple Model Files (continued)

```
-stim_file 10 motion.1D'[0]' -stim_base 10          \
-stim_file 11 motion.1D'[1]' -stim_base 11          \
-stim_file 12 motion.1D'[2]' -stim_base 12          \
-stim_file 13 motion.1D'[3]' -stim_base 13          \
-stim_file 14 motion.1D'[4]' -stim_base 14          \
-stim_file 15 motion.1D'[5]' -stim_base 15          \
-gltsym 'SYM: tpos -epos' -glt_label 1 TPvsEP       \
-gltsym 'SYM: tpos -tneg' -glt_label 2 TPvsTNg      \
-gltsym 'SYM: tpos tneu tneg -epos -eneu -eneg'     \
        -glt_label 3 TvsE                           \
-fout -tout                                         \
-bucket rall_func -fitts rall_fitts                 \
-xjpeg rall_xmat.jpg -x1D rall_xmat.x1D
```

motion regressor
apply to baseline
symbolic GLT
label the GLT
statistic types to output

- 9 visual stimulus classes were given using `-stim_times`
- **important to include motion parameters as regressors**?
  - this would remove the confounding effects due to motion artifacts
  - 6 motion parameters as covariates via `-stim_file` and `-stim_base`
  - `motion.1D` was generated from `3dvolreg` with the `-1Dfile` option
  - we can test the significance of the inclusion with `-gltsym`
    - Switch from `-stim_base` to `-stim_label roll` …
    - Use `-gltsym 'SYM: roll \ pitch \yaw \dS \dL \dP'`

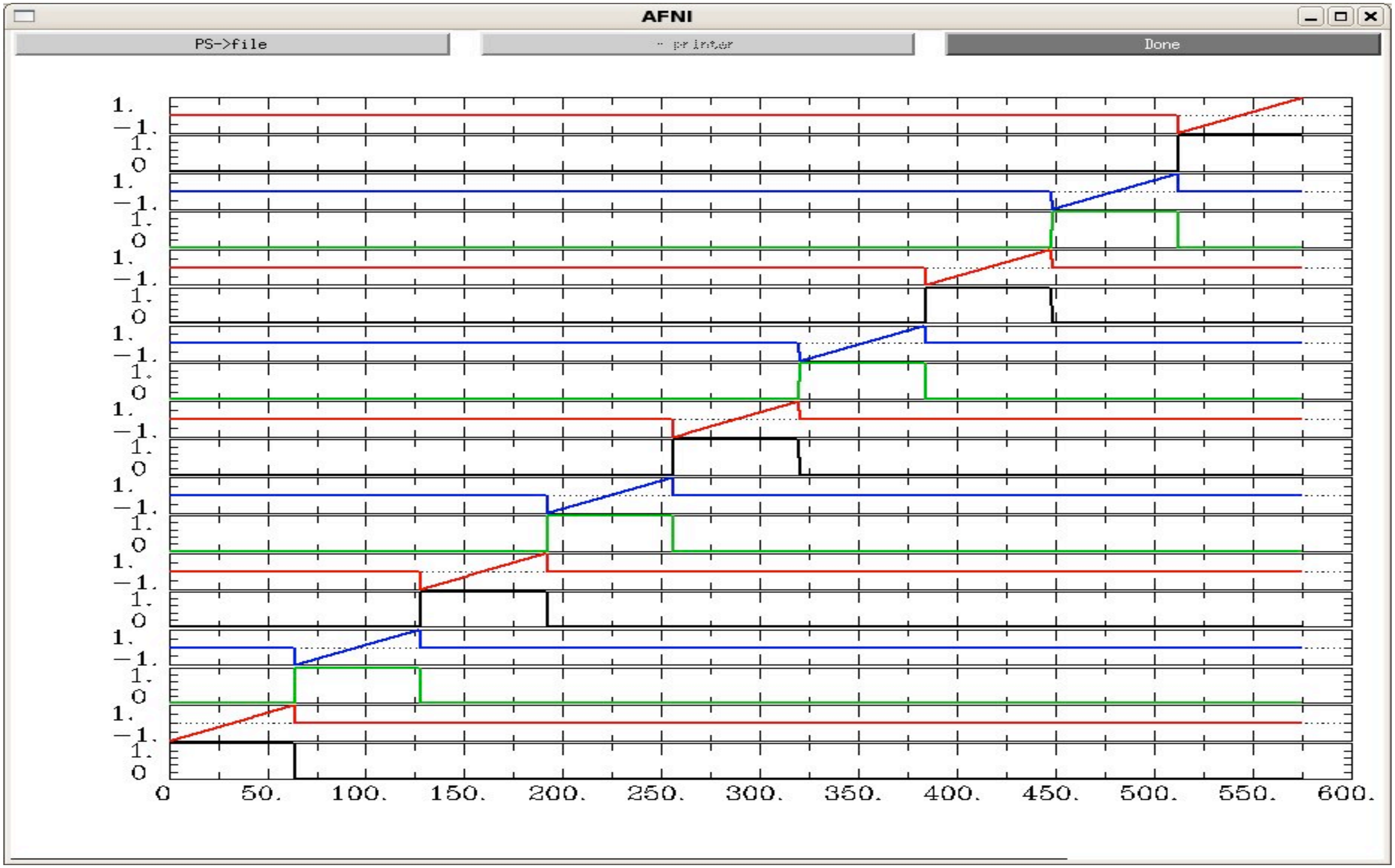
Regressor Matrix for This Script (via -xjpeg)



- 18 baseline regressors
  - linear baseline
  - 9 runs times 2 params
- 9 visual stimulus regressors
  - 3×3 design
- 6 motion regressors
  - 3 rotations and 3 shifts

`aiv rall_xmat.jpg`

Regressor Matrix for This Script (via -x1D)

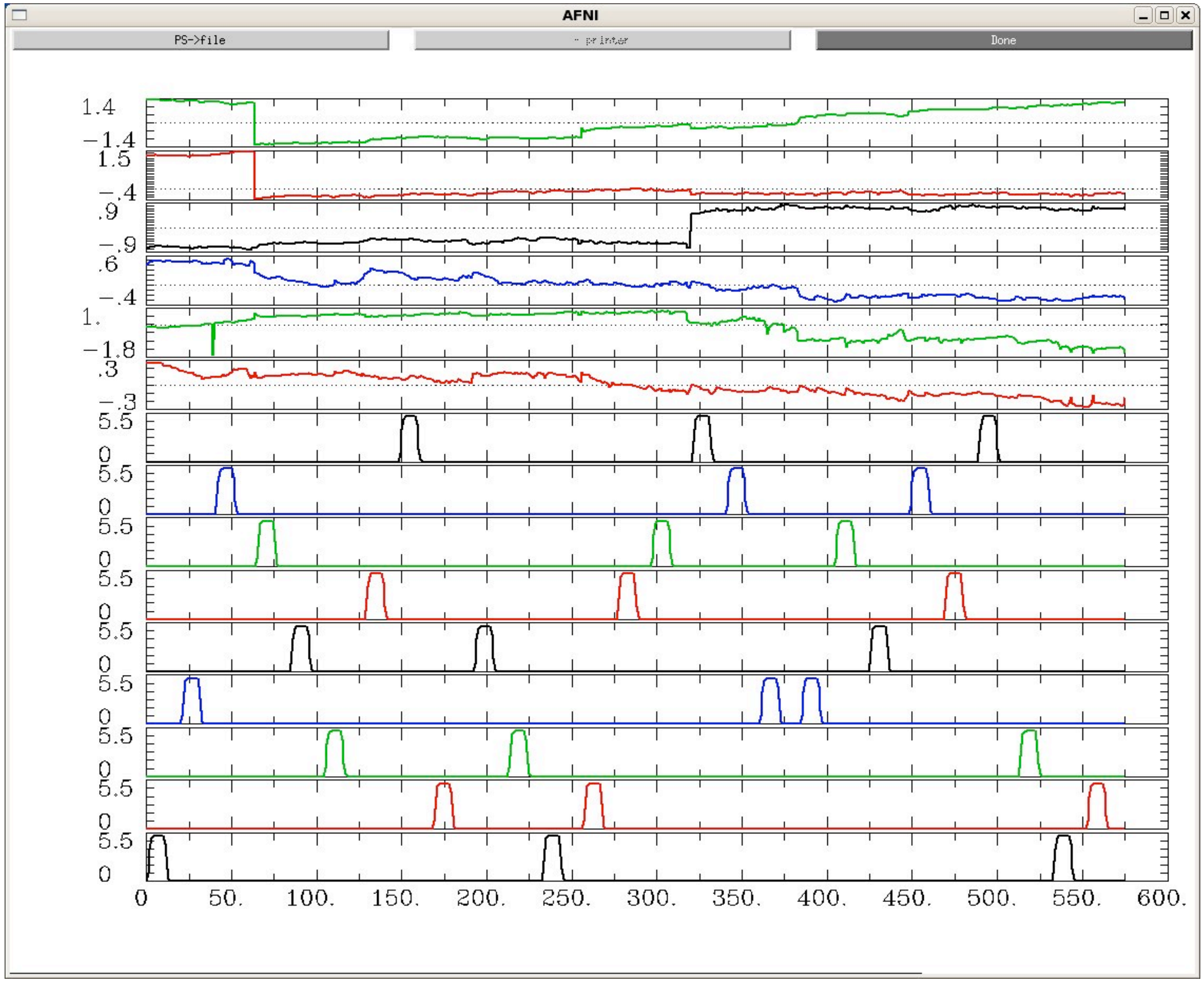


baseline regressors: via **1dplot -sepscl rall_xmat.x1D'[0..17]'**

Regressor Matrix for This Script (via -x1D)

• motion regressors

• visual stimuli




```
1dplot -sepscl rall_xmat.x1D'[18..$]'
```

Options in 3dDeconvolve - 1

```
-concat '1D: 0 64 128 192 256 320 384 448 512'
```

- "File" that indicates where distinct imaging runs start inside the input file
  - Numbers are the time indexes inside the dataset file for start of runs
  - In this case, a text format .1D file put directly on the command line
    - Could also be a filename, if you want to store that data externally

```
-num_stimts 15 -local_times
```

- We have 9 visual stimuli (+6 motion), so will need 9 **`-stim_times`** below
- Times given in the **`-stim_times`** files are *local* to the start of each run (vs. **`-global_times`** meaning times are relative the start of the first run)

```
-stim_times 1
 '1D: 0.0 | | | 120.0 | | | | | 60.0'
 'BLOCK(30)'
```

- "File" with 8 lines, each line specifying the start time in seconds for the stimuli within the corresponding imaging run, with the time measured relative to the start of the imaging run itself (local time)

Options in 3dDeconvolve - 2

`-gltsym 'SYM: tpos -epos'  -glt_label 1 TPvsEP`

- **GLT**s are **G**eneral **L**inear **T**ests
- **3dDeconvolve** provides test statistics for each regressor separately, but if you want to test combinations or contrasts of the β weights in each voxel, you need the `-gltsym` option
- Example above tests the difference between the β weights for the `Positive Telephone` and the `Positive Email` responses
  - Starting with `SYM:` means symbolic input is on command line
    - Otherwise inputs will be read from a file
  - Symbolic names for each regressor taken from `-stim_label` options
  - Stimulus label can be preceded by `+` or `-` to indicate sign to use in combination of β weights
  - Leave space after each label!
- Goal is to test a linear combination of the β weights
  - Tests if $\beta_{tpos} = \beta_{epos}$
  - e.g., does `tpos` get different response from `epos` ?
- Quiz: what would `'SYM: tpos epos fpos'` test?

It would test if $\beta_{tpos} + \beta_{epos} + \beta_{fpos} = 0$

Options in 3dDeconvolve - 3

```
-gltsym 'SYM: tpos tneu tneg -epos -eneu -eneg'
-glt_label 3 TvsE
```

- Goal is to test if $(\beta_{tpos} + \beta_{tneu} + \beta_{tneg}) - (\beta_{epos} + \beta_{eneu} + \beta_{eneg}) = 0$
  - Test average BOLD signal change among the 3 affects in the telephone tasks versus the email tasks

```
-gltsym 'SYM: tpos -epos \ tneu -eneu \ tneg -eneg'
-glt_label 4 TvsE_F
```

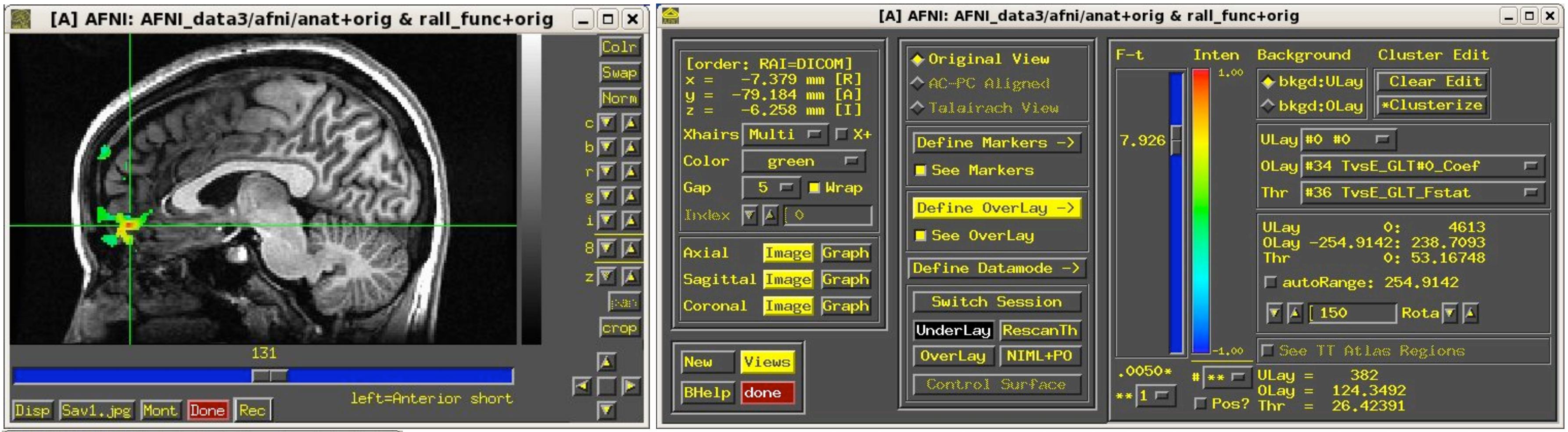
- How to test if $\beta_{tpos} = \beta_{epos}$, $\beta_{tneu} = \beta_{eneu}$, **and** $\beta_{tneg} = \beta_{eneg}$?
  - Difference in telephone vs. email task in any affect?
  - Different test than previous one: composite null hypotheses, multi-DFs, *F* (instead of *t*), vague info (no indication about specific affect & direction)
- `-glt_label 3 TvsE` attaches a meaningful label to resulting sub-bricks
  - Output includes summation of β weights and associated statistics (*t*/*F*)
- Quiz: How to get main effect of Category or Affect?

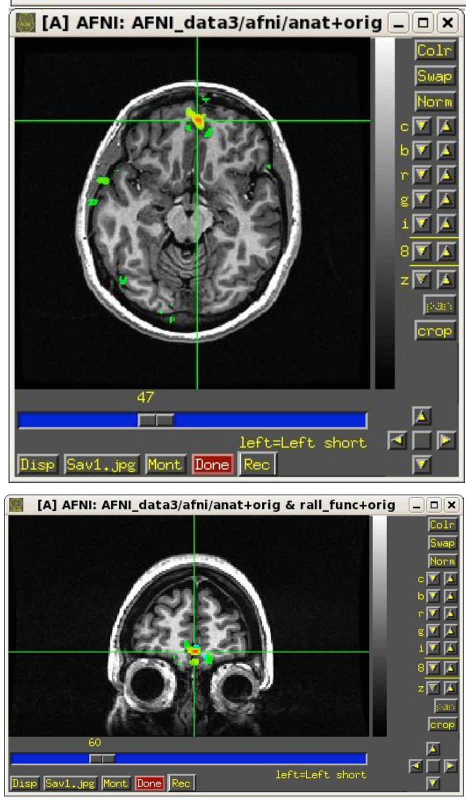
Options in 3dDeconvolve - 4

`-fout -tout` = output both *F*- and *t*-statistics for each stimulus class (`-fout`) and stimulus coefficient (`-tout`) — but not for the baseline coefficients (if you want baseline statistics: `-bout`)

- The full model statistic is an *F*-statistic that shows how well the sum of all 9 input model time series fits voxel time series data
  - Compared to how well *just* the baseline model time series fit the data times (in this example, have 24 baseline regressor columns in the matrix — 18 for the linear baseline, plus 6 for motion regressors)
  - $F = [SSE(r) - SSE(f)]/df(\mathrm{n}) \div [SSE(f)/df(\mathrm{d})]$
- The individual stimulus classes also will get individual *F*- and/or *t*-statistics indicating the significance of their individual *incremental* contributions to the data time series fit
  - e.g., F_{tpos} (#6, equivalent to ***t*** (#5)) tells if the full model explains more of the data variability than the model with `tpos` omitted and all other model components included
  - If DF=1, ***t*** is equivalent to *F*: $t(n) = F^2(1, n)$

Results of **rall_regress** Script





- Images showing results from third GLT contrast: **TvsE**
- Menu showing labels from **3dDeconvolve** run
- Play with these results yourself!

Statistics from 3dDeconvolve

- An *F*-statistic measures significance of how much a model component (stimulus class) reduced the variance (sum of squares) of data time series residual
  - After all the other model components were given their chance to reduce the variance
  - **Residuals** ≡ data – model fit = errors = **`-errts`**
  - A *t*-statistic sub-brick measures impact of one coefficient (of course, **`BLOCK`** has only one coefficient)
- Full *F* measures how much the all regressors of interest combined reduced the variance over just the baseline regressors (**sub-brick #0**)
- Individual partial-model *F*s measures how much each individual signal regressor reduced data variance over the full model with that regressor excluded (e.g., **sub-bricks #3, #6, #9**)
- The **Coef** sub-bricks are the β weights (e.g., **#1, #4, #7, #10**) for the individual regressors
- Also present: GLT coefficients and statistics

# 0 Full_Fstat	#19 fneg#0_Coef
# 1 tneg#0_Coef	#20 fneg#0_Tstat
# 2 tneg#0_Tstat	#21 fneg_Fstat
# 3 tneg_Fstat	#22 fpos#0_Coef
# 4 tpos#0_Coef	#23 fpos#0_Tstat
# 5 tpos#0_Tstat	#24 fpos_Fstat
# 6 tpos_Fstat	#25 fneu#0_Coef
# 7 tneu#0_Coef	#26 fneu#0_Tstat
# 8 tneu#0_Tstat	#27 fneu_Fstat
# 9 tneu_Fstat	#28 TPvsEP_GLT#0_Coef
#10 eneg#0_Coef	#29 TPvsEP_GLT#0_Tstat
#11 eneg#0_Tstat	#30 TPvsEP_GLT_Fstat
#12 eneg_Fstat	#31 TPvsTNg_GLT#0_Coef
#13 epos#0_Coef	#32 TPvsTNg_GLT#0_Tstat
#14 epos#0_Tstat	#33 TPvsTNg_GLT_Fstat
#15 epos_Fstat	#34 TvsE_GLT#0_Coef
#16 eneu#0_Coef	#35 TvsE_GLT#0_Tstat
#17 eneu#0_Tstat	#36 TvsE_GLT_Fstat
#18 eneu_Fstat	

Group Analysis: will be carried out on β or **`GLT`** coefs from single-subject analyses