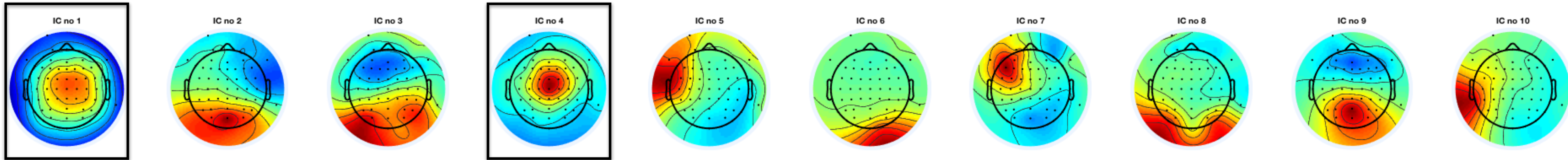


- Session 1 - Why single-trial EEG analyses?
- Session 2 - Pre-processing, introduction to ICA
 - Example session I: Setting-up your data and running a single-trial regression analysis with the *STA-TB*
- Session 3 - ICA as a tool to increase SNR in EEG data
 - Example session II: COMPASS to select ICs
 - **Example session III: EEG regression with independent component activity**
- Session 4 - Within-subject to across-subject analyses
 - Example session IV: Combine data across participants
- Session 5 - Time-frequency decomposition and single-trial analyses
 - Example session V: Run a TF decomposition and GLM analysis
- End and Discussion

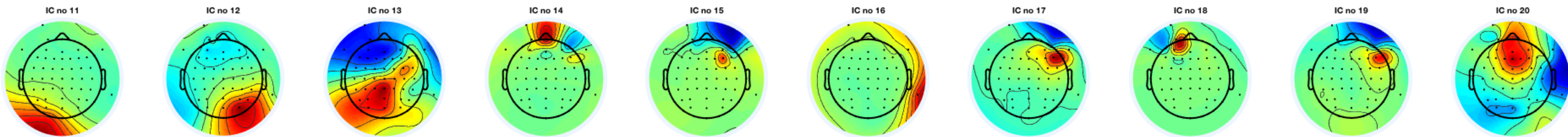
- Instead of channel-data EEG, we can use single (or multiple combined) IC
- We have seen how to select ICs automatically using COMPASS, and will now use the selected components to perform the same single-trial regression analysis as we did before
- Here we will compare if using an IC based approach increases SNR for our basic single-trial analysis

ICs of this participant

both components look like they could
contain error-related signals



we will select both individually
as well as their combination



Call regression with IC

```
[ReggyD, Info] = STA_Fast_Regress(RESP, [], TimeWin, 'model 1', {{select_trials} Predictors {'EEG'} {'modell'}}), ...  
    'PredNames', Reg2Name, 'PredLabels', RegLables, 'bin_size', 4, 'stepsize', 1, ...  
    'binEEG', 3, 'RetAll', 3, 'Downsample', 5, 'ERPimage', 1, ...  
    'UseIca', {1; 4; [1 4]}, 'IcaName', {'ErrC1' 'ErrC2' 'Combo'}, 'IcaCSpace', 0, 'IcaElectrode', 'Cz');
```

Cell array. If {1} will run regression on only this IC, if {1; [1 3 5]} will use activity of IC 1 for first analysis, and [1 3 5] for next.

Name your ICs (otherwise will use IC numbers).

Use backprojection (0, default) or remain in IC space (1)

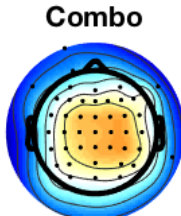
Electrode for backprojection (if IcaCSpace = 0)

Note: if you want to combine your data across participants, you must have the same overall number of components. For example, you can have one subject with **'UseIca'**, {[1 3 5]} another with **'UseIca'**, {2} but not {1; 3} and {[1 3]}

Result

Overview at Combo for Simple Error Model IC Based VP0005 t

Overall R2
n subjects: 1
n Regressors 3
Min 0
Max 0.404 at 60 ms



slight R2 increase

Regressor: Accuracy
-1 = cor
1 = err
Max 16.54 at 210 ms
Min -24.27 at 60 ms
p max = 2.59×10^{-53}
p min = 9.79×10^{-99}

Max 13.85 at 220 ms
Min -21.85 at 60 ms
p max = 2.11×10^{-39}
p min = 6.35×10^{-84}

considerable power increase

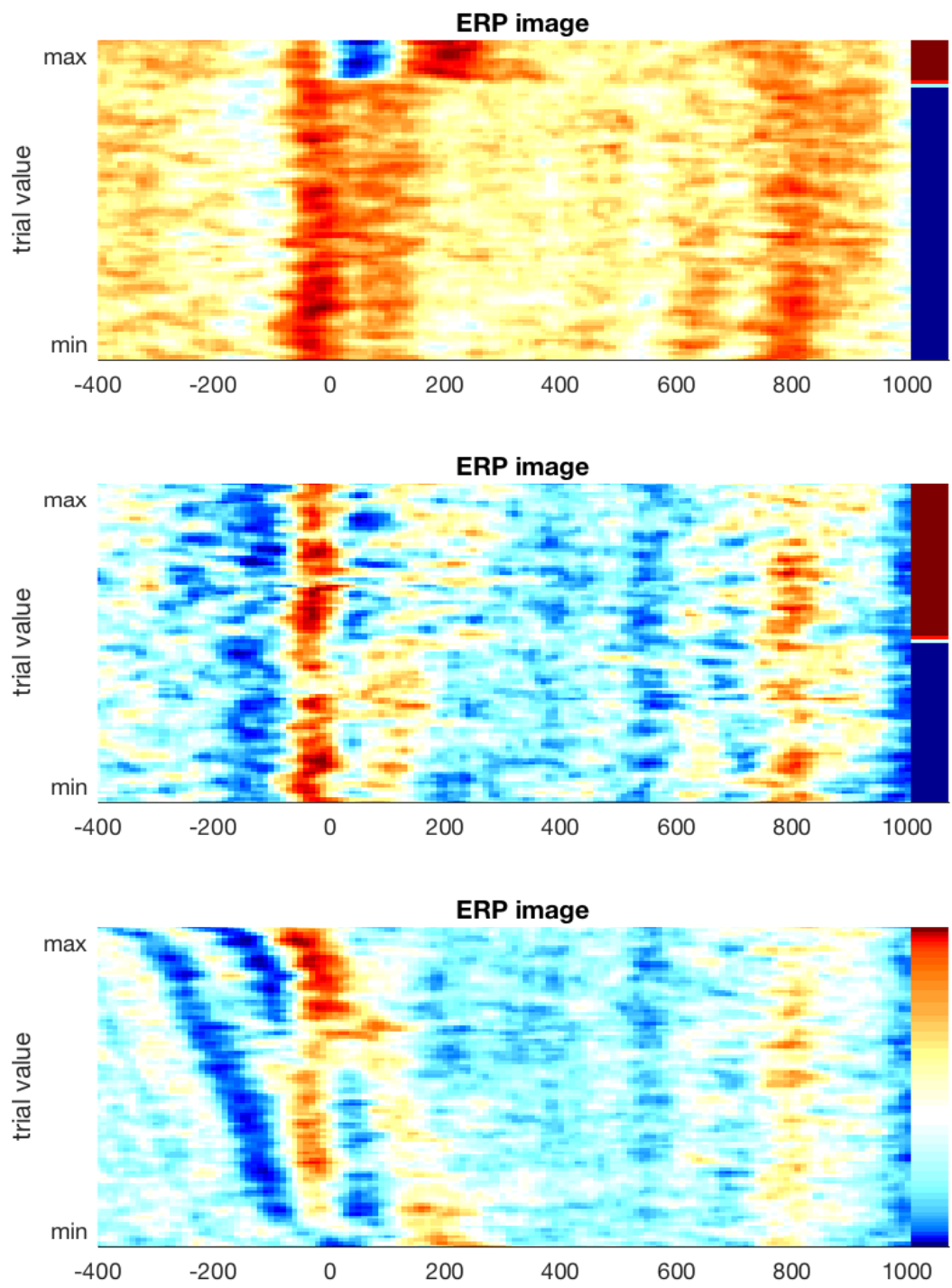
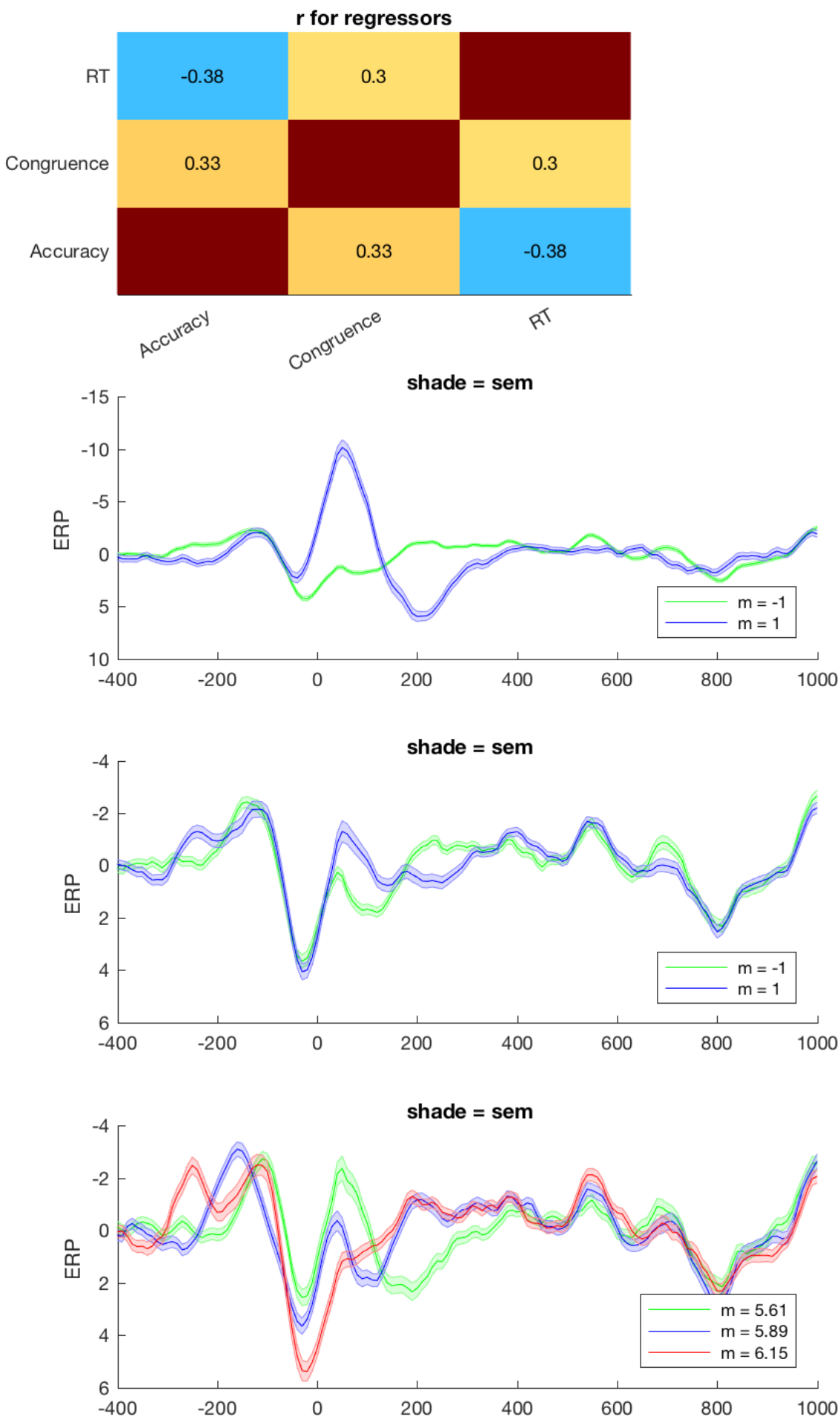
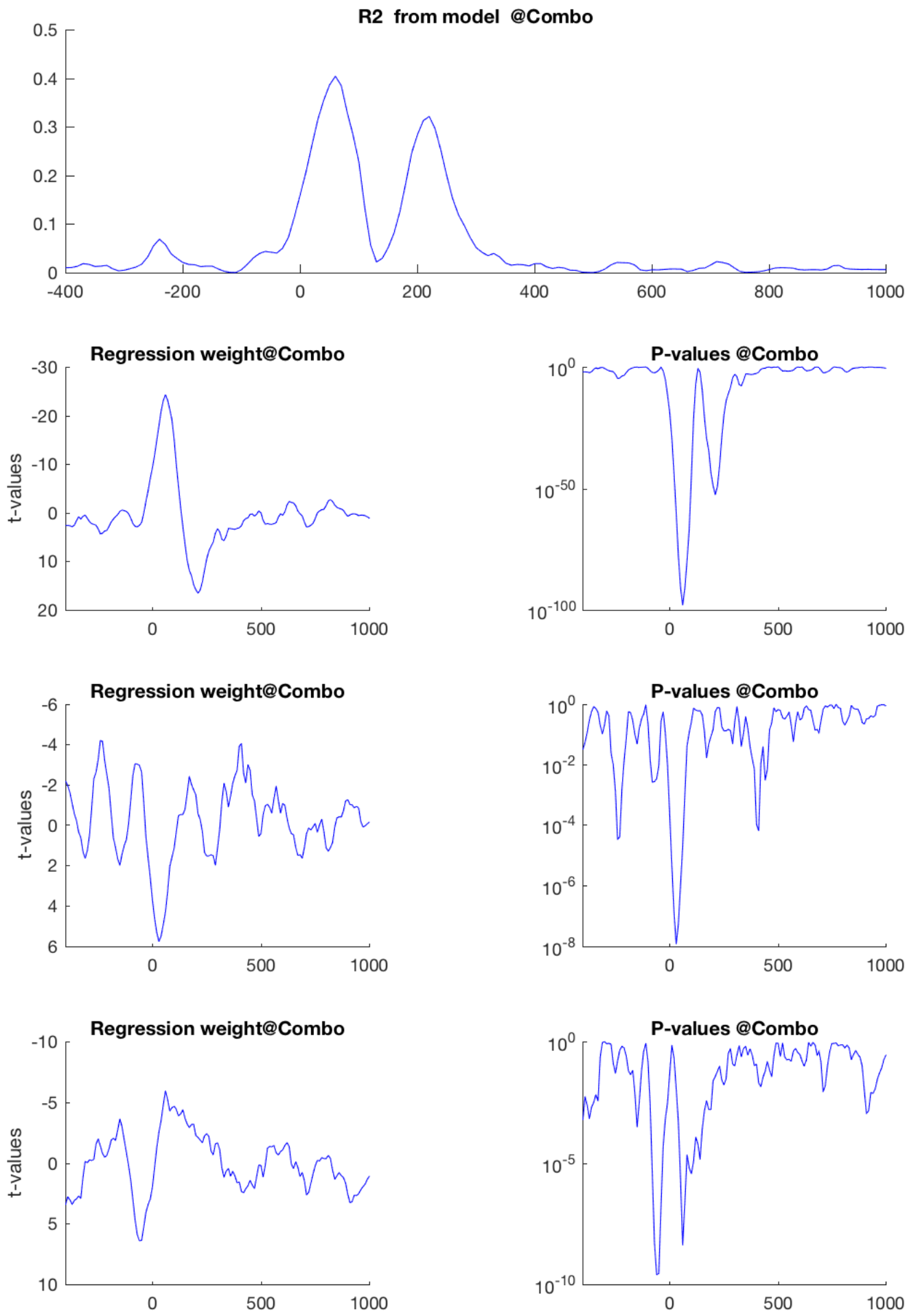
Regressor: Congruence
-1 = con
1 = inc
Max 5.76 at 30 ms
Min -4.17 at -240 ms
p max = 1.18×10^{-8}
p min = 3.31×10^{-5}

Regressor: Congruence
-0.97967 = low
1.0203 = inc
Maplimits -4.95 4.95
Max 5.81 at 30 ms
Min -3.81 at -70 ms
p max = 8.95×10^{-9}
p min = 0.00014778

very similar

Regressor: RT
5.6082 = low
6.1516 = high
Max 6.41 at -60 ms
Min -5.94 at 60 ms
p max = 2.48×10^{-10}
p min = 4.08×10^{-9}

Regressor: RT
-0.28823 = low
0.25512 = high
Maplimits -4.95 4.95
Max 6.27 at -60 ms
Min -5.5 at 60 ms
p max = 5.67×10^{-10}
p min = 5.14×10^{-8}



- Considerable increase in sensitivity even for a factor that is already well represented in the standard regression analysis (*accuracy*)
- If exactly one component is selected, no electrode needs to be specified when averaging across participants (*the relative scalp distribution of activity within a single IC is constant*)
 - dramatically reduces the number of multiple comparisons
 - cave: polarity of IC!
- If more than one IC is selected, an electrode needs to be specified (*default: Cz*)
- Requires relatively uniform decomposition across participants
 - (alternative: group ICA, e.g., EEGIFT (Eichele et al., *Comp Int Neurosci*, 2011))

Load another participant

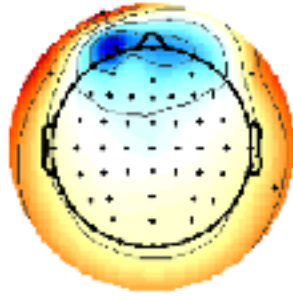
Miss outlier: no
Too few trials? no

n Error All: 115
n Error Incom: 98
n Error Close: 58
n Error Far: 40

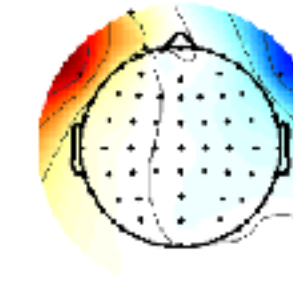
Highest ERN RMS @ Cz = -1.3938
ERN = -10.3153 @ 52 ms
p-value = 0
t-value = -11.8666
U3-value = 0.87826
RT match deviation all = -2.4 ms
Deviation Incompatible ~ = -67.1 ms
p-value close inc = 3.3616e-28
p-value far inc = 5.988e-29
Best U3-value = 0.93043 @ FCz

Factor Far vs Close = 1.1179
ERN Far = -13.9402 @ 52 ms
ERN Close = -12.4695 @ 50 ms

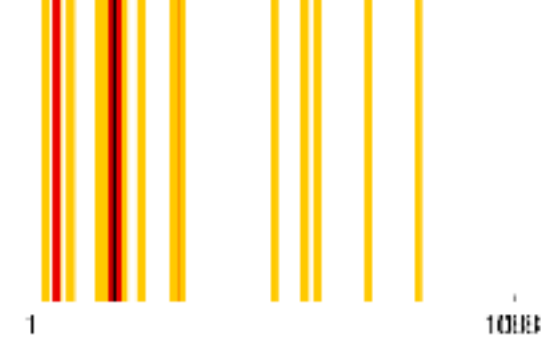
Blink 1 - IC 19



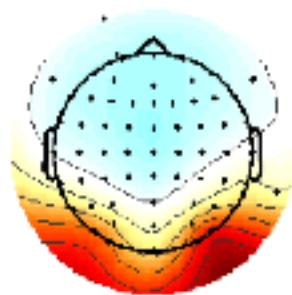
Dipole 1 - IC 48



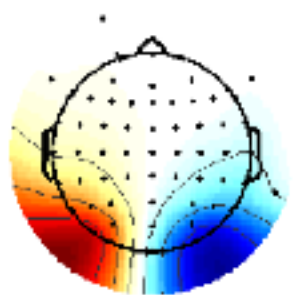
Misses heatmap - n = 18



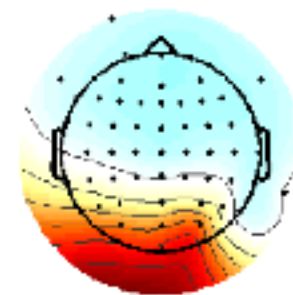
No Rem - IC 1



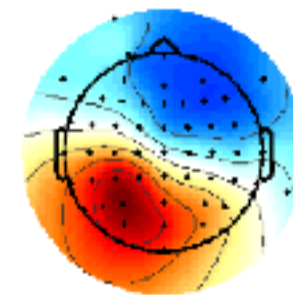
No Rem - IC 2



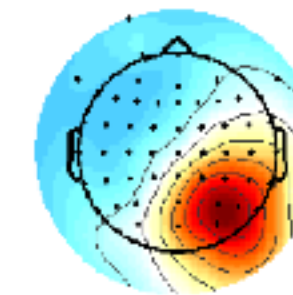
No Rem - IC 3



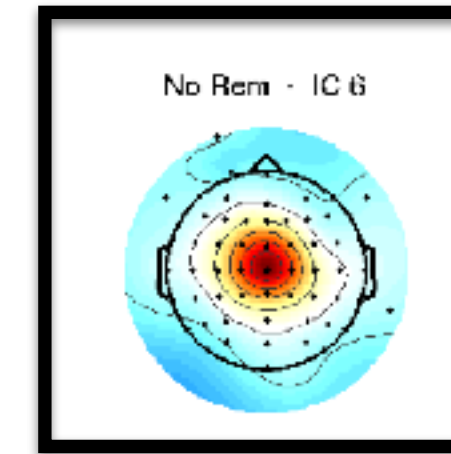
No Rem - IC 4



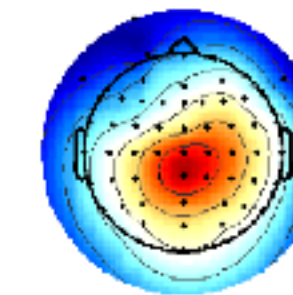
No Rem - IC 5



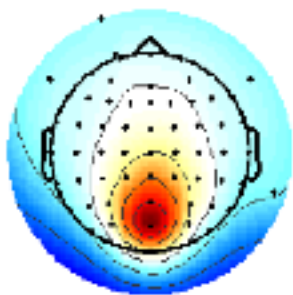
No Rem - IC 6



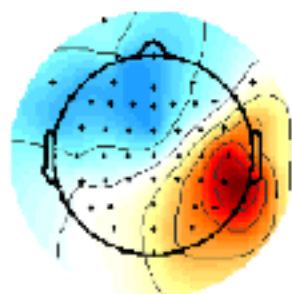
No Rem - IC 7



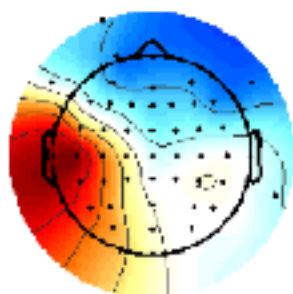
No Rem - IC 8



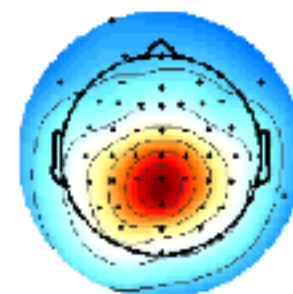
No Rem - IC 9



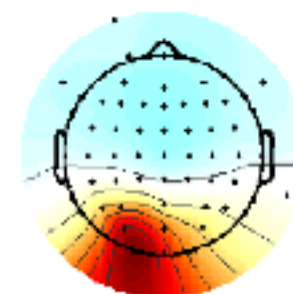
No Rem - IC 10



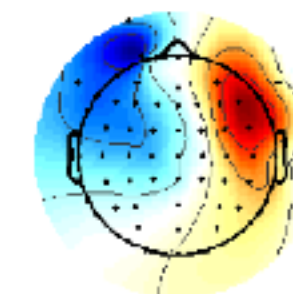
No Rem - IC 11



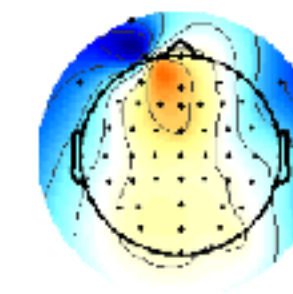
No Rem - IC 12



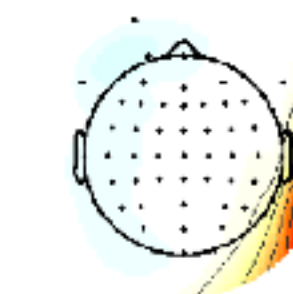
No Rem - IC 13



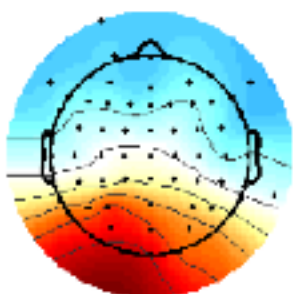
No Rem - IC 14



No Rem - IC 15



No Rem - IC 16



- There are many situations in which we want to predict behaviour from EEG (not vice versa)
- Additionally, in such situations it is especially important to be able to control for confounds
- We will analyze if post-error slowing (*PES*) can be predicted by EEG activity and make use of the full temporal resolution of the signal again
- Therefore, we use the EEG signal (at every point) as a predictor and post-error RT as the observation (Y)

11. EEG as predictor

```
Y_foll_RT      = [D.rt_follow]';           % RT of the following trial
R_foll_congr   = ([D.congr]-1)*2-1;         % congruent = -1, incongruent = 1
R_foll_dist    = ([D.dist_follow]-1)*2-1;   % Flanker distance of the following trial, close = -1, far = 1
R_foll_RSI     = [D.RSI_follow]';          % RSI (response stimulus interval) between the following and the current trial
```

```
Predictors     = {R_foll_congr(select_trials)  R_foll_dist(select_trials)  R_foll_RSI(select_trials)};
Reg2Name       = {'Foll congruence'            'Foll distance'                'Foll RSI'};
RegLables      = [{'con' 'inc'};               {'close' 'far'};              {'250' '700'}];
Observation    = Y_foll_RT(select_trials);
```

use behaviour instead of EEG as Y

```
[ReggyD, Info] = STA_Fast_Regress(RESP, Electrodes, TimeWin, 'model 1', ...
    {{select_trials} Predictors {Observation} {'PESasY'}}, 'PredNames', Reg2Name, 'PredLabels', ...
```

```
*****Running EEG Regression*****
```

```
Using robust regression.
```

```
Bin size is: 4 | Stepsize is : 1
```

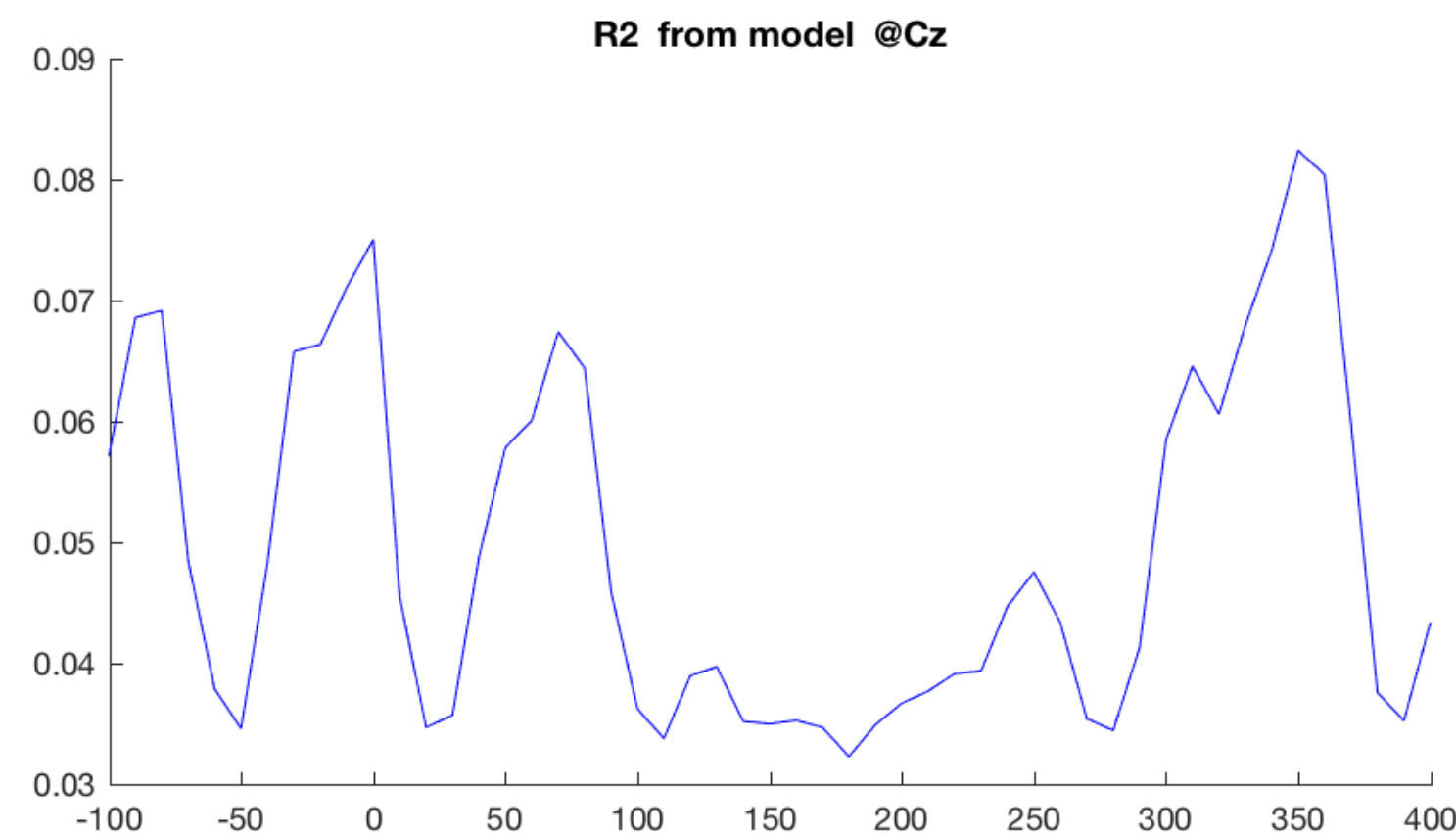
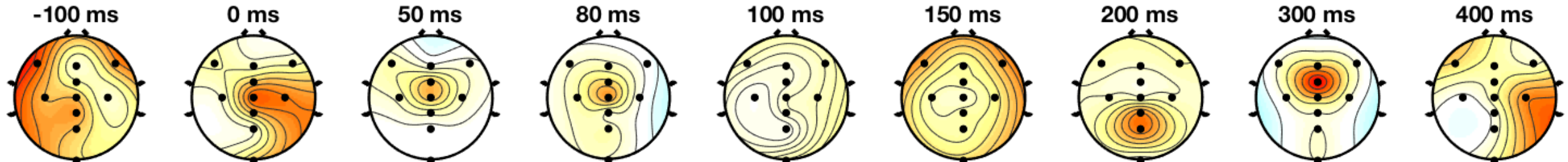
```
Processing dataset from VP0060 AMICA
```

```
Using EEG activity as predictor rather than observation...
```

```
EEG cannot be binned and returned if EEG itself is a regressor... Deactivating.
```

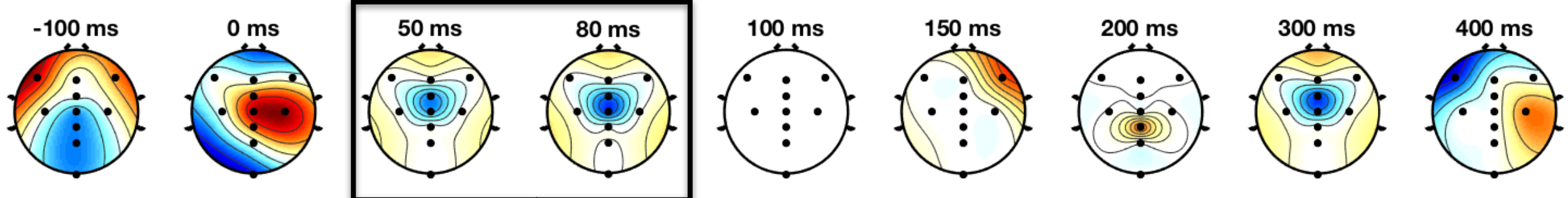
Overview at Cz for Following Trial Model

Overall R2
n subjects: 1
n Regressors 1
Min 0.032
Max 0.082 at 350 ms



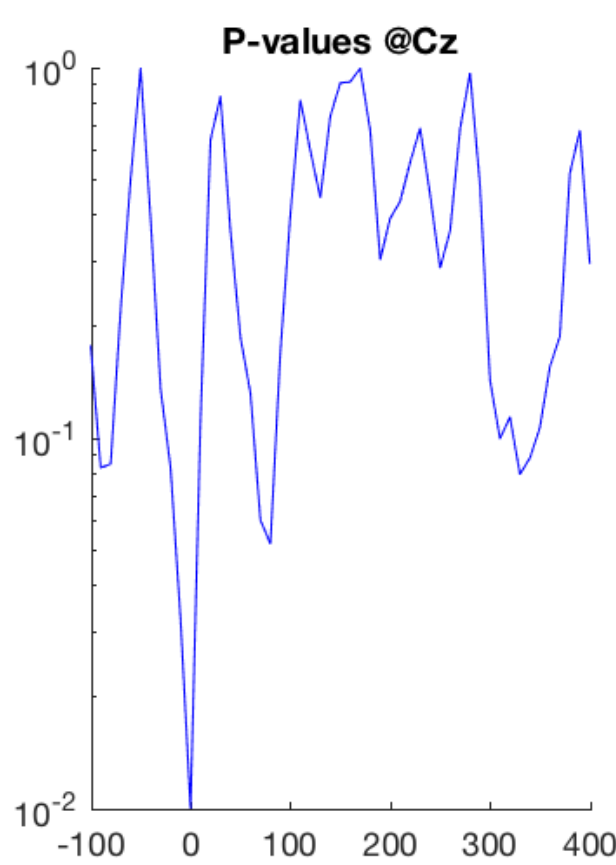
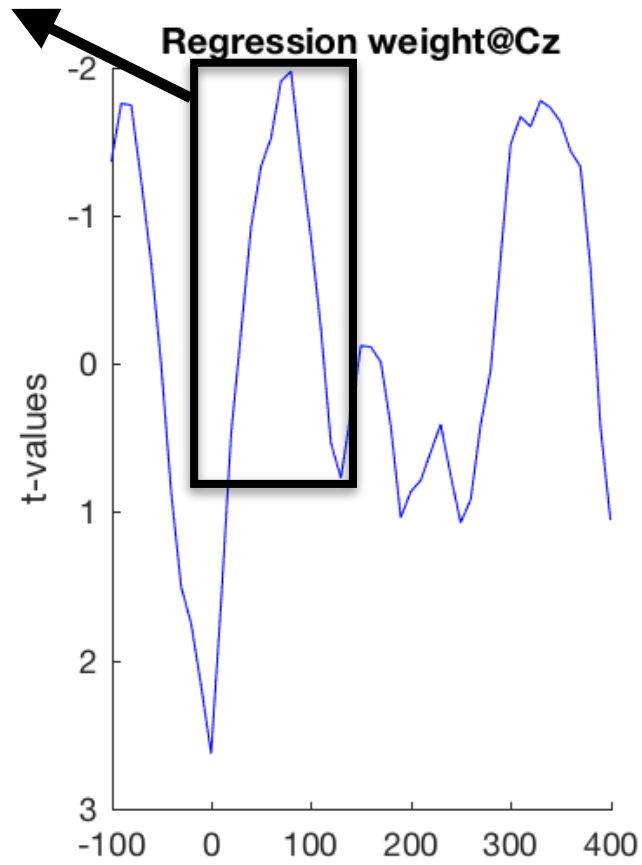
,marginally' significant...

EEG = predictor
Maplimits -2.87 2.87
Max 2.63 at 0 ms
Min -1.97 at 80 ms
p max = 0.0099593
p min = 0.051602



there seems to be an effect...

negative covariation:
more negative EEG → higher RT = more PES



```
[ReggyD, Info] = STA_Fast_Regress(RESP, Electrodes, TimeWin, 'model 1', {{select_trials} Predictors {Observation} {'PESasY'}},...  
    'PredNames', Reg2Name, 'PredLabels', RegLables, 'bin_size', 4, 'stepsize', 1, 'TF', [], ...  
    'binEEG', 3, 'RetAll', 3, 'NormaliseOn', 0, 'Downsample', 5, 'UseIca', {6; 7; [6 7]}, 'IcaName', {'ErrC1' 'ErrC2' 'Combo'})
```

add the ICA call arguments and use
components no 6 and 7
(IC space and electrode can be default)

Result with ICs

Overall R2
n subjects: 1
n Regressors 1
Min 0.033
Max 0.125 at 70 ms

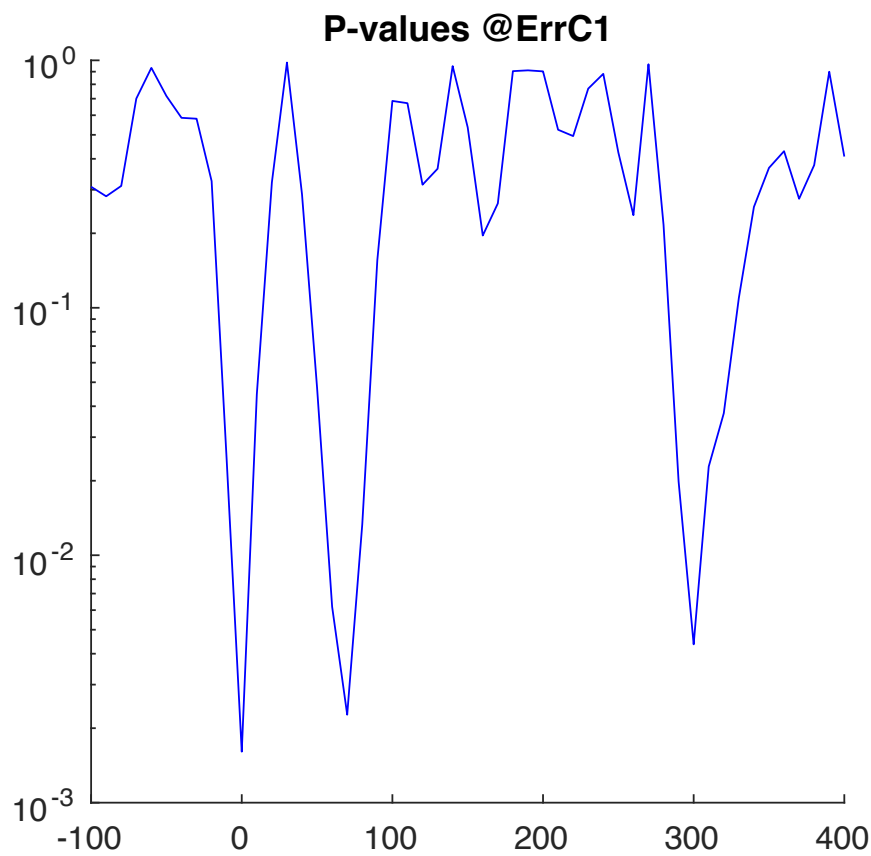
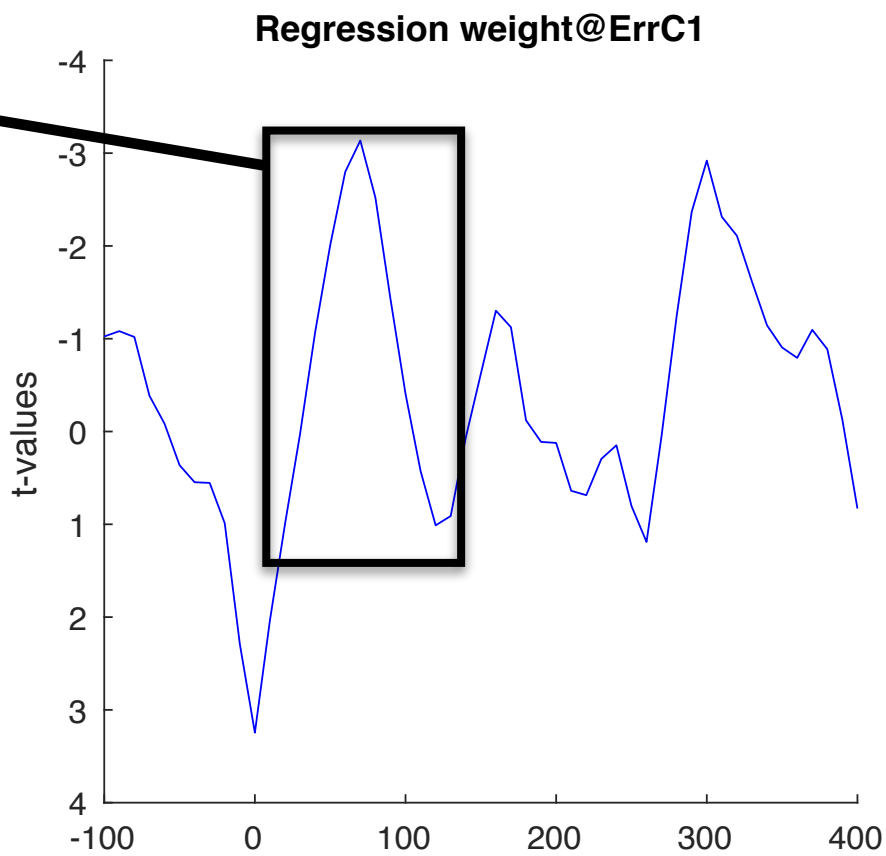
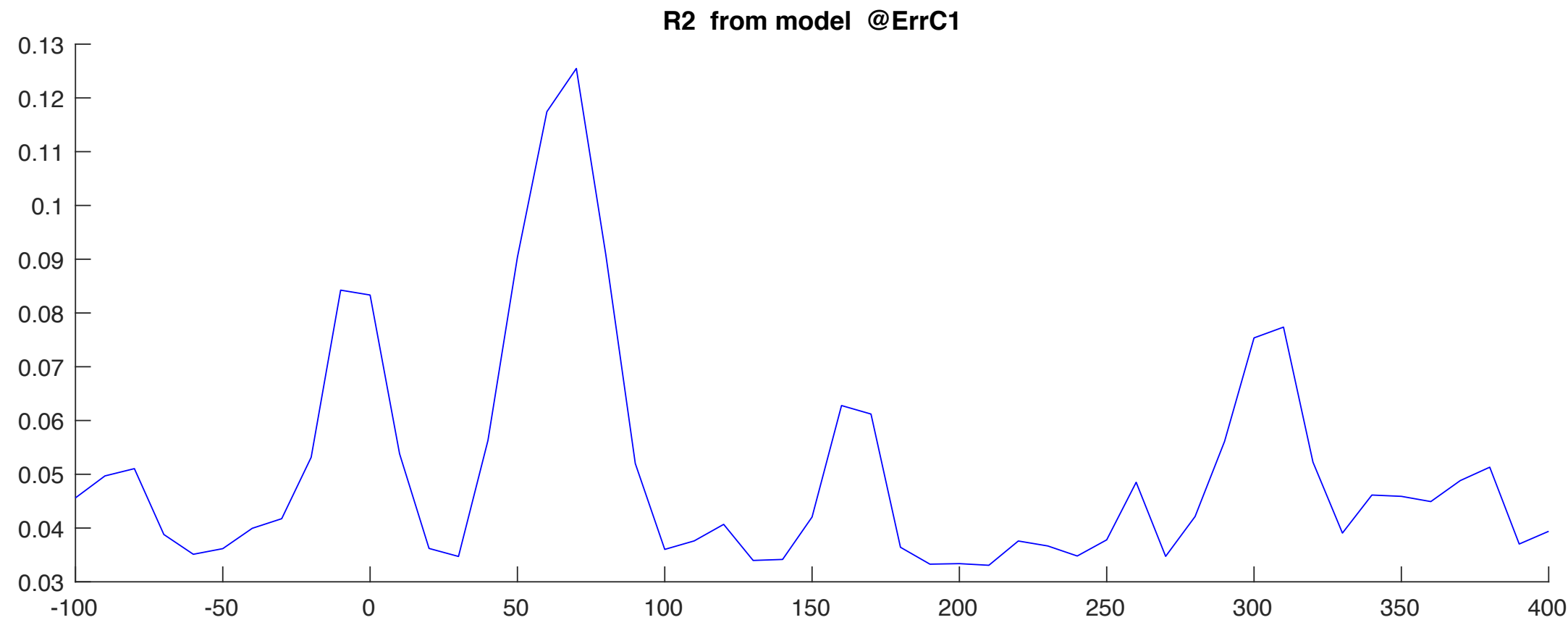


EEG = predictor
Maplimits -3.25 3.25
Max 3.25 at 0 ms
Min -3.14 at 70 ms
p max = 0.0016075
p min = 0.0022674

much better p!

much nicer!

Overview at ErrC1 for Following Trial Model



- Single-trial regression allows to test relatively complex single-trial brain-behaviour interactions while maintaining EEG resolution
 - and again provides an intuitive way to control for confounds
- You can increase the effect of a factor you are interested in by reducing uncorrelated variance
 - it may even happen, that a regressor flips its sign! Example: when accounting for RT, participants might perform worse in condition A than B, whereas they previously were better in condition A (but slower, speed-accuracy tradeoff).
- Using IC instead of sensor-data can significantly improve data quality, especially when small effect-sizes are expected
 - but your IC solution needs to be stable and components need to be well characterized