ERP : an R package for Event-Related Potentials data analysis

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Tutorial, references, slides : erpinr.org

UseR ! 2014, UCLA
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The instrument: a 128-channel geodesic sensor net

- Electroencephalography (EEG) is the recording of electrical activity at scalp locations over time.
- The recorded EEG traces, which are time locked to external events, are averaged to form the event-related (brain) potentials (ERPs).

In addition, the Valence/C2Laterality interaction was qualified by a Valence/C2Laterality/C2Task interaction, which indicated that the Valence/C2Laterality interaction was larger for the Good/Bad task (right: mean difference score for bad stimuli minus good stimuli = 2.84 AV; left: M = 2.38 AV) than for the Abstract/Concrete task (right: bad–good M = 1.17 AV; left: bad–good M = 1.16 AV), $F(1, 16) = 4.84, P = 0.05$, see Fig. 3. Thus, although the Valence/C2Laterality interaction was observed in both the Good/Bad and Abstract/Concrete tasks, which suggests that this interaction may reflect some degree of automatic processing, the 3-way interaction involving task indicates that the Valence/C2Laterality interaction is not immune to reflective processing. For example, although it may be initiated automatically, it is possible that an explicitly evaluative agenda can keep valence-specific information active in working memory (or conversely, that a nonevaluative agenda may suppress such information).

LPP latency

In addition to examining the extent of activation, an advantage of using EEG methods to study evaluative processes is the ability to examine the time course of evaluative processing. For each participant and for each condition, we computed the average onset of the frontal LPP for all electrodes in the right and left anterior scalp regions defined above. The onset was defined as the latency of the peak amplitude of the negative deflection immediately prior to the positive deflection identified as the frontal LPP. The calculated frontal LPP onset was then subjected to a 2 (laterality) × 2 (valence) × 2 (task) ANOVA. Cell means for significant effects are presented in Table 2. A main effect for laterality indicated that on average, the LPP for the right anterior region began earlier ($M = 433$ ms) than did the LPP on the left ($M = 516$ ms), $F(1, 16) = 9.64, P < 0.01$. Importantly, however, this main effect was qualified by a Valence/C2Laterality interaction. In contrast to the suggestion that negative stimuli are processed more quickly than positive stimuli for all processes, we found that, for the right frontal electrodes, the onset of the frontal LPP occurred more quickly for negative stimuli ($M = 410$ ms) than for positive stimuli ($M = 455$ ms), but that for the left frontal electrodes, the onset of the frontal LPP occurred earlier for...
Directed forgetting recognition memory experiment

Figure. Schematic representations of the study phase trial events and their respective timings for the TBR trials (above) and TBF trials (below). See text for further details.
Directed forgetting recognition memory experiment

```r
> library(ERP)
> data(erpcz)
> erpplot(dta=erpcz[,1:1000],frames=1:1000,...)
> legend("bottomleft",legend=c("TBF","TBR"),...)
```
Linear modeling of ERPs

Directed forgetting : paired t-tests

\[ Y_{ijt} = \mu_t + \alpha_{it} + \gamma_{jt} + \varepsilon_{ijt}, \]  

where \( Y_{ijt} \) is the ERP of subject \( i \) in condition \( j \) at time \( t \)

\[ H_{0,t} : \gamma_{2t} = 0, \quad t = 1, 2, \ldots, T. \]

```r
> mod0 = model.matrix(~ Subject, data=erpcz)
> mod1 = model.matrix(~ Subject+Instruction, data=erpcz)
> tests = erpavetest(dta=erpcz[,1:1000], design=mod1, design0=mod0)
```
Linear modeling of ERPs

```r
frames = 1:1000
plot(frames, tests$signal, ...)
points(frames[tests$significant], rep(0, length(tests$significant)), ...)
abline(v=frames[tests$breaks], ...)
```
Linear modeling of ERPs

Quick, simple method ... but
- Ignores the regularity of ERPs over time
- Depends on an arbitrary splitting in time intervals
- Does not control for false positives

Paired comparison at electrode CZ
FDR-controlling procedures

Multiple-testing procedure

- For each $H_{0,t}$, a p-value $p_t$
- For a preset cutoff $p^*$, significant time points $= \left\{ t; p_t \leq p^* \right\}$

False-Discovery Rate control

$$FDR = \mathbb{E} \frac{\# \text{ significant time points among nulls}}{\# \text{ significant time points}}$$

- Far less conservative than Bonferroni correction : popular for large number of tests
- Benjamini & Yekutieli (2001) : BH extended to dependent tests
FDR-controlling procedures

```r
> tests = erptest(dta=erpcz[,1:1000], design=mod1, design0=mod0, method="BH")
```

Paired comparison at electrode CZ
FDR-controlling procedures

```r
> tests = erptest(dta=erpcz[,1:1000], design=mod1, design0=mod0, method="BY")
```

Paired comparison at electrode CZ

![Graph showing ERP curves with paired comparison at electrode CZ.](image)

**Time (ms)**: 0, 200, 400, 600, 800, 1000

**Difference ERP curves**: ±5, 0, ±5
FDR-controlling procedures

```r
> tests = erptest(dta=erpcz[,1:1000],mod1,mod0,method="bonferroni")
```

Paired comparison at electrode CZ
ERP tests are strongly time-dependent
ERP tests are strongly time-dependent

What are the effects of the time dependence?

- A strong regularity of the test statistics process
- Instability of peak detections

The Guthrie-Buchwald (1991) procedure handles this

- Estimate of autocorrelation $\hat{\rho}$
- Simulation of $F$-tests under $H_0$ with AR(1) dependence
- Distribution of lengths of $\mathcal{I}_\alpha = \{ t : p_t \leq \alpha \}$
- An interval is declared significant if its length exceeds $q_{1-\alpha}$ of this distribution
ERP tests are strongly time-dependent

```r
> tests = gbtest(dta=erpcz[,1:1000], mod1, mod0, graphthresh=0.05)
```

![Paired comparison at electrode CZ](image)
ERP tests are strongly time-dependent

Let’s simulate ’ERP-like’ data:

\[ Y_{it} = \mu_t + \beta_t x_i + \varepsilon_{it}, \text{with } \mathbb{V}(\varepsilon_{i1}, \ldots, \varepsilon_{iT}) = \Sigma \]

where \( x_i \) is an arbitrary covariate.
ERP tests are strongly time-dependent

```r
mod1 = model.matrix(~y, data=simerp)
tests = erptest(dta=erpsim[,1:1000], design=mod1, method="BH")
plot(frames, tests$test, ...)
points(frames[tests$significant], rep(0, length(tests$significant)), ...)
```
ERP tests are strongly time-dependent

BH is not robust against such a long-range time dependence

<table>
<thead>
<tr>
<th>Peak height</th>
<th>Independent case</th>
<th>Dependent case</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FDR(^1)</td>
<td>PD(^2)</td>
</tr>
<tr>
<td>5</td>
<td>BH</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>BY</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>GB</td>
<td>-</td>
</tr>
</tbody>
</table>

1. FDR : False Discovery Rate
2. PD : Proportion of peak detection cases
3. PNR : Proportion of no-rejection cases
A flexible joint linear modeling of signal and noise
Directed forgetting: decorrelated paired t-tests

\[ Y_{ijt} = \mu_t + \alpha_{it} + \gamma_{jt} + \lambda'_i f_{ij} + e_{ijt}, \]  

(1)

where \( e_{ijt} \) are uncorrelated residual errors, \( f_{ij} \) are \( q \)-dimensional (unobserved) factors.

Similar ideas in statistical genomics

- Surrogate Variable Analysis, Leek and Storey (2008) [package \texttt{SVA}],
- Factor Analysis for Multiple Testing, Friguet et al (2009) [package \texttt{FAMT}]
- Correlation-adjusted t-score, Zuber and Strimmer (2009) [package \texttt{st}]
- Latent Effect Adjustment after Primary Projection, Sun et al. (2012) [package \texttt{LEAPP}]
Remarks on the Adaptive Factor-Adjustment estimation algorithm

- EM-type algorithm: alternates estimations of effects and factor model for covariance
- Takes advantage of the prior knowledge that noise is some time observed without signal
  - \( S_0 \subset \{ t, \beta_t = 0 \} \) known
  - Pure noise can be estimated out of \( S_0 \) by regression techniques
- Updates \( S_0 \) and iterates
A flexible joint linear modeling of signal and noise
Good prior knowledge

```r
>s0 = c(1 :100,901 :1000)
>tests = erpfatest(dta=erpsim[,1 :1000],design=mod1,nbf=NULL,s0=s0)
```

Simulation
A flexible joint linear modeling of signal and noise

Wrong prior

```r
> s0 = 400 : 600
> tests = erpfatest(dta=erpsim[,1:1000], design=mod1, nbf=NULL, s0=s0)
```

Simulation
A flexible joint linear modeling of signal and noise
No prior : deduced from standard analysis

```r
>s0 = NULL
tests = erpfatest(dta=erpsim[,1:1000],design=mod1,nbf=NULL,s0=s0)
```

Simulation

![Graph showing F-test results over time](image)
A flexible joint linear modeling of signal and noise

Simulation study

![Graph showing the relationship between peak amplitude and false discovery proportion for different methods]

- BH
- BY
- GB
- SVA
- LEAPP
- FA
A flexible joint linear modeling of signal and noise

Simulation study

![Graph showing the probability of no rejection against peak amplitude for different methods: BH, BY, GB, SVA, LEAPP, and FA. The x-axis represents peak amplitude, and the y-axis represents probability of no rejection. The graph compares the performance of these methods in a simulation study.](image-url)
A flexible joint linear modeling of signal and noise

Simulation study

![Graph showing probability of detection against peak amplitude for different methods: BH, BY, GB, SVA, LEAPP, FA. Each method is represented by a different line and marker style.]
Summary

What \texttt{ERP} does not do

- EEG data management
- ERP data preprocessing (filtering, averaging, ...)

What \texttt{ERP} does do

- Significance analysis of ERP data
- Imports ideas from significance analysis of genomic data
- Improves power w.r.t standard procedures

\textbf{R package : ERP} \textsuperscript{4}

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