Brain-Computer Interfacing
WS 2018/2019 – Lecture #02

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Today's Topics

- Evoked potentials, Event-Related Potentials (ERPs)
- Visual Evoked Potentials (VEPs)
- Averaging across trials
- Oddball Paradigm
- The P300 component
- ERP-based BCIs
- Receiver-Operator Characteristics (ROC), r^2-values

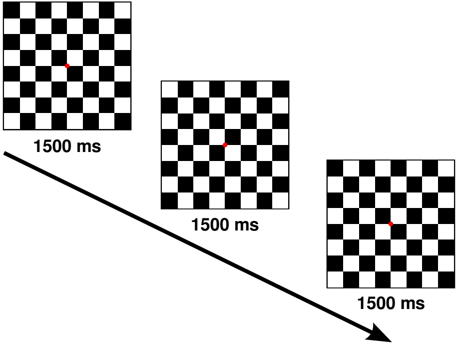
Evoked and Event-Related Potentials

An **Event-Related Potential (ERP)** is the electrical brain activity, as measured by EEG, that is time-locked to some *event*. The event may be an external sensory stimulus (typical case) or internal, associated with the execution of a motor, cognitive, or psychophysiological task. [Key et al, 2005; Patel & Azzam 2005]

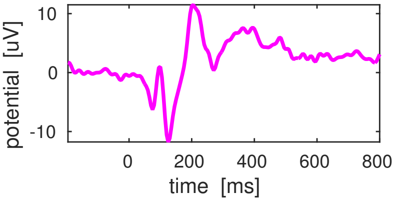
A subclass are the **Evoked Potentials (EPs)** which reflect the processing of a physical stimulus, rather than 'higher' processes, that might involve memory, expectation, or attention.

Visual Evoked Potential (VEP)

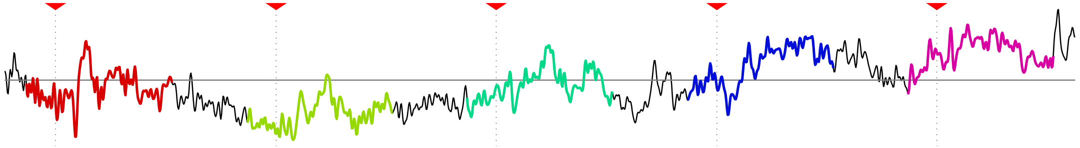
Visual evoked potentials (VEPs) are ERPs that are caused by stimulation of a subject's visual field. Commonly used are, e.g., checkerboard stimuli that flip at an inter-stimulus interval of 1 to 3s. More specifically, these are called Pattern Reversal VEPs in contrast to many different variants of VEPs [Odom et al, 2004] , e.g. Flash VEPs.



VEPs can be observed regardless of attention, but the amplitude depends strongly on the intensity, size, and focality of the stimulus.



Continous Signal (with markers):



Segments (epochs) around stimulus markers:

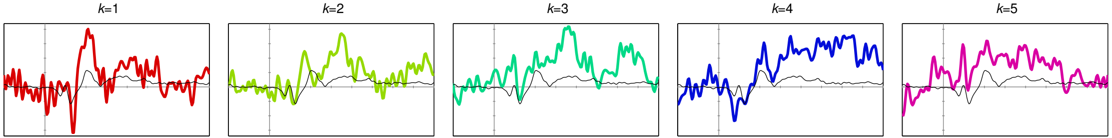
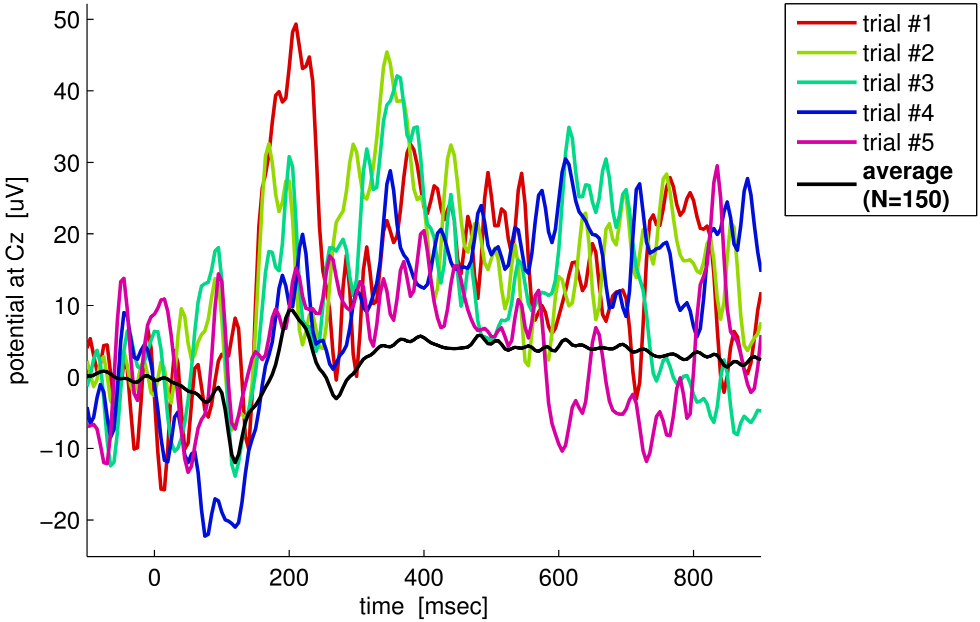


Illustration: Single-Trials and ERPs



Conventions in Notation

- x, N, γ (italics): scalar
- $\mathbf{x}, \boldsymbol{\mu}$ (bold face, lower case): column vector
- $\mathbf{X}, \boldsymbol{\Sigma}$ (bold face, upper case): matrix
- For a matrix $\mathbf{X}$, the term $(\mathbf{X})_{ij}$ denotes the element of $\mathbf{X}$ in the i-th row and j-th column.
- For a finite set $\mathcal{C}$, we denote its cardinality (number of elements) by $|\mathcal{C}|$.

Some math

If the random variable $x_1, \ldots, x_K$ are independent and Gaussian distributed according to $\mathcal{N}(\mu_k, \sigma_k^2)$, the following holds:

- $\alpha x_1 \sim \mathcal{N}(\alpha\mu_1, \alpha^2\sigma_1^2)$
- $\sum_{k=1}^{K} x_k \sim \mathcal{N}(\sum_{k=1}^{K} \mu_k, \sum_{k=1}^{K} \sigma_k^2)$

A Model for the ERP

Generally, the signal-to-noise ratio in raw EEG is bad. The investigator is interested only in few specific signal components that are related (and time-locked) to some event. But in the brain millions of neurons produce signals all the time (background activity). Reducing this noise is a big challenge in EEG analysis.

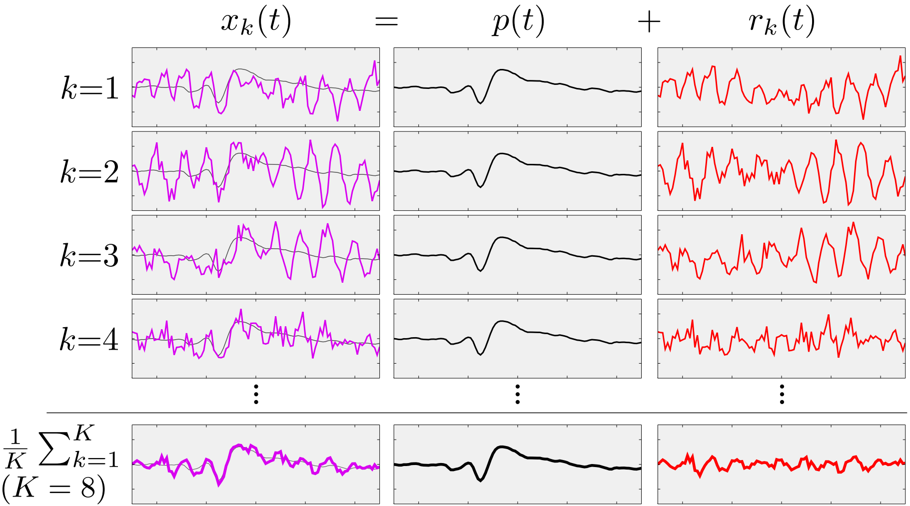
*For **ERPs**, the common technique to investigate the signal of interest is to record a long series of trials and then to average across trials.*

Model assumption: An ERP $p(t)$ that is (linearly) superimposed by background brain activity (and noise) $r(t)$ (**r**esidual), such that the acquired EEG x can be written as

$$x(t) = p(t) + r(t).$$

Averaging across Trials

Let us assume the ERP $p(t)$ is constant in each trial k ($k = 1, \ldots, K$), while the 'residual' $r_k(t)$ is iid $\mathcal{N}(0, \sigma_r^2)$ distributed (for a fixed t):



Averaging across Trials

Let us assume the ERP $p(t)$ is constant in each trial k ($k = 1, \dots, K$), while the 'residual' $r_k(t)$ is iid $\mathcal{N}(0, \sigma_r^2)$ distributed (for a fixed t):

$$x_k(t) = p(t) + r_k(t) \qquad \text{for } k = 1, \dots, K$$

Then averaging across trials lead to

$$\frac{1}{K}\sum_{k=1}^{K} x_k(t) = p(t) + \frac{1}{K}\sum_{k=1}^{K} r_k(t)$$

The noise in the average is $r(t) := \frac{1}{K}\sum_{k=1}^{K} r_k(t) \sim \mathcal{N}(0, \frac{1}{K}\sigma_r^2)$.

[Calculation: $r_k \sim \mathcal{N}(0, \sigma_r^2) \quad \Rightarrow \quad \sum_{k=1}^{K} r_k(t) \sim \mathcal{N}(0, K\sigma_r^2)$
$\Rightarrow \quad \frac{1}{K}\sum_{k=1}^{K} r_k(t) \sim \mathcal{N}(0, \frac{K}{K^2}\sigma_r^2) = \mathcal{N}(0, \frac{1}{K}\sigma_r^2)$]

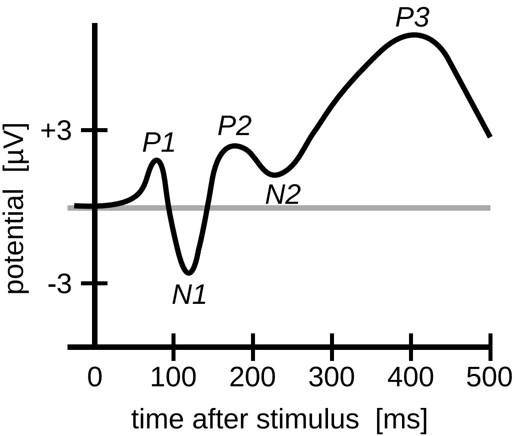
$\Rightarrow$ The amplitude of the noise goes down by a factor of $\sqrt{K}$ in an average across K trials.

Nomenclature

An ERP waveform is typically composed of several ERP components, each of which is related to a relative positive or negative voltage deflection.

- ERPs typically have a label that starts with a letter (**P/N**) which indicates the polarity (positive/negative) of the deflection.
  It is followed by a number indicating
  - either the latency in milliseconds (e.g., *N100*, *N170*, *P300*)
  - or the component's ordinal position in the waveform (e.g., *P1*, *N1*, *P2*, *N2*, *P3*)
- Some ERP components are rather labeled by acronyms that refer to their function, e.g.,
  - *Pe*: **p**ositive deflection related to **e**rroneous decisions
  - *Ne*: **n**egative deflection related to **e**rroneous decisions (also denoted by ERN, **e**rror-**r**elated **n**egativity)
  - *LRP*: **l**ateralized **r**eadiness **p**otential which reflects the preparation of movements).
- There are also extensions or mixed labels like *N2pc* which is a component like the *N2* originating in **p**osterior scalp location **c**ontralateral to the side of directed attention.

Prototypical ERP



- The shown components are also labeled *P100*, *N100*, *P200*, *N200*, *P300*.
- The *P3* component is often composed of two subcomponents labeled *P3a* and *P3b* which originate from different locations in the brain.
- Be aware: sometimes negative polarity is plotted upwards.

ERP-based Brain-Computer Interfaces (BCIs)

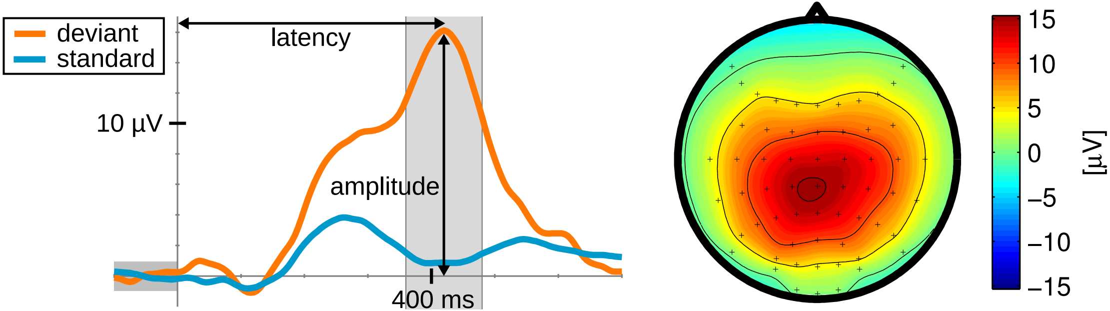
ERPs can be used in the control of a BCI. But

- there must be at least **two conditions** that the user can voluntarily attain, and
- they need to be discriminable in **single-trials**, or at least with just very little averaging.

Oddball Paradigm

- In the classical **oddball paradigm** (experiment) there are two kinds of stimuli (e.g., low and high tones; or green circles and red squares).
- Stimuli are presented at regular intervals in a random sequence.
- One kind of stimuli is more frequent than the the other one, e.g., with a ratio of 80:20.
- The frequent stimuli are called **standards** and the infrequent stimuli **deviants**.
- The test person has the task to 'detect' the deviant stimuli and, e.g., to count their occurences silently.

ERP Response in the Oddball Paradigm

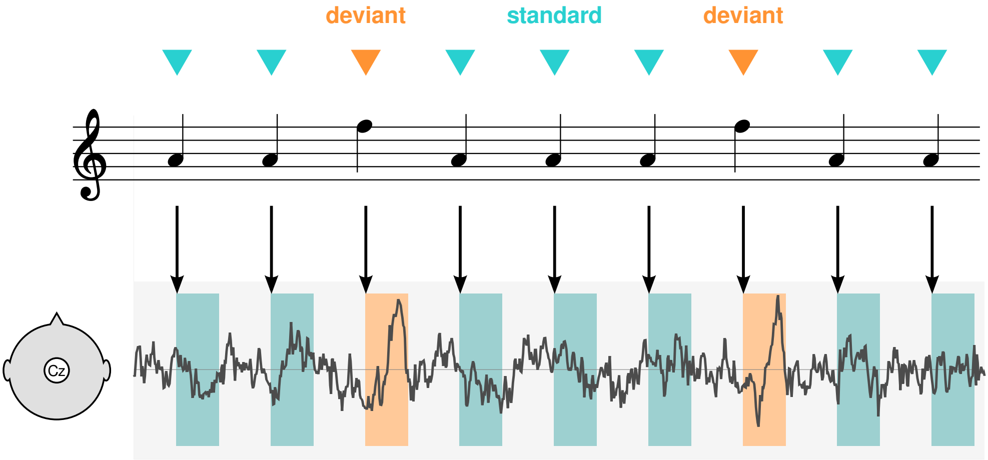


The most prominent ERP component observed in the oddball paradigm is the **P300** which is pronounced after deviant stimuli only.

Factors Influencing the P300

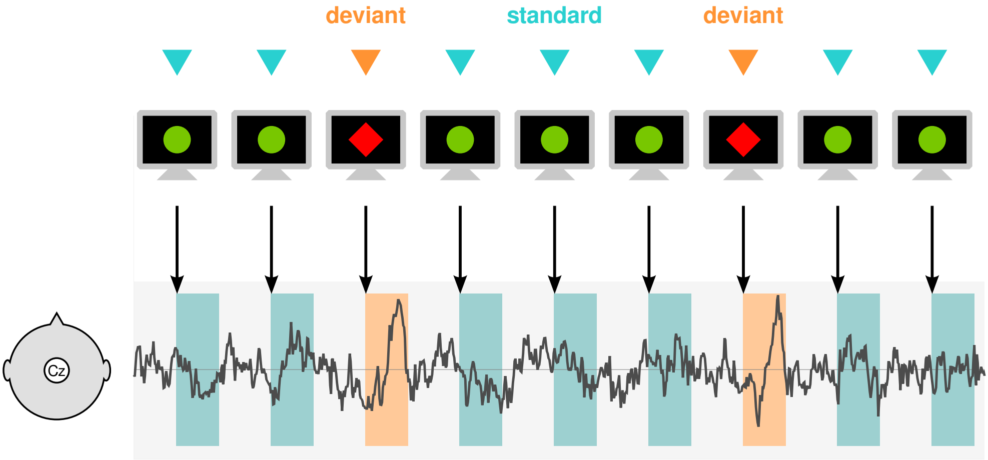
- Shorter **Target-to-Target Intervals (TTI)** reduce P300 amplitude
- **Task relevance** increases P300 amplitude
- **Task difficulty**: too complex and too simple tasks reduce P300 amplitude; latencies are longer for more complex tasks
- **Allocation of attention**: if this resource allocation is reduced, the P300 amplitude decreases and its latency is prolonged
- **Emotional Meaning** for the user increases P300 amplitude

From the Oddball Paradigm to a BCI Speller

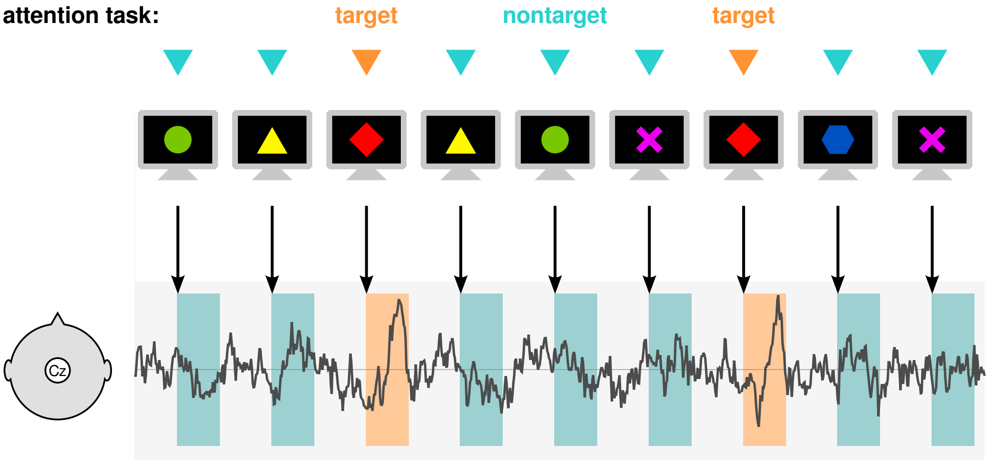


- Segments of the signal (shaded in the figure) are called epochs or single-trials.
- Typically, trials are grouped into several classes (which are, e.g., defined by experimental conditions), here standards and deviants.

From the Oddball Paradigm to a BCI Speller

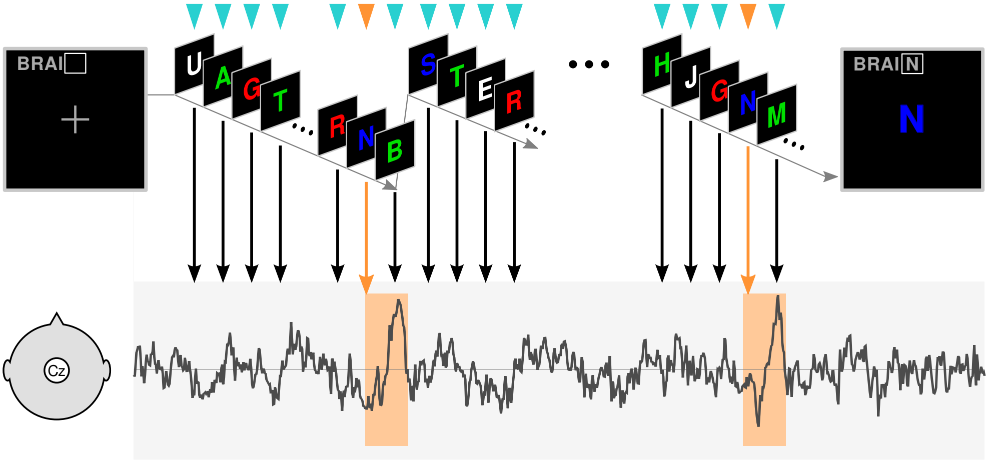


- In the visual domain it works the same.



- Due to the attention task, the two classes of stimuli are also called targets and nontargets.
- Here, five stimuli are presented with the same probability. One of them is defined to be the target in an attention task.
- Thus, the class of nontargets is composed of various stimuli.

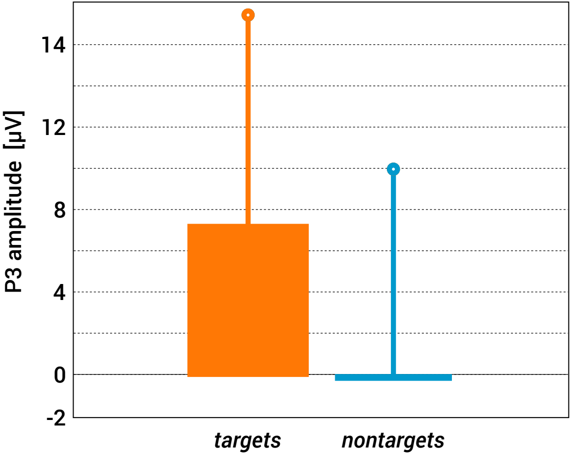
From the Oddball Paradigm to a BCI Speller



- The intended letter is the target and all others are nontargets.
- In BCI epochs are typically strongly overlapping. (Nontarget epochs are not shaded in this figure.)

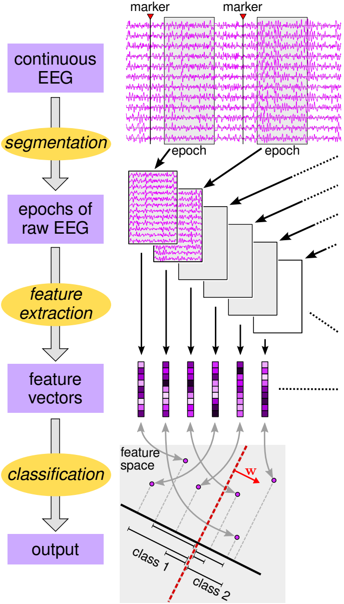
Classical Investigation of Target vs Nontarget

The classical way to compare ERPs of different conditions:



Statistics of peak amplitudes (and latencies).

Outlook: Toward Classification for BCIs



A **classifier** is a function mapping samples of the **feature space** $\mathbb{R}^D$ to **labels**, e.g. for a binary classifier:

$$f : \mathbb{R}^D \to \{1, 2\}$$

(In our example, class labels 1 and 2 correspond to targets and nontargets.)

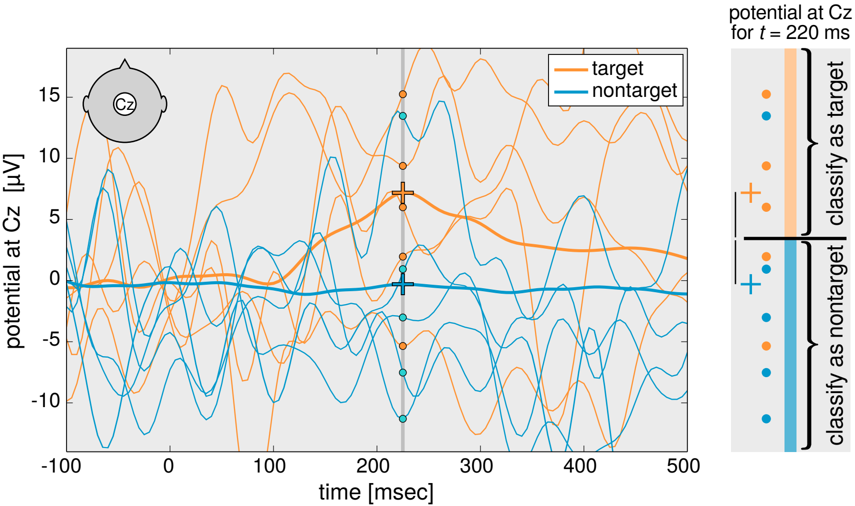
Often samples are mapped to $\mathbb{R}$ first, and then the label is decided by a threshold.

First, a Simple Approach to Classification

- To implement a BCI Speller, we need to distinguish target from nontarget trials.
- From the oddball literature, we conjecture that best discrimination between those classes is granted by the P300 component.
- The P300 component has its spatial focus at electrode position Cz.
- As first step for discrimination, we take as 'feature':

the amplitude at the peak time of the P300 at Cz

Univariate Features: Averages and Single-Trials



- The potential measured 220ms post-stimulus at **Cz** is a one-dimensional observation variable: a **univariate feature**.

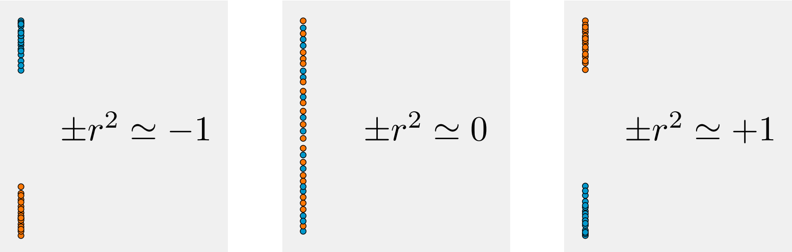
In order to assess the discriminative value of univariate features, we are interested in **measures of separability**.

The **point biserial correlation coefficient** (r^2-value) is defined as

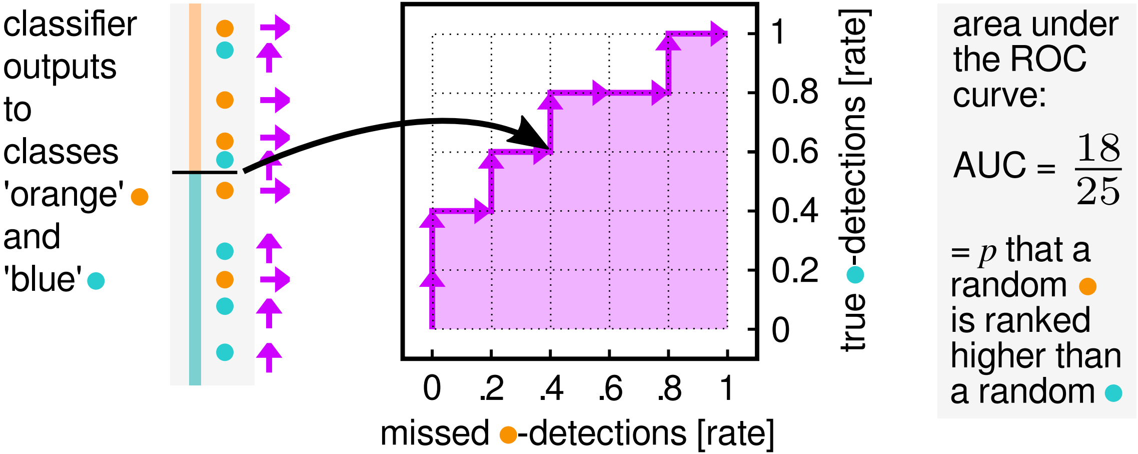
$$r^2(x,y) := \frac{N_1 \cdot N_2}{(N_1 + N_2)^2} \, \frac{(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^2}{\mathrm{var}\,\langle x_i \rangle}$$

with $\mu_1 = \mathrm{mean}\,\langle x_i \rangle_{y_i=1}$ and $\mu_2 = \mathrm{mean}\,\langle x_i \rangle_{y_i=2}$ being the class means and $N_k = |\{i \,|\, y_i = k\}|$ being the number of samples of class k.

The **signed r^2** is obtained by multiplying r^2 with the sign of $\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2$.



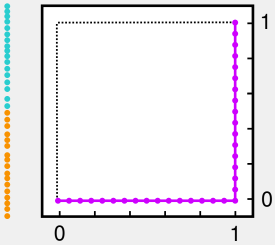
Area under the Curve (AUC) as Measure of Seperation



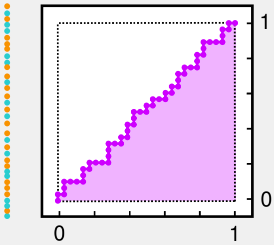
- Area Under the ROC Curve (AUC): **Measure of separation** of two univariate distributions

Examples for ROC Curves and AUC Values

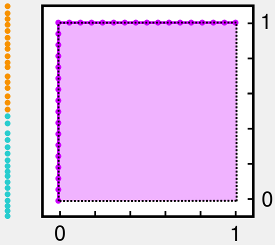
perfectly separated distributions:
AUC = 0



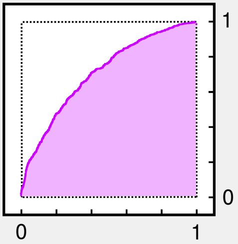
random distributions:
AUC ≈ 0.5



perfectly separated distributions:
AUC = 1



AUC value calculated from the classifier outputs of our example data
AUC ≈ 0.7



From Uni- to Multivariate Features

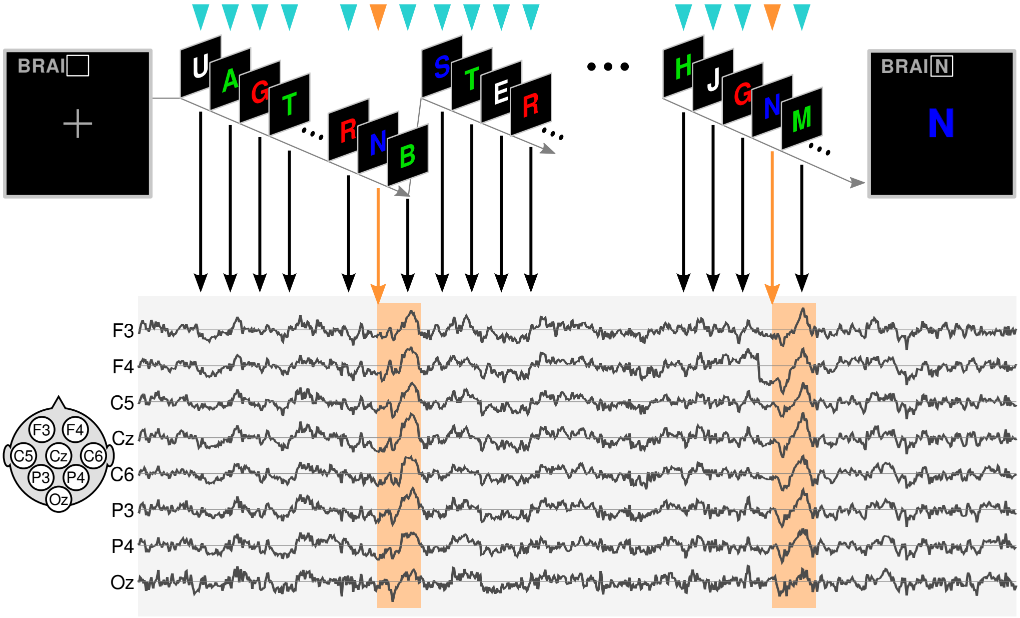
For improved classification of EEG single-trials, we need to accumulate more information in the features.

- sample ERP signals at multiple time points/intervals
  $\rightarrow$ **temporal feature**
- join signals from multiple channels
  $\rightarrow$ **spatial feature**
- do both things
  $\rightarrow$ **spatio-temporal feature**

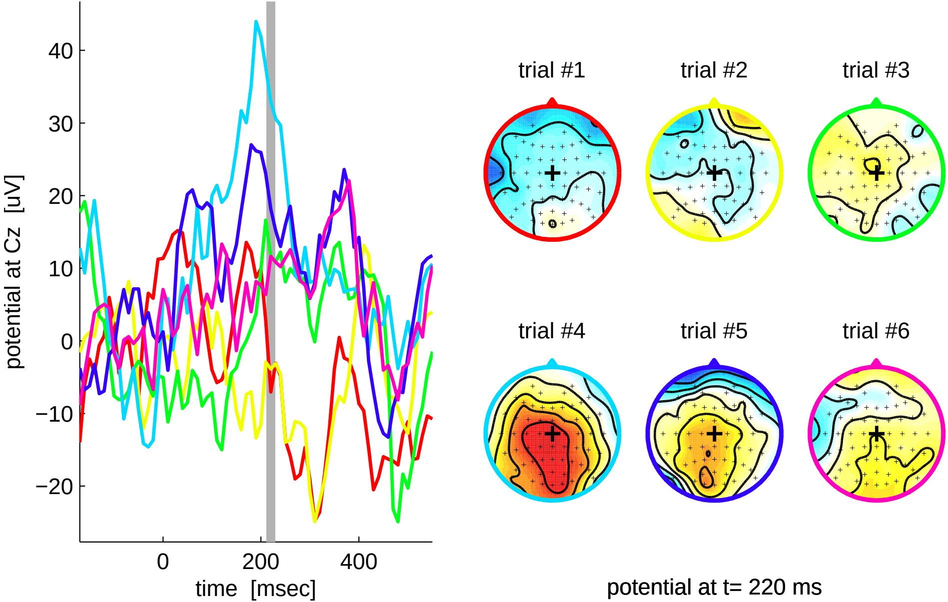
ERP Analysis of Real Data

- For making an ERP analysis, one should not rely on one channel, but record from multiple EEG sensors distributed over the scalp.
- Otherwise an interpretation of ERP components is hardly possible.
- In the next lecture, we will see, why multi-channel recordings are also favorable for classification.

Multi-channel Epochs



Now We Can Plot Topographies of Time Points of Interest



Multivariate ERP Model

We extend the ERP model of last lecture to the multivariate case (having more than one channel).

$$\mathbf{x}_k(t) = \mathbf{p}(t) + \mathbf{r}_k(t) \qquad \text{for trials } k = 1, \ldots, K$$

In the probabilistic view, $\mathbf{x}_\cdot(t)$ and $\mathbf{r}_\cdot(t)$ are both (vector valued) random variables over the trials, from which we observed K-many draws. The noise $\mathbf{r}(t)$ is iid distributed (for each fixed t!), and it is assumed to be Gaussian, say $\mathcal{N}(0, \mathbf{\Sigma}_\mathbf{r})$.

Since $\mathbf{p}(t)$ is assumed to be constant in each trial (simplified assumption), we can easily deduce the distribution of $\mathbf{x}_\cdot(t_0)$ across trials for a fixed t_0:

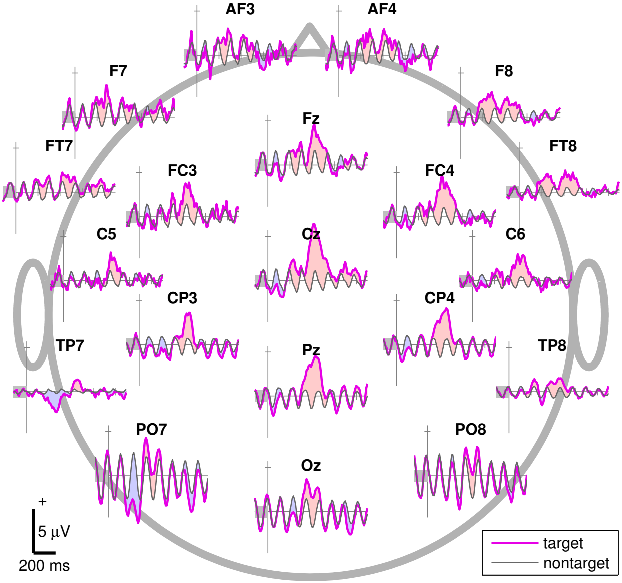
- $\boldsymbol{\mu}_\mathbf{x} = \mathbb{E}\langle \mathbf{x}_k(t_0) \rangle_k = \mathbf{p}(t_0)$
- $\mathbf{\Sigma}_\mathbf{x} = \mathrm{Cov}\,\langle \mathbf{x}_k(t_0) \rangle_k = \mathbf{\Sigma}_\mathbf{r}$

This means that the distribution of $\mathbf{x}_\cdot(t_0)$ is $\mathcal{N}(\mathbf{p}(t_0), \mathbf{\Sigma}_\mathbf{r})$.

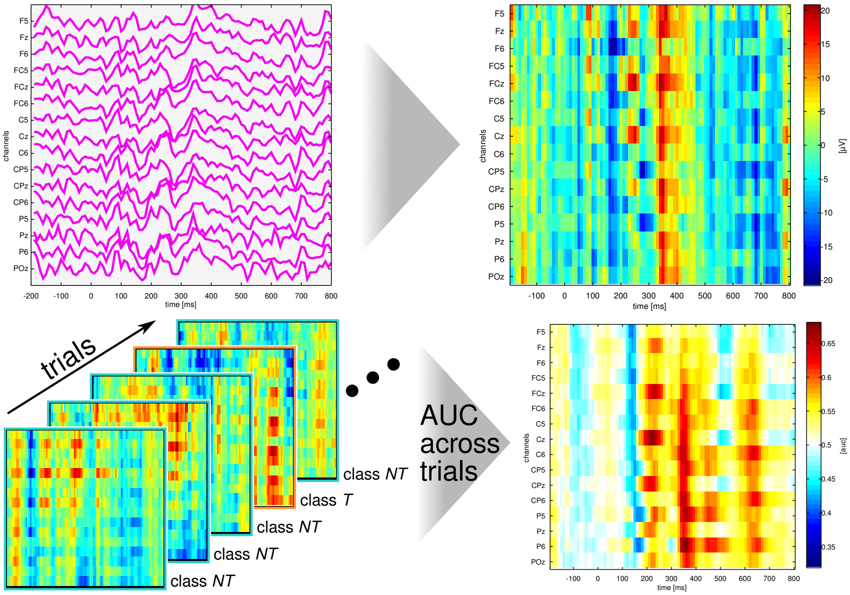
ERP Analysis of BCI Speller Data

- The next slides will show a kind of standard ERP analysis of EEG data that were recorded in a BCI experiment with a speller.
- Data will be presented in several ways to elucidate different aspects.

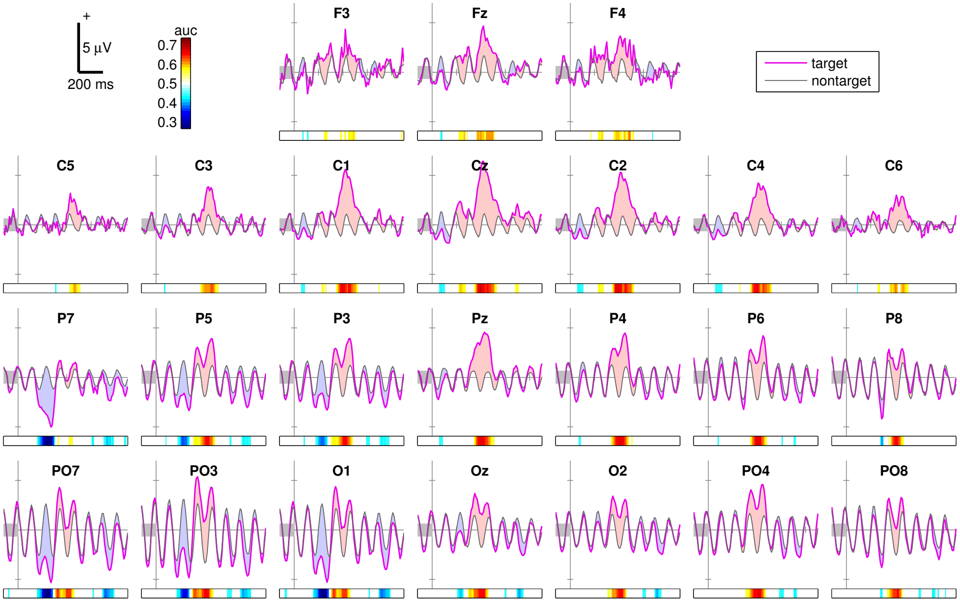
ERPs in a Head Plot



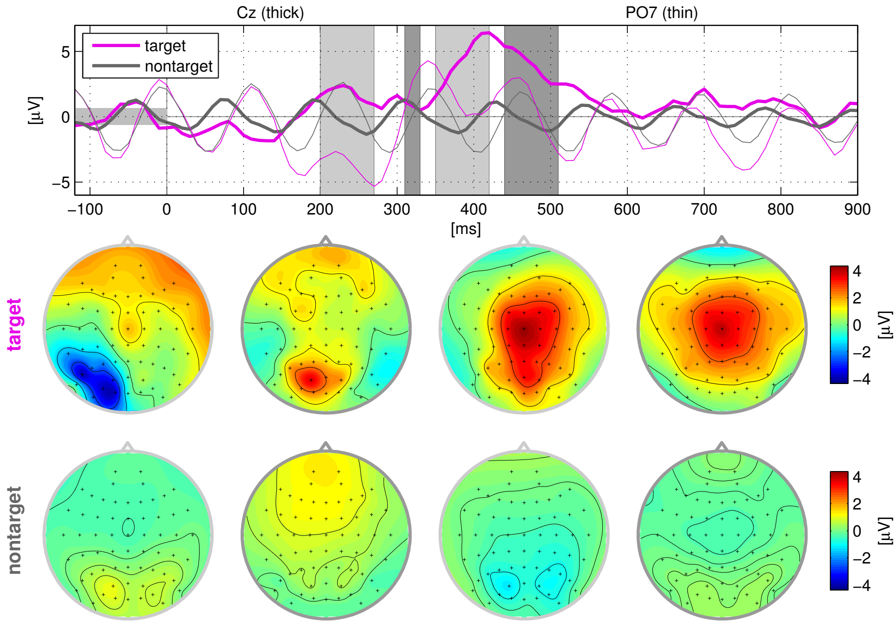
Interlude: Representation as Matrix



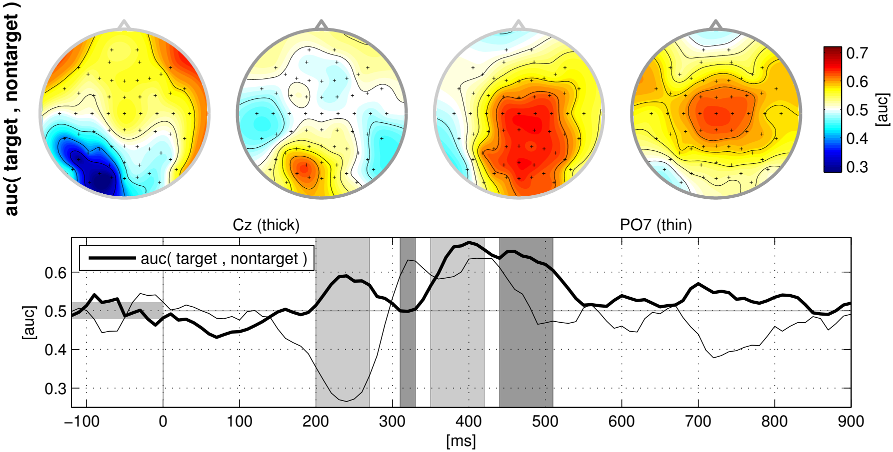
ERPs in a Grid Plot



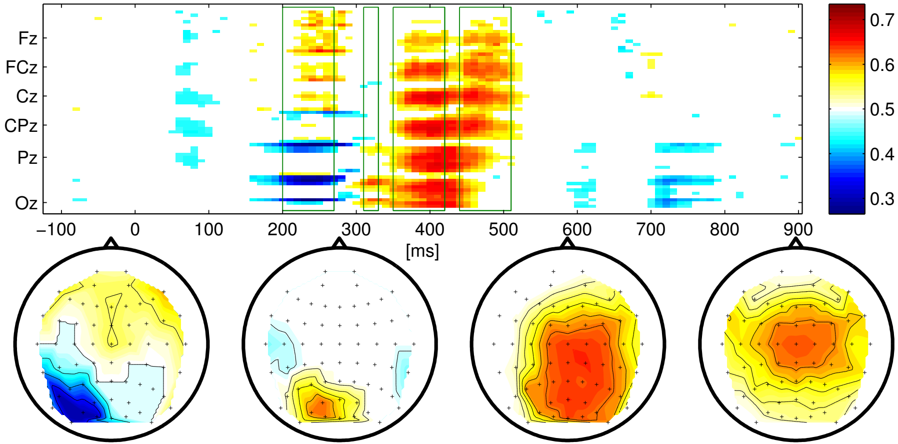
ERP Topographies



ERP Topographies



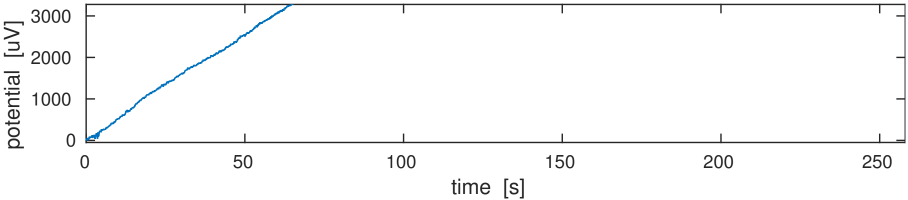
AUC Matrix: Overview of Discriminative Information



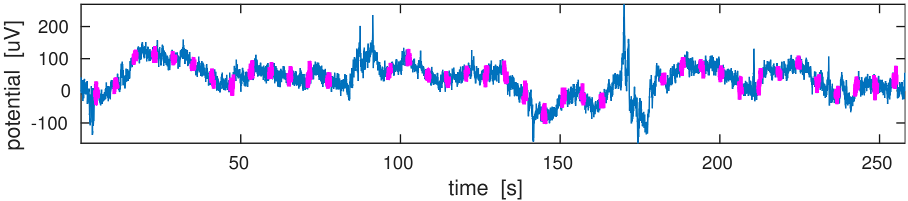
- The AUC matrix shows spatio-temporal evolution, and
- Can be used to select meaningful time intervals

DC Drifts May Raise Need for Baseline Correction

DC drifts affect raw EEG signals: Problem for digitization!

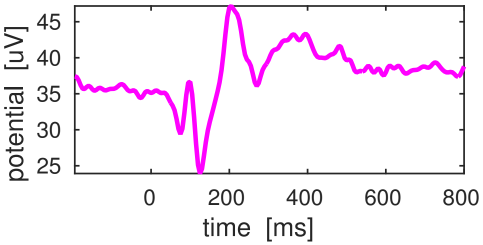


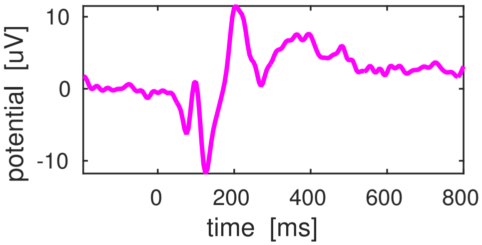
EEG amplifiers typically apply a high-pass filter prior to digitization:



A mild high-pass (e.g., time constant of 10s) still leaves DC fluctuations in the signal, with amplitudes that are much higher than those of ERPs (indicated in magenta color).

DC Drifts May Raise Need for Baseline Correction



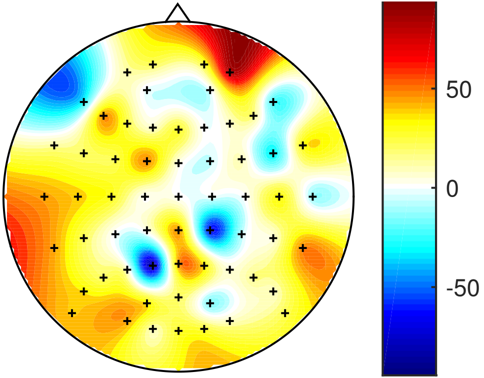


Therefore, the averaged ERPs may still have a DC offset:

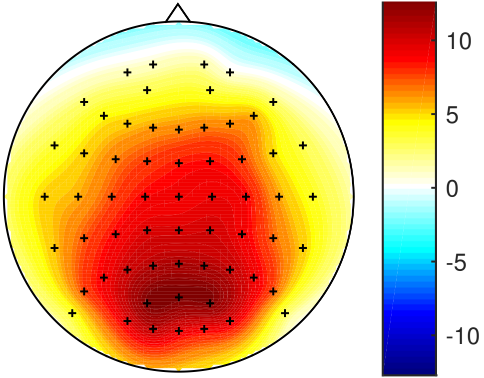
As a remedy, a so-called **baseline correction** is performed. Using a reference interval, say from -200 to 0 ms, one calculates for each single trial the average value across this interval and subtracts it from that trial.

DC Drifts May Raise Need for Baseline Correction

The adverse effect is particularly severe for scalp topographies, since each channel has its own (more or less) random DC shift:



Applying the baseline correction fixes the problem:



Lessons Learnt

After this lecture you should

- know the ERP model
  - and the decay of noise in trial averages
- have basic knowledge about ERPs (naming schemes, etc.)
- be aware of the need to perform a baseline correction for ERPs
- know the concept of an ERP-based speller
- be familiar with two measures of discriminability
- have an idea about the standard ERP analysis

References I

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